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Smallholder farmers' preferences for sustainable intensification attributes in maize production: Evidence from 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 value 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 from a sample of about 700 maize-producing households in northern Ghana, we analyze farmers' preferences with respect to five 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 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 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. The findings can be used 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, supporting national and regional level efforts for R&D prioritization.

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 (Lynam & Herdt, 1989; Hazell, 2009; Pingali, 2012). 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 doubled 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 (Hazell, 2009; Pingali, 2012).

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 & Bharucha, 2014). For instance, studies conducted in Pakistan and India showed that the agro-chemical based

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intensification during the Green Revolution period resulted in the deterioration of soil and water qualities (Murgai et al., 2001; Ali & Byerlee, 2002). Moreover, the focus on a few dominant cereals during that period adversely affected the production of nutritionally important crops contributing to malnutrition among smallholder farmers and beyond (Welch & Graham, 1999; Pingali, 2012). Other scholars argue that the distribution of benefits 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 & Herdt, 1989; Pretty, 1997; Welch & Graham, 1999). For instance, Lynam and Herdt (1989) suggested that the Consultative Group for International Agricultural Research (CGIAR) should incorporate the sustainability concept into its research process. Moreover, in the late 1980s the compatibility of the terms "sustainability" and "intensification" was hinted at while in the mid-1990s, the two terms were coupled to form the concept of sustainable intensification (Pretty, 1997; Pretty & 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 how the term should be defined (Cook et al., 2015; Peterson & Snapp, 2015). Pretty, Toulmin and Williams (2011) defines sustainable intensification 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. However, some scholars 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 & Bharucha, 2014; Smith et al., 2017). More recently, Musumba et al. (2017) developed a framework known as Sustainable Intensification Assessment Framework (SIAF) to incorporate multiple dimensions to the concept of SI. Specifically, the SIAF identifies five domains to define and assess sustainable intensification namely productivity, economic, environment, human, and social. Applied in a few studies (e.g., Silberg et al., 2019; Abdul Rahman et al., 2020), it entails assessing an agricultural technology with respect to the five domains while revealing possible inter-domain trade-offs.

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 (Kassie et al., 2013; Kotu et al., 2017). Meanwhile, the adoption of promising SI technologies remains persistently low in Sub-Saharan Africa, 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 & Umali, 1993; Knowler & 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, applying *ex-ante* quantitative approaches (e.g., Lunduka et al., 2012; Kassie et al., 2017; Waldman et al., 2017; Jourdain et al., 2020). However, some of these studies focus on single technology attributes such as grain yield of a crop variety while farmers' decisions on intensification may be based on a combination of multiple attributes (Lunduka et al., 2012; Kassie et al., 2017; Waldman & Richard, 2018). Moreover, most of the previous studies did not explicitly link farmers' technology preferences to sustainability (Kassie et al., 2017; Waldman et al., 2017; Silberg et al., 2020). In this study, we used a discrete choice experiment to assess the preferences of smallholder farmers for technology attributes within the lenses of sustainability, drawing on the SIAF in northern Ghana. Specifically, we assessed whether the stated preferences of smallholder farmers for maize production technologies match the normative understandings of sustainable intensification among scholars within the context of the SIAF considering possible preference heterogeneities among farmers. Our approach was not normative, however. Instead, we first explored farmers' preferred maize production technology attributes and then analyzed them using the SIAF. In so doing, we did not pre-determine the technologies or a specific mix or design components but focused on desirable attributes that would drive the adoption of SI as perceived by farmers. In line with the suggestion of Lynam and Herdt (1989) on how to incorporate sustainability in agricultural research and that of Cassman and Grassini (2020) on the need for effective R&D prioritization on SI, 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 in similar socio-cultural and agroecological settings. From a methodological perspective, our study contributes to the growing application of discrete choice experiments (DCE) to elicit farmers' preferences in the context of a developing country. Specifically, we complement the few DCE studies in Sub-Saharan Africa that consider both attribute-nonattendance and scale heterogeneity, which are possible sources of bias in discrete choice models (e.g., Oyinbo et al., 2019; Teferi et al., 2020). Moreover, our study adds to the few DCE studies that empirically test the performance of different discrete choice models as a basis for model selection (e.g., Greene and Hensher, 2003; Shen, 2009).

The rest of the paper is organized as follows. Section 2 describes the methodology including the study areas, the sampling procedure, elicitation of farmers' preferences, and the econometric models used for data analysis. Section 3 presents descriptive and model results. Section 4 discusses the findings while providing policy implications.

2. Methods

2.1. The study areas and sampling

The study was conducted in three regions located in the northern part of Ghana constituting the Savannah agroecology (Fig. 1). Agriculture is dominantly rain-fed in all three regions, but farmers use irrigation in pocket areas to produce vegetables. The rainfall is erratic and dry spells are common causing production shocks. The soils in northern Ghana have low fertility with organic matter con-

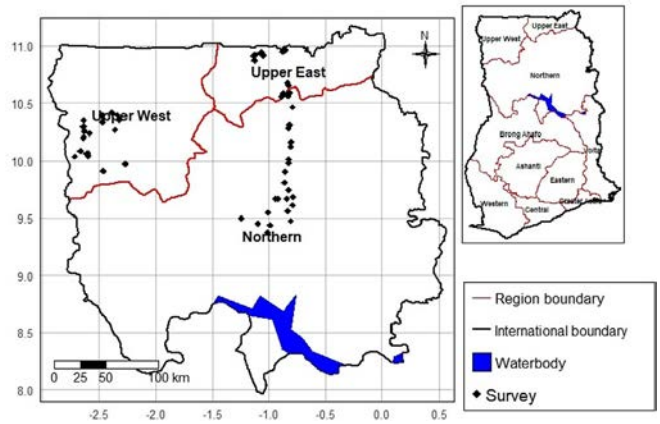

Fig. 1. Location of the study regions in Ghana (This map shows former regional administrative boundaries. Since 2020, the Northern Region has been administered under three separate regions namely, Savannah, Northern, and North East regions.)

tent of < 20 g/kg, total nitrogen of < 2 g/kg and available phosphorus of < 10 mg/kg (Tetteh et al., 2016). 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. The degree of commercialization is low, and farmers depend mainly on their own production for consumption (Martey et al., 2017; Bellon et al. 2020). Productivity is very low with the actual yield ranging from 35% of the potential yield in the case of maize to 55% of the potential yield in the case of soybean (MoFA, 2016). As a result, living conditions of farm households in northern Ghana are generally lower than those in the southern part of the country as manifested by high incidence of malnutrition and poverty. For instance, in 2016/17, the three regions considered in this study contributed to about two-third of the total incidence of extreme poverty in Ghana (GSS, 2018). The three regions are sparsely populated as compared to most regions in southern Ghana, but there are differences among them as well. 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 population density of 118 persons/km^2 (MoFA, 2016).

We anchored our sampling on the Ghana Africa RISING Baseline Survey (GARBES) which was conducted in May 2014 to establish a baseline for the Africa RISING Project in Ghana. GARBES followed a quasi-randomized control trial design and targeted smallholder farmers in the three regions selected for this study. The sample consisted of 615 households in 20 communities in the Northern Region, 447 households in 20 communities in the Upper West Region, and 222 households in 10 communities in the Upper East Region. The detailed description of GARBES can be found in Tinonin et al. (2016). In this study, we considered only 700 households (i.e., about 55%) in the GARBES sample due to budget constraint. We followed two steps to select the study households. First, we adjusted the sample sizes at community level to 55% of the GARBES sample. Second, we selected the sample households based on the systematic random sampling technique.

2.2. Elicitation of farmers' preferences

We used the discrete choice experiment (DCE) framework to elicit farmers' preferences for the attributes of maize-based intensification systems, and the tradeoffs among the attributes to better understand the drivers of adoption decisions. 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 studies to gain insights on how to better design, fine-tune and deliver demand-driven cropping 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).

We followed three steps to implement the DCE. First, we identified ten attributes associated with SI in maize-based cropping systems which farmers would like to implement. We did this through focus group discussions (FGDs) with farmers in the three regions which involved listings and pairwise rankings of the attributes[1]. Considering the difficulty of implementing a DCE with many attributes, we reduced the list to seven based on discussions made with maize breeders and agronomists at Savanna Agricultural Research Institute and International Institute of Tropical Agriculture in Ghana and literature review. The final list of attributes included maize yield, legume yield, risk of crop failure, soil fertility effect, nutritional value of output, labor requirement, and cash requirement[2] (Table 1). These attributes cover the productivity, economic, environment, and human domains of sustainable intensification as conceptualized in the SIAF (Musumba et al., 2017). The social domain was indirectly captured through a disaggregated analysis by the gender of household heads[3].

The first attribute 'maize yield' is defined as the average grain yield that a farmer expects to realize in a maize-based cropping system that he/she chooses to practice. The second attribute, 'legume yield', refers to an average grain legume (e.g., cowpea, soybean, and groundnut) yield that is expected from a maize-legume intercropping system that a farmer chooses to implement. The attribute levels of maize and legume yields were carefully selected based on a possible range of attainable maize and legume yields in northern Ghana[4]. The third attribute, 'risk or probability of crop failure', refers to the probability that a farmer will experience crop failure over a cropping period of five years due to drought, pests, and/or diseases. This is described by four levels, namely no crop failure in five years (0 in 5), one crop failure in five years (1 in 5), two crop failures in five years (2 in 5), and three crop failures in five years (3 in 5).

The fourth attribute, 'soil fertility effect', captures the effects of the maize-based cropping system that a farmer chooses to practice on his/her plot's soil quality, i.e., the environmental footprints of intensification. This is defined by three levels, including negative, neutral, and positive effects on soil fertility. The fifth attribute, 'nutritional value of output', describes the nutritional quality of the crop output expected from the maize-based cropping system that a farmer chooses to practice, i.e., how nutritionally rich in protein and/or micronutrients. This is defined by two levels, namely low and high nutritional value. The attribute level "low nutritional

[1] We conducted two FGDs with male farmers and two FGDs with female farmers in each region. A total of 110 farmers participated in the FGDs with an average of 9 people per FGD.

[2] The excluded attributes are net income, tolerance to pests, and financial benefit for women.

[3] We had difficulty in identifying a technology attribute that can properly capture the social aspect of sustainable intensification. The indicators listed in the SIAF document under the social domain such as social equity, social cohesion, and collective action are not inherently technology attributes, but they are society attributes. We explored the literature on this issue, but we found no work within our reach that has directly captured the social domain in preference list within the DCE framework. Thus, we considered the use of gender to capture it indirectly through a disaggregated analysis by the gender of household heads. We thought that the gender-based analysis would be the best option we could use to capture the social domain, but we do not claim that this is the only way to deal with it.

[4] While the integration of legumes in cereal-based cropping systems offers multiple benefits (Silberg et al., 2019, Vanlauwe et al., 2019), the inclusion of an attribute level "0 bag" allows us to capture sole maize cropping, which is still common among smallholders.

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

Attributes	SI domain	Attribute levels
Maize yield	Productivity	8, 12, 16, 20 100 kg-bags per acre
Legume yield	Productivity	0, 2, 4 100 kg-bags per acre
Risk	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.

value" represents a crop output without a legume and/or a biofortified maize while the "high nutritional value" typifies a crop output that includes a legume and/or a biofortified maize such as a quality protein maize.

The sixth attribute, 'labor requirement', describes the average amount of labor that a farmer needs from the point of planting operations to the point of threshing in a maize-based cropping system that he/she chooses to practice. The last attribute, 'cash requirement', represents the average amount of money that a farmer needs to invest on commercial inputs (seeds, fertilizer, and pesticides) in a maize-based cropping system that he/she chooses to practice. Data on labor and investment in commercial inputs during the 2019 cropping season, as obtained through a pilot survey and focus group discussions informed the range of the attribute levels for labor and cash requirements.

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 in February 2020. 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 Fig. 2. 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).

Finally, prior to the DCE implementation, we randomly assigned the sample households 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 (See Text A in the appendix for the details). In the DCE implementation, we presented each farmer six choice cards one after the other in a random order to avoid ordering effects and asked him/her 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 and supervision.

2.3. 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:

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

where U_{ijs} is the ith farmer's indirect (latent) utility, ASC is the alternative-specific constant representing preferences for the opt-out option, x_{ijs} is a vector of seven attributes describing alternative j with associated preference parameters β_i, the stochastic component $\varepsilon_{ijs}$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[5]) 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 & 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 & 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 & Hensher, 2003; Hensher et al., 2015). The choice probability is expressed as:

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

where each farmer i gets assigned with a certain probability to a latent class g, β_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

[5] As a robustness check to the LCL model, we estimated a Scale Adjusted Latent Class Model (SALC) as applied in empirical DCE studies (e.g., Oyinbo et al., 2019, Teferi et al., 2020). SALC accounts for scale heterogeneity, which is a potential source of bias if not addressed (Louviere & Eagle, 2006; Vermunt & Magidson, 2014). However, the results are not notably different from the standard LCL. Thus, we only report the results of the LCL to save space.

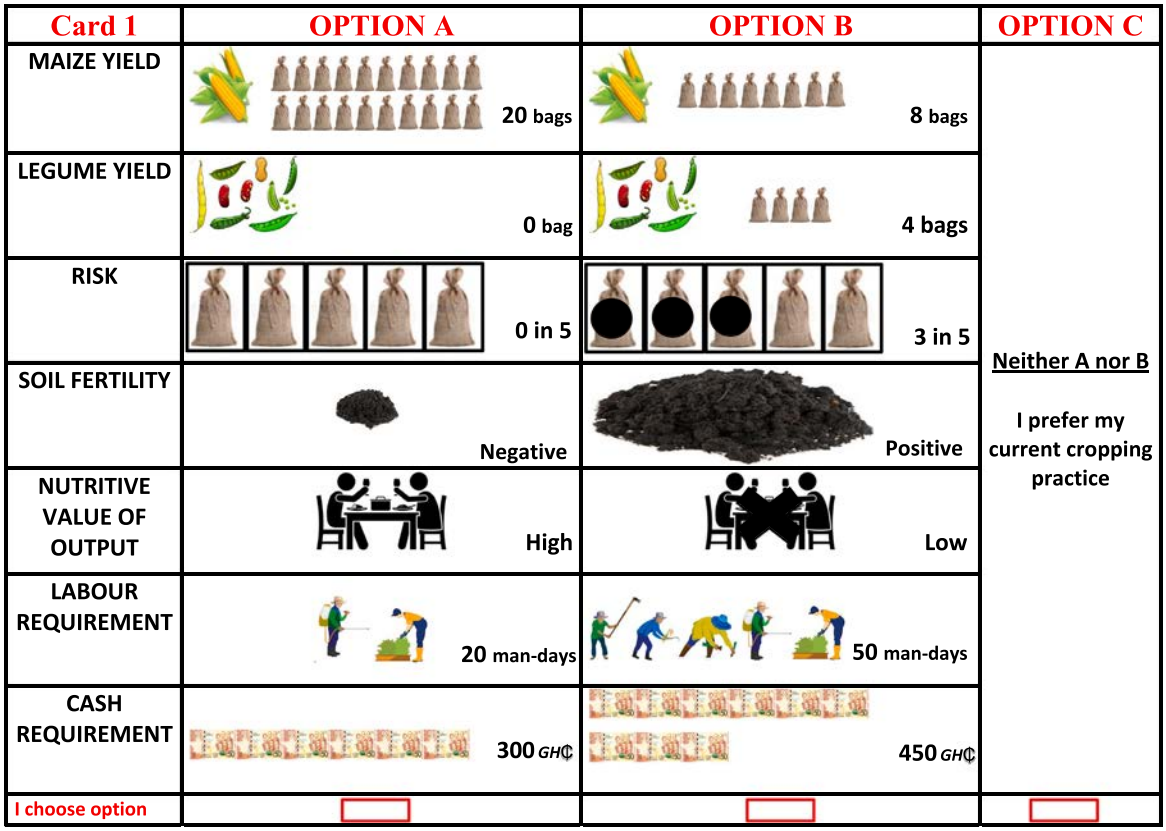

Fig. 2. Example of a choice card used in the choice experiment.

diagnosis. Following Greene & Hensher, 2003; Shen, 2009Greene and Hensher, 2003, we used various approaches to compare the two models including estimated model parameters, kernel density estimators, and McFadden's (1979) overall prediction success index. Furthermore, we performed the test on non-nested choice models based on the AIC as proposed by Ben-Akiva & Swait (1986). The test statistic comparing two non-nested choice models (Model 1 and Model 2) was computed as follows:

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

where L(0) is the initial log-likelihood and Lj is the final log-likelihood of the Model j, and Kj is variables included in Model j[6]. 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:

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

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

We applied 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 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 do not completely ignore an attribute, but rather attach a lower weight to such attribute (Hess & 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 & 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:

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

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 the 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-

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

based disaggregation was to capture the socio-economic, agroecological, and institutional differences among the three regions which might have shaped farmers' technology preferences[7].

3. Results

3.1. Descriptive results

Table 2 shows summary statistics for farmers' characteristics by region and by gender of the household heads. Columns 1–7 show the results of the sub-samples while Column 8 refers to the pooled sample. The mean age was about 54 years which, in the context of farming-dependent communities such as those in northern Ghana, implies that the household heads are likely well experienced in farming. About 84% of the household heads did not have post-primary education. A typical household had about ten members out of which six were adults (i.e., >14 years). Only about 3% of the farmers had access to crop insurance while about 15% of the farmers were engaged in contract farming. About 28% of the households received support from social safety nets programs (cash transfer or in-kind/food transfer). Most of the respondents perceived that the integration of legumes into the maize production system would be good for their farms in terms of enhancing soil fertility (91%), suppressing weeds (89%), and mitigating cereal crop failure (90%). About 71% of the households encountered weather-related shocks such as drought, insect pest infestations, and floods at least once within the five years before the survey time, which perhaps resulted in crop failures. A typical farmer considered that he/she had encountered crop failure if grain yield decreased by 42% or more as compared to that of the normal year. This high threshold level could be associated with the high incidence of weather-related shocks in northern Ghana. There are significant differences among the three regions with regards to most of the variables considered in the descriptive analysis including, among others, farmers' demographic characteristics, farmers' access to crop insurance, farmers' perceptions on benefits of integrating legumes into maize production, farmers' exposure to weather-related shocks, and farmers' awareness of biofortified maize caltivars (Table 2, Columns 1–4). The comparison between household categories in terms of gender did not show much variability (Table 2, Columns 5–7). In fact, male-headed and female-headed households were different only with respect to some demographic variables. However, the result should be taken cautiously due to the small sample size of the female-headed households which may have affected the robustness of the statistical comparison.

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 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 with 57% of the respondents falling 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 sample farmers 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 in our study setting.

The estimated parameters of the MXL model and the LCL model show some similarities and differences. Most of the parameters show consistent signs across the two models. Moreover, most of the significant variables in the MXL model are also significant in the LCL model. However, there are notable differences between these two models as well. The MXL model reveals that the sample farmers are heterogeneous in preferences with respect to maize yield, risk, soil fertility, nutrition, and legume yield attributes. However, the LCL model shows that the farmers vary in preferences with respect to maize yield, positive soil fertility effect, and labor requirement attributes.

The kernel density estimator of the ratios of the two models is displayed in Figs. A1a-c in the appendix. It shows that the distribution concentrates around one for the two hypothetical options associated with new practices (option A, option B[8]), implying that the two models are not different in their abilities to predict choice probabilities (Figs. A1a and A1b). However, the MXL predicts larger choice probabilities relative to LCL for the opt-out option (Fig. A1c). The two models are similar in terms of the overall prediction success which is about 30%. The AIC-based test for non-nested choice model as proposed by Ben-Akiva and Swait (1986) shows that the MXL model has superior performance over 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.

The self-reported information on ANA shows 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 A1). However, the two additional MXL models (conventional ANA and validation ANA models) we ran to control for ANA were not superior to the standard MXL models as indicated by AIC and BIC values suggesting that the standard MXL model is robust to possible ANA bias and its results are valid (see Table A2). 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 (Table 3). With the exception of labor requirement, all attributes considered in the model are significant and with expected signs which shows that they are important factors in influencing farmers' decisions regarding 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 the nutritional attribute about ten times more than they did to maize grain yield attribute

[7] To improve the interpretation of the results by region and gender, as the parameter estimates cannot be meaningfully compared due to differences in scale (Greene & Hensher, 2003; Lancsar, Fiebig & Hole, 2017), we calculated marginal rates of substitution in terms of cash requirement (a direct monetary attribute). These correspond to the amount farmers are willing to pay for an increase in utility of another sustainable intensification attribute.

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

Table 2
Summary statistics of farm households by region and gender.

	Regions				Gender of household head			Total
	NR	UWR	UER	F value/ Chi-sq. value	MHHs	FHHs	*t*-value/ Chi-sq. value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age of household head	54.78	51.95	53.65	2.73*	52.81	59.79	−4.13***	53.61
	(13.51)	(14.83)	(15.61)		(14.18)	(14.58)		(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	5.40	4.79	25.09***	6.00	5.40	1.66*	5.93
	(3.60)	(2.38)	(1.78)		(3.02)	(3.31)		(3.06)
Number of children in a HH	4.60	3.20	2.05	46.40***	3.78	2.96	2.40**	3.68
	(3.35)	(2.01)	(1.65)		(2.79)	(3.36)		(2.89)
Total number of HH members	11.35	8.60	6.84	45.86***	9.78	8.36	2.30**	9.62
	(6.26)	(3.36)	(2.59)		(5.04)	(6.17)		(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	43.43	29.92	71.28***	42.08	39.81	1.43	41.82
	(0.32)	(0.33)	(0.25)		(13.36)	(12.94)		(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, NR = Northern region, UWR = Upper west region, UER = Upper east region, MHHs = Male-headed households, FHHs = Female-headed households, MLI = maize-legume intercropping,
***, **, and * denote statistical significances at 1%, 5%, and 10% levels, respectively.
Figures in parentheses are standard deviations for continuous variables, *t*-values are for continuous variables only.

Table 3
Parameter estimates of MNL, MXL, and LCL models.

	MNL	MXL		LCL	
		Mean	Std. Dev.	LC1	LC2
	(1)	(2)	(3)	(4)	(5)
Class probability	–	–		57%	43%
ASC	−3.684***	−4.676***		−3.302***	−4.431***
	(0.430)	(0.559)		(1.164)	(0.683)
Maize yield	0.099***	0.146***	0.105***	0.208***	0.028
	(0.007)	(0.013)	(0.015)	(0.043)	(0.020)
Legume yield	0.068***	0.090***	0.150***	0.128**	0.058*
	(0.014)	(0.020)	(0.046)	(0.057)	(0.030)
Risk	−0.250***	−0.383***	0.327***	−0.382***	−0.316***
	(0.024)	(0.044)	(0.060)	(0.106)	(0.050)
Positive soil fertility effect[1]	0.627***	0.801***	0.502**	−0.526	1.203***
	(0.071)	(0.108)	(0.202)	(0.499)	(0.195)
Neutral soil fertility effect[1]	0.178**	0.297***	0.020	−1.566**	1.031***
	(0.079)	(0.115)	(0.062)	(0.781)	(0.259)
High nutritional value[2]	1.257***	1.851***	1.326***	1.953***	1.691***
	(0.090)	(0.163)	(0.157)	(0.659)	(0.228)
Labor requirement	0.003	−0.004	0.016	0.020**	−0.012**
	(0.002)	(0.003)	(0.009)	(0.009)	(0.005)
Cash requirement	−0.001***	−0.001***	0.000	−0.002***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Wald Chi-sq (9)	1263.7***	269.6***			
Log-likelihood	−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 statistical significances at 1%, 5%, and 10% levels, respectively.
Standard errors reported between parentheses, MNL = Multinomial Logit, MXL = Mixed Logit, LCL = Latent Class Logit, LC1 = Latent class one, LC2 = Latent class two, ASC = Alternative specific constant, Std. Dev. = Standard deviation,
[1]Reference category is negative soil fertility effect,[2] Reference category is low nutritive value.

and about twice more than they did to the soil fertility attribute[9]. The substantial nutrition-maize yield tradeoff is not surprising given that maize farmers in the study area rely heavily on their maize output for household consumption and that output market participation is quite limited[10]. Maize yield received more weight than legume yield. Farmers preferred technologies with either positive or neutral soil fertility effects over technologies having negative soil fertility effects. However, a technology which had a positive soil fertility effect was valued by the farmers about four times more than a technology which had a neutral soil fertility effect. Risk of crop failure is the most important attribute which negatively affects 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 yield. 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 farmers' preferences for technology attributes. The results show that there were considerable similarities among the three regions in terms of preferences for SI technologies (Table 4). Maize yield, risk, positive soil fertility effect, nutrition, and cash requirement were the attributes which constituted the common domain. Like the case of the pooled sample, these attributes constituted the basis for farmers' preferences for maize production technologies in the three regions. However, there were differences among the regions as well. High labor requirement was negatively associated with the potential uptake of SI maize production technology by farmers in NR while this attribute was not an important evaluation criterion in UWR. Contrary to our expectation, the coefficient associated with labor requirement in UER is positive which could be because of correlation between labor and another attribute which was not included in the model. Farmers in UWR and UER were interested in integrating legumes into the maize system while those in NR were neutral to this attribute. Farmers in NR and UWR preferred technologies having positive or neutral effects on soil fertility while farmers in UER gave attention only to those technologies having positive effects on soil fertility. This could be associated with the heterogeneity between the regions in terms of soil fertility and other agro-ecological factors. The estimated standard deviations show that farmers in NR had heterogeneous preferences with respect to all, but the soil fertility effect attribute. On the contrary, farmers in UER showed homogenous preferences with respect to most of the attributes. Farmers in the UWR showed intermediate preference heterogeneity as compared to farmers in the other two regions. The results of the marginal rates of substitution (MRS) with respect to cash requirement (displayed in Table A3 in the appendix), show that except for positive soil fertility effect in the case of NR and UWR comparison, the tradeoffs were significantly different from zero for all the pairwise comparison between the regions.

We also estimated the MXL model for male-headed and female-headed households separately to capture gender differences in technology preferences (Table 5). Most of the attributes are consistent with earlier results with regards to 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 were interested in improving their utility by changing their existing cropping practices to cropping practices that align with the domains of sustainable intensification. There were preference heterogeneities among farmers within each household category, but with preference heterogeneity for more attributes in the case of male-headed households. The two groups showed similarities in terms of maize yield, risk, positive soil fertility effect, nutrition, labor requirement, and cash requirement. However, they were different in terms of legume yield and neutral soil fertility effect. Male-headed households preferred practices that integrate legume into the maize system whereas female-headed households were neutral to this approach. Similarly, male-headed households were interested in technologies that maintain the fertility of their land while women were neutral to it. The results of the MRS with respect to cash requirement show that the two gender groups were different in terms of the trade-offs between the SI attributes. The MRS values associated with male-headed households were greater (in magnitude) than those associated with female-headed households for yield, risk, positive soil fertility effect, and nutrition.

Apart from region and gender, we explored other sources of variation in farmers' preferences by introducing interactions of some explanatory variables with the attributes considered in the study. The results show that several factors including, among other, household size, exposure to weather shocks, access to social safety nets, participation in contract farming, and awareness of biofortified maize cultivars were significant sources of preference heterogeneity among the farmers (Table 6). Farmers having larger household size showed less preference for legumes, perhaps because they focused on the staple crops having higher yields (e.g., maize) to fulfill their relatively large food requirement. There was positive interaction between farmers' preferences for a better nutrition outcome and their experiences to weather shocks. This could be because of the association of nutrition with the integration of legumes into the maize system (crop diversification) the latter being commonly used by smallholder farmers to overcome weather shocks. Farmers who received support from safety nets tended to avoid technologies with higher cash requirement which could be because of the cash constraints they faced. Farmers who were engaged in contract farming tended to go for more risky maize technologies. Households who were aware of bio-fortified maize had greater value for maize yield than those who were not aware which implies that farmers prefer maize technologies which increased yield without much compromising nutritional quality.

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 of SI. Their choices are similar across gender categories and regions which are also consistent with the findings of empirical studies that show that maize farmers put a strong emphasis on the high yield trait when deciding on the adoption of a new technology (Ortega et al., 2016; Kassie et al., 2017; Silberg et al., 2020). This could be because of the relatively low average actual maize

[9] Given the substantial trade-offs that we find, it is important to consider whether this is a consequence of irrational choice behavior. Following empirical applications in previous DCE studies (e.g., Oyinbo et al., 2020), we used a dominant choice card to gauge the respondents understanding of the choice context, which serves as an *ex-ante* mitigation strategy to irrational behavior of respondents. Failure of a respondent to correctly respond to the dominant choice card warranted further explanation to ensure that the respondent understands the DCE set-up before commencing the experiment. However, given that there is no consensus on how to use responses from dominant tests in *ex-post* analysis to account for irrational behavior (Ryan & Bate, 2001; Lancsar & Louviere, 2006; Tervonen et al., 2018), we did not record farmers responses to the dominant choice card. More empirical DCE studies may help to clarify the use of responses from dominant tests.

[10] The average marketed surplus ratio is about 22% for the three regions (Martey et al., 2017)

Table 4
Parameter estimates of MXL model, by region.

	Northern		Upper West		Upper East	
	Mean (1)	Std. Dev. (2)	Mean (3)	Std. Dev. (4)	Mean (5)	Std. Dev. (6)
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[1]	0.641***	0.625*	0.938***	0.277	0.885***	0.645
	(0.173)	(0.323)	(0.170)	(0.344)	(0.304)	(0.407)
Neutral soil fertility effect[1]	0.400**	0.086	0.430**	−0.202	−0.234	0.049
	(0.193)	(0.145)	(0.179)	(0.626)	(0.332)	(0.091)
High nutritional value[2]	2.157***	1.666***	1.541***	−0.945***	1.592***	0.779*
	(0.297)	(0.300)	(0.217)	(0.268)	(0.424)	(0.463)
Labor requirement	−0.014**	0.027**	−0.004	−0.001	0.014*	0.002
	(0.006)	(0.011)	(0.005)	(0.004)	(0.008)	(0.007)
Cash requirement	−0.001**	0.000	−0.001***	−0.000	−0.002***	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Wald Chi-sq (9)	96.8***		3149.9		52.0***	
Log-likelihood	−875.7		−642.4		−254.4	
AIC	1785.3		1318.9		542.9	
BIC	1899.3		1427.3		639.5	
N	6,048		4,356		2,178	

Notes: ***, **, and * denote statistical significances at 1%, 5%, and 10% levels, respectively.
Standard errors reported between parentheses,
MXL = Mixed Logit, ASC = Alternative specific constant, Std. Dev. = Standard deviation,
[1]Reference category is negative soil fertility effect,[2] Reference category is low nutritive value.

Table 5
Parameter estimates of MXL, by gender category.

	Male-headed households		Female-headed households	
	Mean (1)	Std. Dev. (2)	Mean (3)	Std. Dev. (4)
ASC	−4.679***		−5.741**	
	(0.625)		(2.511)	
Maize yield	0.144***	0.104***	0.243***	0.149
	(0.015)	(0.017)	(0.090)	(0.094)
Legume yield	0.088***	−0.105	0.169	0.562**
	(0.021)	(0.064)	(0.104)	(0.267)
Risk	−0.389***	−0.328***	−0.497**	0.510**
	(0.051)	(0.071)	(0.228)	(0.234)
Positive soil fertility effect[1]	0.822***	0.435*	0.886*	1.377
	(0.117)	(0.233)	(0.506)	(0.894)
Neutral soil fertility effect[1]	0.377***	0.036	−0.362	−0.242
	(0.127)	(0.146)	(0.506)	(1.140)
High nutritional value[2]	1.822***	1.316***	2.371***	−1.586*
	(0.174)	(0.176)	(0.710)	(0.929)
Labor requirement	−0.005	−0.020**	−0.010	−0.005
	(0.004)	(0.009)	(0.012)	(0.007)
Cash requirement	−0.001***	0.000	−0.004***	−0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Wald Chi-sq (9)	204.9***		17.2**	
Log-likelihood	−1600.6		−192.2	
AIC	3235.2		418.4	
BIC	3359.6		508.1	
N	11,142		1,440	

Notes: ***, **, and * denote statistical significances at 1%, 5%, and 10% levels, respectively.
Standard errors reported between parentheses,
MXL = Mixed Logit, ASC = Alternative specific constant, Std. Dev. = Standard deviation,
[1]Reference category is negative soil fertility effect,[2] Reference category is low nutritive value.

yield in the study areas as compared to the potential yield (MoFA, 2016). Farmers attach a high value to legume yield as indicated by the positive coefficients corresponding to the legume yield attribute in all regressions. This could be because legumes are commonly integrated into the maize system in northern Ghana and hence the findings suggest that yield improvement strategies should consider both crops. However, our results show that farmers attach a higher value to maize yield than to legume yield which

Table 6
Parameter estimates of MXL with interactions between sustainable intensification attributes and household characteristics.

	Household size (no. of HH members)	Experience weather shocks (yes = 1)	Participate in contract farming (yes = 1)	Receive support from social safety net (yes = 1)	Aware of biofortified crop (yes = 1)
	(1)	(2)	(3)	(4)	(5)
Mean parameters					
ASC	−4.692***	−4.741***	−4.555***	−4.632***	−4.610***
	(0.568)	(0.587)	(0.535)	(0.555)	(0.562)
Maize yield	0.154***	0.157***	0.139***	0.140***	0.123***
	(0.021)	(0.020)	(0.014)	(0.015)	(0.015)
Legume yield	0.159***	0.055*	0.087***	0.070***	0.086***
	(0.041)	(0.030)	(0.021)	(0.022)	(0.026)
Risk	−0.426***	−0.382***	−0.409***	−0.390***	−0.354***
	(0.079)	(0.070)	(0.048)	(0.050)	(0.053)
Positive soil fertility effect[1]	0.788***	0.706***	0.801***	0.827***	0.884***
	(0.220)	(0.182)	(0.116)	(0.123)	(0.137)
Neutral soil fertility effect[1]	0.021	0.441**	0.317**	0.439***	0.354**
	(0.217)	(0.195)	(0.125)	(0.131)	(0.151)
High nutritional value[2]	1.974***	1.116***	1.764***	1.673***	1.928***
	(0.270)	(0.199)	(0.161)	(0.166)	(0.184)
Labor requirement	0.001	−0.016***	−0.004	−0.007*	−0.004
	(0.006)	(0.005)	(0.003)	(0.004)	(0.004)
Cash requirement	−0.001**	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.0003)	(0.000)	(0.000)	(0.000)
Interactions					
Maize yield X	−0.001	−0.016	0.026	0.023	0.047***
	(0.002)	(0.019)	(0.025)	(0.020)	(0.018)
Legume yield X	−0.007**	0.048	−0.008	0.073*	0.008
	(0.004)	(0.038)	(0.053)	(0.043)	(0.037)
Risk X	0.005	0.003	0.273***	0.037	−0.055
	(0.006)	(0.073)	(0.090)	(0.079)	(0.068)
Positive soil fertility effect[1] X	0.003	0.165	0.170	−0.106	−0.186
	(0.020)	(0.205)	(0.260)	(0.218)	(0.190)
Neutral soil fertility effect[1] X	0.030*	−0.216	−0.116	−0.614**	−0.115
	(0.018)	(0.228)	(0.333)	(0.245)	(0.216)
High nutritional value[2] X	−0.014	1.124***	0.509	0.661**	−0.236
	(0.021)	(0.248)	(0.389)	(0.283)	(0.236)
Labor requirement X	−0.001	0.018***	0.006	0.011	−0.001
	(0.000)	(0.006)	(0.008)	(0.007)	(0.006)
Cash requirement X	0.001	0.000	−0.001	−0.001***	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Std. Dev. parameters					
Maize yield	0.104***	0.108***	0.100***	0.104***	−0.101***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Legume yield	−0.127**	0.140***	−0.136***	0.143***	0.144***
	(0.052)	(0.049)	(0.052)	(0.048)	(0.049)
Risk	0.326***	0.322***	0.305***	0.331***	0.318***
	(0.065)	(0.063)	(0.065)	(0.064)	(0.064)
Positive soil fertility effect[1]	−0.503***	−0.563***	0.468**	0.474**	−0.457**
	(0.187)	(0.185)	(0.200)	(0.204)	(0.226)
Neutral soil fertility effect[1]	0.079	0.049	−0.013	0.063	0.048
	(0.078)	(0.073)	(0.067)	(0.067)	(0.111)
High nutritional value[2]	−1.329***	1.300***	1.336***	1.289***	1.304***
	(0.160)	(0.155)	(0.159)	(0.150)	(0.149)
Labor requirement	0.017*	0.015*	0.012	0.014	0.014
	(0.009)	(0.008)	(0.011)	(0.010)	(0.010)
Cash requirement	0.0002	−0.000	0.0001	0.0002	0.000
	(0.000)	(0.000)	(0.000)	(0.0003)	(0.000)
Log-likelihood	−1800.6	−1784.8	−1799.0	−1793.2	−1802.1
AIC	3651.2	3619.5	3648.0	3636.4	3654.1
BIC	3837.2	3805.6	3834.0	3822.4	3840.1
N	12,582	12,582	12,582	12,582	12,582

Notes: ***, **, and * denote statistical significances at 1%, 5%, and 10% levels, respectively.
Standard errors reported between parentheses,
MXL = Mixed Logit, ASC = Alternative specific constant, Std. Dev. = Standard deviation,
[1]Reference category is negative soil fertility effect,[2] Reference category is low nutritive value,
The interaction terms are without standard deviation parameters because they were assumed to be fixed

is consistent with the findings of Ortega et al. (2016) and Waldman et al. (2017) while they are different from 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 farmlands (Fearon et al., 2015). This has raised sustainability concerns on the subsidy programs. The findings of this study suggest that a more integrated strategy could bring a more sustainable outcome in maize production than a strategy focusing merely on synthetic 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 technology adoption decisions (Waldman et al., 2017; Jourdain et al., 2020; Silberg et al., 2020). There is a slight difference between women and men in terms of the soil fertility attribute. Women showed interest in technologies that improve the fertility of their lands while male farmers showed interest in technologies that either improve or maintain the fertility of their lands. This could be because women in general cultivate less fertile plots and hence, they may have perceived that improving soil fertility is an imperative exercise while maintaining it would not bring much benefit in their context.

We found that farmers place high value on technologies which reduce the risk of crop failure. This could be because of the high vulnerability of the farming systems in northern Ghana to weather-related shocks. Studies conducted 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., 2021). This is due to the difference between legumes and maize in terms of tolerance to biotic and abiotic stresses and the synergy created between them in terms of agroecological processes such as biological 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 varieties tolerant to (biotic and abiotic) stresses and early maturing varieties. In Ghana, maize varieties such as Omankwa, Aburohemaa, and Abontem are drought- and Striga-tolerant (DTMA, 2013), but they are not widely cultivated (Poku et al., 2018)[11]. Therefore, promoting the integration of legumes into the maize cropping system and the use of stress-tolerant varieties as well as improving farmers' access to the varieties can be a useful strategy which agricultural development practitioners (including the Ministry of Food and Agriculture and NGOs) may adopt to reduce farmers' vulnerability to weather-related shocks in northern Ghana. Furthermore, the introduction of weather-index-based crop insurance schemes which are tailored to smallholder farmers can reduce the risk-aversion level of the farmers thereby enhancing their willingness to try new technologies

We included two indicators to capture the economic dimension of sustainability: i.e., labor requirement and cash requirement. Farmers were sensitive to cash outlays and, *ceteris paribus*, selected technologies having a lower cash requirement. This was expected given the severe cash constraints among most smallholder farmers and their limited access to institutional credit (Awunyo-Vitor & Al-Hassan, 2014; Denkyirah et al., 2016). The labor requirement of a technology did not affect farmers' preferences in the pooled sample. However, the result of the region-wise disaggregated analysis showed that farmers in the Northern Region were interested in labor saving maize practices while those in the other two regions did not show this behavior. This could be because labor is relatively scarce in the Northern Region as compared to both the Upper West and Upper East regions[12]. The result shows that sustainability concerns with respect to labor are location specific suggesting that researchers and development practitioners should consider labor endowment in designing, developing, and promoting maize technologies among smallholder farmers.

Positive nutritional gain was an aspect of maize production technology for which farmers showed strong preferences suggesting that policy responses would be needed to address the calls. 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 which can be suitable for households who have limited access to farmland 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% cultivated 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.

Finally, the following messages can be drawn from our findings. First, sustainable intensification is not just a fad within the academic and research circles but something that farmers are interested in. This is in support of the current global emphasis on sustainable development. Second, while farmers value all the sustainable intensification attributes considered in the study, they are not homogeneous in their preferences but vary by region, by gender, and depending on other factors such as household size, exposure to weather shocks, access to social safety nets, participation in contract farming, and awareness of biofortified maize cultivars suggesting that development actions are more likely to succeed when they consider such heterogeneities and adapt to local conditions. Third, farmers' interests in multiple attributes suggest that agricultural researchers should adopt multidimensional and holistic technology assessment approaches in lieu of the conventional reductionist approaches which focus on a single attribute at a time. In this regard, the SIAF can be used to set evaluation criteria in designing and testing of technologies (or a mix of technologies) targeting smallholder farmers producing maize. Such tools can be useful to optimize trade-offs and synergies among desirable technology attributes thereby enhancing maize technology adoption among smallholder farmers.

CRediT authorship contribution statement

Bekele Hundie Kotu: Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Oyakhilomen Oyinbo:** Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Irmgard Hoeschle-Zeledon:** Project administration, Writing – review & editing. **Abdul Rahman Nurudeen:** Writing – review & editing. **Fred Kizito:** Writing – review & editing. **Benedict Boyubie:** Data curation.

[11] The widely cultivated variety, Obatanpa, is susceptible to Striga (DTMA, 2013).

[12] The household land-labor-ratio in the Northern, Upper West and Upper East regions are 1.2, 0.8, and 0.5, respectively. The figure corresponding to the Northern Region is significantly higher than the ones corresponding to the other two regions.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2021.105789.

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