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KU Leuven - BELGIUM

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KU LEUVEN

Division of Bioeconomics
Department of Earth and Environmental Sciences
University of Leuven
Geo-Institute
Celestijnenlaan 200 E – box 2411
3001 Leuven (Heverlee)
Belgium
http://ees.kuleuven.be/bioecon/

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Oyakhilomen OYINBO [1], Jordan CHAMBERLIN [2], Bernard VANLAUWE [3], Liesbet VRANKEN [1], Alpha KAMARA [4], Peter CRAUFURD [5] and Miet MAERTENS [1]

Abstract

Agricultural extension to improve yields of staple food crops and close the yield gap in Sub-Saharan Africa often entails general recommendations on soil fertility management that are distributed to farmers in a large growing area. Site-specific extension recommendations that are better tailored to the need of individual farmers and fields, and enabled by digital technologies, could potentially bring about yield and productivity improvements. In this paper, we analyze farmers' preferences for site-specific nutrient management recommendations provided by an ICT-based extension tool that is being developed for extension services in the maize belt of Nigeria. We use a choice experiment to provide ex-ante insights on the adoption potentials of site-specific advisory services from the perspective of farmers. We control for attribute non-attendance and account for class as well as scale heterogeneity in preferences using different models, and find robust results. We find that farmers have strong preferences to switch from general to ICT-enabled site-specific soil fertility management recommendations which lend credence to the inclusion of digital technologies in agricultural extension. We find heterogeneity in preferences that is correlated with farmers' resource endowments and access to services. A first group of farmers are strong potential adopters; they are better-off, less sensitive to risk, and have higher preferences for investing in farm inputs. A second group of farmers are weak potential adopters; they have lower incomes and fewer productive assets, are more sensitive to yield variability, and prefer less capital and labor intensive production techniques. Our empirical findings have implications for the design, targeting and potential uptake of ICT-based extension tools to meet the needs of different farmers.

Key Words: Agricultural technology adoption, Agricultural extension, ICT-based extension, Site-specific extension, Soil fertility management, Maize yield

JEL classification: D83, O13, O33, Q12, Q16

Corresponding author: oyakhilomen.oyinb@kuleuven.be

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[1] Division of Bio-economics, Department of Earth and Environmental Sciences, University of Leuven, Belgium
[2] International Maize and Wheat Improvement Center (CIMMYT), Addis Ababa, Ethiopia
[3] International Institute of Tropical Agriculture (IITA), Nairobi, Kenya
[4] International Institute of Tropical Agriculture (IITA), Kano, Nigeria
[5] International Maize and Wheat Improvement Center (CIMMYT), Nairobi, Kenya

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1 Introduction

The yields of major food crops, such as maize, are lagging behind in Sub-Saharan Africa (SSA), and are often far below their potential (Tittonell et al., 2013; Vanlauwe et al., 2015a; Guilpart et al., 2017). This contributes to persistent poverty among smallholder farmers, slow agricultural growth and dependency on food imports, and food insecurity among a rapidly growing population (Barrett and Bevis, 2015; van Ittersum et al., 2016; Komarek et al., 2017; Ragasa and Mazunda, 2018). Poor soil fertility is a major biophysical factor limiting maize yields in SSA in general (Kihara et al. 2016) and in Nigeria in particular (Shehu et al., 2018). Nutrient-related constraints in maize production include macronutrient (nitrogen (N), phosphorus (P) and potassium (K)) deficiencies, especially N, as well as secondary nutrient and micronutrient deficiencies and soil acidity (Kihara et al., 2016; Vanlauwe et al., 2015b).

Improving soil fertility is challenging because of the large spatio-temporal heterogeneity in biophysical and socio-economic conditions of smallholder farming systems (Tittonell et al., 2010; Vanlauwe et al., 2015b; Njoroge et al., 2017; MacCarthy et al., 2018). Given an average low level of input use, it is often argued that smallholder farmers in SSA need to intensify the use of external inputs, especially inorganic fertilizer, in order to improve yields and productivity (Chianu and Tsujii, 2005; Duflo et al., 2011; Wiredu et al., 2015; Sheahan and Barrett, 2017). Yet, empirical findings for Nigeria (Liverpool-Tasie et al., 2017), Kenya (Sheahan et al., 2013) and Zambia (Burke et al., 2017) show that the profitability of intensified fertilizer use in maize production is low in some areas, primarily because of poor maize yield response to fertilizer. These studies argue that a low marginal physical product of applied N is a more important factor limiting the profitability and the use of fertilizer in some regions than market-related and institutional constraints such as high transaction costs, and imperfections in credit and input markets. Improving the yield response to fertilizer and the marginal physical product of applied fertilizer requires extension services on soil fertility management to be adapted to the local context of farmers (Vanlauwe et al., 2015b).

Yet, in SSA, and elsewhere, agricultural extension most often entails general recommendations for improved soil fertility management that are disseminated to farmers in a large growing area, covering e.g. a region, a district or a province (Tittonell et al., 2013; Kihara et al., 2016; Shehu et al., 2018). Such agricultural extension practices fail to take into account the heterogeneous and complex biophysical and socio-economic conditions of smallholder farming (MacCarthy et al., 2018; Kihara et al., 2016). Site-specific agricultural extension, on the other hand, includes recommendations that are tailored to the situation of an individual farmer or field. Such recommendations might be more effective to bring about yield and productivity improvements than conventional extension practices (Ragasa and Mazunda, 2018). To improve the capacity of agricultural extension providers in the delivery of site-specific extension recommendations to farmers, information and communication technology (ICT) driven decision support tools (DSTs) offer great potential (Kragt and Llewellyn, 2014; Vanlauwe et al., 2015b; Vanlauwe et al., 2017). The role of digital technologies in agriculture in developing countries is increasing (Bernet et al., 2001; Fu and Akter, 2016; Verma and Sinha, 2018) and these technologies might provide a cost-effective and innovative way to providing site-specific fertilizer recommendations to smallholder farmers (Njorege et al., 2017).

In this paper, we analyze farmers' preferences for site-specific nutrient management (SSNM) recommendations for maize provided by an ICT-based extension tool called Nutrient Expert (NE) (Pampolino et al., 2012). The NE tool is being developed for extension in the maize belt of Nigeria and ex-ante insights on farmers' preferences for the expected information content and recommendation alternatives from the tool can contribute to its development. We use a choice experiment to provide ex-ante insights on the adoption potentials of site-specific advisory services enabled by digital tools from farmers' perspectives, identify heterogeneous preference classes and the drivers of farmers' preferences.

We contribute to the general literature on agricultural technology adoption, and specifically to the literature on DSTs for improved soil fertility management. Our findings add insights to the R4D literature and are relevant for the development community. The current empirical literature includes ex-post studies that analyze farmers' adoption behavior after technologies have been introduced (e.g. Lambrecht et al., 2014; Mponela et al., 2016; Morello et al., 2018) and a growing number of ex-ante studies that use choice experiments to analyze farmers' adoption behavior in the design stage of a technology (e.g. Lambrecht et al., 2015,

Mahadevan and Asafu-Adjaye, 2015; Dalemans et al., 2018; Tarfasa et al., 2018). However, none of the available studies focuses on farmers' adoption of site-specific extension recommendations and also farmers' willingness to accept such recommendations from ICT-based extension tools has not been researched (Fu and Akter, 2016; Verma and Sinha, 2018). The only available empirical study on preferences for ICT-based extension tools focuses on the extension providers rather than the ultimate beneficiaries (farmers) (Kragt and Llewellyn, 2014). Building on Kragt and Llewellyn (2014), we also contribute to the choice experiment literature by extending the application of the methodology in optimizing design of DSTs but with a more rigorous empirical estimation. We specifically take into account both farmers' response error and attribute non-attendance using different econometric models, which is an advancement in comparison with previous choice experiment studies that address only one of these issues.

The remainder of the paper is organized as follows. In Section 2 we provide some background on maize production, soil fertility and conventional extension in Nigeria as well as the development of a nutrient expert tool. In Section 3 we explain the methodological approach of the paper. In Section 4 we report the results of the empirical analysis and provide a discussion of the results in section 5. Section 6 concludes the paper.

2 Background

2.1 Maize production in Nigeria

A crop of notable interest for food security and the most widely grown in SSA is maize (van Ittersum et al., 2016). As in other countries in SSA, maize is a very important crop in Nigeria, where it is largely cultivated by smallholder farmers (Abdoulaye et al., 2018). Yet, on-farm yields are low and far below attainable yields in experimental stations, leading to a substantial yield gap (Shehu et al., 2018). Maize yields in Nigeria have consistently lagged behind those in the rest of the world – with maize yield in Nigeria being only one fourth of the average global yield in 2016 – and are currently even lagging behind on the average yield in Africa (Fig. 1).

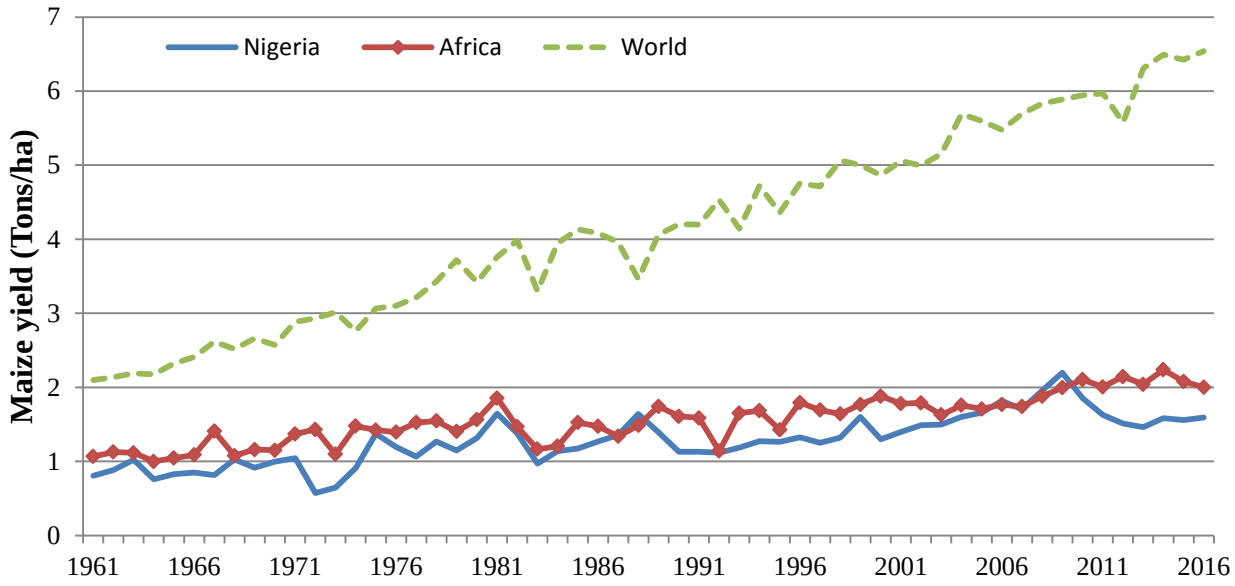

Fig. 1: Maize yield trend in Nigeria, Africa and the world at large (FAOSTAT, 2018).

2.2 Soil fertility and conventional extension

The average low maize yield in Nigeria is related to inherent poor soil fertility, and continuous cropping and mining of soil nutrients (Tarfa et al., 2017; Ande et al., 2017). Soil nutrient deficiencies are common with N as the most limiting nutrient for maize production in the Nigerian savannas (Chianu and Tsuji, 2005; Shehu et al., 2018). Fertilizer use to address nutrient deficiencies is low. Average fertilizer use on arable land is estimated to be 8.3 kg nutrient per ha in 2015 (FAO, 2017). This is despite the commitment of Nigeria and other African countries to increase fertilizer use from 8 to 50 kg nutrients per ha by 2015 (Sanginga and Woomer, 2009; Vanlauwe et al., 2015b). Low fertilizer use has been attributed to market constraints such as a lack of fertilizer availability during the season and high transportation costs, as well as to a poor yield responses to fertilizer applications (Chianu and Tsuji, 2005; Ande et al., 2017; Tarfa et al., 2017). Although the agricultural extension system is generally weak in Nigeria, considerable extension services are directed to maize production because of its importance for food security (Ande et al., 2017). The extension system provides general fertilizer recommendations, which is 120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha for maize in the Northern guinea savanna of Nigeria (Shehu et al., 2018; Tarfa et al., 2017). Yet, maize farmers use on average only between 40 to 45 kg N per ha (Liverpool-Tasie et al., 2017), which is less than half the recommendation of 120 kg N per ha. The use of this general recommendation is not consistent with the principle of dynamically adjusting fertilizer application based on crop need, and field- and season-specific

conditions (Pampolino et al., 2007), and likely does not result in fertilizer use that is economically optimal.

2.3 Nutrient expert tool

Promoting the right dose of inorganic fertilizer to farmers is only possible if extension service providers are able to offer site-specific rather than one-size-fits all recommendations (Bernet et al., 2001). The project 'Taking Maize Agronomy to Scale (TAMASA)' is co-developing a user-friendly, scalable nutrient management extension tool, known as Nutrient Expert (NE), with the aim of providing site-specific soil fertility management recommendations to maize farmers in Nigeria, Tanzania and Ethiopia[6]. This effort is expected to result in a mobile phone-based, easy-to-use and interactive tool that enables extension agents to generate fertilizer and management recommendations adapted to the specific situation of an individual farmer's field in real-time (Pampolino et al., 2012). The tool is based on SSNM principles of applying fertilizer according to crop needs by promoting the right fertilizer source (i.e. the type of fertilizer needed), at the right rate (i.e. the amount of fertilizer), at the right time (i.e. the timing of fertilizer application), in the right place (i.e. the availability of nutrients) (4R's of nutrient use). The tool relies on the quantitative evaluation of the fertility of tropical soils (QUEFTS) model to predict the yield responses. The inputs required to generate recommendations include a target maize yield, farmer's current crop management practices (inorganic and organic fertilizer use, variety type, yield etc.), characteristics of the growing environment (water availability, risk of flood/drought etc.), soil characteristics (soil texture, soil color, history of manure use etc.) and price of inputs and maize. The outputs of the tool include information on SSNM (N, P, K application guide and associated crop management practices) to achieve the target maize yield and a simple profit analysis to compare farmers' current practice and the recommended practices. The tool allows farmers to adjust recommendations according to their available budget. The tool development process is expected to consist of data collection (multi-location nutrient omission trials), model development (algorithm, decision rules and programming) and field validation (model testing and refining) (Pampolino and Zingore, 2015). In this paper, we examine farmers' preferences for fertilizer recommendations and thereby generate insights for optimizing tool design.

[6] Development of NE tool is a collaborative effort of IPNI, CIMMYT, IITA, extension service providers, national institutes, government agencies, input dealers and farmers with IPNI leading the process.

3 Methodology

3.1 Research area and sampling

The research was conducted in Kaduna, Katsina and Kano states in the maize belt of Nigeria, where maize is mainly grown under a smallholder rain-fed system across diverse agro-ecological conditions. These states were purposively selected because of their strategic position in maize production and to pilot research activities for the development of the NE tool. A two-stage sampling design was used to sample households in these states. In the first stage, 22 sampling grids of 10 x 10 km were randomly generated across the primary maize areas in the three states with geospatial inputs to ensure spatial representativeness. These 22 sampled grids include 99 randomly selected villages belonging to 17 local government authorities (LGAs), the administrative unit below the state. All these villages were included in the sample. In the second stage, a sampling frame of maize-producing farm-households was constructed for each of the selected 99 villages. In each of the villages, eight households were randomly selected from a village listing of maize-producing farm-households, which results in a total sample of 792 households.

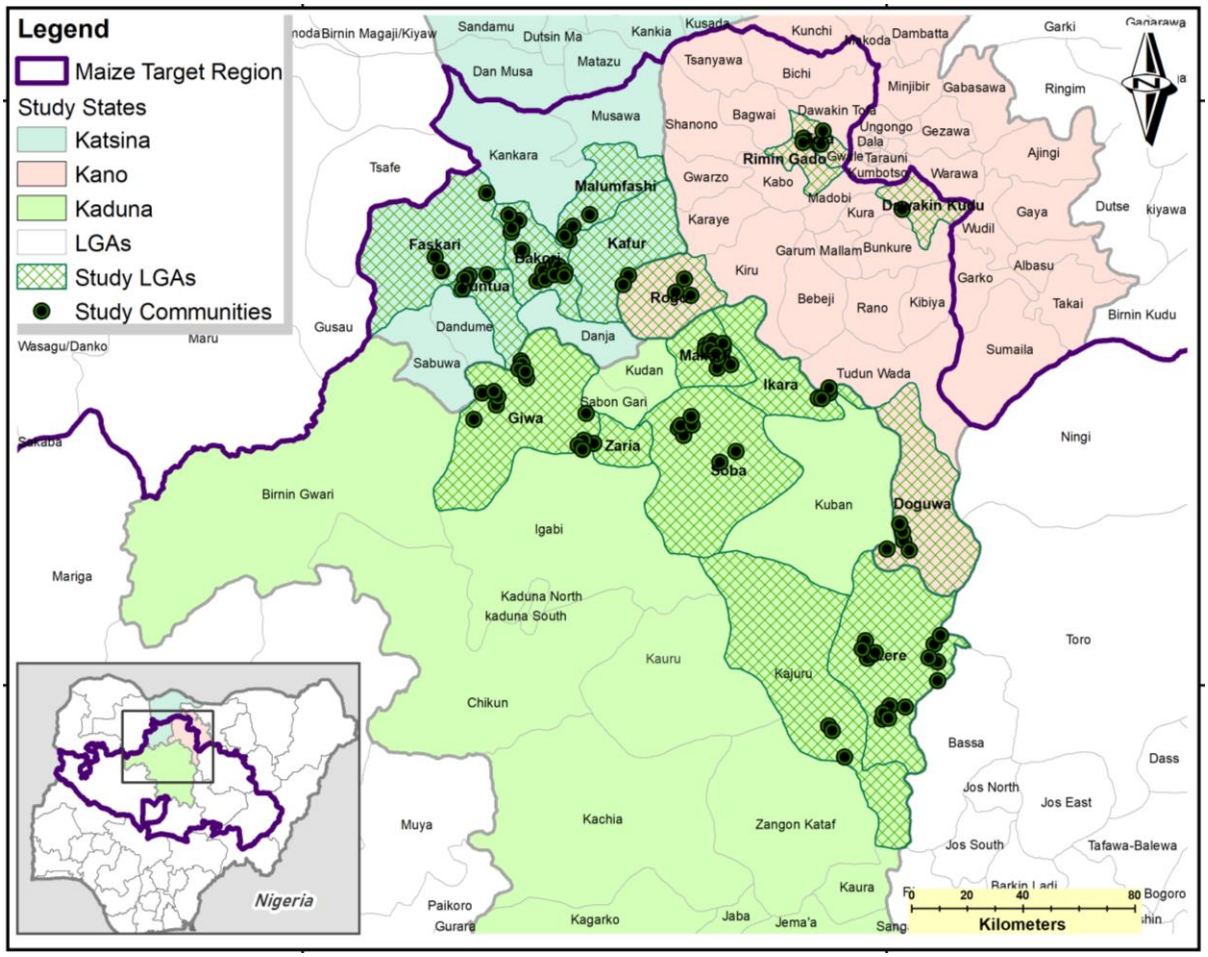

Fig. 2: Map of the study area

3.2 Design and implementation of a choice experiment

In this research area, we implemented a discrete choice experiment (CE) with the 792 sampled farmers during the maize harvest period of 2016 and complemented the CE data with a farm-household survey. A discrete CE is a survey-based method for eliciting preferences of respondents. These preferences are derived from respondents' repeated choices between two or more discrete alternatives of a 'good', 'service' or 'course of action' described by various levels of specific attributes of these products (Pouta et al., 2014). This approach makes it possible to evaluate farmers' preferences for SSNM recommendations prior to the development of the NE tool and take into account these preferences in designing, fine-tuning and delivering the tool. CEs first emerged in marketing studies and now cut across several disciplines, including agricultural sciences where CEs are increasingly applied in ex-ante agricultural technology

adoption studies (Mahadevan and Asafu-Adjaye, 2015; Lambrecht et al., 2015; Coffie et al., 2016; Kassie et al., 2017; Tarfasa et al., 2018; Dalemans et al., 2018). Theoretically, the CE method is based on Lancaster's economic theory of value (1966) and random utility theory (McFadden, 1974). Practically, collecting CE data entails the identification of relevant attributes, the identification of levels for each of these attributes, an experimental design into different choice sets, the construction of choice cards with these choice sets, and the implementation of the CE among respondents. We discuss these steps below.

3.2.1 Identification of attributes and attribute levels

To identify relevant attributes or technology traits associated with SSNM, we consulted scientists within and outside the project team and conducted focus group discussions with farmers. Ten relevant attributes were identified, of which the six most important as revealed from the consultations were included in the CE in order to reduce the complexity of the choice tasks and limit the occurrence of random non-deterministic choices (Beck et al., 2013). The attributes and their levels are summarized in table 1. The first two attributes directly relate to fertilizer use in the context of SSNM. The first attribute is 'fertilizer application rate', defined as the quantity of inorganic fertilizer required to supply the necessary nutrients to achieve a target maize yield on a specific field. This is described by three levels: the current application rate (not site-specific), a site-specific rate below the current rate, and a site-specific rate above the current rate. The second attribute is 'fertilizer application method', which relates to how fertilizer is applied to guarantee optimal uptake of nutrients by maize plants and ensure that desired maize yields are attained. The levels of this attribute are broadcasting and dibbling/spot application.

The third and fourth attributes relate to returns in terms of yield and variability in yield associated with using SSNM. The third attribute is 'expected yield', expressed as average yearly maize yield expected on a hectare over a production period of 5 years. This attribute is defined by five levels, ranging from 1 to 6 tons/ha, carefully selected within the range of attainable maize yields in the research area. The fourth attribute is 'yield variability' or yield risk, i.e. the probability of a bad production year. This attribute is described by five levels expressing the number of production years, ranging from 0 to 4 out of 5, maize yield will be below one ton per hectare.

The fifth attribute 'seed type' relates to type of maize seed, a vital complementary input in addition to fertilizer to improve maize yields. Fertilizer recommendations are often combined with recommendations on improved seed in extension services due to interaction effects of fertilizer and improved seeds, especially as promoted in integrated soil fertility management (Vanlauwe et al., 2015b). The levels of this attribute are improved seed variety and traditional seed variety.

The last attribute is a monetary attribute defined as the 'cost of fertilizer and seed' in local currency (Nigerian Naira - NGN) per hectare. This represents the fertilizer and seed investment cost associated with adopting a given extension recommendation. This attribute is defined by five levels, ranging from 35,000 to 85,000 NGN per hectare, that were determined based on a range of actual costs incurred on fertilizer and seed during the 2016 growing season, for which information was obtained through focus group discussions and a pilot survey.

Table 1: Attributes and attribute levels

Attributes	Attribute levels
Fertilizer application rate	Current rate (not site-specific) Site-specific fertilizer rate (SSFR): below current rate Site-specific fertilizer rate (SSFR): above current rate
Fertilizer application method (FAM)	Broadcasting, Dibbling
Expected yield	1 to 2, 2 to 3, 3 to 4, 4 to 5, 5 to 6 tons/ha
Yield variability (yield risk)	0 (0 in 5 years), 1 (1 in 5 years), 2 (2 in 5 years), 3 (3 in 5 years), 4 (4 in 5 years)
Seed type (ST)	Traditional variety, Improved variety
Cost of fertilizer and seed (CFS)	35000, 45000, 55000, 65000, 75000, 85000 NGN/ha

Note: 305 NGN (Nigerian Naira) is equivalent to 1 USD at the survey time.

3.2.2 Experimental design and choice cards

For the experimental design we use a fractional factorial design; more specifically a Bayesian D-efficient design which minimizes the D-error and improves efficiency. As proposed by Scarpa et al. (2013), and to improve efficiency, we conducted a pilot version of the CE prior to the actual design. For this pilot CE we used an orthogonal design. With the data from this pilot CE, a multinomial logit model was estimated and parameter estimates were used as Bayesian priors (random priors distribution) in generating the ultimate D-efficient design. This design resulted in

12 paired choice sets that were randomly blocked into two blocks of six choice sets. The blocking facilitates the implementation among farmers and improves the quality of responses.

Twelve laminated choice cards were constructed for the 12 paired choice sets – see an example in figure A1 in appendix. In order to make the CE more comprehensible among less educated farmers in the sample, we include pictures for different attributes in the choice cards. Each choice card consists of two generic scenarios (options A and B) of SSNM recommendations. A status quo option which represents the current practice of farmers is included in all choice cards as option C. This makes the CE more realistic as farmers have the option of choosing their current practice if it appears superior and reduces potential bias arising from forced choices (Lancsar et al., 2017).

3.2.3 CE and survey implementation

In the CE implementation, each farmer was offered six choice cards and asked to repeatedly make a choice between the three options on each card. Prior to the CE, farmers were sensitized on its purpose, contents and how to correctly participate. We used a short cheap talk script (Cummings and Taylor, 1999) to explain to farmers the importance of making truthful choices and thereby limit hypothetical bias arising from divergence between choices made in the hypothetical CE scenarios and (unobserved) actual choices when exposed to site-specific recommendations from ICT-based tools. After the introductory session, the choice cards were presented to each farmer by an enumerator and each farmer freely made a choice between the three options on each of the six cards. The CE was complemented with a farmer survey. The survey questionnaire consists of plot-, household- and community-level components. The modules of the questionnaire include household demographics, access to services, assets, income, fertilizer use, crop production and community infrastructure. To improve the quality and timely availability of the data, the survey was implemented using computer-assisted personal interviewing software and tablets.

3.3 Econometric framework

The random utility theory behind CEs assumes that the utility of farmer *i* of choosing alternative *j* among all alternatives offered in a choice set *s* is given by an indirect or unobservable utility which consists of deterministic (explainable) and random (unexplainable) components as follows:

$$U_{ijs} = V_{ijs} + \varepsilon_{ijs} = ASC + \sum_{k=1}^{6} \beta_i x_{ijs} + \varepsilon_{ijs} \quad i = 1, \ldots, N; j = 1, \ldots, J; s = 1, \ldots, S \qquad (1)$$

Where U_{ijs} is the i^{th} farmer's indirect or latent utility, V_{ijs} is the systematic part of the utility function, x_{ijs} is a vector of attributes describing alternatives j with associated preference parameters β_i, ε_{ijs} is an unobserved random term that is independently and identically distributed (iid) across individuals and alternatives, ASC is an alternative-specific constant which represents preferences for the status quo option.

Drawing upon this model, we estimate a latent class model (LCM) with our empirical data. In the context of this study, the LCM assumes that a heterogeneous population of farmers belongs to a discrete number of preference classes, known as latent classes, with each farmer having a positive probability of membership of each class (Kragt and Llewellyn, 2014). The preference parameters in equation 1 become class-specific parameters β_c. This implies that preferences are homogeneous within each latent class c but heterogeneous across classes. Hence, the probability of farmer i choosing alternative j in choice set s is conditional on the farmer's membership of latent class c.

$$Pr_{ijs}|c = \frac{\exp(\beta_c x_{ijs})}{\sum_{t=1}^{J} \exp(\beta_c x_{its})} \qquad (2)$$

The class membership probability is modeled using a multinomial logit specification as a function of farmer-specific characteristics[7] known to be relevant for soil fertility-related technology adoption from theory and the empirical literature (Feder et al., 1985; Foster and Rosenzweig, 2010; Chianu and Tsuji, 2005; Lambrecht et al., 2014; Wiredu et al., 2015; Mponela et al., 2016; Morello et al., 2018). The selected variables are age and education level of the farmer, household labor (human capital), membership in a farmer association (social capital), access to off-farm income, access to agricultural credit (financial capital), the value of assets (physical capital), access to extension services and distance to a tarmac road (access to institutions and infrastructure).

[7] Some authors advocate the estimation of LCMs without a class membership function (Van den Broeck et al., 2017; Dalemans et al., 2018). With our data, this results in convergence problems and less intuitive results – the results of models without a membership functions are shown in Table A1 in appendix but are not discussed in the text.

$$Pr_{ijs}|c = \frac{\exp(\gamma_c' z_i)}{\sum_{q=1}^{C} \exp(\gamma_q' z_i)} \quad (3)$$

Where z_i is a vector of farmer-specific characteristics and γ_c' is a vector of parameters of z_i. Both choice and membership probabilities are jointly estimated with the assumption that scale parameters are normalized to one, as required for identification (Boxall and Adamowicz, 2002).

The ASC is dummy-coded as 1 if a farmer chooses the current practice and 0 otherwise. A negative coefficient for the ASC implies a positive utility of moving away from the current practice to following ICT-enabled SSNM. The categorical attributes are dummy-coded for ease of interpretation of coefficients (Van den Broeck et al., 2017). To improve the explanatory power of the model, we use farmer-specific status quo attribute levels in the estimation (Kings et al., 2007).

A growing body of literature shows that choice modeling can produce biased estimates of preferences if scale and preference parameters are confounded (Louviere and Eagle, 2006). The implication is that the LCM can yield spurious classes with heterogeneity largely an issue of scale (random choices) and less of taste (preference) (Vermunt and Magidson, 2014). As a robustness check, we estimate a scale-adjusted LCM (SALCM) to address this issue of potential confounding of scale (λ_d) and preference (β_c) parameters. The choice probability then becomes conditional on an individual farmer's membership of latent preference class c and scale class d.

$$Pr_{ijs}|c,d = \frac{\exp(\lambda_d \beta_c x_{ijs})}{\sum_{t=1}^{J} \exp(\lambda_d \beta_c x_{its})} \quad (4)$$

Another source of bias is violation of the continuity axiom of choice. This axiom implies that respondents consider all the attributes of the alternatives in their choice process (Kragt, 2013; Coffie et al., 2016). Violation of this axiom is commonly referred to as attribute non-attendance (ANA) and implies non-compensatory decision making behavior of respondents. In the context of this study, farmers may not make the expected full trade-offs between all attributes of the various alternatives. We rely on self-reported or stated ANA responses of farmers elicited at the end of the CE (Serial-based ANA) and estimate two stated ANA models to check the robustness of our results. The first approach referred to as the conventional ANA model involves constraining parameters of ignored attributes to zero in the utility function, implying that failure to attend to an attribute by a respondent leads to zero marginal utility for that attribute (Kragt, 2013; Campbell et al., 2018; Caputo et al., 2018).

$$U_{ijs}|c = ASC + \sum_{k=1}^{6-\tau} \beta_c x_{ijs} + \varepsilon_{ijs} \quad (5)$$

Where τ are ignored attributes, as self-reported by farmers. The specialized literature shows that ANA does not necessarily imply zero utility weight for an attribute but often indicates that respondents assign a lower importance to the attribute, and is best captured by a lower magnitude of the marginal utility for non-attenders than attenders (Hess and Hensher, 2010; Kragt, 2013). This motivates the estimation of a second ANA model known as validation ANA model. This model involves estimating two parameters for each attribute depending on whether the attribute is reported to be ignored or considered by respondents in their choice making (Hess and Hensher, 2010; Scarpa et al., 2013; Alemu et al., 2013; Caputo et al., 2018). Following Caputo et al. (2018), the utility coefficients conditional on attendance is indicated with the superscript 1 (β_c^1) and those conditional on non-attendance with superscript 0 (β_c^0).

$$U_{ijs}|c = ASC + \sum_{k=1}^{6-\tau} \beta_c^1 x_{ijs} + \sum_{k=1}^{\tau} \beta_c^0 x_{ijs} + \varepsilon_{ijs} \quad (6)$$

This approach helps to validate the first ANA model. Based on the validation method, choice behavior of respondents is expected to be in line with their self-reported ignored attributes if the estimated coefficients of ignored attributes are not significantly different from zero.

In summary, we estimate the following models: a standard latent class model (LCM) in STATA 15, a scale-adjusted latent class model (SALCM) in Latent Gold Choice 5.1, a conventional attribute non-attendance model (conventional ANA), and a validation attribute non-attendance model (validation ANA) in NLOGIT 5.

4 Results

4.1 Descriptive results

Table 2 describes individual-, household- and farm-level characteristics of sampled farmers with a distinction between farmers with and without experience with conventional extension on soil fertility management. Farmers are on average 44.7 years old and have an average of 5.2 years of schooling. Farm-households are rather large with on average 9.4 members. Farmers have on average 3.2 ha of land and 19 years of farming experience. About 21% of the sampled farmers

have access to credit, 34% are member of a farmer association and 16% produce maize under a contract-farming arrangement. We observe significant differences between farmers with and without experience with conventional extension services in terms of the household size, income, the farm area and farm assets, the participation in contract-farming and in farmer associations, and farmers' location with respect to roads. Differences in non-land asset ownership between the two groups of farmers are generally not significant. Apart from a small difference in intercropping practice, there are no significant differences in agricultural input application and farm management practices between farmers with and without extension experience. On average farmers apply 127 kg of NPK fertilizer per ha, and 89 kg of urea per ha and 28% of farmers use improved maize seeds, resulting in an average input cost of 39,000 NGN and an average maize yield of 2.1 tons per ha. The application of NPK (15:15:15 and 20:10:10) and urea (46 N) is equivalent to 61 kg N, 19 kg P_2O_5 and 19 kg K_2O per ha, which is below the general recommendation of 120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha.

Table 2: Summary statistics of farmers' characteristics

	Whole sample		Farmers with extension experience[1]		Farmers without extension experience[1]		
	Mean	SD	Mean	SD	Mean	SD	Sig.
Age of head (years)	44.70	12.03	44.84	12.51	44.61	11.75	
Education of head (years)	5.16	6.01	5.42	6.08	5.02	5.97	
Health of head (%)[2]	96.43		96.96		96.12		
Adults (no.)	3.56	1.97	3.74	2.36	3.45	1.68	*
Children (no.)	5.88	4.49	6.71	5.41	5.38	3.76	***
Access to credit (%)	20.7	0.40	21.30	0.41	20.41	0.40	
Access to off-farm income (%)	94.98		94.06		96.52		***
Maize contract farming (%)	16.37		12.17	0.33	18.86		**
Member of association (%)	33.71		26.52		37.98		***
Farming experience (years)	19.11	0.43	19.71	0.71	18.75	0.53	
Farm assets[3] (1,000 NGN)	51.36	11.45	40.71	68.40	57.83	134.69	*
Transport assets (1,000 NGN)	201.85	459.05	187.3	357.31	210.13	508.28	
Livestock assets (1,000 NGN)	394.51	586.67	386.6	491.77	399.22	637.08	
Durable assets[4] (1,000 NGN)	22.66	52.86	22.53	39.38	22.74	59.35	
Annual income[5] (1,000 NGN)	177.63	221.35	209.90	251.03	158.45	199.54	***
Total farm area (ha)	3.23	3.63	2.82	3.05	3.47	3.91	**
Maize focal plot area[6] (ha)	0.82	1.04	0.84	0.98	0.81	1.06	
Use improved seed (%)	28.04		28.26		27.91		
NPK fertilizer (kg/ha)	126.96	102.84	123.58	97.72	128.96	105.83	
Urea fertilizer (kg/ha)	88.79	95.09	87.75	94.69	89.40	95.44	
Input cost/ha[7] (1,000 NGN)	38.61	25.11	38.67	22.47	38.58	26.58	
Maize-legume intercrop (%)	30.15		26.09		32.55		*
Maize yield (tons/ha)	2.05	0.91	1.95	0.85	2.12	0.95	***
Distance to tarmac road (km)	4.08	5.15	3.07	3.45	4.68	5.85	***
Northern guinea savanna (%)	80.71		83.91		78.81		
Southern guinea savanna (%)	3.40		3.90		3.1		
Sudan savanna (%)	15.88		12.17		18.08		*

Significant differences from a t-test indicated with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] Extension experience through a face-to-face contact with extension agents, on-farm trials, field demonstrations or any extension-related training in the last three years,

[2] Percentage of farmers who self-report to be healthy throughout the year,

[3] Value of non-land assets, including farm equipment and machinery,

[4] Value of durable assets such as TV, radio, refrigerator, mobile phone, sewing machine etc,

[5] Per-adult equivalent household annual income from all sources,

[6] Maize focal plot is defined as the plot a household considers as their most important maize plot,

[7] Input cost only refers to cost of fertilizer and seed for maize in the 2016 season,

NGN: 305 NGN (Nigerian Naira) is equivalent to 1 USD at the survey time.

4.2 Econometric results

Before discussing the results in detail, we elaborate on scale heterogeneity and ANA. First, scale heterogeneity is addressed in the SALCM. In this model, the scale factor of scale class one is fixed to unity for identification purposes while that of scale class two is estimated. The latter is very small (0.13), indicating that farmers in scale class two make less consistent choices resulting in higher error variance. As the large majority of farmers (96%) belong to scale class one (and make consistent choices) and the parameter estimate of the scale factor is weakly significant, we can conclude that there is only weak evidence of heterogeneity in scale across the two classes. Second, the descriptive information in table 3 shows that 42% of farmers ignored at least one attribute, which justifies the estimation of the ANA model. The results of the validation ANA model show that the choice behavior of farmers in the CE corroborates their self-reported ANA as almost all parameter estimates of the self-reported ignored attributes are not significantly different from zero. This implies that self-reported ANA does not bias the results in the conventional ANA model and that restricting the parameters of ignored attributes to zero works well for our data. This is line with the findings of Caputo et al. (2018) and in contrast to Alemu et al. (2013) on ANA validation models at choice task and serial levels respectively.

Table 3: Descriptive information on stated ANA

# ignored attributes	Share of respondents (%)	Ignored attributes	Share of respondents (%)
0	57.7	Fertilizer application rate	15.1
1	10.4	Fertilizer application method	30.3
2	14.4	Expected yield	4.4
3	16.9	Yield variability	9.1
4	0.7	Seed type	20.4
		Cost of fertilizer and seed	13.1

We estimate four LCMs with two to seven latent classes in order to sufficiently represent the preference heterogeneity in our data. Based on the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) (Boxall and Adamowicz, 2002), a two-class model is selected as the one with the best fit. The results of the estimated LCMs with two latent classes are presented in Table 4, including the LCM, SALCM, conventional ANA and validation ANA models. The parameter estimates are consistent across the different models, implying robust

results. The SALCM has the best fit according to the AIC and BIC but has a weakly identified ASC as indicated by a very large standard error. As this is associated with imprecise estimates (Vermunt and Magidson, 2014)[8], we base our discussion primarily on the standard LCM which is the second best fit and results in estimates that are comparable with the other models.

The results of the LCM show that the estimated coefficient of the ASC is highly significant and negative for both latent classes of farmers. This implies that overall, farmers have positive preferences for site-specific fertilizer recommendations over the current extension practice. Both classes have significant positive preferences for site-specific fertilizer application rates. Yet, latent class one farmers (LC1) have a significant positive preference for a site-specific fertilizer rate that is above their current fertilizer application rate while latent class two farmers (LC2) have a significant positive preference for a site-specific fertilizer rate that is below their current application rate. The coefficients for seed type show that only LC1 farmers have a positive preference for using an improved seed variety; for LC2 farmers this coefficient is not significant. In addition, in LC1 there is a positive preference for a higher fertilizer and seed cost while in LC2 this is negative. The latter is consistent with the law of a downward sloping demand curve. The former is not but is consistent with a higher willingness of these farmers to invest in better farm inputs. The coefficient on fertilizer application method (dibbling) is significantly negative in LC2, which indicates these farmers prefer to apply fertilizer through broadcasting rather than through dibbling. The significant positive preference for maize yield and the significant negative preference for yield variability in both classes implies that farmers are interested in site-specific recommendations that result in higher and more stable yields, which is in line with the *a priori* expectations and with farmers being risk averse.

[8] The issue of weak identification is common in LCM and often results from model estimation algorithm converging on local maxima instead of global maximum. As recommended and implemented in other empirical studies that used SALCM (Vermunt and Magidson, 2014; Thiene et al. 2012), we tried various values of starting sets and iterations per set to achieve convergence on global maximum but ASC was still weakly identified.

Table 4: Results of different latent class models estimating farmers' preferences for ICT-based extension

	LCM		SALCM		conventional ANA		validation ANA			
							AC	AI	AC	AI
Class	LC1	LC2	LC1	LC2	LC1	LC2	LC1		LC2	
Class probability	64%	36%	65%	35%	63.5%	36.5%	66%		34%	
ASC	-5.667***	-5.263***	-24.105	-9.381	-5.694***	-5.367***	-5.693***		-5.268***	
	(0.703)	(0.609)	(31.319)	(10.611)	(0.652)	(0.562)	(0.680)		(0.583)	
SSFR	0.058	0.579***	0.073	0.562***	0.029	0.483***	0.029	0.300*	0.499***	0.811**
(Below current rate)	(0.077)	(0.180)	(0.079)	(0.191)	(0.082)	(0.168)	(0.078)	(0.174)	(0.186)	(0.363)
SSFR	0.246***	-0.156	0.249***	-0.190	0.258***	-0.297	0.295***	0.097	-0.508	0.513
(Above current rate)	(0.076)	(0.280)	(0.079)	(0.291)	(0.080)	(0.241)	(0.079)	(0.172)	(0.399)	(0.386)
Dibbling	-0.073	-0.351***	-0.085	-0.333**	-0.052	-0.398***	-0.068	-0.132	-0.396***	-0.182
	(0.057)	(0.126)	(0.059)	(0.132)	(0.065)	(0.133)	(0.064)	(0.091)	(0.143)	(0.209)
Expected yield	0.046**	0.243***	0.045**	0.270***	0.034*	0.233***	0.044**	0.071	0.289***	0.169
	(0.020)	(0.071)	(0.020)	(0.074)	(0.020)	(0.048)	(0.019)	(0.079)	(0.081)	(0.183)
Yield variability	-0.054**	-0.528***	-0.059**	-0.542***	-0.046*	-0.519***	-0.056**	-0.061	-0.561***	-0.629***
	(0.024)	(0.073)	(0.025)	(0.077)	(0.023)	(0.065)	(0.023)	(0.058)	(0.088)	(0.130)
Improved seed	0.253***	0.154	0.252***	0.178	0.233***	0.057	0.246***	0.327***	0.093	-0.067
	(0.060)	(0.147)	(0.062)	(0.157)	(0.064)	(0.141)	(0.063)	(0.113)	(0.167)	(0.258)
CFS (10000 NGN)	0.029*	-0.068*	0.028*	-0.067*	0.038**	-0.089***	0.030*	-0.041	-0.071	0.195**
	(0.017)	(0.038)	(0.017)	(0.040)	(0.017)	(0.034)	(0.016)	(0.049)	(0.044)	(0.092)
N	1106		1106		1106		1106			
Log likelihood	-2375.63		-2369.74		-2406.18		-2365.50			
AIC	4803.27		4793.48		4864.40		4811.00			
BIC	4993.46		4912.95		5026.00		5059.70			

LCM = standard latent class model, SALCM = scale-adjusted latent class model; conventional ANA = conventional attribute non-attendance model; validation ANA = validation attribute non-attendance model; LC = latent class; AC= attributes considered or attended to, AI= attributes ignored or non-attended to,

The SALCM model has two scale classes: scale class 1 with a probability of 96% and a scale factor set to unity; scale class 2 with a probability of 4% and a scale factor of 0.13.

Standard error reported between parentheses. Significant coefficients at * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$

To gain better insights on the trade-off farmers make between attributes and improve the interpretation of the results, we estimate marginal rates of substitution (MRS) (Green and Hensher, 2003; Lancsar et al., 2017). With an unexpected positive parameter for the cost attribute in LC1, the estimation of MRS in monetary terms is not meaningful for this class. Instead, we estimate MRS in terms of yield variability as a benchmark in order to provide information on the relative importance of attributes. Table 5 shows the estimated MRS which have to be interpreted as the yield risk farmers are willing to accept for an increase in another attribute. The results show that in both classes farmers are willing to accept some yield variability for a higher average yield, but for LC1 farmers this trade-off is on average larger, as revealed from the difference in magnitude of the estimated mean MRS. In addition, LC1 farmers are willing to accept an increased yield risk with the investment in improved seeds and higher fertilizer use stemming from site-specific recommendations, while LC2 farmers are not. The latter farmers are only willing to accept increased yield risk with reduced investment in fertilizer. In summary, LC1 farmers are willing to bear more risk of taking up intensification technologies to improve their maize productivity.

Table 5: Marginal rate of substitution (MRS) between yield variability and other attributes for two latent class groups of farmers

	Expected yield	SSFR (below current rate)	SSFR (above current rate)	Dibbling	Improved seed
LC 1					
Mean	0.860	-	4.572	-	4.693
95% ll	0.056	-	1.093	-	1.572
95% ul	4.179	-	22.673	-	22.108
LC 2					
Mean	0.46	1.097	-	-0.296	-
95% ll	0.238	0.443	-	-1.166	-
95% ul	0.642	1.989	-	0.985	-

MRS is calculated as the negative of the ratio of each attribute coefficient to the yield variability coefficient, ll=lower limit, up= upper limit, 95% confidence intervals are estimated using the Krinsky and Robb method with 2000 draws, MRS is not reported for insignificant coefficients as indicated by '-'.

The results of the multinomial logit models estimating the membership in latent classes are reported in table A2 in the appendix – these results shows that age, education, farmer association, assets, access to agricultural credit, access to extension and distance to road

significantly influence class membership. Table 6 shows the differences in individual-, household- and farm-level characteristics between the two classes of farmers defined based on their preferences for ICT-enabled SSNM. We find significant differences in most of the characteristics, which contributes to explaining the differences in preference pattern between the latent classes. The results show that in comparison with LC2, farmers in LC1 are relatively younger, invest more in farm inputs and are generally better-off in terms of access to resources (including family labor, income and different types of assets) and access to services and institutions such credit, farmer associations, contract farming arrangements, and extension services. Farmers in LC2 appear better-off in terms of education and access to roads, which is unexpected as a higher education and access to road infrastructure is expected to increase openness to technological interventions. However, the benefits of education in enhancing learning processes of a new technology might be minimal for technologies with traits that are familiar to the end-users, which likely applies for fertilizer use. In terms farming experience, there are no significant differences between the two classes of farmers. Given the observed differences, we can describe LC1 farmers as more resource endowed farmers and LC2 farmers as less resource endowed, and further explain the observed preference patterns.

Table 6: Farmer characteristics by preference classes

	Latent class 1 (64%)		Latent class 2 (36%)		
	Mean	SD	Mean	SD	Sig.
Age of head	43.52	11.64	46.90	12.41	***
Education of head	4.37	5.68	6.63	6.30	***
Health of head	96.51		96.30		
Adults	3.60	2.19	3.50	1.46	***
Children	6.02	4.72	5.62	3.99	***
Access to credit	26.68		9.72		***
Access to off-farm income	96.51		92.13		***
Maize contract farming	17.96		13.43		***
Member of association	40.40		21.30		***
Farming experience	19.12	10.48	19.10	10.68	
Farm assets	60.68	132.35	34.40	67.70	***
Transport assets	227.01	489.86	158.01	394.69	***
Livestock assets	439.94	651.94	292.57	382.21	***
Durable assets	24.41	63.65	19.41	20.51	***
Annual income	192.72	244.84	149.62	165.07	***
Total farm area	3.19	3.48	3.32	3.86	*
Maize focal plot area	0.80	1.04	0.84	1.03	**
Extension experience	39.65		32.87		***
Use improved maize	30.92		22.69		***
NPK fertilizer	125.4	101.83	129.85	104.41	**
Urea fertilizer	94.59	94.42	78.01	95.18	***
Input cost/ha	39.51	25.64	36.93	23.94	***
Maize-legume intercrop	28.93		32.41		***
Yield	2.1	0.92	2.0	0.90	***
Distance to tarmac road	4.78	5.95	2.81	2.71	***
Northern guinea savanna	81.55		79.17		***
Southern guinea savanna	3.24		3.70		
Sudan savanna	15.21		17.13		***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ independent sample t-tests of significant differences between the two classes of farmers, Variables are as defined in table 2.

5 Discussion

We find that farmers are in general favorably disposed to site-specific extension over the traditional extension practice of disseminating general recommendations. This suggests that farmers recognize the heterogeneity in their farming systems and the need for recommendations to be tailored to their specific growing conditions which can be done with ease using DSTs (Rose et al., 2016). However, farmers have heterogeneous preferences for SSNM recommendations and this observed heterogeneity is correlated with farmers' resource endowments and access to services. We identify two groups of farmers (latent classes) with different preferences. The first

group (LC1 representing 64% of the sample) includes innovators or strong potential adopters of SSNM recommendations. Farmers in this group are generally better-off, less sensitive to risk, have higher preferences for investment in farm inputs, and are indifferent between more or less labor intensive production techniques. This is in line with the expectation that better-off farmers are more responsive to new technologies despite the riskier outcomes of new technologies (Foster and Rosenzweig, 2010). The second group (LC 2 representing 36% of the sample) includes more conservative farmers or weak potential adopters. Farmers in this group have lower incomes and lower productive assets, are more sensitive to yield variability, and prefer less capital and labor-intensive production techniques.

Both the strong and weak potential adopters exhibit strong positive preferences for higher yield, which is consistent with other CE studies that reveal maize farmers' preferences for high yielding technologies (Ortega et al., 2016; Kassie et al., 2017). In addition, they both exhibit disutility for risk, which signals a safety-first behavior to smooth income and consumption (Feder et al., 1985). Yet, the weak potential adopters are less willing to accept increased yield risk for an increase in yield level (or more willing to forego yield gains for stability in yield) than the strong potential adopters. This implies that the adoption behavior of farmers is not only strongly influenced by the expectation of higher yields but also by the expected risk exposure associated with higher yielding interventions. This is in line with the finding of Coffie et al. (2016) on the negative effect of risk exposure in farmers' preferences for agronomic practices.

The weak potential adopters show an aversion for labor-intensive fertilizer application methods and higher yielding intensification options with high cost implications. This is in line with the findings of Coffie et al. (2016) and reaffirms the issue of labor constraint for agricultural technology adoption. The strong potential adopters prefer high yielding intensification options with high investment costs, which is rather unexpected. This likely indicates their willingness to invest more in farm inputs of higher quality and their perception of a positive correlation between higher input cost and higher yields. Empirical CE studies with positive cost coefficients also attribute this somewhat unexpected finding to be most likely due to a positive price-quality expected relationship, especially for new products (Lambrecht et al., 2015; Mueller Loose et al., 2013; Romo-Muñoz et al., 2017). These findings imply that less endowed and more risk averse farmers are better served with cost-saving recommendations and yield-stabilizing technologies,

while better endowed and less risk averse farmers can benefit most from very high yielding site-specific recommendations.

From a methodological point of view, we show that it is worthwhile to ensure robustness of results by addressing issues of heterogeneity in error variances and ANA in CE studies. As differences in scale imply differences in choice consistency (Lancsar et al., 2017), this should motivate studies to take into account scale heterogeneity to avoid biased estimates of preferences and spurious preference classes (Thiene et al., 2012; Dalemans et al., 2018). We find that the majority of farmers exhibit consistent choices, which is not surprising as they are largely familiar with the attribute and attribute levels presented in the CE and can readily express their preferences. This is in line with Czajkowski et al. (2015) who note that respondents have a more deterministic choice process from an appreciable level of information and experience on the attributes of a product being valued. Failure to account for ANA is an additional possible source of bias in discrete CEs (Kragt, 2013; Coffie et al., 2016; Hess and Hensher, 2010; Caputo et al., 2018). The estimation of an ANA model validates our finding on the preference for higher yielding recommendations with higher investment costs for the strong potential adopters. Such an unexpected result could also stem from non-attendance to the cost attribute (as in Campbell et al., 2018) but this is ruled out in the ANA model. Overall, our results are consistent across all the models, which suggests that any possible bias from scale and ANA issues is relatively small. However, this may not always be the case for other studies that do not account for these issues.

Finally, our results entail some specific implications for the development of the NE and similar tools as well as broader policy implications. The direct implication of the farmers' homogenous preferences for high yielding recommendations and risk aversion for the design of ICT-based extension tools is that in the development process, more attention should be paid on ensuring that tools are robust in estimating expected yields for farmers. Most importantly, our results strongly indicate the need to optimize design of tools to allow for a feature/module for providing information on yield variability (riskiness of expected outcomes) and not only on attainable yield levels to help farmers make better informed decisions. This is rarely taken into account as most DSTs are designed to produce recommendations for farmers on the basis of an expected yield level without providing further information on the uncertainty of the expected outcomes. Therefore, improving the design of extension tools to enable provision of information on the riskiness of expected yields will be more rewarding for farmers. In addition, our results

point to the need for extension services that are designed to take into account the heterogeneity in farmers' behavioral responses (Lopez-Ridaura et al., 2018). This implies flexibility in extension tools to switch between low-investment, low-risk, low-return recommendations and high-investment, high-risk, high-return recommendations depending on the risk and investment profile of the individual farmer. In terms of broader policy implications, farmers' general interest in site-specific recommendations from ICT-based tools lends credence to the theoretical motivation for addressing informational inefficiencies in agriculture using digital technologies (Janssen et al., 2017; Verma and Sinha, 2018). Digital inclusion policies to bridge the digital divide can include fostering the use of digital technologies in providing quality extension to farmers. The use of ICT-based extension tools that are farm- and field-specific and flexibly take into account farmers' needs may integrate complementary services – such as credit provision, subsidized inputs and insurance schemes – that are well-targeted and increase the uptake of extension recommendations by farmers as well the efficiency of service provision to farmers.

6 Conclusion

In this paper, we analyze farmers' preferences for site-specific nutrient management recommendations provided by ICT-based extension tools such as Nutrient Expert that is being developed for extension services on soil fertility management in the maize belt of Nigeria. We use a discrete choice experiment to provide ex-ante insights on the adoption potentials of ICT-based advisory services on soil fertility management from the perspective of farmers. The choice experiment was carried out, along with a farmer survey, among 792 farmers in three states in the maize belt of Nigeria. Different econometric models are used to control for attribute non-attendance and account for class as well as scale heterogeneity in preferences. The findings reveal that farmers have strong preferences to switch from general to ICT-enabled site-specific soil fertility management recommendations. We find substantial heterogeneity in farmer preferences for extension recommendations and distinguish between strong and weak potential adopters of more intensified maize production. Strong potential adopters are better-off farmers with higher incomes, more assets and better access to services; they are less sensitive to risk and have higher preferences for investing in farm inputs and more capital- and labor-intensive production systems with higher expected return, even at a higher risk in terms of yield variability. Weak potential adopters are more conservative farmers with lower incomes and less

productive assets; they are more sensitive to yield variability, and prefer less capital- and labor-intensive production techniques with a lower but more stable return. In general, our findings imply that farmers in the research area support the use of ICT-based site-specific extension services, which calls for agricultural extension programs to contribute to closing the digital divide through the inclusion of ICT-based technologies in the extension system. More specifically, our findings document the importance of flexible extension systems that take into account the willingness of farmers to invest in farm inputs and take risk, and inform farmers correctly on expected yield and returns as well as on the variability in yield and potential losses.

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Appendix

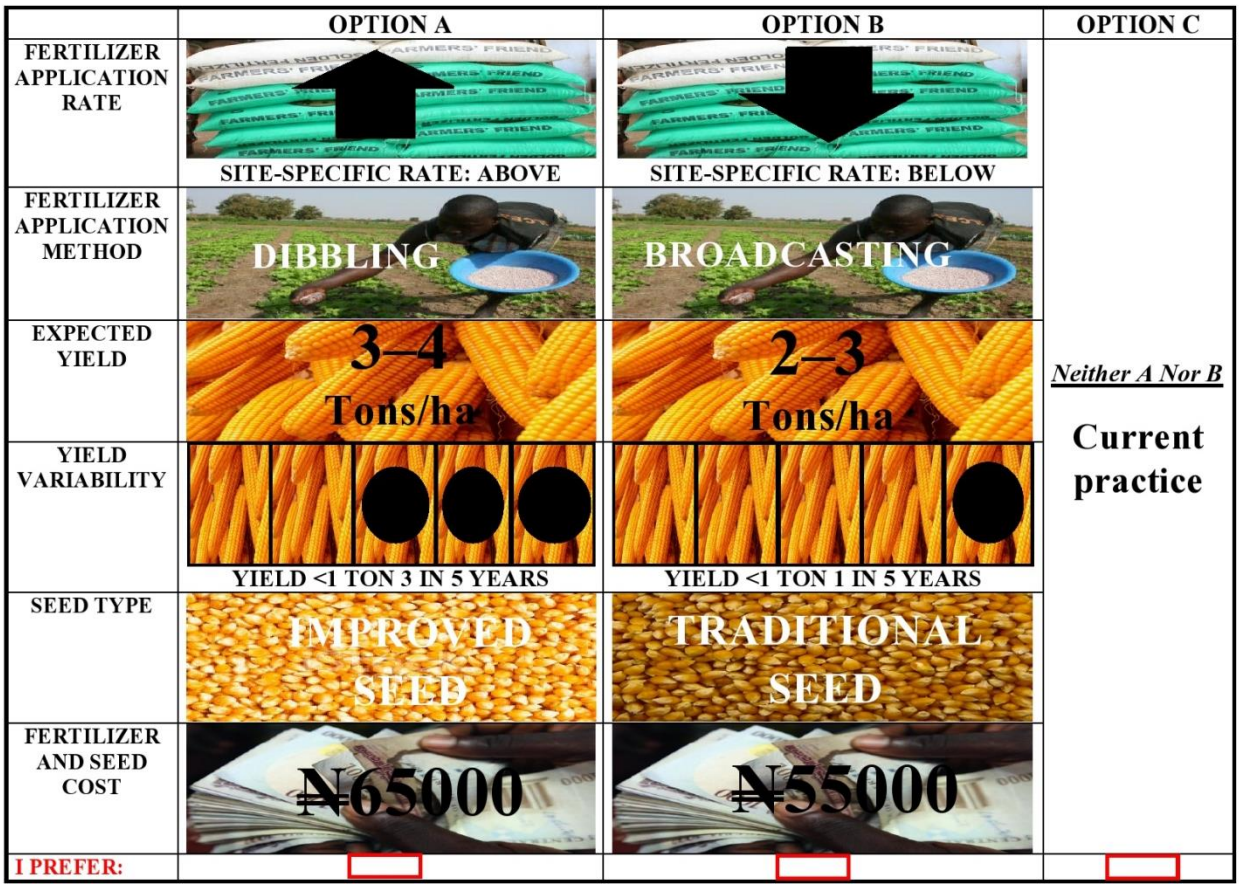

Figure A1: Example of a choice card

Table A1: Latent class model of farmers' preferences for ICT-based extension (without membership function) [1]

	LCM		SALCM		conventional ANA		Validated ANA			
							AC	AI	AC	AI
Class	LC1	LC2	LC1	LC2	LC1	LC2	LC1		LC2	
Class probability	63%	37%	80%	20%	64%	36%	61%		39%	
ASC[2]	-4.748***	-20.051	-60.379	-124.727	-4.782***	-35.647	-5.502***		-5.501***	
	(0.388)	(393.955)	(48.411)	(180.966)	(0.387)	(0.2D+07)	(0.747)		(0.669)	
SSFR	0.125	0.328*	0.445***	-0.434	0.111	0.227	0.065	0.258	0.304*	0.846**
(Below current rate)	(0.084)	(0.177)	(0.145)	(0.539)	(0.090)	(0.200)	(0.090)	(0.192)	(0.171)	(0.342)
SSFR	0.270***	-0.229	0.426**	-0.531	0.271***	-0.357	0.339***	0.056	-0.467	0.545
(Above current rate)	(0.082)	(0.297)	(0.179)	(0.719)	(0.084)	(0.281)	(0.090)	(0.203)	(0.364)	(0.417)
Dibbling	-0.081	-0.303**	-0.402***	-0.978	-0.074	-0.355**	-0.080	-0.125	-0.294**	-0.149
	(0.061)	(0.129)	(0.129)	(1.187)	(0.071)	(0.148)	(0.071)	(0.101)	(0.138)	(0.192)
Expected yield	0.047**	0.220***	0.147***	1.476*	0.040*	0.216***	0.037*	0.0674	0.250***	0.162
	(0.022)	(0.063)	(0.037)	(0.814)	(0.022)	(0.051)	(0.022)	(0.095)	(0.072)	(0.186)
Yield variability	-0.047*	-0.512***	-0.478***	0.121	-0.040	-0.532***	-0.036	-0.075	-0.512***	-0.522***
	(0.026)	(0.086)	(0.098)	(0.546)	(0.028)	(0.093)	(0.029)	(0.067)	(0.090)	(0.127)
Improved seed	0.279***	0.031	0.116	5.534**	0.273***	-0.080	0.290***	0.317**	-0.023	-0.001
	(0.063)	(0.154)	(0.122)	(2.563)	(0.067)	(0.184)	(0.072)	(0.123)	(0.156)	(0.224)
CFS (10000 NGN)	0.032*	-0.070*	-0.052	0.207	0.037**	-0.089**	0.034*	-0.051	-0.063	0.182**
	(0.017)	(0.040)	(0.036)	(0.129)	(0.019)	(0.038)	(0.019)	(0.055)	(0.039)	(0.090)
Log likelihood	-2405.50		-2391.00		-4067.06		-4067.06			
AIC	4845.00		4820.00		4895.20		4856.90			
BIC	4969.36		4904.07		5000.90		5049.60			

LCM = standard latent class model, SALCM = scale-adjusted latent class model; conventional ANA = conventional attribute non-attendance model; validation ANA = validation attribute non-attendance model; LC = latent class; AC= attributes considered or attended to, AI= attributes ignored or non-attended to,

[1] Without membership function, the signs and significance of coefficients as well as latent classes closely compares to the results with membership function except for SALCM,

[2] ASC is weakly identified in SALCM and class 2 of the other models as can be seen from the large values of the estimates due to a non-convergence challenge,

Number of observations is 1106,

SALCM has two scale classes. Scale class 1has class probability of 48% and a scale factor set to unity. Scale class 2 has class probability of 52% and a scale factor of 0.08,

Standard error reported between parentheses,

Significant coefficients at * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table A2: Results of multinomial logit models estimating membership function

	LCM	SALCM	conventional ANA	validation ANA
Constant	-2.953*	-1.526*	-2.818*	-2.214
	(1.587)	(0.813)	(1.511)	(1.440)
Age	-0.046***	-0.024***	-0.043***	-0.049***
	(0.015)	(0.008)	(0.014)	(0.014)
Education	-0.089***	-0.046***	-0.079***	-0.088***
	(0.030)	(0.016)	(0.026)	(0.026)
Labor	0.105	0.066	0.093	0.108
	(0.102)	(0.052)	(0.110)	(0.093)
Farmer association	0.747**	0.410**	0.776**	0.794**
	(0.372)	(0.193)	(0.336)	(0.336)
Off-farm income	0.699	0.345	0.539	0.565
	(0.596)	(0.306)	(0.591)	(0.563)
Assets	0.318***	0.181***	0.312***	0.279**
	(0.130)	(0.066)	(0.119)	(0.113)
Agricultural credit	1.175***	0.620***	1.068**	1.188***
	(0.452)	(0.229)	(0.423)	(0.432)
Extension	0.671**	0.331**	0.460	0.729**
	(0.315)	(0.162)	(0.296)	(0.300)
Distance to road	0.132***	0.060***	0.112***	0.124***
	(0.049)	(0.023)	(0.043)	(0.044)

Significant coefficients at * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$, Latent class 2 as reference class.