Maize Farmers' Preferences for ICT-based extension services: Evidence from a Choice Experiment in Nigeria

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Abstract:

Efforts aimed at addressing low productivity of maize in Nigeria and most parts of SSA via improved soil fertility management have largely been based on the conventional blanket extension recommendations rather than site-specific recommendations which take into consideration the heterogeneity in farmers' growing conditions. To contribute in addressing this challenge, a computer-based tool known as Nutrient Expert (NE) for maize is been developed. In anticipation of the introduction of the tool, we use discrete choice experiment to evaluate maize farmers' preferences for site-specific extension recommendations at the development phase of the tool where farmers' preferences can improve the tool development. We find that farmers' have strong preference for site-specific extension recommendations on nutrient management over the traditional blanket recommendations. However, there is heterogeneity of preferences giving rise to two segments of farmers' (innovators and conservatives) defined largely by differences in resource endowment. Our empirical findings have implications for improvement, potential uptake and targeting of the tool to meet the needs of different categories of farmers.

Acknowledgement: We deeply appreciate the support of Bill and Melinda Gates Foundation (BMGF) for funding Taking Maize Agronomy to Scale (TAMASA) project and the PhD research activities that produced this paper.

JEL Codes: Q16, C25

#1681

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Keywords: Adoption, Choice experiment, Extension, Maize, Nutrient Expert, Yield

1. Introduction

Sub-Saharan Africa (SSA) is confronted with the challenges of food insecurity and rural poverty which are strongly linked to low crop productivity due to poor soil fertility management amongst other factors[1] (Tittonell et al., 2013; Vanlauwe et al., 2015a; Komarek et al., 2017). This is exacerbated by the low levels of external inputs use to offset the declining soil fertility of the region (Binswanger-Mkhize and Savastano, 2017). Besides the challenge of low agricultural productivity in SSA, the rapidly growing and urbanizing population has led to increased food demand which makes intensification of agriculture a necessity especially in more densely populated areas (Droppelmann et al., 2017). However, the much anticipated agricultural intensification has not kept pace with the increasing population pressure and market access as expected (Binswanger-Mkhize and Savastano, 2017). This has resulted in incessant dependent on food import and also, area expansion where possible to meet the growing food demand (van Ittersum et al., 2016).

Efforts aimed at improving soil fertility in Nigeria and most parts of SSA have largely been based on general or blanket extension recommendations on fertilizer use which does not take into consideration the heterogeneity in farmers growing conditions (Tittonel et al., 2013; Kayuki et al., 2017). The key limitation of such blanket or regional recommendations is that it ignores the spatial and temporal variability in production factors of farmers (MacCarthy et al., 2017) and often limit them from maximizing net returns on their investment largely due to information constraint on site-specific or plot-specific fertilizer recommendations that befits their growing conditions (Rware et al., 2016). Intensification of input use such as fertilizer in SSA is gaining more prominence in maize production especially due to the huge potential of maize as a food security crop (Sheahan and Barrett, 2017). However, empirical findings from Nigeria show that profitability of fertilizer use for maize production is not favourable and this is due to poor yield response (marginal physical product of applied nitrogen) of maize to fertilizer use amongst other issues (Liverpool-Tasie et al., 2017). This suggests that policy options to drive fertilizer use and increase returns to investment by addressing market-related issues (transaction cost, credit and output market) without putting in place measures to ensure high yield response will not be sustainable (Burke et al., 2017). This is especially for smallholder farmers whose soils are less

[1] The full range of factors limiting crop productivity include biophysical, agronomic and socioeconomic issues (Tamene et al., 2016)

responsive to fertilizer due to negative nutrient balance which is indicative of prolonged soil nutrient mining (Burke et al., 2017). Sustainable intensification will require nutrient management options that take into account site-specific nutrient response patterns and local socio-economic context (Droppelmann et al., 2017). Consequently, farmers need access to information on site-specific soil fertility management to improve nutrient response and returns on investment in fertilizer use (Kihara et al., 2016). However, the extension system which is saddled with the responsibility of advising farmers on correct use of modern inputs, crop management and market-related issues is weak (Rware et al., 2016).

Despite the push for technological innovations to drive agricultural intensification in SSA, empirical evidence from Nigeria's maize-based systems shows that it is not sufficient, highlighting the need for other preconditions for intensification (Smith et al., 1994), such as institutional innovations. A well-functioning extension system and markets are needed to support any intensification process (Otsuka and Larson, 2013). To improve the capacity of the extension system in Nigeria and SSA at large towards delivery of site-specific extension recommendations to support intensification, information and communication technology (ICT) driven decision supports tools (DSTs) offer great potentials (Vanlauwe et al., 2017). Such tools can enhance the capacity of agricultural extension system in reaching out to wider spectrum of smallholder farmers and enable them make better informed farm management decisions (Kragt and Llewellyn, 2014). More importantly, it can aid the extension system in providing agronomic advice that accounts for heterogeneity in crop management, soil, climatic and socioeconomic conditions of farmers (Vanlauwe et al., 2015b). This is necessary for local adaption of soil fertility management technologies to suit the heterogeneous smallholder farming systems. The use of DSTs offers a more feasible and cost effective option for site-specific extension recommendations on nutrient management especially as soil analysis is out of the reach of smallholder farmers (Njorege et al., 2017). To fill the gap for the much needed site-specific extension recommendations and enhance the capacity of extension service providers to deliver such recommendations, a Bill and Melinda Gates Foundation (BMGF) supported project known as Taking Maize Agronomy to Scale (TAMASA) is co-developing[2] useable and scalable nutrient management tool known as Nutrient

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

Expert (NE) for maize in Nigeria, Tanzania and Ethiopia. NE decision support tool for maize is an easy-to-use, interactive and computer-based tool that enables researchers, extension agents and crop advisors to quickly develop fertilizer and management recommendations for an individual farmer's field (Pampolino et al., 2012). The variability in farmers' growing environments is taken into account in generating the science-based recommendations for profitable target yield with options for adjusting recommendations based on farmers' budget (Pampolino and Zingore, 2015). In nut shell, the tool is based on the principles of site-specific nutrient management (SSNM) which is focused on making fertilizer management compatible with the economic, social and environmental goals of sustainable development (Xu et al., 2014).

Despite the potentials of ICT-based DSTs such as NE tool, there is no empirical study that have evaluated farmers' preferences and adoption potentials for extension recommendations from DSTs especially at the development phase of the tool where farmers' inputs can improve the tool development. In the context of NE tool, there are gaps in research related to the tool development that need to be addressed in an ex-ante framework at the farmers' level. The first question that has to be addressed is whether farmers' have strong preferences for site-specific extension advice from NE tool in comparison with more traditional blanket or regional extension recommendations. The second question relates to which characteristics of extension advice from NE tool are most attractive to farmers and the trade-offs that farmer's make for the characteristics. The third question is about the presence of heterogeneity of farmers' preferences that can result in different farmer segments. Lastly, the underlying factors that could condition the preference segments and potential adoption of recommendations from the tool are questions of pertinent interest. This is very important because the demand for NE tool is conditional upon farmers' demand for recommendations from the tool.

The remainder of the paper is organized as follows. In Section 2 we explain the methodological approach employed in the paper. In Section 3 we report the results of the empirical analysis and the discussion. Finally, Section 4 concludes the paper and provides relevant implications.

2. Methodology

2.1 Research area and sampling framework

The study area for this research is the maize-based region of TAMASA project implementation in Northern Nigeria covering Kano, Kaduna and Katsina states. The research was conducted in the Focal Area (FA) of TAMASA in these states covering about 1.7 million hectares of cropland. The FA of TAMASA project implementation in Nigeria is shown in figure 1. The sampling procedure for the research is aligned with the spatial sampling framework of TAMASA project implementation in Nigeria. This was developed with geospatial inputs to ensure spatial representation of the target maize-based system in addition to ensuring selection of representative sample of maize-based farming households. Multistage sampling procedure was used in selecting the maize-based farming households. This involved the random selection of 8 maize-based farming households from the sampling frame of maize-based farming households in 99 villages to give a sample size of 792 maize-based farming households. However, only 774 maize-based farming households actually participated in the CE.

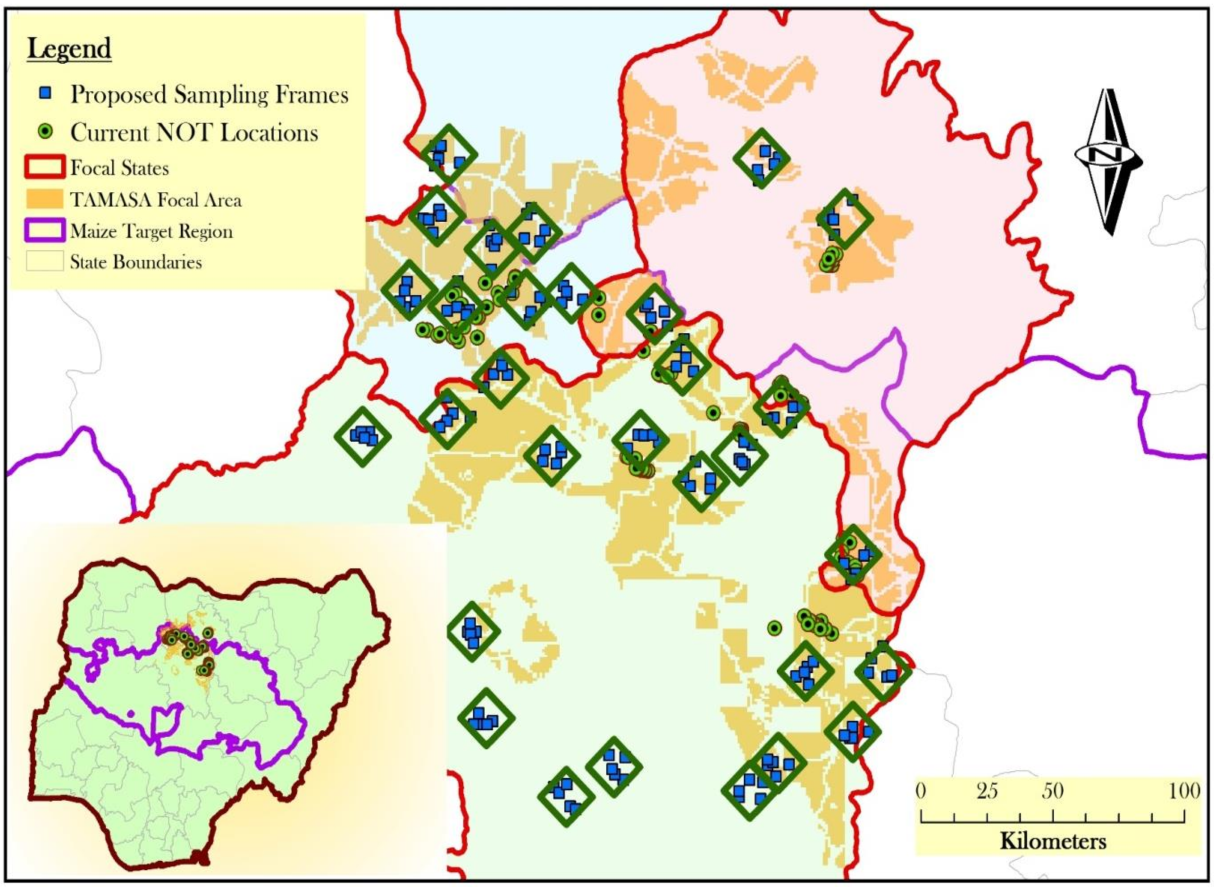

Figure 1: Map of Nigeria showing the study area

2.2 Data Collection

The data collection is based on a Choice Experiment (CE) implemented during the maize harvest period of 2016 as a component of the first round of TAMASA Agronomy Panel Survey

(APS)[3] in Nigeria. The CE was followed by household- and plot-level components of the survey. The data collection was conducted with the assistance of survey teams comprising of trained enumerators and supervisors from the International Institute of Tropical Agriculture (IITA), Kano, Nigeria, Centre for Dryland Agriculture, Bayero University Kano, Nigeria and technical support from International Maize and Wheat Improvement Center (CIMMYT), Ethiopia. To improve the quality of data collection and ensure real time access to the data, the survey was implemented using computer assisted personal interview instruments (CAPI) on Open Data Kit (ODK) platform rather than paper-based instruments.

2.3 Choice experiment

A choice experiment is a survey-based method for eliciting respondents' preferences expressed by the respondents' choice between two or more discrete alternatives of a good, service or course of action that are described by their attributes or characteristics (Pouta et al., 2014). The application of CE was initially in the domain of marketing studies and it now cuts across several disciplines such as agriculture, environment, health, transport, education. Its application in the field of agriculture and agro-based research is increasing (Balcombe et al., 2014; Ortega et al., 2016; Kikulwe et al., 2010; Romo-Muñoz et al., 2017; Caputo et al., 2017; Rakotonarivo et al., 2017) and even getting broader application in ex ante agricultural technology adoption (Lambrecht et al., 2015; Coffie et al., 2016; Kassie et al., 2017). In a typical ex-ante agricultural technology setting, CE can be designed to mimic real world adoption decisions of farmers for technologies yet to be developed or in the process of development. This is done by presenting farmers with different hypothetical options or alternatives of a technology defined by different levels of the traits or attributes of the technology and asking them to select the most preferred technological options. CE method draws upon Lancaster's economic theory of value (1966) and random utility theory (McFadden, 1974). The Lancaster theory states that any good, or service can be described in terms of its attributes/characteristics and their levels and consumers make their purchase decisions based on the attributes of the good rather than the good itself.

2.2.1 Design of choice experiment

The first step in the design of the CE is identification of the attributes or technological traits associated with extension recommendations from NE tool and their levels to be included in the CE. In order to achieve this, we consulted scientists' within and outside TAMASA project and

[3] APS is a three-period panel survey (2016, 2017 and 2018) undertaken by TAMASA project.

farmers' through a focused group discussion (FGD). Several characteristics or attributes were identified but only six of the most important attributes were included in the CE to reduce the complexity of the choice tasks. This is very important as increase in choice sets complexity leads to more random choices (less deterministic choices) by respondents' (Beck et al., 2013). The first and second attributes of the CE directly relate to fertilizer use in the context of site-specific nutrient management (Pampolino and Zingore, 2015). The first attribute is fertilizer application rate which describes the quantity of inorganic fertilizer required to supply the nutrients necessary to achieve a target maize yield on farmers' field. The second attribute is fertilizer application method which relates to how fertilizer is applied on maize fields to guarantee optimal uptake of the nutrients by maize plants and ensure that the desired maize yield is attained.

The third and fourth attributes relate to returns in terms of yield and variability of yield associated with using extension recommendations on soil fertility management. The third attribute is expected yield expressed as the average yield of maize on a hectare of maize field over a production period of five years in response to the utilization of a given extension recommendation. The fourth attribute is yield variability (yield risk) which describes the risk associated with a given expected yield level. In other words, the variance around the expected mean yield of maize given by the probability of obtaining actual yields below the expected yield over a period five years (probability of undesired outcome or probability of a bad production year). This attribute is defined by five levels based on the number of production years (out of five years) the yield of maize is below one tonne per hectare.

The fifth attribute relate to the use of complementary input to fertilizer towards achieving a target maize yield. Maize seed type is the fifth attribute and its inclusion is because it is usually associated with extension recommendations on fertilizer use due to the complementarity of fertilizer and improved seeds especially as promoted in integrated soil fertility management (ISFM) (Vanlauwe et al., 2015b). The last attribute is the monetary attribute expressed as the cost of fertilizer and seed in the local currency (Naira) per hectare of maize field. This represents the fertilizer and seed investment cost associated with adopting a given extension recommendation on soil nutrient management. Five levels of this attribute was defined based on the actual costs incurred on fertilizer and seed during the 2016 growing season obtained through the FGD and pilot survey implemented in the research area. The range of realistic cost of fertilizer and seed per hectare was determined based on the actual investment cost incurred.

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

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

Note: 305 Naira (N) is equivalent to 1 USD at the time of the survey

The second step is the experimental design based on the selected attributes and their various levels in NGENE software. We used a fractional factorial design; specifically a Bayesian D-efficient design which minimize the D-error and improve the efficiency of the design. Prior to the Bayesian D-efficient design as equally implemented by Scarpa et al. (2013) and Caputo et al. (2017), we conducted a pilot survey based on orthogonal design and the data were used to estimate a multinomial logit model. The coefficients of the estimated model were then used as Bayesian priors (random priors distribution) in generating the D-efficient design. Also, the pilot survey was used to gain insight into farmers' comprehension of the CE. The design produced 12 paired choice sets that were randomly blocked into two blocks of 6 choice sets. The blocking was necessary to make the CE less cumbersome for farmers and improve the quality of responses since the CE is a component of a larger survey. The third step is the construction of 12 laminated choice cards from the 12 paired choice sets generated from the experimental design. Due to low literacy of most farmers in the research area, the choice cards have pictures for different attributes to enhance the farmers' comprehension of the CE. Each choice card consists of two generic scenarios known as options A and B which contains different scenarios of NE-based extension recommendations. A status quo option which represents the current agricultural practice of farmers is included in all choice cards as option C to make the choice exercise realistic and avoid forced choices. A sample of the choice card is presented in figure 2.

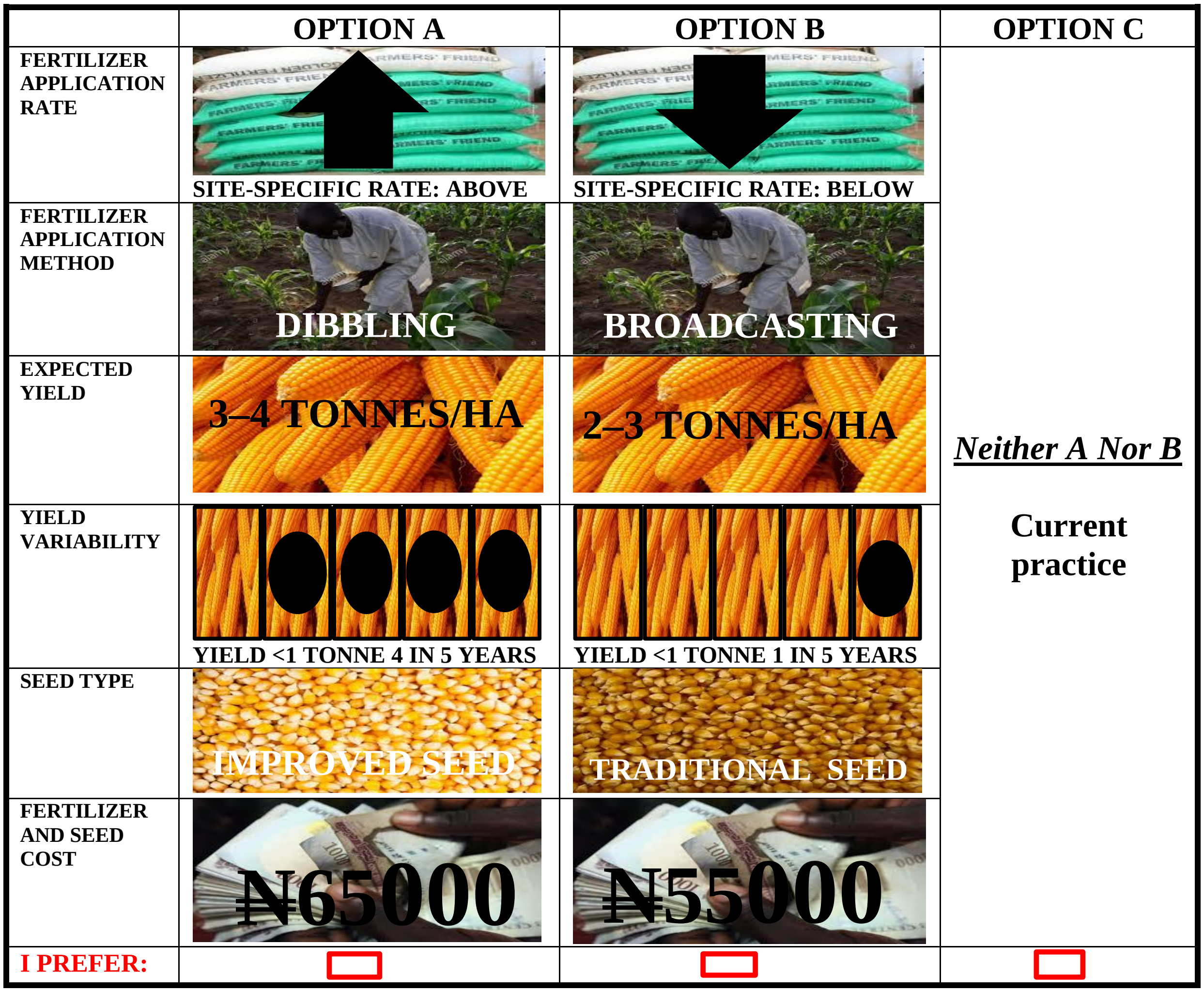

Figure 2: Sample of choice chard

2.2.2 Implementation of choice experiment

In the CE implementation, each farmer was offered 6 choice cards to make a choice between the two generic NE-based extension recommendations (options A and B) and their current farming practice (option C). The presentation of the cards was done in a random order to avoid ordering effects that could constitute bias. Due to the hypothetical nature of CE, we made concerted efforts from the CE design to the implementation to minimize hypothetical bias that could undermine the validity of our results (Loomis, 2014). Prior to the commencement of the CE, the farmers' were usually sensitized on the purpose of the CE and how to correctly respond to the options in the choice cards and we ensured that every farmer understood the contents of the CE. We used a cheap talk script with budget constraint reminder to minimized hypothetical bias.

2.4 Econometric framework

The econometric basis of CE is random utility theory (Kikulwe et al., 2010). The theory assumes that an i^{th}farmer's utility of choosing alternative j among all alternatives offered in a choice set s is given by an indirect or unobservable utility which consists of a deterministic (explainable) component and a random (unexplainable) component as follows:

$$U_{ijs} = V_{ijs} + \varepsilon_{ijs} = \sum_{k=1}^{K} \beta_k x_{ijsk} + \varepsilon_{ijs} \qquad i = 1, \dots, N; j = 1, \dots, J;\ s = 1, \dots, S \tag{1}$$

Where U_{ijs} = i^{th} farmers' indirect or latent utility from choosing alternative j in choice set s, V_{ijs}= the systematic portion of the utility function which is linear in attributes k of alternative j, x_{ijsk} = vector of attributes describing alternatives j with associated preference parameters β_k, ε_{ijs} = unobserved random term which is independently and identically distributed (iid)

In estimating a conditional logit model (CLM), the utility function for an i^{th}farmer's choice of alternative j in choice set s is given as follows:

$$U_{ijs} = Asc_j + \sum_{k=1}^{6} \beta_k x_{ijsk} + \varepsilon_{ijs} \tag{3}$$

Based on the CLM (McFadden, 1974), the probability that farmer i chooses alternative j in choice set s is given as follows:

$$Pr_{ijs} = \frac{\exp(\beta_k x_{ijsk})}{\sum_{t=1}^{J} \exp(\beta_k x_{itsk})} \tag{4}$$

A key assumption of the model is that the preference parameters do not vary across farmers implying that accounting for heterogeneity in farmers' preferences for extension recommendations from NE tool cannot rely on CLM (Kragt and Llewellyn, 2014; Gelaw et al., 2016). This led to the estimation of latent class model (LCM) which accounts for unobserved heterogeneity by assuming that a heterogeneous population of farmers belongs to a discrete number of preference segments otherwise known as latent classes and each farmer has a positive probability of membership in each class. The utility function now becomes:

$$U_{ijs} = Asc_j + \sum_{k=1}^{6} \beta_{ck} x_{ijsk} + \varepsilon_{ijs} \tag{5}$$

However, the probability of an i^{th}farmer choosing alternative j in a choice set s is conditional upon the individual farmer's membership of latent class c and the membership likelihood is modeled as a function of the individual-specific characteristics of the farmer. The choice probability and membership likelihood function are jointly estimated (Boxall and Adamowicz, 2002):

$$Pr_{ijs}|c = \frac{\exp(\gamma_c' z_i)}{\sum_{q=1}^{C} \exp(\gamma_q' z_i)} \quad (6)$$

Where z_i is the vector of the individual-specific characteristics which can explain the sources of heterogeneity in preferences between classes and γ_c' is the vector of parameters of z_i.

An alternative specific constant (ASC) was included in the utility function to capture preference for the status quo option and this was dummy coded as 1 if a farmer chose his current practice and 0 if any of the two experimentally generated options of NE-based extension recommendation was chosen. A negative coefficient of ASC implies a positive utility of moving away from their current practice to a site-specific nutrient management. The categorical attributes (fertilizer application rate, fertilizer application method and seed type) were effects coded to avoid confounding the ASC with the base levels of these attributes (Bech and Gyrd-Hanson, 2005). Since the key interest of this study is on preference heterogeneity, the scale parameters in the utility and membership functions are normalized to one for identification purpose (Boxall and Adamowicz, 2002).

One of the basic assumptions of choice modeling is the continuity axiom of choice which suggests that respondents consider all attributes of the alternatives of a good or service offered to them in making their decision to choose out of the alternatives (Kragt, 2013; Glenk et al., 2015; Coffie et al., 2016; Ratokonarivo et al., 2017). Violation of this assumption is referred to as attribute non-attendance (ANA) and this implies non-compensatory decision making behaviour of respondents. Failure to account for ANA can lead to biased parameter estimates of attributes and more, importantly biased willingness to pay (WTP) estimates (Glenk et al., 2015). We rely on self-reported/stated ANA responses of farmers elicited at the end of the CE (Serial-based ANA approach) and implemented three approaches out of the several stated ANA approaches in empirical literature to account for ANA and ensure that our results are robust. The first approach (zero utility weight approach) involves constraining the parameter of ignored attribute to zero in the utility function suggesting that failure to attend to an attribute by a respondent leads to zero marginal utility for the attribute (Kragt, 2013; Campbell et al., 2018). The second approach (covariate approach) involves conditioning the utility parameters on the stated attribute importance

(SAI) information elicited from respondents ranking of the attributes based on their importance (see Balcombe et al., 2014; Coffie et al. 2016 for details). The third approach (two coefficients per attribute approach) involve estimating two parameters for each attribute with one for attendance (considered all attributes) and another for non-attendance (ignored at least one attribute) (Scarpa et al., 2013; Caputo et al., 2017).

3. Empirical results and discussion

We estimated CLM and LCMs with two to seven latent classes in order to sufficiently represent the preference segments in our data using STATA 15. Based on the result in Table 1A in the appendix, the model with two classes was selected as it has the lowest Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) indicating the best fit.

3.1 Descriptive characteristics of farmers' by preference classes

The results in Table 2 show the differences in individual-, household- and farm-level characteristics between the two segments of farmers defined based on their preferences for site-specific nutrient management recommendations. There are distinct differences in some of the characteristics which could contribute in explaining the preference pattern between the two classes or segments of farmers. Our descriptive results show that in comparison to farmers in the second segment, farmers in the first segment are relatively younger, healthier, more experienced in maize cultivation, invest more on farm inputs and are better off in terms of access to resources and services such as family labour, credit, farmer association, contract farming, extension and assets. Using resource endowment characteristics that entail human, physical, social and financial resources of farmers, we can describe the first segment of farmers as more resource endowed and the second segment as less resource endowed. This suggests that the first segment of farmers is more likely to adopt improved technologies than the second segment since they face less resource constraints in agricultural technology adoption.

Table 2: Summary statistics of farmers' characteristics by preference classes

Characteristics	Latent class 1 (63%)		Latent class 2 (37%)		
	Mean	Std. Dev.	Mean	Std. Dev.	Sig.
Age of household head (years)	43.93	11.69	46.03	12.46	***
Education of household head (years)	4.35	5.72	6.59	6.23	***
Health of household head(%)[1]	97.19		95.11		***
Adults (No.)	3.63	2.22	3.45	1.41	***
Children (No.)	6.02	4.74	5.62	3.99	***
Household size (No.)	9.65	6.16	9.07	4.69	***
Access to credit (%)	27.30		9.33		***
Access to extension[2] (No.)	2.72	2.22	2.25	1.69	***
Maize contract participation (%)	18.37		12.89		***
Membership of association (%)	39.54		23.55		***
Maize farming experience (years)	19.31	10.41	18.78	10.79	***
Farm assets[3] (Naira)	58384.70	125798.1	39380.77	90530.18	***
Transport assets (Naira)	228634.3	494682	157786.8	388279.3	***
Livestock assets (Naira)	442828	661587	295096	368250.7	***
Household durables[4] (Naira)	24782.45	64154.78	18952.36	21261.59	***
Total annual income (Naira)	905912.2	1821469	1280592	2479024	***
Total farm area (ha)	3.20	3.50	3.28	3.83	
Maize focal plot area (ha)	0.77	0.99	0.89	1.09	***
Fertile soil[5] (%)	43.11		35.56		***
Soil test[6] (%)	2.38		0.53		***
Extension experience[7] (%)	39.54		33.33		***
NPK fertilizer use (Kg/ha)	117.76	99.75	106.85	88.41	***
Urea fertilizer use (Kg/ha)	75.85	79.15	64.09	72.66	***
Input investment costs/ha[8] (Naira)	35052.46	20226.47	31321.51	18814.46	***
Maize-legume intercrop (%)	27.81		34.22		***
Improved maize seed adoption (%)	31.11		22.67		***
Distance to tarmac road (km)	4.85	6.04	2.76	2.52	***

Note: *** p <0.001 t-tests of significant differences between the two segments of farmers. 305 Naira is equivalent to 1 USD at the time of the survey. [1]Household head is healthy throughout the year, [2]Number of extension agent-farmer contacts in 2016 maize growing season, [3]Non-land assets which includes farm implements and machinery, [4]Durable assets such as furniture, TV, radio, refrigerator, mobile phone, sewing machine and other household durables, [5]Farmers' perception of inherent soil fertility of their maize plot, [6]Soil testing has been done on maize plot in the last three years, [7]Farmer's use of regional fertilizer recommendation on maize plot consistently in the last three years, [8]Fertilizer and seed investment per hectare of maize in 2016 maize growing season

3.2 Segment-specific preference heterogeneity

The results of the estimated LCM with two latent classes or farmer segments are presented in Table 3. The coefficient of alternative-specific constant (ASC) is highly significant and negative for both segments of farmers. This implies that overall the maize farmers' have positive preference for site-specific extension recommendations on nutrient management over their current practice. The strong preference for site-specific recommendations over the conventional or traditional blanket recommendations suggest that the farmers' recognize the heterogeneity of their farming systems and the need for extension recommendations to be tailored to their specific growing conditions towards improving their productivity and welfare.

Both segments of farmers have significant positive preference for site-specific fertilizer application rates. However, there is variability in the type of fertilizer application rates the farmers prefer and the farm input investment cost they are willing to accept. The first segment of farmers have a positive preference for site-specific fertilizer recommendation rates that are above their current application rates and also, have positive preference for higher investment on fertilizer and seed associated with higher maize yielding recommendations. This is rather unexpected as farmers are expected to have negative preference for higher investment costs associated with higher yielding extension recommendations. However, a plausible reason for this finding could be due to correlation of higher investment costs with higher yield (price and quality of output) especially for responsive soils thus implying that less cash constrained farmers maybe more willing to invest more on higher yielding site-specific recommendations than more cash constrained farmers. Empirical CE studies with positive price coefficients (Lambrecht et al., 2015; Romo-Muñoz et al., 2017) have equally attributed this somewhat counterintuitive finding to be most likely due to positive price-quality nexus especially for new products. This lends credence to the double effect of price[4] (Palma et al., 2016). This finding further suggests that this class of farmers is less sensitive of investments cost and maybe more inclined to output maximization rather than input cost minimization. This implies that farmers in this segment can benefit from very high yielding site-specific recommendations from NE tool as the descriptive results in Table 2 show that they appear to be more resource endowed that farmers in class two. On the other hand, the preference for high yielding recommendations with higher investment cost could be that some of the farmers ignored the cost attribute in their choices in line with the finding of Campbell et al. (2018). This lends credence to estimation of ANA model to validate this finding. The second segment of farmers have positive preference for site-specific fertilizer recommendation rates that are strictly below their current application rates and have a negative preference for recommendations with higher investment cost on fertilizer and seed consistent with the downward sloping demand theory. This

[4] In traditional economic theory, price is expected to have a negative effect on purchase probability due to consumers' budget constraints but under some circumstances, a positive effect may also exist especially when price is a cue for quality (Palma et al., 2016).

implies that although this segment of farmers are favorably disposed to site-specific extension recommendations, the likelihood of adopting recommendations whose cost implication is beyond the budget level of their current practice is very low especially for cash constrained or conservative farmers. This indicates that this class of farmers is highly sensitive of investment cost in agricultural technology adoption and maybe more inclined to input cost minimization objective rather than output maximization in their production decisions.

The coefficient of fertilizer application method (dibbling) is significant and negative for class one farmers which indicates they prefer broadcasting method of fertilizer application to dibbling. This implies that they have a negative preference for fertilizer recommendations that encourage the use of a more labor intensive fertilizer application method and hence, are more inclined to the use of broadcasting method which is less labor demanding. This is in line with the findings of Coffie et al. (2016) and reaffirms the issue of labor constraint as one of the barriers to agricultural technology adoption (Jack, 2013). This is even more challenging for resource poor smallholder farmers who are interested in site-specific nutrient management for maize but cannot mobilize sufficient labor during the peak periods of labor demand. The use of incorrect application method could undermine the optimal uptake of applied nutrients and maize yield associated with site-specific nutrient management recommendations. For class two farmers, the coefficient is not significantly different from zero.

Both segments of farmers have statistically significant positive preferences for maize yield which implies that they are interested in higher yielding recommendations in line with *a priori* expectation. This finding is consistent with other CE studies that reported maize farmers' positive preference for high yielding technologies (Ortega et al., 2016, Kassie et al., 2017). This further indicates that the adoption behavior of the farmers can be strongly influenced by the expected higher yield associated with site-specific extension recommendations. Beyond the homogeneous preference for expected high yield, both segments of farmers' have statistically significant negative preferences for yield variability (yield risk) associated with higher yielding recommendations. This implies that the farmers are more likely to adopt extension recommendations that offer greater stability of yield overtime due to their susceptibility to production risk factors coupled with the challenge of missing insurance markets. This corroborates the findings of Coffie et al. (2016) on the negative effect of risk exposure in farmers' preferences for agronomic practices. To gain better insights on the trade-offs farmers are willing to make between higher yield and yield risk, we estimated marginal rate of substitution (MRS) between expected yield and yield variability which is equivalent to their willingness to forgo some yield gains for reduction in yield variability or increase in yield stability. The MRS estimates show that both segments of farmers are willing to forgo some yield gains for stability in yield which implies that they are indeed sensitive to risk and this signals their safety-first behavior. However, farmers in segment two are willing to forgo more yield gains for stability in yield than farmers in segment one suggesting that they are more sensitive to risk exposure. Overall, the farmers place more weight on yield stability than expected yield which points to their risk aversion for higher yielding recommendations associated with more exposure to production risk.

The coefficient of seed type (improved seed variety) for class two farmers is not significant which implies that this segment of farmers is indifferent between improved and traditional maize varietal types. Unlike farmers in class two, we find a significant positive preference for improved seed variety associated with site-specific nutrient management recommendations by farmers in class one. This implies that farmers in class one are more favorably disposed to adopting improved maize seeds and equally benefitting from the yield gains of fertilizer and improved seeds complementarity. As expected, maize yield response to fertilizer use is strengthened when improved seeds are cultivated pointing to positive synergistic effects of fertilizer and improved seeds (Vanlauwe et al., 2015b).

In explaining the membership of farmers into either of the two preference segments, we include independent variables that are relevant in influencing agricultural technology adoption. The factors that were significant in explaining class membership of the farmers include the human, physical, social and financial capital endowments of the farmers which represents the sources of preference heterogeneity. Based on the preference heterogeneity between the two farmer segments, 63% of the farmers which represents segment one can be described as strong potential adopters (innovators) of site-specific nutrient management recommendations. The strong potential adoption by this segment of farmers is motivated by the estimates of the LCM and profile of the farmer segments which show that they are more resource endowed (less cash constrained), less sensitive of exposure to risk, more conscious of soil fertility improvement, less sensitive of investment cost associated with higher yielding recommendation and better inclined to output maximization benefits of NE tool. The opposite is the case of farmers in segment two (37%) who can be described as weak potential adopters (conservatives) of site-specific nutrient management recommendations.

Table 3: Latent class model of farmers' preferences for NE fertilizer recommendations

	Latent class 1 (63%)		Latent class 2 (37%)	
	Coeff.	Std. Error	Coeff.	Std. Error
Utility function				
ASC	-5.374***	0.475	-5.948***	0.655
SSFR (Below current rate)	-0.032	0.046	0.379***	0.097
SSFR (Above current rate)	0.139***	0.044	-0.262*	0.138
FAM (Dibbling)	-0.043	0.029	-0.136***	0.059
Expected yield	0.036*	0.019	0.242***	0.057
Yield variability	-0.042*	0.023	-0.523***	0.068
ST (Improved seed variety)	0.123***	0.030	0.073	0.068
CFS (Costs)	0.032**	0.017	-0.072**	0.035
Membership function				
Age	-0.043***	0.015		
Education	-0.066***	0.028		
Labour	0.179*	0.099		
Association	0.638*	0.342		
Income	-0.336***	0.137		
Assets	0.433***	0.136		
Agricultural credit	1.284***	0.473		
Extension experience	0.662**	0.301		
Road infrastructure	0.147***	0.047		
Farm size	-0.278**	0.144		
Constant	0.201	1.947		
Log likelihood	-2371.98			
Number of parameters	27			
Number of observations	11106			
AIC	4797.95			
BIC	4995.46			

Note: SSFR= Site-specific fertilizer rate, FAM= Fertilizer application method, ST= Seed type, CFS = costs of fertilizer and seed. Estimates of MRS between yield and yield variability is 1.19 (-2.12, 7.89) and 2.160 (1.60, 3.45) for farmers' in segment one and two respectively. Significance of coefficients at * p <0.1, ** p <0.05 and *** p <0.001.

To ensure internal validity of estimated choice models, robustness checks should be conducted through testing axioms of choices among other emerging methodological issues in choice modeling (Lancsar et al., 2017). In line with this, we address the issue of attribute non-attendance by estimating stated ANA models. The results of three stated ANA models are presented in Table 2A in the appendix. The results show similar outcomes with our estimated model suggesting that our model is robust. In other words, our findings on farmers preferences for site-specific nutrient management recommendations and the implications put forward are still valid.

4. Conclusion

Given the on-going development of NE tool to enhance the capacity of extension system in providing site-specific fertilizer recommendations to maize farmers, we use discrete choice experiment to explore the farmers' preferences for site-specific extension recommendation on nutrient management. Our empirical results show that the farmers' have strong preference for site-specific recommendations over the traditional blanket recommendations. The results also show a distinct heterogeneity of farmers' preferences for site-specific recommendations arising from the existence of two preference segments from the estimated models. The first segment of farmers (innovators) who are more resource endowed appear to be more conscious of improving their soil fertility as they prefer site-specific fertilizer application rates above their current application rates and are more favorably disposed to higher investment outlay associated with much higher yielding recommendations (higher utility-higher cost). The second segment of farmers (conservatives) have an opposite preference pattern to the first segment of farmers which implies that uptake of site-specific extension recommendations by this segment of farmers can be impeded by investment cost on fertilizer and seed which could be attributed to cash constraint. From policy perspective, this finding suggest that the current input subsidy scheme of the Federal Government of Nigeria should be better targeted to very cash constrained farming households to enable them adopt site-specific extension recommendations geared toward improving their productivity and economic well-being.

Our finding on heterogeneity of farmers preferences for site-specific recommendations reinforces the need for appropriate targeting of interventions to meet the needs of different categories of end-users in order to produce the expected benefits. With a clear cut preference structure between the two categories of farmers, high cash constrained farmers can be better targeted with recommendations having lower investment outlay and higher cost saving benefits on inputs from NE tool. This implies that designing alternative platforms of the tool that can properly take into account the investment portfolios and yield targets of different segments of farmers can greatly influence the adoption behavior of farmers. Furthermore, this will strengthen the inclusiveness of the tool as it offers benefits to both less resource endowed and more resource endowed farmers.

Our finding show that extension recommendations with higher expected yields above farmers current yields are necessary but not sufficient to influence farmers decision making on adoption of extension recommendations from NE tool. A key potential behavioral barrier to uptake of site-specific recommendations from the tool is exposure to risk as both segments of farmers attach strong importance to risk aversion coupled with the missing insurance market. This suggests that well-concerted efforts geared towards mitigating risk associated with uptake of recommendations from the tool can greatly influence their adoption behavior. From policy perspective, our study contribute in providing empirical information which can form basis for appropriate policy framework towards increasing productivity of maize through site-specific nutrient management of which NE tool offers huge opportunities. Given the ability of NE tool to offer agronomic advice on site-specific nutrient management and farmers strong preference for such advice, the weak capacity of the extension system in offering site-specific advisory services and reaching out to wider coverage of farmers can be addressed. Furthermore, with the availability of ICTs such as smart phones, the use of NE tool can easily be integrated in the extension system for better service delivery to farmers

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Appendix

Table 1A: Criteria for the selection of optimal number of preference segments

Classes	Log-likelihood	No. of parameters	AIC	BIC
1	-3112.952	8	6241.904	6302.239
2	-2371.979	27	4950.551	4923.551
3	-2336.295	46	5024.563	4978.563
4	-2306.126	65	5109.605	5044.605
5	-2277.796	84	5198.324	5114.324
6	-2254.887	103	5297.886	5194.886
7	-2218.281	122	5370.054	5248.054

Table 2A: Latent class model of farmers' preferences for NE fertilizer recommendations

	Approach 1	Approach 2	Approach 3	
			AA	ANA
Class one	66.5%	65%	61%	70%
ASC	-5.402***	-5.242***	-5.298***	-4.885***
SSFR (Below current rate)	0. 025	-0.102	-0.056	0.080
SSFR (Above current rate)	0. 224***	0.153	0.132*	0.077
FAM (Dibbling)	-0. 071	-0.031	-0.016	-0.099**
Expected yield	0. 020	0.030	0.031	0.039
Yield variability	-0. 054**	-0.058*	-0.054*	-0.067*
ST (Improved seed variety)	0. 224	0.034	0.111***	0.128***
CFS (Cost)	0. 026*	0.035	0.043**	-0.002
SSFR (Below current rate)*Z1		0.488***		
SSFR (Above current rate)*Z1		0.254		
FAM (Dibbling)*Z2		-0.074		
Expected yield*Z3		0.023		
Yield variability*Z4		0.018		
ST (Improved seed variety)*Z5		0.297*		
CFS (Cost)*Z6		-0.007		
Class two	33.5%	35%	38%	30%
ASC	-5.837***	-5.926***	-59.449	-5.664***
SSFR (Below current rate)	0. 445***	0.563*	0.338**	0.522**
SSFR (Above current rate)	-0.320	-0.313	-0.194	-0.483
FAM (Dibbling)	-0.365***	-0.082	-0.183***	-0.039
Expected yield	0.257***	0.166**	0.280***	0.362**
Yield variability	-0.527***	-0.337***	-0.464***	-0.896***
ST (Improved seed variety)	0.088***	-0.190	0.090	0.112
CFS (Cost)	-0.078**	-0.211***	-0.110***	0.032
SSFR (Below current rate)*Z1		0.005		
SSFR (Above current rate)*Z1		0.312		
FAM (Dibbling)*Z2		-0.324		
Expected yield*Z3		0.252*		
Yield variability*Z4		-0.424**		
ST (Improved seed variety)*Z5		0.700*		
CFS (Cost)*Z6		0.298***		
Log likelihood	-2503.812	-2345.962	-1667.969	-689.786
Number of parameters	27	41	27	27
Number of observations	11106	11106	7794	3312
AIC	5061.6	4773.925	3389.938	1433.571
BIC	5230.5	5073.85	3577.888	1598.414

Note: Significance of coefficients at * p <0.1, ** p <0.05 and *** p <0.001. Approach 1: Accounting for ANA (Zero utility weight approach), Approach 2: Accounting for ANA (Covariate approach), Approach 3: Accounting for ANA (Two coefficients per attribute approach), AA=attribute attendance, ANA=Attribute non-attendance. Approach 1 was estimated in NLOGIT 5 while Approaches 2 and 3 were estimated in STATA 15.