Are Smallholder Farmers Interested in Practicing Sustainable Intensification? A Choice Experiment on Farmers' Preferences for Sustainability Attributes of Maize Production in Ghana

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Abstract

While sustainable intensification has been aggressively promoted as an agricultural development strategy among smallholder farmers since the beginning of the last decade, there is a dearth of evidence on whether farmers are interested in practicing it and how much values they put to its different components. This study aims at analyzing farmers' preferences for maize production technologies within the lens of sustainable intensification. Employing a discrete choice experiment to generate over 12,500 observations, we analyze farmers' preferences with respect to diverse domains of sustainable intensification including productivity, economic, human, environmental, and social conditions. We find that farmers are favorably disposed to maize-based cropping systems that align with the domains of sustainable intensification over their current cropping practices. While farmers value all of the sustainable intensification attributes considered in the study, we observe substantial heterogeneities among them in the pooled sample and in the sub-samples between regions and gender categories. The findings suggest that sustainable intensification is not just a fad within the academic and research circles but it is something farmers are interested in and that development actions are more likely to succeed when they consider preference heterogeneities among farmers and adapt to local conditions.

Key words: sustainable intensification, maize, preferences, choice experiment, Ghana

1. Introduction

The global strategy for agricultural development has shifted from a system of putting more land under cultivation (extensification) to a system of using more inputs per unit of land while increasing resource use efficiency (intensification) since the beginning of the second half of the 20th century. This is because of the increasing scarcity of suitable land for agriculture (Godfray et al. 2010, Pingali 2012, Jayne et al. 2014). Various magnitudes of investments have been made to improve the productivity of smallholder agriculture in many countries including the establishment of international agricultural research centers mandated to generate technological spillovers for countries that underinvest in agricultural research and to build local research capacities (Pingali 2012, Hazell 2009, Lynam and Herdt 1989). These investments coupled with improvements in national institutions and policies brought radical productivity changes in the 1960s through to the 1980s among smallholder farmers in Asia and Latin America which was termed as the "Green Revolution". The Green Revolution could double the yield of staple cereals (rice, maize, and wheat) which in turn resulted in substantial reductions in food insecurity and poverty in many countries of the regions (Pingali 2012, Hazell 2009).

Nevertheless, several adverse effects of the Green Revolution approach became visible over time including groundwater depletion, soil degradation, loss of biodiversity, and water pollution (Shiva 1991, Pretty and Bharucha 2014). For instance, studies conducted in Pakistan and India showed that the agro-chemical based intensification during the Green Revolution resulted in the deterioration of soil and water qualities (Murgai et al. 2001, Ali and Byerlee 2002). Moreover, the focus on a few dominant cereals during the period adversely affected the production of nutritionally important crops contributing to malnutrition among smallholder farmers and beyond (Welch and Graham 1999, Pingali 2012). Other scholars argue that the distribution of benefit was highly skewed toward some social groups (such as male farmers and the better off ones) while others (such as women and the poor) did not benefit due to poor institutions such as insecure land rights and poorly developed markets (Hazell 2009, Pingali 2012).

These limitations brought about attitudinal change among scholars over the years, some of whom suggested a paradigm shift in the approaches of agricultural development (Lynam and Herdt 1989, Pretty 1997, Welch and Graham 1999). For instance, Lynam and Herdt (1989) suggested that the Consultative Group for International Agricultural Research (CGIAR) would incorporate the sustainability concept into its research process. Moreover, in the late 1980s the compatibility of the terms "sustainability" and "intensification" was hinted while, in the mid-1990s, the two terms were coupled to form the concept of sustainable intensification (Pretty 1997, Pretty and Bharucha 2014). Since then, the concept of sustainable intensification (SI) has continued to spread among researchers, academia, development practitioners, and others. However, it was only at the beginning of the last decade that SI began to receive widespread attention. Publications such as Royal Society (2009) and FAO (2011) played a crucial role in bringing the concept to the attention of donor organizations, international research institutes, and development organizations in the recent decade while the inclusion of the term "sustainability" in the UN development goals has made the concept even more popular.

While SI is gaining more and more popularity, there are still diverse views among scholars about what the term entails (Cook et al. 2015, Peterson and Snapp 2015). Sustainable intensification can be defined as a farming trend where more and more outputs are produced from the same area of land while negative environmental impacts are reduced, and at the same time positive ones are enhanced (Pretty et al. 2011). However, some criticize that this definition would draw attention only to the biophysical dimension of sustainability while ignoring other dimensions such as the socioeconomic elements suggesting a more comprehensive definition which includes three aspects of sustainability, namely ecological, economic, and social justice (Hayati et al. 2010, The Montpelier Panel Report 2013, Pretty and Bharucha 2014, Smith et al. 2017). More recently, Musumba et al. (2017) developed a framework known as the Sustainable Intensification Assessment Framework (SIAF) to assess sustainable intensification. SIAF builds on the prior three dimensions of intensification and has been applied in a few studies (e.g. Silberg et al. 2019, Abdul Rahman et al. 2020). It encompasses five domains of sustainable intensification namely productivity, economic, environment, human, and social. Each of the domains has specific indicators that are used as a metric across different spatial scales. The metrics for each indicator are categorized across spatial scales: field, farm, household, and landscape. The framework entails assessing an agricultural technology with respect to all five domains and revealing the trade-offs which may occur between indicators across the domains.

While SI in a broad sense entails the application of multiple technologies and management practices, there is no specific recipe to attain sustainability. In fact, components and optimal mixes vary depending on local contexts and individual farmers' preferences (Kotu et al. 2017, Kassie et al. 2013). On the other hand, the adoption of promising SI technologies remains persistently low in SSA, which partly explains the substantial yield gap of staple crops in the region. Previous *ex-post* studies documented a broad range of factors explaining the adoption and diffusion of agricultural technologies (e.g., see Feder and Umali 1993, Knowler and Bradshaw 2007 for detailed reviews, and Kassie et al. 2013, Kotu et al. 2017 for specific empirical analyses). These *ex-post* studies analyzed a wide range of farmer-related factors, including socioeconomic and institutional contexts, but did not provide much *ex-ante* insights about technology-related factors, the trade-offs farmers are willing to make for these factors, and how the factors influence farmers' adoption decisions for a portfolio of possible SI systems.

Recently, more attention has been given to technology-related factors in assessing technology adoption among smallholder farmers, especially in an *ex-ante* quantitative manner (e.g., Lunduka et al. 2012, Kassie et al. 2017, Waldman et al. 2017, Jourdain et al. 2020). However, most of these studies focus on technology attributes of a single technology, especially crop variety (e.g., Lunduka et al. 2012, Kassie et al. 2017, Waldman and Richard 2018). Yet, farmers' decisions on intensification go beyond a single technology. Moreover, most of the previous studies did not consider sustainability in their assessments of farmers' preferences for technologies or cropping systems. In this study, we used a discrete choice experiment to assess farmers' technology preferences within the lenses of sustainability, drawing on the SIAF in northern Ghana. Specifically, we assessed whether farmers' stated preferences for maize production technologies match the normative understandings of sustainable intensification among scholars within the context of SIAF considering possible preference heterogeneities among farmers. We tested two main hypothesis (1) farmers prefer to change their current practice with regards to maize production to a more sustainable practice and, (2) farmers are not homogenous in terms of preferences of technology attributes. Our approach was not normative, however. Instead, we first explored smallholder farmers' preferred technology attributes and then analyzed them using the SIAF. In so doing, we did not pre-determine technologies or specific mix or design components but focused on desirable attributes that would drive the adoption of sustainable intensification, as perceived by farmers. In line with Lynam and Herdt's (1989) suggestion on how to incorporate sustainability in agricultural research and Cassman and Grassini (2020) on the need for effective R&D prioritization on sustainable intensification, the findings of this study can be useful to set an evaluation criterion in designing and testing technologies (or a mix of technologies) for sustainable maize production among smallholder farmers in northern Ghana as well as similar socio-cultural and agroecological settings. From a methodological perspective, our study contributes to the growing application of discrete choice experiments to elicit farmers' preferences in developing country contexts and to the few studies that consider attribute-nonattendance and scale heterogeneity, which are possible sources of bias, and empirically test the performance of different discrete choice models as a basis for model selection.

The rest of the paper is organized as follows: Section 2 provides a brief description of the study areas. Section 3 describes the methodology including the design and implementation of the discrete choice experiment and the economiteric models used for data analysis. Section 4 presents the results and Section 5 discusses the findings while providing policy implications.

2. The study area

The study was conducted in three northern regions of Ghana namely, Northern Region, Upper West Region, and Upper East Region which are located in the Savannah (Figure 1). Agriculture is dominantly rain-fed in all three regions, but farmers use irrigation in pocket areas to produce vegetables. The rainfall is sometimes erratic and dry spells are common causing production shocks. Maize is the dominant crop followed by rice and pearl millet (Kotu et al. 2017). Legumes such as groundnut, soybean, and cowpea also form an important part of the farming system. Legumes are usually grown solely in rotation with cereals but in some cases, they are intercropped with cereals. Productivity is very low with the actual yield ranging from 35% (in Maize) to 55% (in Soybean) of the potential yield (MoFA 2016). As a result the living standard is generally lower than the southern part of the country manifested by high incidence of malnutrition and poverty. For instance, in 2016/17, this part of the country contributed to about two-third of the total incidence of extreme poverty in the country (GSS, 2018). The three regions are sparsely populated as compared to most regions in southern Ghana, but there are differences among them. The Northern and Upper West regions have lower and similar population densities (35 persons/km^2 and 38 persons/km^2, respectively) whereas the Upper East Region has a much larger population density (118 persons/km^2) (MoFA 2016).

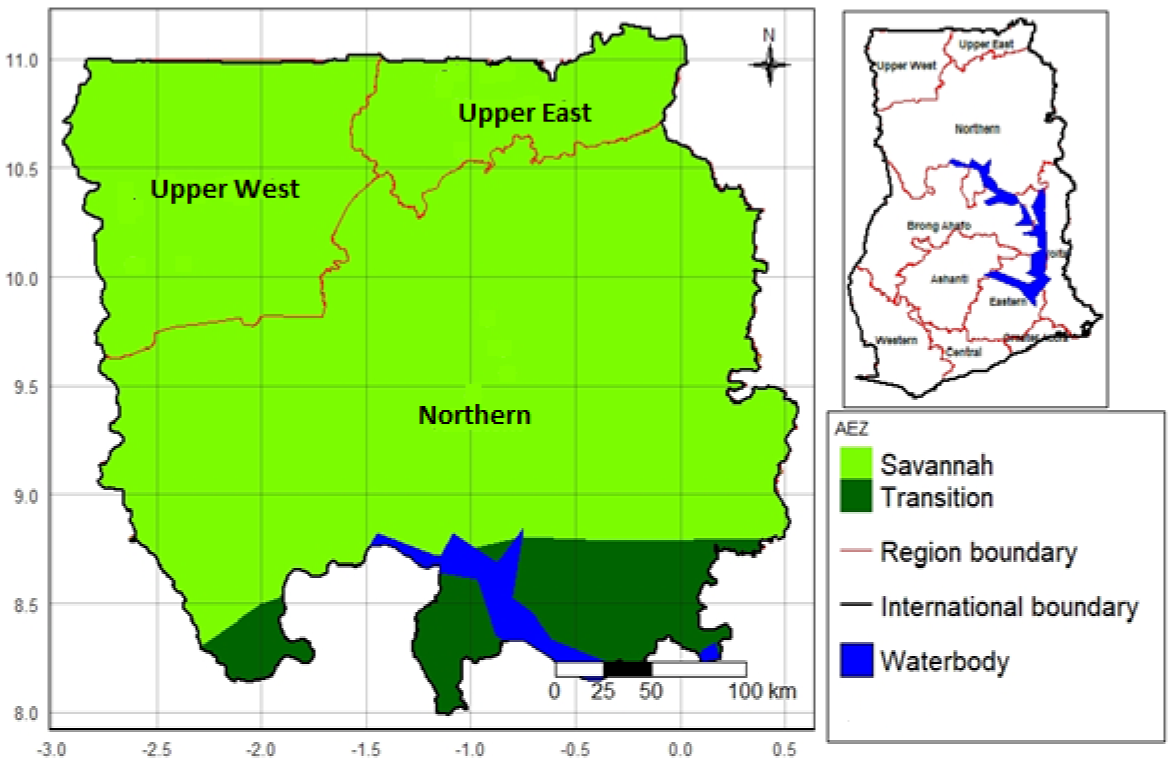

Figure 1: Location of the study regions in Ghana[1]

We used the list of farm-households interviewed during the Ghana Africa RISING baseline survey (GARBES) in 2014 as a sampling framework. GARBES followed a quasi experimental design and covered a total of 1284 households in the study regions. The detailed description of the sampling approach can be found in Tinonin et al. (2016) (also see annex A1). Due to budget constraint, we took about 55% of the GARBES samples in each community which resulted in the total sample of 700 households. The survey was conducted with the discrete choice experiment (DCE) framework[2]. We followed three steps to implement the experiment. First, we identified seven relevant attributes associated with SI of maize-based cropping systems based on a review of SI literature, expert consultations and focused group discussions with smallholder farmers within the study areas[3]. These include maize yield, legume yield, risk of crop failure,

[1] This map shows former regional administrative boundaries. Since 2020, the Northern Region has been administered under three separate regions namely, Savannah, Northern, and North East regions.

[2] DCE is a survey-based stated preference elicitation method that is applied in different fields, including agriculture, marketing, health, etc. The method is increasingly applied in ex-ante agricultural technology adoption settings to gain insights on how to better design, fine-tune and deliver demand-driven cropping systems technologies and management practices to meet the needs of smallholder farmers (e.g. Ortega et al. 2016, Waldman et al. 2018, Jourdain et al. 2020, Silberg et al. 2020).

[3] We followed these steps to select the attributes: 1) during the FGD, we requested farmers to list all attributes associated with a good maize production technology; (2) we requested them to rank the attributes using the pair ranking technique; (3) we aggregated the rankings of the attributes across different FGDs and came up with an overall ranking for the study areas; (4) we selected nine top ranked attributes; (5) the number of attributes was

soil fertility effect, nutritional value of output, labor requirement and cash requirement (Table 1). These are associated with different SI domains as described in SIAF (Musumba et al. 2017).

Table 1: Attributes and attribute levels used in the choice experiment

Attributes	SI domain*	Attribute levels
Maize yield	Productivity	8, 12, 16, 20 100kg-bags per acre
Legume yield	Productivity	0, 2, 4 100kg-bags per acre
Risk (occurrence of crop failure)	Productivity	0 in 5 years, 1 in 5 years, 2 in 5 years, 3 in 5 years
Soil fertility effect	Environment	Negative, neutral, positive
Nutritive value of output	Human condition	Low, high
Labor requirement	Economic	25, 50, 75, 100 person-days per acre
Cash requirement	Economic	150, 300, 450, 600 Ghc per acre

Note: 1Ghc ≊ 0.175 USD during the time of the survey.

*We captured the social dimention indirectly through a gender disaggregated analysis.

Second, we developed the experimental design, which entails combining the various attributes and attribute levels into different pairs of mutually exclusive hypothetical options of maize-based intensification systems (i.e. choice sets). We used a Bayesian efficient design to minimize the D-error and improve the precision of parameter estimates (Rose and Bliemer 2009). Following Scarpa et al. (2013), we first generated an orthogonal design and implemented a pilot DCE survey among 56 farmers. We used the pilot data to estimate a multinomial logit model and used the parameter estimates as Bayesian priors in generating the Bayesian efficient design. We used the Ngene software to generate the design, resulting in 12 paired choice sets (D_b-error = 0.015). The choice sets were randomly grouped into two blocks of six choice sets to minimize the cognitive burden of evaluating several choice sets (Hensher et al. 2015). We constructed 12 laminated choice cards from the choice sets, and each card consisted of two unlabeled hypothetical options of maize-based intensification systems (options A and B) and an opt-out (option C). A sample of the cards is presented in Figure 1. The opt-out option represents the current maize-based cropping practice of farmers – i.e. the 'status quo' option. Inclusion of the opt-out option helps to avoid possible bias associated with forcing farmers to choose options A and B, as farmers should have the option of retaining their current practice if it offers more utility over options A and B (Hensher et al. 2015).

reduced to seven based on expert opinion and literature; (6) the final attributes were again discussed with farmers for validation.

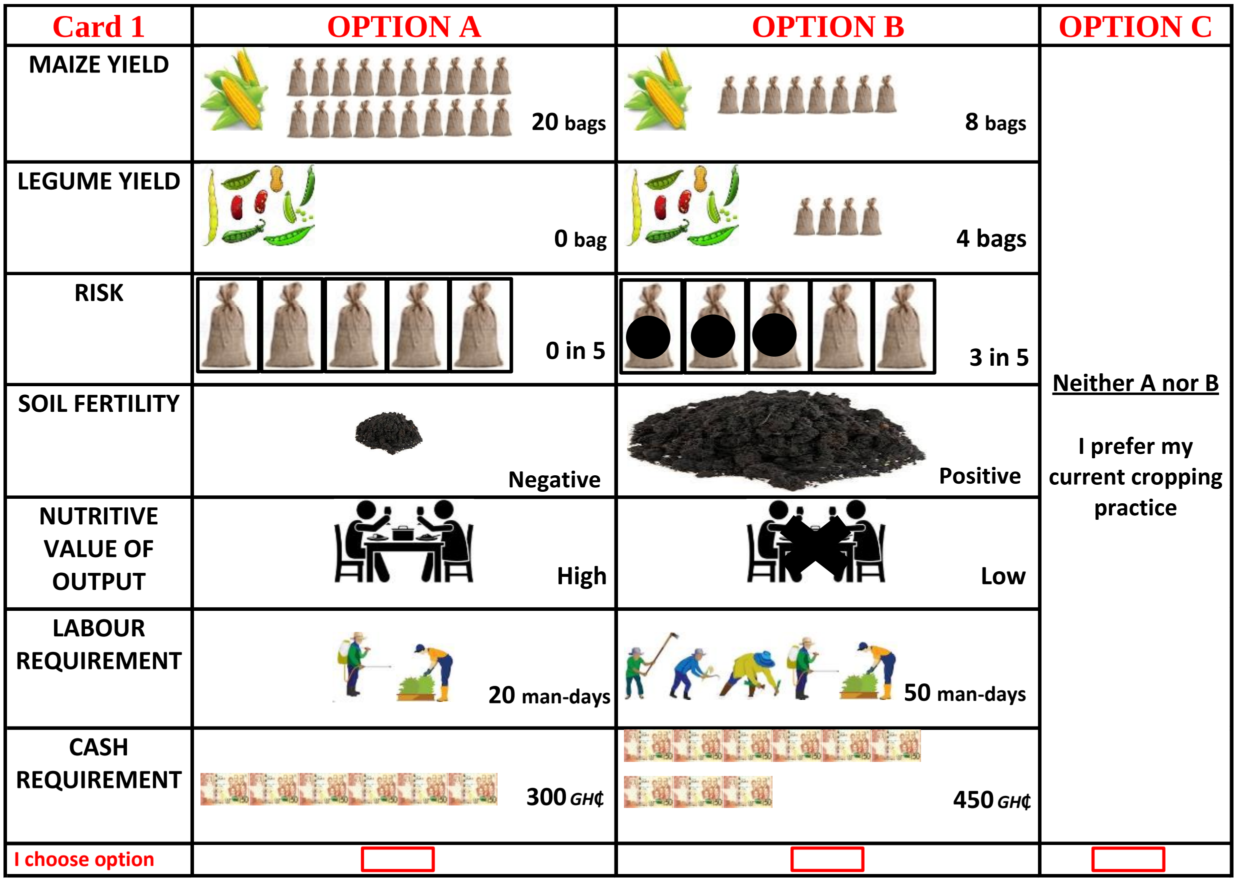

Figure 1: Example of a choice card used in the choice experiment

Third, prior to the DCE implementation, we randomly assigned the farmers to one of the two blocks of choice cards. A detailed explanation was provided to the farmers before commencing the DCE, including the purpose of the DCE, the attributes and attribute levels, and the hypothetical setting. In the DCE implementation, each farmer was presented six choice cards, one after the other in a random order to avoid ordering effects, and was asked to choose the most preferred option. The farmers evaluated the attribute levels of each option on the choice cards and freely made a choice on each of the six choice occasions. This allowed us to infer an indirect utility function based on the different attributes and attribute levels of the DCE. At the end of the DCE, the farmers were asked follow-up questions, including attributes ignored, perceptions of the choice tasks and other questions related to the attributes and the DCE in general. The survey was implemented in June 2020 via a face-to-face interview by trained enumerators and supervisors using a computer-assisted personal interviewing approach – Open Data Kit application on tablets to improve the efficiency of data collection.

3.2 Econometric analysis

Analysis of data from the DCE was based on random utility theory (McFadden 1974)**.** The theory assumes that the utility of farmer i choosing alternative j among hypothetical alternatives of maize-based intensification systems offered in choice set s is given by an indirect utility, which consists of deterministic and stochastic components expressed as:

$$U_{ijs} = ASC + \sum_{k=1}^{6} \beta_{ik} x_{ijks} + \varepsilon_{ijs} \quad i = 1, \ldots., N;\ j = 1, \ldots., J;\ s = 1, \ldots., S \tag{1}$$

Where U_{ijs} is the i^{th} farmer's indirect (latent) utility, ASC is the alternative-specific constant representing preferences for the opt-out option, $\boldsymbol{x}_{ijs}$ is a vector of seven attributes describing alternative j with associated preference parameters $\boldsymbol{\beta}_i$, the stochastic component ε_{ijs} is assumed to be independent and identically distributed (iid).

We estimated three different models namely the Multinomial Logit (MNL), the Mixed Logit (MXL) and the Latent Class Logit (LCL[4]) models. The purpose of estimating the three models was to select the best-fit model to fix our discussion as the performance of discrete choice models varies depending on the situation on the ground with regards to heterogeneities (both preference and scale) within the target population (Greene and Hensher 2003, Shen 2009). The MNL model assumes homogeneous preferences among individuals. This model has been used as a base model in many DCE studies. The MXL model is the most flexible as it allows parameters associated with the attributes to vary across individuals with a known population distribution (Greene and Hensher 2003, Train 2009). Hence it performs better than the MNL model in the context of preference heterogeneity, but it requires specification about the distribution of the parameters.

The LCL model assumes that a heterogeneous population of farmers belongs to a discrete number of latent classes, and preferences are assumed to be homogeneous within each latent class but differ across classes (Greene and Hensher 2003, Hensher et al. 2015). The choice probability is expressed as:

$$P_{ijs}|g = \prod_{s=1}^{S} \frac{\exp(\boldsymbol{\beta}'_g x_{ijs})}{\sum_{t=1}^{J} \exp(\boldsymbol{\beta}'_g x_{its})} \tag{2}$$

Where each farmer i gets assigned with a certain probability to a latent class g, $\boldsymbol{\beta}_g$ is the vector of class-specific parameter estimates.

The LCL model is more flexible than the MNL model as it captures preference heterogeneity between members of different latent classes, but it is less flexible than the MXL model as it assumes homogeneity of preferences within members of a specific latent class (Shen 2009). Thus, the selection between the MXL model and the LCL model is not straightforward but requires subtle diagnosis. Following Greene and Hensher (2003) and Shen (2009), we used various approaches to compare the two models including estimated model parameters, kernel density estimators, McFadden's (1979) overall prediction success index, and Ben-Akiva and Swait's (1986) test on non-nested choice models. Furthermore, we performed

[4] As a robustness check to LCL model, we estimated Scale Adjusted Latent Class Model (SALC). SALC accounts for scale heterogeneity, which is a potential source of bias if not addressed (Louviere and Eagle 2006; Vermunt and Magidson 2014). However, the results are not different from the standard LCL. Thus, we only report the results of the LCL to save space.

the test on non-nested choice models based on the AIC proposed by Ben-Akiva and Swait (1986). The test statistic comparing two non-nested choice models (Model 1 and Model 2) was computed as follows:

$$\rho_j^2 = 1 - \frac{L_j - K_j}{L(0)}, \ \ j = 1,2 \tag{3}$$

Where L(0) is the initial loglikelihood and Lj is the final loglikelihood of the Model j, and Kj is variables included in Model j[5]. If we assume that Model 2 is the true model, the probability that $\rho_2^2 > \rho_1^2$ is asymptotically bounded by the following equation:

$$\Pr\left(|\rho_2^2 - \rho_1^2| \geq Z\right) \leq \Phi\left(-\sqrt{-2ZL(0) + (K_1 - K_2)}\right) \tag{4}$$

Where Φ is the standard normal cumulative distribution function and Z is the difference between the fitness measure of the two models.

We estimated two models to account for attribute non-attendance (ANA), a situation where respondents do not consider all the attributes of the alternatives in making their choices (Alemu et al. 2013, Scarpa et al. 2013). This is often considered a potential source of bias to parameter estimates of DCE. Following Caputo et al. (2018), we used self-reported data on attributes ignored to estimate stated ANA models – conventional and validation ANA models, as robustness checks to the basic MXL model. In the conventional ANA model, parameters of attributes ignored (τ) by some farmers were constrained to zero in the utility function, as a way to account for ANA.

$$U_{ijs} = ASC + \sum_{k=1}^{6-\tau} \beta_{ik} x_{ijks} + \varepsilon_{ijs} \tag{5}$$

While the conventional ANA model assumes a zero-marginal utility for an ignored attribute, it is likely that respondents did not completely ignore an attribute, but rather attached a lower weight to such attribute (Hess and Hensher 2010, Alemu et al. 2013). This motivated the estimation of the validation ANA model, where two parameters were estimated for each attribute, conditional on whether the attribute was reported to be ignored or considered by farmers in making their choices (Hess and Hensher 2010, Scarpa et al. 2013; Alemu et al. 2013, Caputo et al. 2018, Oyinbo et al. 2020). This model also helped to validate the stated ANA responses of the farmers. The utility coefficients conditional on attendance were denoted with the superscript 1 (β_i^1) and those conditional on non-attendance with superscript 0 (β_i^0) in the utility function:

$$U_{ijs} = ASC + \sum_{k=1}^{6-\tau} \beta_{ik}^1 x_{ijks} + \sum_{k=1}^{\tau} \beta_{ik}^0 x_{ijks} + \varepsilon_{ijs} \tag{6}$$

[5] K_1=K_2 in our case while the two models (MXL and LCL) are functionally different.

Finally, we estimated MXL models with subsamples of farmers to explore heterogeneity in preferences and tradeoffs, with respect to two policy-relevant variables for intensification, gender and region, based on theoretical and empirical literature (Ortega et al. 2016, Waldman et al. 2017, 2018). The consideration of gender differences allowed us to partly capture the social domain of the SIAF, as described in Musumba et al. (2017). The aim of the region-based disaggregation was to capture the socio-economic, agroecological, and institutional differences among the three regions which might have shaped farmers' technology preferences.

3. Results

3.1. Descriptive results

Tables 2 shows summary statistics for farmers' characteristics by region and by gender of the household heads. The mean age was about 54 years which implies that the household heads are likely well experienced in farming. About 54% of the household heads did not have post-primary education. A typical household had about ten members out of which six were adults. About 28% of the households had institutional support such as social safety net and crop insurance. Most of them perceived that the integration of legumes into the maize production system would good for their farms in terms of enhancing soil fertility (91%), suppressing weeds (89%), and mitigating crop failure (90%). About 71% of the households encountered weather-related shocks such drought, insect pest infestations, and floods at least once in the past five cropping seasons, perhaps which resulted in crop failures. A typical farmer considered that he/she had encountered crop failure if grain yield decreased by at least 42%. This high threshold level could be associated with the fact that northern Ghana is prone to weather-related shocks. The three regions are significantly different from each other in terms of most of the variables considered in the descriptive analysis. The three regions are different with respect to most of the variables as indicated by the F and Chi-square statistics. However, comparison between household categories in terms of gender did not show much variability. In fact, male-headed and female-headed households were different only in terms of age of household head, education of household head and household size while they are similar in terms of all other variables considered in the analysis.

Table 2: Summary statistics (percent, mean, and std dev.) of farm households by region and gender

	Regions			**F value/Chi-sq. value**	**Gender of Household Head**			Total
	NR	UWR	UER		MHHs	FHHs	***t-value / Chi-sq. value***	
Age of household head	54.78 (13.51)	51.95 (14.83)	53.65 (15.61)	2.73*	52.81 (14.18)	59.79 (14.58)	-4.13***	53.61 (14.39)
HH head has no post-primary education	89%	85%	69%	25.01	83%	93%	4.75**	84%
Number of adults in a HH	6.73 (3.60)	5.40 (2.38)	4.79 (1.78)	25.09***	6.00 (3.02)	5.40 (3.31	1.66*	5.93 (3.06)
Number of children in a HH	4.6 (3.35)	3.20 (2.01)	2.05 (1.65)	46.40***	3.78 (2.79)	2.96 (3.36)	2.40**	3.68 (2.89)
Total number of HH members	11.35 (6.26)	8.60 (3.36)	6.84 (2.59)	45.86***	9.78 (5.04)	8.36 (6.17)	2.30**	9.62 (5.20)
Did your HH have crop insurance coverage in the last cropping season?	1%	2%	11%	28.06***	3%	5%	1.02	3%
Did your HH participate in contract farming in the last cropping season?	24%	5%	13%	40.76***	15%	16%	0.33	15%
Did you receive support from social safety net programs in the past 12 months?	22%	18%	61%	84.40***	27%	30%	0.29	28%

Are you aware of the potential of MLI in soil fertility improvement?	95%	88%	95%	24.21***	91%	91%	0.02	91%
Are you aware of the potential of MLI in reducing weed infestation?	89%	83%	93%	2.91	89%	89%	0.01	89%
Are you aware of the potential of MLI in mitigating total crop failure?	90%	84%	99%	19.85***	90%	93%	0.70	90%
Did your HH experience drought, flood, etc.in the past five year?	78%	55%	84%	49.50***	71%	74%	0.28	71%
How much yield loss of a HH's usual yield (%) in a normal year is perceived to be a crop failure?	44.95 (0.32)	43.43 (0.33)	29.92 (0.25)	71.28***	42.08 (13.36)	39.81 (12.94)	1.43	41.82 (13.20)
Did your HH experience a crop failure in the past five years?	96%	88%	92%	12.24***	92%	93%	0.02	92%
Are you aware of biofortified maize cultivars?	53%	22%	69%	87.46***	45%	45%	0.02	45%
Did your HH cultivate a biofortified maize in the last cropping season?	20%	12%	36%	29.14***	20%	19%	0.00	20%
Did your HH consume biofortified maize in the past 12 months?	26%	12%	42%	40.30***	23%	29%	0.07	24%
N	336	242	121		619	80		699

Notes: HH= household head, MHHs = Male-headed households, FHHs = Female-headed households, MLI = maize-legume intercropping
*,**,*** show statistical significance at 10, 5%, and 1% levels
Figures in parenthesis are standard deviations for continuous variables. t-values are for continuous variables only.

3.2. Comparison of the DCE models

The results of the three models are displayed in Table 3. The Wald Chi-square is highly significant in all the models implying that the attributes considered for the analysis taken together are important to explain the choice behavior of farmers regarding sustainable intensification of maize production. Most of the parameters show consistency in signs across the three models suggesting that any of the models can be used to explain the choice behaviors of the farmers although the robustness of the results may vary among the models. The LCL model has two latent classes having 57% of the respondents in LCL1 and the remaining in LCL2. The significance of the standard deviations in the MXL model and the differences observed between the two latent classes in the LCL model show that there exists preference heterogeneity among the target population with respect to the selected technology attributes which, in turn, implies that the MXL and the LCL models are superior to the MNL model in explaining farmers' preferences.

The estimated model parameters showed some similarities and differences between the MXL model and the LCL model. Most of the parameters showed consistent signs across the two models. Moreover, most of the significant variables in the MXL model were also significant in the LCL model. However, there were substantial differences between the two models as well. The MXL model showed that farmers were heterogenous in preferences with respect to maize yield, risk, soil fertility, nutrition, and legume yield. However, the LCL model showed that the preference of farmers in the two latent classes varied in maize yield, positive soil fertility effect, and labor requirement.

Table 3: Parameters estimates of MNL, MXL, and LCL Models

	MNL	MXL		LCL	
		Mean	Std. Dev.	LCL1	LCL2
Class probability	-	-		57%	43%
ASC	-3.6844***	-4.6763***		-3.3015***	-4.4306***
	(0.4301)	(0.5589)		(1.1640)	(0.6833)
Maize yield	0.0991***	0.1458***	0.1045***	0.2076***	0.0282
	(0.0065)	(0.0133)	(0.0148)	(0.0431)	(0.0196)
Legume yield	0.0681***	0.0897***	0.1503***	0.1276**	0.0584*
	(0.0144)	(0.0200)	(0.0463)	(0.0569)	(0.0302)

Risk	-0.2500***	-0.3826***	0.3266***	-0.3819***	-0.3162***
	(0.0243)	(0.0435)	(0.0596)	(0.1061)	(0.0495)
Positive soil fertility effect	0.6266***	0.8014***	0.5024**	-0.5259	1.2034***
	(0.0712)	(0.1084)	(0.2020)	(0.4988)	(0.1947)
Neutral soil fertility effect	0.1782**	0.2968***	0.0203	-1.5661**	1.0311***
	(0.0791)	(0.1152)	(0.0622)	(0.7805)	(0.2589)
High nutritional value	1.2570***	1.8506***	1.3257***	1.9530***	1.6909***
	(0.0896)	(0.1633)	(0.1573)	(0.6589)	(0.2276)
Labor requirement	0.0027	-0.0044	0.0160	0.0198**	-0.0116**
	(0.0020)	(0.0032)	(0.0088)	(0.0091)	(0.0047)
Cash requirement	-0.0006***	-0.0009***	0.0004	-0.0024***	-0.0006***
	(0.0001)	(0.0002)	(0.0003)	(0.0009)	(0.0002)
Wald Chi-sq (9)	1263.7***	269.6***			
Loglikelihood	-1847.5	-1805.6		-1811.0	
AIC	3713.0	3645.1		3660.1	
BIC	3780.0	3771.6		3801.4	
N	12,582	12,582		12,582	

Notes: ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively. Standard errors reported between parentheses.

The kernel density estimator of the ratios of the two models is displayed in Figures A2a-c in the annex. It shows that the distribution concentrates around one for the two hypothetical options associated with new practices (option A, option B[6]), implying that the two models are not different in terms of predicting choice probabilities (Figure A2a and A2b). However, the MXL predicted larger choice probabilities relative to LCL for the opt-out option (Figure A2c). The two models are similar in terms of the overall prediction success which is about 30%. The AIC based test as proposed by Ben-Akiva and Swait (1986) for non-nested choice model show that the MXL model has superior performance to the LCL model. Overall, taking together the outcomes of the above comparison, we focus on the results of the MXL model in our result presentation.

[6] Since our choice experiment is not labelled, the results do not have any intuitive interpretation.

The self-reported information on ANA showed that about 29% of the farmers ignored at least one of the attributes during the choice experiment suggesting that ANA should be taken care of in our analysis (see Table A3). Therefore, we ran two additional MXL models (conventional ANA and validation ANA models) to control for ANA. However, the ANA models were not found to be superior to the standard MXL models as indicated by AIC and BIC values suggesting that the standard MXL model was robust to possible ANA bias and its results are valid (see Table A4). Most of the ignored attributes in the validation model are significant which indicates that respondents did not totally ignore the attributes but likely attached lower weights in their choice behavior.

3.3. MXL results

The opt-out (ASC) coefficient is negative, which means that, on average, farmers perceived that they would derive utility from improvements in the existing maize production practices. Except the labor requirement attribute all attributes considered in the model are significant and with expected signs which shows that they are important factors in influencing farmers' decisions regaring sustainable intensification of maize production. Farmers paid much attention to the nutritional outcomes as indicated by the relatively large coefficient associated with high nutritional value. In fact, farmers gave weight to nutritional attribute about ten times more than they did to maize grain yield attribute and about twice more than they did to the soil fertility attribute. Maize grain yield received more weight than legume yield. Farmers preferred technologies having either positive or neutral soil fertility effects to technologies having negative soil fertility effects. However, a technology which had a positive soil fertility effects was valued by the farmers about four times more than a technology which had a neutral soil fertility effects. Risk of crop failure is the most important attribute which negatively affected the potential adoption of new maize production technologies. It negatively affected technology adoption choices much more than the cash requirement attribute, which suggests that while the farmers have positive preferences for high yield, they are very much interested in more stable yields. Except for labor and cash requirements, there is substantial heterogeneity in preferences for the attributes.

We conditioned the choice probabilities with a region-specific variable to explore spatial heterogeneity of farmer's preferences for technology attributes. The results show that there are considerable similarities and differences among the three regions in terms of preferences for SI technologies (Table 4). High labor requirement reduced the chance of maize production technology to be chosen by farmers in NR. However, high labor requirement was desirable in UER while this attribute was not an important evaluation criterion in UWR. The positive coefficient associated with labor requirement in UER could be due to the relatively high population density in this region which may have induced labor abundance (MoFA 2016). Farmers in NR and UWR preferred technologies having positive or neutral effects on soil fertility while farmers in UER give attention only to those technologies having positive effects on soil fertility. While legume yield was associated with positive preferences in all regions, the relative importance of legumes over maize was lower in NR than UWR as well as UER. Again, the difference could be associated with the heterogeneity between the regions in terms of soil fertility and other agroecological factors. While nutritional value of output received the highest weight among all other attributes in all regions, farmers in NR attached relatively higher value on nutrition as compared to farmers in UWR and UER. While farmers in all regions preferred technologies producing stable yields, those in UWR were more willing to accept yield reduction for more stable yield compared to farmers in NR and UER. Across the three regions, cash requirement had a significant negative effect on the adoption of new maize-based intensification options, which is consistent with *a priori* expectations. The estimated standard deviations show that farmers in NR were the most heterogeneous in preferences; they had heterogeneous preferences with respect to all, but the neutral soil fertility effect attribute. On the contrary, farmers in UER showed homogenous preferences with respect to most of the attributes. Farmers in the UWR had modest preference heterogeneity.

Table 4: Parameters estimates of MXL model, by region

	Northern		Upper West		Upper East	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
ASC	-4.455***		-18.627***		-2.836*	
	(0.746)		(0.487)		(1.504)	
Maize yield	0.157***	0.102***	0.116***	0.113***	0.206***	0.077*
	(0.024)	(0.027)	(0.019)	(0.021)	(0.034)	(0.046)
Legume yield	0.039	0.170**	0.104***	0.136*	0.195***	0.094
	(0.030)	(0.086)	(0.032)	(0.071)	(0.051)	(0.145)
Risk	-0.427***	0.382***	-0.358***	0.317***	-0.422***	0.253
	(0.079)	(0.104)	(0.063)	(0.090)	(0.121)	(0.172)

Positive soil fertility effect	0.641*** (0.173)	0.625* (0.323)	0.938*** (0.170)	0.277 (0.344)	0.885*** (0.304)	0.645 (0.407)
Neutral soil fertility effect	0.400** (0.193)	0.086 (0.145)	0.430** (0.179)	-0.202 (0.626)	-0.234 (0.332)	0.049 (0.091)
High nutritional value	2.157*** (0.297)	1.666*** (0.300)	1.541*** (0.217)	-0.945*** (0.268)	1.592*** (0.424)	0.779* (0.463)
Labor requirement	-0.014** (0.006)	0.027** (0.011)	-0.004 (0.005)	-0.001 (0.004)	0.014* (0.008)	0.002 (0.007)
Cash requirement	-0.001** (0.0003)	0.0004 (0.0007)	-0.001*** (0.0003)	-0.0003 (0.0009)	-0.002*** (0.001)	0.0002 (0.0003)
Wald Chi-sq (9)	96.84***		3149.88		51.97***	
Loglikelihood	-875.65		-642.43		-254.44	
AIC	1785.3		1318.85		542.88	
BIC	1899.3		1427.30		639.54	
N	6048		4356		2178	

Notes:
Asterisks ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively.
Standard errors reported between parentheses.

We also estimated the MXL model for male-headed and female-headed households separately to capture gender differences in terms of technology preferences (Table 5). Most of the attributes are consistent with earlier results in terms of statistical significance and directions of relationship with farmers' choice behavior. The ASC is negative and significant for both male-headed and female-headed households which indicates that both categories of households would improve their utility by changing their existing cropping practices to cropping practices that aligns with the domains of sustainable intensification. There are preference heterogeneities among farmers within each household category, but with preference heterogeneity for more attributes in the case of male-headed households. While both categories of households showed strong positive preferences for maize yield and legume yield, the relative importance of legumes over maize was much higher in female-headed households. Male-headed households showed strong positive preferences for technologies having either positive or neutral soil fertility effects while female-headed households showed weakly significant but positive preferences for technologies having positive soil fertility effects only. Female-headed households paid more value to the nutrition outcomes of a technology than to the soil fertility outcomes and this was supported by the much higher weight they placed on legumes relative to the male-headed households. Both groups required higher yield and lower risk to adopt new maize-based intensification options. However, in terms of maize yield-risk tradeoffs, the male-headed households were more willing to accept a yield reduction for a more stable yield compared with the female-headed households, i.e. they required a much higher expected maize yield to adopt new sustainable intensification options associated with more risk. This result is quite surprising given that male-headed households are often considered as having more access and control over resources, which allows them to take on more risky investments.

Table 5: Parameters estimates of MXL, by gender category

	Male-headed households		Female-headed households	
	Mean	Std. Dev.	Mean	Std. Dev.
ASC	-4.6786*** (0.6247)		-5.7409** (2.5110)	
Maize yield	0.1440*** (0.0154)	0.1043*** (0.0170)	0.2432*** (0.0897)	0.1490 (0.0944)
Legume yield	0.0877*** (0.0212)	-0.1047 (0.0641)	0.1694 (0.1038)	0.5624** (0.2665)
Risk	-0.3889*** (0.0507)	-0.3278*** (0.0707)	-0.4972** (0.2278)	0.5099** (0.2341)
Positive soil fertility effect	0.8219*** (0.1166)	0.4349* (0.2329)	0.8858* (0.5057)	1.3768 (0.8941)
Neutral soil fertility effect	0.3768*** (0.1266)	0.0362 (0.1458)	-0.3618 (0.5055)	-0.2420 (1.1395)
High nutritional value	1.8220*** (0.1740)	1.3161*** (0.1757)	2.3709*** (0.7102)	-1.5858* (0.9290)
Labor requirement	-0.0045 (0.0035)	-0.0201** (0.0087)	-0.0097 (0.0119)	-0.0054 (0.0068)
Cash requirement	-0.0006*** (0.0002)	0.0001 (0.0003)	-0.0044*** (0.0014)	-0.0006 (0.0010)
Wald Chi-sq (9)	204.92***		17.24**	
Loglikelihood	-1600.59		-192.21	
AIC	3235.19		418.41	
BIC	3359.60		508.05	

N	11,142	1,440

Notes: ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively.
Standard errors reported between parentheses.

4. Discussion and policy implications of findings

Our findings show that farmers are favorably disposed to maize-based cropping systems that align with the domains of sustainable intensification over their current cropping practices. This lends credence to the emerging research, development and policy interests on sustainable intensification of cropping systems. Farmers place value on high yield, a component of the productivity domain. Their choices are consistent across gender categories and regions, and are also consistent with the findings of empirical studies that show that maize farmers strongly consider high yield technological trait in considering adoption of new technologies (Ortega et al. 2016, Kassie et al. 2017, Silberg et al. 2020). This could be because of the relatively low average actual maize yield as compared to the potential yield (MoFA 2016). Farmers place high value on legume yield as indicated by the positive coefficients corresponding to the legume yield attribute. This could be because legumes are commonly integrated into the maize system in Northern Ghana and hence the findings suggest yield improvement strategies should consider both crops. However, our results show that farmers place higher value on maize yield than legume yield which is consistent with the findings of Ortega et al. (2016) and Waldman et al. (2017), but at variance with the findings of Silberg et al. (2020).

Declining soil fertility is a major bottleneck of crop production in Ghana (Bationo et al 2018). The government of Ghana has been subsidizing industrial fertilizers for many years so that farmers increase application rates. However, the subsidy program has not been effective and much of the production growth still comes from expansion of farmland (Fearon et al. 2015). This has raised sustainability concerns on the subsidy programs. The findings of this study suggests that a more integrated approach could bring a more sustainable outcome in maize production than focusing merely on chemical fertilizers. The integration of legumes into the maize system, as preferred by the farmers, can have both productivity and environmental implications raising the sustainability scores of the farming ecology. Our result supports earlier studies which show that farmers consider soil fertility as an important factor in their adoption decisions (Waldman et al. 2017, Jourdain et al. 2020, Silberg et al. 2020). There is slight difference between women and men in terms of the soil fertility attribute. Women showed interest in technologies having positive soil fertility effects while male farmers showed interest in technologies havening at least neutral soil fertility effect. This could be because women in general cultivate less fertile plots and hence, they may perceive that only technologies having positive soil fertility effects would be useful in their context.

We found that farmers place high value to technologies which reduce risk of crop failure. This could be because of the high vulnerability of farming systems in Northern Ghana to weather-related shocks. Studies in Northern Ghana show that integrating legumes into maize cultivation through intercropping or rotation with legumes can reduce the risk of encountering crop failure and financial losses (Kermah et al. 2017, Abdul Rahman, et al. 2020). This is because of the difference between legumes and maize in terms of stress tolerance levels and the synergy created between them in terms of agroecological processes such as soil nitrogen fixation and soil moisture conservation (Kermah et al. 2017, Silberg et al. 2019, Vanlauwe et al. 2019). Risk can also be reduced through genetic means by introducing stress-tolerant varieties and early maturing varieties. In Ghana, varieties such as Omankwa, Aburohemaa, and Abontem are characterized as drought- and striga-tolerant[7] (DTMA 2013), but they are not widely cultivated (Poku et al. 2018). Furthermore, the introduction of weather-index crop insurance schemes which are tailored to smallholder farmers can enhance the risk-aversion level of the farmers thereby enhancing their willingness to try diverse technologies.

We included two indicators to capture the economic dimension of sustainability: i.e. cash requirement and labor requirement. Farmers were sensitive to cash outlays and, *ceteris paribus*, select technologies having lower cash requirement. This was expected given the severe cash constraint among most smallholder farmers and their limited access to institutional credit (Awunyo-Vitor and Al-Hassan 2014, Denkyirah et al. 2016). Labor requirement of the technology did not affect the preferences of farmers for intensification technologies in the pooled sample. However, a closer look at the data showed that preferences varied by region which could be because of the difference in labor availability between regions. In Northern and Upper West regions, which are characterized by low population density, farmers were interested in labor-saving technologies. On the contrary, in Upper East Region, where population density is relatively high and labor is cheaply available, farmers were willing to adopt labor-intensive technologies. This shows that sustainability concerns with respect to labor are location specific, which can inform better targeting of labor-intensive (or saving) technologies to meet the needs of various locations.

Positive nutritional gain was an aspect that farmers strongly considered in technology adoption. While both women and men prefer technologies with positive nutritional outcome, women placed higher value to such technologies than men which could be related to their responsibility to feed their households. Diversification of cropping systems is one way of addressing the nutritional needs of smallholder farmers. Studies in northern Ghana indicate that households who have diversified their cropping system enjoy better nutrition than those who exercise specialized cropping (Signorelli et al. 2017, Bellon et al. 2020). This suggests that promoting diversified production systems in lieu of specialized ones can be a suitable policy intervention to enhance nutrition. Biofortification is another way of improving household nutrition and can be suitable for households who have limited land access to meet their nutrition needs through crop diversification. In Ghana, quality protein maize (QPM) is produced but not all households have access to the seeds. Our analysis showed that about 45% of the sample farmers were aware of biofortified maize but only about 20% were aware of cultivating it. Therefore, improving the access of the farmers to seeds of existing QPM varieties and introducing more biofortified varieties is necessary to improve nutrition among the smallholder farmers.

[7] Obatanpa variety is susceptible to *Striga* (DTMA 2013).

In summary, the following messages can be drawn from our findings. First, sustainable intensification is not just a fad within the academic and research circles, but it is something that farmers are interested in. Second, while farmers value all of the sustainable intensification attributes considered in the study, they are not homogennuous in their preferences but vary in the pooled sample and in the sub-samples between regions and gender categories suggesting that development actions are more likely to succeed when they consider such heterogeneities and adapt to local conditions. Third, it is useful to adopt multidimensional assessment frameworks to identify best-fitting sustainable intensification practices in lieu of the conventional technology assessment approaches which emphasize a single attribute at a time. In this regard, the SIAF can be used to set evaluation criteria in designing and testing technologies (or a mix of technologies) having high probabilities of adoption among smallholder farmers.

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References

Abdul Rahman, N., Larbi, A., Kotu, B., Asante, M.O, Akakpo, D.B, Mellon-Bedi, S., Hoeschle-Zeledon, I. (2020). Maize-legume strip-cropping effect on productivity, income and income risk of farmers in Northern Ghana. *Agronomy Journal*, 1-12. https://doi.org/10.1002/agj2.20536

Alemu, M.H., Mørkbak, M.R., Olsen, S.B., Jensen, C.L. (2013). Attending to the Reasons for Attribute Non-attendance in Choice Experiments. *Environmental and Resource Economics*, 54, 333–359. DOI 10.1007/s10640-012-9597-8

Ali, M. and Byerlee, D. 2002. Productivity growth and resource degradation in Pakistan’s Punjab: A decomposition Analysis. *Economic Development and Cultural Change*, 50(4), 839–863.

Awunyo-Vitor, D. and Alhassan, R.M. (2014). Credit constraints and smallholder maize production in Ghana. *International Journal of Agricultural Resources, Governance and Ecology*, 10(3), 239-256.

Bationo, A., Fening, J.O., Kwaw, A. (2018). Assessment of Soil Fertility Status and Integrated Soil Fertility Management in Ghana. In: A. Bationo, D. Ngaradoum, S. Youl, F. Lompo, J.O. Fening (Eds.), *Improving the Profitability, Sustainability and Efficiency of Nutrients Through Site Specific Fertilizer Recommendations in West Africa Agro-Ecosystems* (pp 93-138). Springer. DOI: 10.1007/978-3-319-58789-9_7

Bellon, M.R., Kotu, B.H., Azzarri, C., Caracciolo, F. (2020). To diversify or not to diversify, that is the question. Pursuing agricultural development for smallholder farmers in marginal areas of Ghana. *World Development*, 125, 104682. https://doi.org/10.1016/j.worlddev.2019.104682

Caputo, V., Van Loo, E.J., Scarpa, R., Nayga, R.M., Verbeke, W. (2018). Comparing serial, and choice task stated and inferred attribute non-attendance methods in food choice experiments. *Journal of Agricultural Economics*, 69, 35-57.

Cook, S., Silici, L., Adolph, B., Walker, S. (2015). Sustainable intensification revisited. IIED Issue Paper.

Denkyirah, E.K., Abdul Aziz, A., Denkyirah, E.K, Nketiah, O.O., Okoffo, E.D. (2016). Access to credit and constraint analysis: the case of smallholder rice farmers in Ghana. *Journal of Agricultural Studies*, 4(2), 53-72.

DTMA (Drought Tolerant Maize for Africa) (2013). New Drought Tolerant Maize Varieties for Ghana, A Quarterly Bulletin of the Drought Tolerant Maize for Africa Project, Vol. 2 No. 1, Mar 2013

FAO. (2011). Save and grow: a policymaker's guide to the sustainable intensification of smallholder crop production. Rome: FAO.

Fearon, J., Adraki, P.K., Boateng, V.F. (2015). Fertilizer Subsidy Programme in Ghana: Evidence of Performance after Six Years of Implementation. *Journal of Biology, Agriculture and Healthcare*, 5(21), 100-107.

Feder, G., Umali, D., 1993. The adoption of agricultural innovations: a review. *Technological Forecasting and Social Change*, 43, 215–239.

Godfray, H. C., Beddington, J.R., Crute, I. R., Haddad, L., Lawrence, D. Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C. (2010). Food Security: The Challenge of Feeding 9 Billion People. *Science*, 327, 12 FEBRUARY.

Greene, W. and Hensher, D. A (2003). Latent Class Model for Discrete Choice Analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, 37, 681–698.

Hayati, D., Ranjbar, Z., and Karami, E. (2010). Measuring Agricultural Sustainability. In E. Lichtfouse (ed.), *Biodiversity, Biofuels, Agroforestry and Conservation Agriculture, Sustainable Agriculture Reviews* (pp 73-100).

Hazell, P. B. R. (2009). The Asian green revolution, Discussion Paper #00911. Washington, DC: International Food Policy Research Institute.

Hensher, D.A., Rose, J.M., Greene, W.H. (2015). *Applied Choice Analysis* (2nd ed.). Cambridge: Cambridge University Press.

Hess, S. & Hensher, D.A. (2010). Using conditioning on observed choices to retrieve individual-specific attribute processing strategies. *Transportation Research Part B: Methodological*, 44(6), 781-790.

Jayne, T. S., Chamberlin, J., Headey, D. D. (2014). Land pressures, the evolution of farming systems, and development strategies in Africa: A synthesis. *Food Policy*, 48, 1–17.

Jourdain, D., Lairez, J., Striffler, B., Affholder, F. (2020). Farmers' preference for cropping systems and the development of sustainable intensification: A choice experiment approach. *Review of Agricultural, Food & Environmental Studies*, https://doi.org/10.1007/s41130-020-00100-4

Kassie, G.T., Abdulai, A., Greene, W.H., Shiferaw, B., Abate, T., Tarekegn, A., Sutcliffe, C. (2017). Modeling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in Rural Zimbabwe. *World Development*, 94, 465–477.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., Mekuria, M. (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change*, 80, 525–540.

Kermah, M., Franke, A.C., Adjei-Nsiah, S., Ahiabor, B.D.K., Abaidoo, R.C., Giller, K.E. (2017). Maize-grain legume intercropping for enhanced resource use efficiency and crop productivity in the Guinea savanna of northern Ghana. *Field Crops Research*, 213, 38–50.

Knowler, D., Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: a review and synthesis of recent research. *Food Policy*, 32, 25–48.

Kotu, B.H., Alene, A., Manyong, V., Hoeschle-Zeledon, I., Larbi, A. (2017). Adoption and impacts of sustainable intensification practices in Ghana. *International Journal of Agricultural Sustainability*, 15(5), 539-554.

Lunduka, R., Fisher, M., Snapp, S. (2012). Could farmer interest in a diversity of seed attributes explain adoption plateaus for modern maize varieties in Malawi? *Food Policy*, 37, 504–510.

Lynam, J.K. and Herdt, R.W. (1989). Sense and Sustainability: Sustainability as an Objective in International Agricultural Research. *Agricultural Economics*, 3, 381-398

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.) *Frontiers in Econometrics* (Chapter 4). New York: Academic Press.

MoFA (Ministry of Food and Agriculture), Agriculture in Ghana: Facts and Figures, October 2016. http://mofa.gov.gh/site/wp-content/uploads/2018/05/Agric%20in%20Ghana%20F&F%202016_Final.pdf.)

Murgai, R., Ali, M., Byerlee, D. (2001). Productivity growth and sustainability in post-green revolution agriculture: The case of the Indian and Pakistan Punjabs. *World Bank Research Observer,* 16(2), 199–218.

Musumba, M., Grabowski, P., Palm, C., Snapp, S. (2017). *Guide for the Sustainable Intensification Assessment Framework*. Kansas State University: Manhattan, NY, USA.

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 Development*, 87, 139-151.

Oyinbo, O., Chamberlin, J., Maertens, M. (2020). Design of Digital Agricultural Extension Tools: Perspectives from Extension Agents in Nigeria. *Journal of Agricultural Economics*, 71(3), 798–815.

Peterson, B. and Snapp, S.(2015). What is sustainable intensification? Views from experts. *Land Use Policy*, 46, 1–10.

Pingali, P.L. (2012). Green Revolution: Impacts, limits, and the path ahead. *PNAS,* 109(31), 12302–12308.

Poku, A., Birner, R., Gupta, S. (2018). Why do maize farmers in Ghana have a limited choice of improved seed varieties? An assessment of the governance challenges in seed supply. *Food Security*, 10, 27–46.

Pretty, J. (1997). The sustainable intensification of agriculture. *Natural Resources Forum*, 21, 247–256.

Pretty, J. and Bharucha, Z.P. (2014). Sustainable intensification in agricultural systems. *Annals of Botany*, 1-26.

Rose, J.M. and Bliemer, M.C.J. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews*, 29, 587-617.

Royal Society (2009). Reaping the benefits: science and the sustainable intensification of global agriculture. London: The Royal Society.

Scarpa, R., Zanoli, R., Bruschi, V., Naspetti, S. (2013). Inferred and stated attribute non-attendance in food choice experiments. *American Journal of Agricultural Economics*, 95(1), 165-180.

Shen, J. (2009). Latent class model or mixed logit model? A comparison by transport mode choice data. Applied Economics, 41(22), 2915-2924.

Shiva, V. (1991). The green revolution in the Punjab. *The Ecologist*, 21(2), 57–60.

Signorelli, S., Haile, B., Kotu, B. (2017). Exploring the Agriculture-Nutrition Linkage in Northern Ghana. IFPRI Discussion Paper #01697, December 2017.

Silberg, T.R., Richardson, R.B., Lopez, M.C. (2020). Maize farmer preferences for intercropping systems to reduce Striga in Malawi. *Food Security*, 12, 269-283.

Silberg, T.R., Chimonyo, V.G.P., Richardson, R.B., Snapp, S.S., Renner, K. (2019). Legume diversification and weed management in African cereal-based systems. *Agricultural Systems*, 174, 83-94.

Smith, A., Snapp, S., Chikowo, R., Thorne, P., Bekunda, M., Glover, J. (2017). Measuring sustainable intensification in smallholder agroecosystems: A Review. *Global Food Security*, 12, 127–138.

The Montpellier Panel (2013). Sustainable intensification: A new paradigm for African agriculture (A 2013 Montpelier Panel Report). London.

Tinonin, C., Azzarri, C., Haile, B., Comanescu, M., Roberts, C., Signorelli, S. (2016). Africa RISING baseline evaluation survey (ARBES) report for Ghana. Washington, DC: International Food Policy Research Institute.

Train, K.E. (2009). *Discrete choice methods with simulation* (2nd ed.). New York: Cambridge University Press.

Vanlauwe, B. Hungria, M., Kanampiu, F. & Giller, K.E. (2019). The role of legumes in the sustainable intensification of African smallholder agriculture: Lessons learnt and challenges for the future. *Agriculture, Ecosystems & Environment*, 284(15), 106583.

Waldman, K.B. and Richardson, R.B. (2018). Confronting tradeoffs between agricultural ecosystem services and adaptation to climate change in Mali. *Ecological Economics*, 150, 184-193.

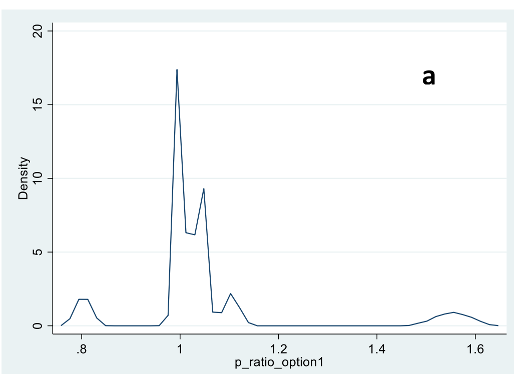
Waldman, K.B., Ortega, D.L., Richardson, R.B. & Snapp, S.S. (2017). Estimating demand for perennial pigeon pea in Malawi using choice experiments. *Ecological Economics*, 131, 222-230.

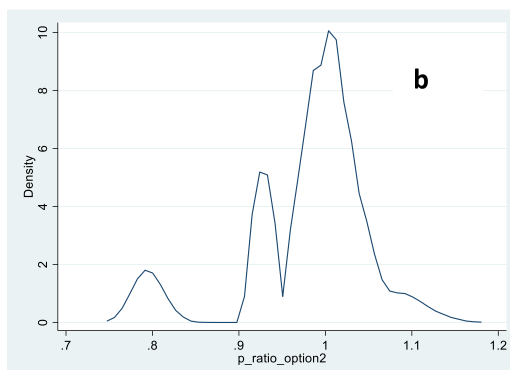
Welch R.M., Graham R.D. (1999). A new paradigm for world agriculture: productive, sustainable, nutritious, healthful food systems. *Field Crops Research*, 60,1-10.

Annexes

A1. Sampling of Ghana Africa RISING Baseline Survey

The survey was conducted in May 2014 to establish a baseline for the project "Africa, Research In Sustainable Intensification for the Next Generation-Africa RISING". The survey covered 25 project intervention communities and 25 control communities. Sampling of the survey households took two steps. The first step of the sampling strategy consisted in the stratification of the communities on the lines of the development domains at the district level. The second stage randomly selected households within each community. In particular, a constant number of control households (n=20) was randomly selected in each of the 25 control communities for a total of 500 control households. In regard to the 25 intervention communities, the sampling strategy was to randomly select a constant number of households (n=8) not directly benefitting from AR intervention and a constant number of 6 households interested in joining the program in 2014. Finally, 462 households that directly benefitted from the AR 2013 program were selected to participate to the survey. The total sample size 1,284 households, of which 784 households in intervention communities and 500 in control communities. Household interviews were guided by a structured questionnaire which was administered using Computer Assisted Personal Interviewing (CAPI) supported by Survey CTO software on tablets.





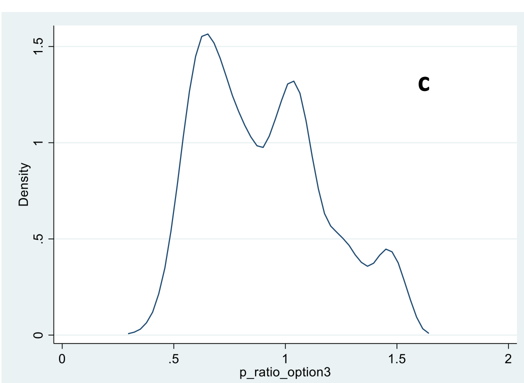


Figure A2: Kernel density estimator of the ratios of LCL and MXL models for three technology options

Table A3: Self-reported information on ANA – serial stated ANA

No. of ignored attributes	Share of farmers (%)	Ignored attributes	Share of farmers (%)
0	71.2	Maize yield	0.1
1	13.5	Legume yield	9.3
2	10.0	Risk	12.4
3	4.9	Soil fertility effect	2.6
4	0.1	Nutritional value	2.9
5	0.3	Labor requirement	17.3
		Cash requirement	5.4

Table A4: Results of MXL models showing farmers' preferences for sustainable intensification controlling for ANA

	Conventional ANA		Validation ANA			
			Considered attributes		Ignored attributes	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
ASC	-4.516***		-4.696***			
	(0.540)		(0.564)			
Maize yield	0.138***	0.010***	0.147***	0.104***	0.356***	0.0001
	(0.011)	(0.014)	(0.013)	(0.015)	(0.042)	(0.002)
Legume yield	0.082***	0.141***	0.085***	0.151***	0.160**	0.137
	(0.020)	(0.047)	(0.021)	(0.049)	(0.069)	(0.199)
Risk	-0.390***	0.323***	-0.416***	0.349***	-0.182**	0.028
	(0.041)	(0.058)	(0.047)	(0.061)	(0.078)	(0.115)
Positive soil fertility effect	0.852***	0.511***	0.856***	0.586***	-0.104	0.020
	(0.106)	(0.174)	(0.111)	(0.168)	(0.452)	(0.025)
Neutral soil fertility effect	0.327***	0.036	0.337***	0.054	0.013	0.024
	(0.114)	(0.209)	(0.121)	(0.099)	(0.419)	(0.032)
High nutritional value	1.906***	1.326***	1.862***	1.323***	2.153***	1.714**
	(0.152)	(0.150)	(0.161)	(0.158)	(0.784)	(0.869)
Labor requirement	-0.004	0.0001	-0.005	0.002	-0.001	0.037***
	(0.003)	(0.003)	(0.003)	(0.016)	(0.007)	(0.010)

Cash requirement	-0.001***	-0.001***	0.002**
	(0.0002)	(0.0002)	(0.0007)
N	12582	12582	
Log likelihood	-1811.96	-1790.03	
AIC	3655.90	3642.10	
BIC	3757.40	3838.60	

Notes: *** and ** denote any variable significant at 1% and 5% levels respectively.
Standard errors reported between parentheses.