ARENBERG DOCTORAL SCHOOL
FACULTY OF BIOSCIENCE ENGINEERING

Site-specific nutrient management advice and agricultural intensification in maize-based systems in Nigeria

Oyakhilomen Oyinbo

Supervisors:
Prof. Miet Maertens (KU Leuven)
Prof. Roel Merckx (KU Leuven)
Prof. Jan Diels (KU Leuven)
Dr. Jordan Chamberlin (CIMMYT, Kenya)

Dissertation presented in partial fulfilment of the requirements for the degree of Doctor of Bioscience Engineering (PhD)

December 2019

SITE-SPECIFIC NUTRIENT MANAGEMENT ADVICE AND AGRICULTURAL INTENSIFICATION IN MAIZE-BASED SYSTEMS IN NIGERIA

Oyakhilomen OYINBO

Supervisors:
Prof. Miet Maertens (KU Leuven)
Prof. Roel Merckx (KU Leuven)
Prof. Jan Diels (KU Leuven)
Dr. Jordan Chamberlin (CIMMYT, Kenya)

Members of the Examination Committee:
Emeritus Prof. Josse De Baerdemaeker (Chair – KU Leuven)
Prof. Liesbet Vranken (KU Leuven)
Prof. Steven Bouillon (KU Leuven)
Prof. Peter Goos (KU Leuven)
Prof. Erwin Bulte (Wageningen University, Netherlands)

Dissertation presented in partial fulfilment of the requirements for the degree of Doctor of Bioscience Engineering

December 2019

Doctoraatsproefschrift nr. 1605 aan de faculteit Bio-ingenieurswetenschappen van de KU Leuven

Uitgegeven in eigen beheer, Oyakhilomen Oyinbo, Leuven, Belgium

Acknowledgements

First and foremost, I am eternally grateful to the Almighty God for the successful completion of my PhD program. I want to return all the glory, honor and adoration to Him for His faithfulness to me and my family throughout the course of my program. At first sight, it may seem as if one can independently go through the challenging moments of a PhD journey. However, it is worth noting that I would not have been able to complete the journey without receiving the support and encouragement of a lot of wonderful people in different ways, directly or indirectly.

At this point, I have a lot of people to appreciate. First of all, I wish to express my heartfelt and profound gratitude to my supervisor, Prof. Miet Maertens. Miet, I want to thank you for giving me the opportunity to undertake a PhD program under your scholarly guidance. Thank you for your patience, enthusiasm, encouragement and strong commitment to my progress from my enrollment into the pre-doc to the doctoral program. Indeed, you have been very supportive all the way, and I am extremely grateful for all the critical comments, valuable suggestions and feedback that you gave me at every stage of my research, which has immensely enriched the respective chapters of this dissertation. Truly, I feel very happy and fulfilled working with you over the period of my program because of the opportunity of learning a lot from you – both in terms of research- and non-research related issues. I am also grateful to you for supporting my participation in academic conferences, for providing me a pleasant working environment at the division, and for making my stay in Leuven worthwhile.

I would like to deeply appreciate my co-supervisors: Prof. Roel Merckx, Prof. Jan Diels and Dr. Jordan Chamberlin. Roel and Jan, I thank you for your scholarly inputs and critical comments, which help to improve the quality of my work, and for keeping track of my progress from the pre-doc up to the defense stage. Jordan, I would like to thank you for been a part of my PhD journey. I am thankful to you for meticulously reviewing my research proposal and the draft papers, and for all the discussions we had, especially about the conceptual framework in chapter four of this dissertation. You have greatly contributed to this dissertation, especially by your unflinching support in the design and conduct of my field activities as part of the Taking Maize Agronomy to Scale in Africa (TAMASA) project implementation in Nigeria. I am very grateful to you for the experience I had in managing the three rounds of farm-household panel surveys and learning about the whole process in the use of Computer-assisted Personal Interviews (CAPI) for farm-household surveys. I look forward to more collaboration with you. I will like to appreciate Prof. Liesbet Vranken for giving me useful comments and feedbacks on the choice experiments in this thesis and for accepting to be part of my jury. I will also like to deeply appreciate all other jury members: the chairman, Prof. Josse De Baerdemaeker, Prof. Steven Bouillon, Prof. Peter Goos and Prof. Erwin Bulte for contributing immensely to this dissertation through their constructive comments and suggestions.

Despite my quest for a top-notch PhD, I would not have been able to achieve it in KU Leuven without a scholarship. To this end, I wish to acknowledge the Bill and Melinda Gates Foundation [grant number OPP1113374] for the financial support for my PhD through the International Maize and Wheat Improvement Centre (CIMMYT) led project ‘TAMASA’. My gratitude goes to the TAMASA project leader, Dr. Peter Craufurd for providing visionary leadership for the project implementation in general and in particular, for giving me valuable comments, suggestions and support for my PhD research activities. Despite your busy schedule, you were able to review a draft paper for me. I am extremely grateful to Dr. Bernard Vanlauwe, who was very supportive, particularly during the discussions about my research proposal and my research stay at the International Institute of Tropical Agriculture (IITA), Kano station with Miet. Thank you for been a source of inspiration to me and many other young African researchers affiliated to IITA and other CGIAR centres. I am extremely grateful to the station representative of IITA, Kano station, Dr. Alpha Kamara for contributing immensely to my PhD program in different ways. In the first place, I would not have embarked on this PhD if you had not motivated me to do so. Thank you for advising and encouraging me to look beyond my comfort zone in Zaria and seek for a better PhD experience elsewhere. I am also grateful to you for supporting my research stay at IITA, Kano station and for the many discussions we had about conducting quality empirical research in IITA. At first, I was very reluctant to stay in Kano but you made me feel comfortable with the idea of staying in Kano, and supported me with a conducive working environment. Apart from that, you were very instrumental to the successful planning and implementation of my field activities. My sincere gratitude goes to Prof. Jibrin M. Jibrin, the director Centre for Dryland Agriculture (CDA), Bayero University, Kano, Nigeria for contributing to my field activities. Thank you for your strong commitment to the conduct of the three rounds of panel survey by ensuring that CDA was actively involved in the whole exercise.

Many thanks go to TAMASA team members at IITA, Kano station. I would like to thank the TAMASA-Nigeria country coordinator, Prof. Ibrahim Baba for his contributions, particularly in facilitating the logistics for my field activities. Thank you for leading all the discussions we had with other project partners about my field work, and ensuring that I got their continuous support throughout the field activities. I am wholeheartedly grateful to Dr. Julius Adewope, who supported me with the spatial sampling framework of farm-households, and for supervising the production of the maps used in this dissertation. My deepest appreciation goes to Mr. Kamal, who supported me in various ways, including the preliminary visits to the survey communities, the training of enumerators for the farm-household surveys, the training of extension agents for the pilot of Nutrient Expert tool, and the supervision of my field activities. Also, I am grateful to Mrs. Helen Jerome, who was primarily responsible for the production of the maps used in this dissertation, and to Mrs. Princess Ifeanyi, who gave me the necessary administrative support during my field work and my stay in Kano. I will like to thank all other IITA, Kano station staff, especially Mr. Rabo, Dr. Lucky, Mr. Reuben, Mr. Tofa, Mr. Olumide and the IITA postgraduate research fellows for their support and friendship during my stay in Kano.

My profound gratitude goes to all the people and institutions that participated in the planning and conduct of the data collection, and the pilot of Nutrient Expert tool as part of the randomized controlled trial implemented in this dissertation. I deeply appreciate all the well-trained enumerators who diligently participated in the three-period farm-household panel survey and the agricultural extension agents survey. Notable among them are Abu, Atiku, Nura, Salisu, Francis, Kalu, Fidelis, Jamilu, Wilson, Mohammed, Josiah, Richard, Ahmadu, Joel, Desmond, Grace and others. Also, I am grateful to Baba, Ismail, Hailru, Mbavai, Luqman and AY, who supervised the survey teams in the data collection, and made sure the data collection plan was adhered to. My sincere gratitude goes to the agricultural extension agents who contributed to the implementation of the randomized controlled trial by piloting the use of Nutrient Expert tool in the treatment villages, and the field support staff who supervised the exercise. Special thanks go to the following institutions, Kaduna State Agricultural Development Agency (KADA), Katsina State Agricultural and Rural Development Authority (KTARDA), Kano State Agricultural and Rural Development

Authority (KNARDA) and Sasakawa-Global 2000 for their support. I am extremely grateful to the 792 maize farmers and the 320 extension agents who accepted to be respondents for the farm-household and extension agents surveys respectively, and for dedicating their time for the surveys. Also, I will like to recognize the efforts of the community leaders in the survey communities and my contact persons in the extension organizations for their roles in facilitating the field activities.

My PhD experience at the Division of Bioeconomics was truly amazing. Thanks to the many wonderful and helpful colleagues: Erik, Tessa, Frederik, Pieter, Monica, Jana, Bernd, Michiel, Fikadu, Natalia, Teopista, Goedele, Isabelle, Moses, Joseph, Anna, Eewoud, Floris, Kaat, Genaye, Tafesse, Tijstke, Nuria, Cindybell, Karin, Diana, Kewan, Marie, Charlotte, Ashenafi, Iris, Tilahun, Lucia and Kato. Thank you for the scholarly comments and feedbacks during seminar presentations, the insightful methodological discussions, the memorable social events and the moments we shared at the lunch room and the Geo-garden. Also, I would like to appreciate my case administrator at the international office, Heidi, Hilde at the ICT unit and Karlien for their support.

I had an overwhelming support from my friends and family during the course of my PhD program. I am most grateful and indebted to my beloved wife, Grace Oyinbo for her love, prayers, encouragement and invaluable support. It was really difficult but you had the strength to combine family, work and your PhD study during my stay in Belgium. Thank you for taking care of our daughters, Eliora and Aviya throughout this period. I truly owe my PhD success to you. My profound gratitude goes to my parents, Mr. and Mrs. Peter Oyinbo and parents-in-law, Prof. and Mrs. Peter Rekwot for their prayers and moral support. Thank you for your parental love and care to me, and especially to my lovely wife and kids during my stay in Belgium. Also, I am grateful to my siblings and in-laws for their support throughout my study period.

Back in Nigeria, I would like to appreciate my colleagues at the Department of Agricultural Economics and the Department of Agricultural Extension and Rural Development, Ahmadu Bello University, Zaria, Nigeria for their support. Also, I am grateful to the management of the University for giving me study leave to undertake this PhD project.

Oyakhilomen Oyinbo

Summary

Despite the potentially large gains from intensification and agricultural productivity growth in Sub-Saharan Africa (SSA), yields of staple crops, such as maize are far below attainable yields. Depletion of soil fertility associated with low and inappropriate use of nutrients play a crucial role in this. Yet, fertilizer use is low in SSA, which partly relates to information constraints. Relaxing such constraints via agricultural extension interventions is expected to produce positive outcomes but do not always result in the intended effects, which may be connected with the highly heterogeneous smallholder farming systems. Yet, traditional extension systems in SSA countries, including Nigeria, provide general fertilizer use recommendations, which do not account for the substantial variation in production conditions. A potential intervention in this regard is site-specific nutrient management (SSNM) paradigm. In light of the rapid digital transformation, digital decision support tools (DSTs) can be leveraged to allow provision of SSNM extension advice. There are research gaps in the theoretical and empirical literature on design, adoption and impact of DST-enabled site-specific extension services, and in the broader literature related to fertilizer use in maize. This PhD thesis focuses on a nutrient management DST for maize 'Nutrient Expert' in northern Nigeria, and addresses some of the gaps.

In chapter 2, I analyze farmers' preferences for intensification of maize production supported by DST-enabled SSNM recommendations in the maize belt of Nigeria. I use data from a choice experiment (CE) among farmers, and estimate different econometric models to control for attribute non-attendance and account for preference as well as scale heterogeneity. The findings show that overall, farmers have strong preferences to switch from general to DST-enabled SSNM recommendations, which lend credence to the inclusion of digital tools in agricultural extension. Also the findings show two latent classes or preference groups of farmers, early and late adopters of intensified maize production, and the heterogeneous preferences can be related to the farmers' resource endowment, sensitivity to risk and access to services and institutions. The findings imply that improving the design of DSTs to enable provision of information on the riskiness of expected investment returns and flexibility in switching between low- and high-risk recommendations will help farmers to make better informed farm decisions.

In chapter 3, I analyze preferences of extension agents for the design of a nutrient management DST for extension, and their willingness to use such tool. I use data from a CE among extension agents, and estimate different models to capture preference heterogeneity

and account for attribute non-attendance. The findings show that the extension agents in general have a high willingness to use DSTs for SSNM extension advice, which supports the emerging policy interest in design of such DSTs for maize. They prefer a DST with a more user-friendly interface that requires less time to generate an output but have substantial heterogeneous preferences for other design features. The findings also show two preference groups of extension agents, the more committed agents – who prioritize the effectiveness-related features of DSTs, and the more pragmatic agents – who care more about practical features of DSTs. The differences in observed characteristics between the two groups are very small, which suggests that unobservable characteristics likely play a role in explaining preference heterogeneity. The findings imply that accommodating preference differences may facilitate the adoption of DSTs by extension agents and thus enhance the scope for such tools to impact the production decisions of farmers.

In chapter 4, I analyze the impact of farmers' access to SSNM recommendations for maize enabled by a DST on fertilizer use rates, fertilizer management practices, maize yield and revenue. I implement a randomized controlled trial with two treatment groups, T1 without and T2 with additional information on variability of expected returns and a control group. I use three-period panel data to estimate the impact. The findings show that SSNM recommendations bring about improvements in fertilizer management practices, yield and gross revenue after one-year treatment but not fertilizer use for T1. This suggests that optimal management practices can improve yield and revenue by reducing technical inefficiencies. The findings also show that yield and revenue gains are quite similar for the two treatment groups despite considerable increase in fertilizer by T2 over T1. This suggests that the increase in fertilizer does not result in substantial revenue gains, which may be connected to low yield responses to higher fertilizer levels. The findings also show that SSNM recommendations, combined with additional information on the distribution of expected returns, appears to induce more fertilizer use after one year and foster continued fertilizer investment after two years. In addition, the findings show that there are only gradual increases in investment, maize yield and especially net revenue after two years.

Overall, this dissertation shows that there is high adoption potential of nutrient management DSTs for maize by extension agents, and of extension advice from such DSTs by farmers, which aligns with the widespread interest and investments in site-specific and digital tools for agricultural applications in developing countries. Yet, the findings show economically small but significant effects of DST-enabled SSNM recommendations on intensification of maize production. This underscores the need for more research with longer periods and with complementary interventions to allow better understanding of the impact of DST-enabled site-specific recommendations in the long run while accounting for other shortcomings.

Samenvatting

Ondanks de potentieel grote winsten uit intensivering en productiviteitsgroei in de landbouw in Sub-Sahara-Afrika (SSA), liggen de opbrengsten van de voornaamste gewassen, zoals maïs, ver onder de haalbare opbrengsten. Uitputting van de vruchtbaarheid van de bodem door het lage en niet-optimale gebruik van meststoffen spelen hierin een cruciale rol. Het gebruik van meststoffen blijft laag in SSA, deels omwille van informatie beperkingen. Het opheffen van dergelijke beperkingen via landbouwadviesinterventies wordt verondersteld een oplossing te bieden, maar heeft niet altijd het beoogde effect. Dit kan gerelateerd zijn aan de diversheid van kleinschalige landbouwsystemen. Traditionele landbouwadviesinterventies in SSA landen, waaronder Nigeria, geven algemene aanbevelingen in verband met gebruik van kunstmest, die de aanzienlijke variatie in de productieomstandigheden niet in rekening nemen. Een mogelijke oplossing in dit opzicht is het site-specifieke nutriëntenbeheer (SSNM) paradigma. Door de snelle digitale transformatie kunnen digitale beslissingsondersteunende hulpmiddelen (*decision support tools*, DSTs) worden ingezet om SSNM advies mogelijk te maken. Er zijn leemtes in de theoretische en empirische literatuur over het ontwerp, de adoptie en de impact van DST-ondersteunde site-specifieke adviesdiensten, en in de bredere literatuur met betrekking tot het gebruik van kunstmest in maïs. Dit proefschrift richt zich op een nutriëntenbeheer DST voor maïs 'Nutrient Expert' in het noorden van Nigeria, en vult een aantal van de hierboven vermelde onderzoek leemtes.

In hoofdstuk 2 analyseer ik de voorkeuren van landbouwers voor intensivering van de maïsproductie op basis van DST-ondersteunde SSNM aanbevelingen in de maïsgordel van Nigeria. Ik maken gebruik van gegevens uit een keuze-experiment bij de boeren, en schatten verschillende econometrische modellen om te controleren voor attribuut verzuim en om preferenties en heterogeniteit in schaal in rekening te nemen. De bevindingen tonen aan dat boeren een sterke voorkeur hebben om over te schakelen van algemene naar DST-ondersteunde SSNM aanbevelingen, wat wijst op het potentiele succes van digitale hulpmiddelen in landbouwadvies. De bevindingen tonen ook twee latente klassen of voorkeurgroepen van boeren, vroege en late adopters van geïntensiveerde maïsproductie. Deze heterogene voorkeuren kunnen worden gerelateerd aan de beschikbare hulpbronnen, de gevoeligheid voor risico’s en de toegang tot diensten en instellingen van boeren. De bevindingen impliceren dat verbeteringen aan het ontwerp van DSTs die voorziening van informatie over de risico's van de verwachte rendementen en flexibiliteit bij het schakelen

tussen lage en hoge risico aanbevelingen mogelijk maken, de boeren zullen helpen om beter geïnformeerde beslissingen te nemen.

In hoofdstuk 3 analyseer ik voorkeuren van landbouwadviseurs voor het ontwerp van een nutriëntenbeheer DST, en hun bereidheid om een dergelijke tool te gebruiken. Ik maken gebruik van gegevens uit een keuze-experiment onder adviseurs, en schatten verschillende modellen om de heterogeniteit in preferenties vast te leggen en attribuut verzuim in rekening te nemen. De bevindingen tonen aan dat de adviseurs over het algemeen een grote bereidheid hebben om DSTs voor SSNM adviesinterventies te gebruiken, wat de opkomende politieke belangstelling in dergelijke DSTs voor maïs ondersteunt. Ze geven de voorkeur aan een DST met een gebruiksvriendelijke interface die minder tijd vraagt om resultaten te genereren, maar voor andere ontwerpelementen zijn de voorkeuren zeer heterogeen. De resultaten wijzen ook op twee groepen adviseurs, de meer betrokken agenten die prioriteit geven aan de effectiviteit-gerelateerde functies van DSTs, en de meer pragmatische agenten die meer waarde hechten aan de praktische eigenschappen van DSTs. De verschillen in waarneembare kenmerken tussen beide groepen zijn heel klein, wat suggereert dat niet-waarneembare kenmerken waarschijnlijk een rol spelen bij het verklaren van de heterogeniteit in voorkeuren. De bevindingen impliceren dat men het gebruik van DSTs kan vergemakkelijken door rekening te houden met verschillen in voorkeuren bij adviseurs en dat men daarmee het potentieel van dergelijke tools om de productie beslissingen van boeren te beïnvloeden kan vergroten.

In hoofdstuk 4 analyseer ik de impact van de toegang van boeren tot SSNM aanbevelingen voor maïs met behulp van een DST op het gebruik van kunstmest, kunstmest managementpraktijken, de opbrengst van maïs en inkomsten. Ik implementeren een gerandomiseerd onderzoek met controlegroep en twee behandelingsgroepen, zonder (T1) en met (T2) aanvullende informatie over de variabiliteit van de verwachte rendementen. We maken gebruik van panel data over drie periodes om de impact te schatten. De bevindingen tonen aan dat SSNM aanbevelingen leiden tot verbeteringen in de meststof managementpraktijken, in de opbrengst en in de bruto-inkomsten na één jaar behandeling, maar niet in het gebruik van kunstmest voor T1. Dit suggereert dat optimale managementpraktijken de opbrengst en inkomsten kunnen verbeteren door het reduceren van de technische inefficiënties. De resultaten tonen ook aan dat de groei in opbrengst en inkomsten zeer vergelijkbaar is tussen de twee behandelingsgroepen ondanks de aanzienlijke stijging van de meststof gebruik door T2 in vergelijking met T1. Dit suggereert dat een hoger gebruik van kunstmest niet leidt tot een aanzienlijke groei in inkomsten, wat gerelateerd kan zijn met lage effect van hogere kunstmest niveaus op opbrengsten. De resultaten tonen ook aan dat SSNM aanbevelingen, in combinatie met aanvullende informatie over de verdeling van de verwachte rendementen, meer gebruik van kunstmest blijken te veroorzaken na één jaar en continue kunstmest investeringen na twee jaar blijken te bevorderen. Daarnaast tonen de bevindingen dat er slechts een geleidelijke toename is van investeringen, opbrengst van maïs en in het bijzonder netto-inkomsten na twee jaar.

Tot slot, dit proefschrift laat zien dat er een groot potentieel is van nutriëntenbeheer DSTs voor maïs bij landbouwadviseurs, en van advies uit dergelijke DSTs bij boeren. Dit sluit aan bij de wijdverspreide interesse en investeringen in site-specifieke en digitale hulpmiddelen voor landbouwapplicaties in ontwikkelingslanden. Echter, de bevindingen tonen economisch kleine maar significante effecten van DST-ondersteunde SSNM aanbevelingen op de intensivering van de productie van maïs. Dit onderstreept de noodzaak van meer onderzoek over langere periodes en met aanvullende interventies om tot een beter begrip van de impact van de DST-ondersteunde site-specifieke aanbevelingen op de lange termijn te komen, rekening houdend met de andere tekortkomingen.

List of Abbreviations and Acronyms

4Rs	Right Fertilizer Source, Right Rate, Right Placement and Right Time of Application
AI	Attributes Ignored
AC	Attributes Considered
AIC	Akaike Information Criterion
ASC	Alternative-Specific Constant
ANA	Attribute Non-attendance
BIC	Bayesian Information Criteria
C	Control
CDA	Centre for Dry land Agriculture
CE	Choice Experiment
CIMMYT	International Maize and Wheat Improvement Centre
DiD	Difference-in-Difference
DST	Decision Support Tool
EAs	Extension Agents
FAOSTAT	Food and Agriculture Organization of the United Nations Statistical Database
FDR	False Discovery Rate
FGD	Focused Group Discussion
FAW	Fall Army Worm
GPS	Global Positioning System
Ha	Hectare
HH	Household
ICT	Information and Communication Technology
IID	Independently and Identically Distributed
IITA	International Institute of Tropical Agriculture
IPNI	International Plant Nutrition Institute
ISFM	Integrated Soil Fertility Management
ITT	Intent-to-Treat
K	Potassium
K_2O	Potassium Oxide
KADA	Kaduna State Agricultural Development Agency

Kg	Kilogram
KNARDA	Katsina State Agricultural and Rural Development Authority
KTARDA	Kano State Agricultural and Rural Development Authority
LCM	Latent Class Model
LGAs	Local Government Authorities
MRS	Marginal Rates of Substitution
MXL	Mixed Logit
N	Nitrogen
NAERLS	National Agricultural Extension and Rural Liaison Services
NGN	Nigerian Naira
NE	Nutrient Expert
P	Phosphorus
P_2O_5	Phosphorus Pentoxide
QUEFTS	Quantitative Evaluation of the Fertility of Tropical Soils
RCT	Randomized Controlled Trial
SALCM	Scale-Adjusted Latent Class Model
SSA	Sub-Saharan Africa
SSNM	Site-Specific Nutrient Management
Std. Dev.	Standard Deviation
T1	Treatment One
T2	Treatment Two
TAMASA	Taking Maize Agronomy to Scale in Africa
TPP	Total Physical Product
TVP	Total Value Product
USD	United States Dollar

Table of Contents

Chapter 1

General Introduction

1. Agricultural intensification for sustainable development in Sub-Saharan Africa

Agriculture is very important for the development of Sub-Saharan Africa (SSA) and other developing regions – in terms of its contribution to GDP, employment, and export earnings. It is considered to have a central role in spurring industrial growth and achieving economic growth, particularly in early stages of development (World Bank, 2007; Byerlee et al., 2009; Binswanger-Mkhize et al., 2010; Diao et al., 2010; Dercon and Gollin, 2014; Tomich et al., 2019). More importantly, agricultural productivity growth in SSA is widely recognized as instrumental to reduction of rural poverty and food insecurity since a high share of its poor population live in rural areas and are mostly dependent on agriculture for their livelihoods (Haggblade et al., 2007; Christiaensen et al., 2011; Otsuka and Muraoka, 2017; Ligon and Sadoulet, 2018). While other regions of the world have made notable progress in addressing poverty and hunger, SSA lags behind and now accounts for about half of the world's 736 million extreme poor and over one-fifth of the world's 822 million hungry people[1] (World Bank, 2018a; FAO, 2019). The crucial role of agricultural productivity growth in realizing the twin goals of eradicating extreme poverty and hunger in SSA (Sustainable Development Goals 1 and 2) and more broadly in facilitating structural transformation cannot be overemphasized (Barrett et al., 2018; Mason-D'Croz et al., 2019; Dawson et al., 2019).

Despite the potentially large gains from intensification and agricultural productivity growth – documented by the Green Revolution in Asia – agricultural productivity is on average low and has virtually stagnated in SSA (Evenson and Gollin, 2003; Pingali, 2012; Bulte et al., 2014; Otsuka and Muraoka, 2017). In particular, the yields of major food crops, such as maize and cereals in general, are lagging behind yields in other parts of the world and are often far below their potential, leading to substantial yield gaps, e.g. on-farm maize yields are around 1 to 2 tons per ha despite potential yields of up to 7 tons per ha (Tittonell et al., 2013; van Ittersum et al., 2016; Guilpart et al., 2017). This contributes to slow agricultural growth, persistent rural poverty and food insecurity, and continuous dependence on food

[1] Extreme poor in this context refers to people who live on less than 1.9 USD a day based on 2011 purchasing power parity (PPP) dollars (World Bank, 2018a), while hungry people refers to people who are undernourished, i.e. lack sufficient dietary energy for a normal, active, healthy life (FAO, 2019).

imports (Barrett and Bevis, 2015; Vanlauwe et al., 2015a; Komarek et al., 2017). Low adoption of agricultural technologies, particularly inorganic fertilizer and improved management practices by farmers is often cited as one of the key factors that contribute to the persistence of low productivity (de Janvry and Sadoulet, 2010; Emerick et al., 2016; McAuthor and McCord, 2017).

Given the rapid expansion of demand for food by a growing population and the limited opportunities for agricultural growth via cropland expansion in SSA, a focus on increasing agricultural productivity via intensification of agriculture is almost inevitable[2] (Headey et al., 2014; Jayne et al., 2014; Binswanger-Mkhize and Savastano, 2017; Droppelmann et al., 2017). A widespread adoption of modern inputs and management practices is a key pathway for raising agricultural productivity and narrowing the yield gap between SSA and the rest of the world (Beaman et al., 2013; Sheahan et al., 2013; Burke et al., 2017). Agricultural productivity growth can contribute enormously to rural incomes, and create indirect benefits, including lower staple food prices, employment creation and other multiplier effects (de Janvry and Sadoulet, 2002; Zeng et al., 2015; Alwang et al., 2019). It is still unclear why the adoption of seemingly promising technologies, notably inorganic fertilizer, by farmers remains low in SSA – which is often referred to as an agricultural technology adoption puzzle (de Janvry et al., 2017; Abay et al., 2018; Michler et al., 2019).

Several constraints have been put forward in the theoretical and empirical agricultural technology adoption literature to explain the low adoption of productivity-enhancing inputs (inorganic fertilizer) and management practices in many parts of SSA. These include low and heterogeneous returns to investment (Suri, 2011; Chianu et al., 2012; Holden, 2018), risk (Feder et al., 1985; Dercon and Christiaensen, 2011; Karlan et al., 2014; Benson and Mogues, 2018), low quality of inputs (Bold et al., 2017), cash or credit constraints (Croppenstedt et al., 2003; Lambrecht et al., 2014; Koussoube and Nauges, 2017; Jama et al., 2017), high transaction costs (Minten et al., 2013), time-inconsistent behavior (Duflo et al., 2011), low and variable yield responses (Burke et al., 2017; Jayne et al., 2019) and lack of relevant or reliable information (Foster and Rosenzweig 1995; Conley and Udry, 2010; Magruder, 2018), among others. This has resulted in a growing number of policy interventions – extension,

[2] Although intensification, i.e. increasing crop yields on currently cultivated cropland is highly desirable, and is a core goal in SSA, it has to be done in a sustainable way by reducing its negative environmental impacts, which was a pitfall of the Asian Green Revolution (Pingali, 2012; Godfray, 2015; Rockström et al., 2017; Jayne et al., 2019). To this end, van Loon et al. (2019a) suggest that increases in nutrient inputs in SSA should be associated with good nutrient management to improve nutrient use efficiency, and foster sustainable intensification.

input subsidy, credit, insurance, savings, contracts and postharvest interventions to help lift some of these constraints that farmers face.

1.1 Agricultural extension and soil fertility management

Depletion of soil fertility due to poor soil fertility management strongly contributes to the substantial yield gap in SSA, particularly for cereals such as maize (Sanchez, 2002; Barrett and Levis, 2015; Tittonell and Giller, 2013; Ragasa and Chapato, 2017; Berazneva et al., 2018; ten Berge et al., 2019). The often cited soil nutrient deficiencies include macronutrient (nitrogen (N), phosphorus (P) and potassium (K)) deficiencies, especially N, as well as secondary nutrient and micronutrient deficiencies (Kihara et al., 2016a; Vanlauwe et al., 2015b; Shehu et al., 2018; ten Berge et al., 2019). Yet, the use of fertilizer to address the soil nutrient deficiencies remains on average low in most parts of SSA (Xu et al., 2009; Harou et al., 2017; Njogore et al., 2018; Theriault et al., 2018; Jayne et al., 2019). In addition, the traditional fallow system to replenish soil fertility is no longer possible in most areas while a continuous cropping system without adequate soil management results in mining of soil nutrients and soil degradation (Bamire and Manyong, 2003; Tarfa et al., 2017; Berazneva et al., 2019). This calls for more intensified use of external inputs, particularly inorganic fertilizer as a vital entry point for soil fertility management and yield improvement (Sanginga and Woomer, 2009; Vanlauwe et al., 2015b; Sheahan and Barrett; 2017; Holden, 2018).

Information constraints – including imperfect information about the existence, availability, proper use of a technology (know-how), and the (expected) benefits of its use are often considered important barriers to farmers' optimal adoption decisions (Lambrecht et al., 2014; Beaman and Dillon, 2018; Buehren et al., 2019; van Campenhout et al., 2019; BenYishay and Mobarak, 2019). In the context of fertilizer, information constraints on correct fertilizer use (e.g. what rate to apply, what sources, when to apply, and how to apply) can contribute to explaining the limited use of fertilizer and the returns for smallholder farmers (Asfaw and Admassie, 2004; Abdoulaye and Sanders, 2005; Duflo et al., 2008; Chianu et al., 2012; Marenya and Barrett, 2009; Harou et al., 2017; Benson and Mogues, 2018; Jayne et al., 2019). Agricultural extension (advisory) services are expected to be instrumental in relaxing the production and market-related information constraints of smallholder farmers and allow of better informed farm investment decisions (Bernet et al., 2001; Genius et al., 2014; Fu and Akter, 2016; Pan et al., 2018; Shikuku, 2019). Yet, extension services do not always produce the intended effects in terms of improvements in knowledge, technology adoption, market participation, productivity and farmer welfare (Feder et al., 2004; Davis et al., 2008; Fafchamps and Minten, 2012; Ragasa and Mazunda, 2018; Mitra et al., 2018; Buehren et al., 2019; Camacho and Conover, 2019).

The limited effects of some extension interventions, soil fertility improvement interventions in particular, may be connected with the substantial spatial and temporal heterogeneity in biophysical and socio-economic conditions of smallholder farmers in SSA[3] (Tittonell et al., 2010; Vanlauwe et al., 2015b; Njoroge et al., 2017; MacCarthy et al., 2018). Localized policy interventions are often suggested for smallholder farmers over one-size-fits-all interventions (Bernet et al., 2001; Birner et al., 2009; Giller et al., 2011; Kihara et al., 2016a, Droppelmann et al., 2017; Valdivia et al., 2017; Barrett et al., 2017; Theriault et al., 2018; Gars and Ward, 2019). Conversely, interventions to promote the use of modern inputs, particularly fertilizer, without accounting for heterogeneity assumes a uniform production function among smallholders, which may contribute to explaining the low adoption of modern inputs in most parts of SSA (Suri, 2011; Abay et al., 2018; Otsuka and Muraoka, 2017).

Yet, traditional extension systems in most SSA countries, including Nigeria, provide generalized or 'blanket' fertilizer use recommendations to farmers across highly heterogeneous environments (Xu et al., 2009; Kihara et al., 2016a; Shehu et al., 2018; Njoroge et al., 2018; Amapu et al., 2018; Burke et al., 2019; Tovihoudji et al., 2019; Ichami et al., 2019; van Loon et al., 2019b). Such recommendations are often provided to farmers at scales beyond the farm, village, district, province, state or region, and do not account for the substantial variation in production conditions, particularly the heterogeneity in soil quality and microclimate (Smale et al., 2013; Vanlauwe et al., 2015b; Njoroge et al., 2017; MacCarthy et al., 2018; Jayne et al., 2019). A typical example is the general extension recommendation to use 120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha for maize in northern Nigeria (Amapu et al., 2018; Shehu et al., 2018). The use of this generalized recommendation corresponds to an optimal fertilizer rate for an average plot, and may result in fertilizer rates that are economically sub-optimal for many farmers because the expected yield responses to fertilizer are likely not the same across diverse plots.

[3] The pronounced diversity of agro-ecological conditions in SSA in comparison with Asia explain in part the limited success of Green revolution in SSA (Evenson and Gollin, 2003; Pingali, 2012).

Given the highly variable smallholder farming systems, site-specific extension services are increasingly considered for effective soil fertility management (Vanlauwe et al., 2015b; Wossen et al., 2019). These are extension services that are tailored to the crop-, site- and season-specific conditions of individual farmers, and a typical example in the context of fertilizer use is the concept of Site-Specific Nutrient Management (SSNM) recommendations (Pampolino et al., 2007; Pampolino et al., 2012; Johnston and Bruulsema 2014; Xu et al., 2016). SSNM is a science-based approach that entails 4Rs of nutrient management, which includes promoting application of the right fertilizer rate, with the right fertilizer source, at the right time, and in the right place, and allows for dynamic adjustment of fertilizer application based on crop need for a given plot, and in a given cropping season (Pampolino et al., 2007; Pasuquin et al., 2014; Singh, 2019). The approach is management- and knowledge-intensive and requires proper knowledge to be implemented by smallholder farmers, which implies a crucial role of extension services. The use of SSNM under researcher-managed trials has been shown to produce improvements in yield response to fertilizer and agronomic returns while reducing negative environmental externalities associated with loss of unutilized nutrients – potentially supportive of sustainable agricultural intensification (Wang et al., 2001; Dobermann et al., 2002; Pampolino et al., 2007; Satyanarayana et al., 2011; Xu et al., 2014; Sapkota et al., 2014; Banayo et al., 2018; Buresh et al., 2019).

Apart from the neglect for plot-specific yield response to fertilizer, generalized fertilizer use recommendations are based on predicted average expected economic returns and do not provide additional information about the variability or riskiness of the expected fertilizer investment returns associated with variation in climate and/or market (output price) conditions. The sources of stochastic variation – climate and market fluctuations across seasons induces uncertainty about the returns to investment for smallholder farmers as documented in both theoretical and empirical agricultural technology adoption literature (Feder and Umali, 1993; Marra et al., 2003; Magruder, 2018; Rosenzweig and Udry, 2019). Output price variation can be of interest to smallholder farmers in SSA, where the seasonal price variation for maize is largest among cereal crops (Gilbert et al., 2017). Unlike the market for rice, domestic maize markets are poorly integrated to the international market in SSA and Nigeria in particular (Hatzenbuehler et al., 2017; Pierre and Kaminski, 2019).

1.2 Digital agricultural extension decision support tools

Diffusion of information about improved technologies and management practices in SSA was traditionally led by public (government) agricultural extension systems and operated under the supply-driven Training and Visit (T&V) extension approach (Feder et al., 1986; Ander and Feder, 2007; Davis et al., 2008; Birner et al., 2009; de Janvry et al., 2016). This approach entails transfer of information by village extension agents from the domain of research to contact (lead) farmers, who in turn transfer the extension messages to their peers – i.e. lab to farm diffusion of technologies and management practices (Kondylis et al., 2017; Niu and Ragasa, 2018; Shikuku, 2019; BenYishay and Mobarak, 2019). This approach has largely been modified to allow of more effective decentralized and demand-driven extension services, yet the use of contact farmers is still part of most extension systems (Davis et al., 2008; de Janvry et al., 2016). In recent years, there has been a rise in private sector participation in provision of agricultural extension services – e.g. from input suppliers, input service providers, agro-dealers, community-based organizations and non-governmental organizations (Adebayo et al., 2015; de Janvry et al., 2016; Davis and Spielman, 2017).

Apart from the face-to-face extension agent-farmer contact (direct extension visits), other approaches to facilitate dissemination of information have evolved over time, including the use of farmer field schools, demonstration plots, field days, social networks and farmer-to-farmer extension using peer farmers (Feder et al., 2004; Beaman and Dillon, 2018; Nakano et al., 2018; Takahasi et al., 2019; Shikuku et al., 2019). There is a rapid advancement in Information and Communication technologies (ICTs), which has led to a growing policy interest in the use of digital innovations in agriculture, particularly in provision of production and market-related extension services (Nakasone et al., 2014; Beuermann, 2015; Aker and Ksoll, 2016; Janssen et al., 2017; Verma and Sinha, 2018; Camacho and Conover, 2019). This includes the use of ICT platforms, such as radio, television, video, and telephone (for Short Messaging Services (SMS) and Interactive Voice Responses (IVR)), which are considered low-cost approaches for provision of extension messages to farmers and can facilitate wider extension coverage (Aker et al., 2011; Fu and Akter, 2016; Larochelle et al., 2019; van Campenhout et al., 2019).

Despite the evolution of different extension approaches, the challenge of providing locally-tailored extension services under heterogeneous production conditions has not been adequately addressed by extension systems, who often lack the capacity to do so (Smale et al., 2013; Ande et al., 2017; de Janvry et al., 2017). Conversely, most extension systems have not been seen as efficient in addressing site- and management-specific information constraints of individual smallholder farmers, i.e. they still largely rely on dissemination of general extension recommendations (Naswem and Ejembi, 2017). In more recent times, the use of computer-based decision support tools (DSTs), particularly via modern digital technologies, such as smartphones and tablets, which accommodates software applications – web applications (web apps) or mobile applications (mobile apps) is increasingly considered in provision of information for optimal decision making[4]. Such digitally-supported DSTs are promoted in agricultural extension for more effective delivery of agronomic advice tailored to the site-specific conditions of individual farmers (Bernet et al., 2001; Rose et al., 2016; Vanlauwe et al., 2017; Ogunti et al., 2018; MacCarthy et al., 2018; Jayne et al., 2019). In general, DSTs usually guide end-users through different steps – collect data about farm(er) conditions, analyze the data and generate outputs (evidence-based recommendations), which can allow of better informed production and market-related decisions by smallholder farmers (Kragt and Llewellyn, 2014; Rose et al., 2016). Conversely, agricultural extension DSTs allow of data-driven optimal on-farm decisions but also learning opportunities about specific farm management subjects (as a learning tool) by extension agents and farmers (Evans et al., 2017; Lundstrom and Lindlbom, 2018).

While the development of agronomic advisory DSTs in developed countries has been in place for quite some time (Cox 1996; Bernet et al., 2001; Welch et al., 2002; Small et al., 2015; Rossi et al., 2014; Ravier et al., 2016), it is gradually emerging in developing regions, particularly in SSA. Despite the potential gains of DSTs, their use by farmers and extension agents has been less than expected at scale (Hochman and Carberry, 2011; Cerf et al., 2012; Prost et al., 2012; Ravier et al., 2016; Rose et al., 2016; Lindblom et al., 2017). A lack of co-design in the development process, i.e. ignoring active engagement of all stakeholders, including farmers and extension agents in the development of a DST, can substantially contribute to low take-up (Rose et al., 2016; Ditzler et al., 2018).

In the context of soil fertility management, a nutrient management extension DST for maize 'Nutrient Expert (NE)' has been co-developed in Nigeria, Tanzania and Ethiopia to enable extension service providers to transition from the provision of generalized fertilizer

[4] Although, a DST is considered as any software-based tool enabled by mobile electronic devices in recent times to enhance optimal decision making by end-users, DST platforms broadly include conventional computers, such as desktop and laptop computers, and paper-based platforms, such as maps and charts (Rose et al., 2016).

use recommendations to SSNM extension recommendations[5]. The description and development process of the Nutrient Expert tool are discussed in detail in Section 3.3, and this thesis substantially focuses on the tool – from the design stage to the farm-level impact evaluation stage in Nigeria.

2. Research gaps and objectives

I identify specific research gaps in the current theoretical and empirical literature on design, adoption and impacts of digital and site-specific extension services, and in the broader agricultural technology adoption literature related to fertilizer use in maize production. First and foremost, the empirical literature on design of digital agricultural extension DSTs is thin, and most of the previously documented literature is based on case studies of DSTs in developed country context (e.g. Antonopoulou et al., 2010; Kragt and Llewellyn, 2014; Small et al., 2015; Lacoste and Powles, 2016; Lundstrom et al., 2017; Lundstrom and Lindlbom, 2018; Oliver et al., 2017; Rose et al., 2016, 2018, among others). Despite the think pieces about DSTs, the empirical literature is still sparse in SSA, and in particular for nutrient management DSTs for maize, which may be connected to the fact that design of digital DSTs began only recently in the region. In response to the challenges posed by the substantial heterogeneity of smallholder farming systems, and the opportunities created by the recent advances in digital technologies, the design of digital DSTs is likely to increase. This thesis complements and builds on the nascent literature, and aims at informing the design of advisory DSTs in SSA.

Second, the existing literature on agricultural technology adoption in general and soil fertility management in particular includes a large stream of *ex-post* studies that deal with farmers' adoption behavior after technologies and crop management practices have been introduced (e.g. Lambrecht et al., 2014; Mponela et al., 2016; Morello et al., 2018). Very few *ex-ante* studies address farmers' adoption behavior in the design stage of a technology (e.g. Lambrecht et al., 2015; Dalemans et al., 2018; Tarfasa et al., 2018). Yet, none of these studies focus on farmers' preferences for intensification of maize production that is supported by DST-enabled site-specific extension services *ex-ante*, i.e. before the introduction of DSTs for nutrient management advice for maize in SSA. Conversely, the current literature does not empirically analyze how farmers trade off specific attributes of a high-input, -output, -

[5] A growing number of extension DSTs are being developed or have recently been developed for crop variety selection, weed management, plant density guide, water management and fall army worm management in SSA.

investment and -risk production system, in the context of extension recommendations, particularly in the design stage of a nutrient management DST for maize. In chapter 2, I use data from a discrete choice experiment (CE) among maize producing households in northern Nigeria, where a DST for nutrient management was being developed to address this shortcoming in the literature, and generate *ex ante* insights for optimizing the design of DSTs. In addition, while several empirical studies that use CE do not account for scale heterogeneity and/or attribute non-attendance, which are potential sources of bias in CE, I address both issues using different econometric models.

Third, the current literature on design of DSTs does not adequately address the preferences of extension agents for the design of nutrient management DSTs and their willingness to use such tools in an *ex ante* quantitative way, except for Kragt and Llewellyn (2014). The latter assess the preferences of extension agents for the design of a DST for weed management in Australia. I build on this study in various ways: a focus on a DST for nutrient management for maize, on a different farming system and on a developing country context. In addition, I build on the method by using more recent data and a much larger sample of extension agents and by addressing attribute non-attendance (ANA), which was not considered in the previous study. Apart from Kragt and Llewellyn (2014), other studies only investigate the uptake of DSTs by extension agents in an *ex post* qualitative way (Rose et al., 2016, 2018). In chapter 3, I implement a discrete choice experiment among extension agents in the design stage of a nutrient management DST in the research area to address the limitations in the current literature. This allows us to have an *ex-ante* understanding of the potential uptake of DSTs and the specific practical and effectiveness-related design features that are more (or less) appealing to extension agents towards improving the design and uptake of DSTs.

Fourth, there is an increase in the application of discrete choice experiments in the agricultural economics literature, primarily with a focus on farmers and food consumers (e.g. Breustedt et al., 2008; Asrat et al., 2010; Jaeck and Lifran, 2014; Lambrecht et al., 2015; Coffie et al., 2016; Van den Broeck et al., 2017; Dalemans et al., 2018; Gamboa et al., 2018; Arora et al., 2019). Yet, the use of CEs to inform agricultural extension initiatives *ex ante* is still very limited – only Kragt and Llewellyn (2014) has implemented a CE among extension agents to my knowledge. In chapter 3, I contribute to the scant literature on application of CE among extension agents, which can open up further research along this direction in SSA and elsewhere. The use of CE method in this way can generate useful *ex-ante* insights to inform research, development and policy initiatives for the design of other DSTs towards improving the efficiency of extension systems.

Fifth, a large stream of literature points to the implication of the highly heterogeneous conditions of smallholder farmers in limiting generalized interventions (e.g. Tittonell et al., 2010; Giller et al., 2011; Tittonell et al., 2011; Berkhout et al., 2011; Kihara et al., 2016b; de Janvry et al., 2017; Njoroge et al., 2017; MacCarthy et al., 2018; Shehu et al., 2018; van Loon et al., 2019b). In the context of soil fertility, the use of SSNM extension interventions in the agronomic literature is considered potentially more relevant to smallholder farmers than generalized extension recommendations (Pampolino et al., 2012; Xu et al., 2014). On the other hand, the rapid transformation in digital technologies offers opportunity for the use of digital DSTs to provide site-specific recommendations (Fu and Akter, 2016; Larochelle et al., 2019). Yet, it remains unclear whether, and to what extent the use of site-specific extension interventions enabled by digital DSTs can stimulate the adoption of agricultural technologies and management practices, and the associated yield and revenue gains in SSA. In addition, it is unclear whether information interventions about fertilizer management practices provided to farmers in the context of SSNM can substantially address technical inefficiency. I address these gaps in the current literature in Chapter 4. To do this, I implement a randomized controlled trial and estimate the farm-level causal effects of the information interventions using panel data of three household survey rounds.

Lastly, some theoretical and empirical studies suggest that smallholder farmers are more likely to give up productivity gains for stability in returns to investments in the face of uncertainty about the expected returns (e.g. Feder et al., 1985; Asrat et al., 2010; Dercon and Christiaensen, 2011; Musaka, 2018). Conversely, it has become important to consider not just the mean outcomes of technology adoption but also the variability of the expected outcomes (Silehi et al., 2010; Bulte et al., 2014; Musaka, 2018; Vanlauwe et al., 2019a). Some studies suggest that additional information about the use of a technology can reduce uncertainty about the expected outcomes, and enhance adoption decisions (e.g. Just and Zilberman, 1983; Feder and Umali, 1993; Saha et al., 1994; Marra et al., 2003; Koundouri et al., 2006; Genius et al., 2014). To this end, farmers may be more likely to make better informed fertilizer investment decisions if provided with additional information about variability of the expected investment returns and not only the expected level of returns but this remains an empirical question in the literature. To my knowledge, there are no studies that empirically test whether provision of complementary information about variability of the expected returns (i.e. uncertainty induced by variation in market and climatic conditions across seasons) as a way to lift uncertainty impacts farmers' responses to DST-enabled SSNM recommendations. In chapter 4, I address this limitation in the literature by using three-period panel data from a randomized controlled trial among maize producing households in the research area.

In summary, the overall objective of this PhD thesis is to analyze in detail the design, adoption and impact of a nutrient management DST for site-specific extension services in the maize belt of northern Nigeria. I specifically look at farmers' preferences for extension recommendations enabled by DSTs, extension agents' preferences for the design of a nutrient management DST, and farm-level impact of DST-enabled SSNM extension recommendations. To achieve this, I focus on both farmers and extension agents as the research subjects of the thesis, and I use different methods and an extensive database, including data from two discrete choice experiments and three-period panel data from a randomized controlled trial in the research area. Ultimately this PhD thesis contributes to different strands of the scientific literature, including literature on digital DST design, agricultural technology adoption, discrete choice experiments, experimental impact evaluation, crop yield gap, agricultural extension in general and digitally-supported extension in particular.

3. Background of the research

In this section, I specifically provide detailed background information about Nigeria, including maize production, fertilizer use, TAMASA project and description of the research area.

3.1 Maize production in Nigeria

Maize (*Zea mays* L.) is one of the most important staple food crop for millions of people and has gradually become a cash crop due to its increasing industrial demand, especially in the livestock feed industry (Iken and Amusa, 2004; Olaniyan, 2015; Abdoulaye et al., 2018). It is widely cultivated across diverse agro-ecologies, including the rainforest and savanna agro-ecologies, and much higher production potential is in the savannas, particularly in northern Guinea savanna (Carsky et al., 1998; Ibrahim et al., 2014). The high yield potential is because it offers more favorable environmental conditions, especially higher solar radiation and lower night temperatures (Badu-Apraku et al., 2011). Maize is produced under rainfed system mainly by smallholder farmers who cultivate an average of less than 2 ha (Liverpool-Tasie et al., 2017, Gil et al., 2019).

Over the last five decades, there has been substantial maize improvement research by collaborative efforts of international and national agricultural research institutes, resulting in several improved maize varieties and agronomic practices in general (Badu-Apraku et al., 2013; Olaniyan, 2015). Especially the development of early and extra-early maturing maize varieties for Sudan savanna, where the length of growing period is very short, has contributed to the widespread cultivation of maize, even in drier agro-ecologies (Badu-Apraku et al., 2018). In addition, maize farmers receive relatively more extension support and have better access to inputs, subsidized fertilizer and improved seeds, in comparison with farmers cultivating other food crops in Nigeria and SSA in general (Smale et al., 2013; Ibrahim et al., 2014; Liverpool-Tasie et al., 2017).

In spite of the food and cash prospects of maize cultivation, and the considerable research and extension efforts, empirical findings show that yields on farmers' fields generally stagnate around 1 to 2 tons per ha (Wossen et al., 2017; Abdoulaye et al., 2018; Baiyegunhi et al., 2018; Oyinbo et al., 2019a). This falls short of the potential yield of over 7 tons per ha. More specifically, rainfed maize has both the greatest yield potential and the largest yield gap relative to other cereals in Nigeria as in other countries in SSA (van Ittersum et al., 2016). Over the years, maize production increased substantially in terms of area harvested from 1.4 million ha in 1961 to 6.5 million ha in 2017, and in terms of production quantity from 1.1 million tons in 1961 to 10.4 million tons in 2017 (Fig. 1.1 and 1.2). By this, the maize area harvested is the largest in Africa and the production volume is the second largest – second to South Africa (FAOSTAT, 2018).

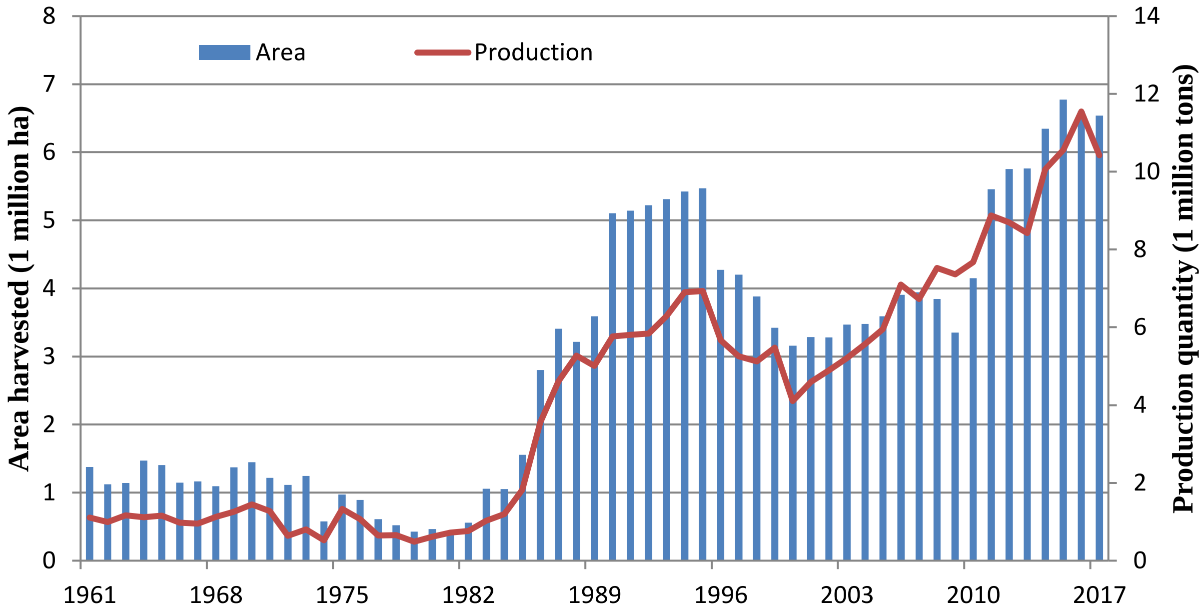

Fig. 1.1: Maize area harvested and production quantity trend in Nigeria, 1961 – 2017. Source: Author's computation based on data from FAOSTAT.

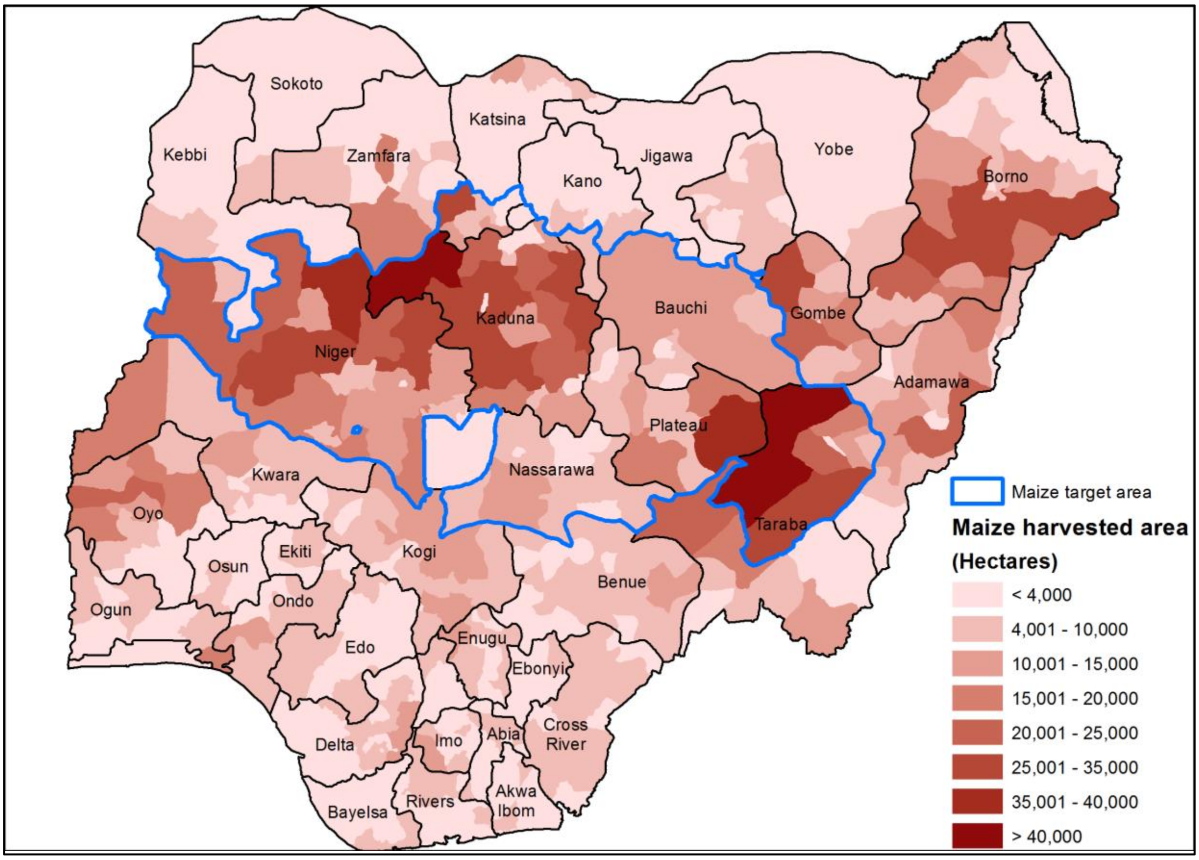

Fig. 1.2: Map of Nigeria showing the distribution of maize harvested area across the 36 states of Nigeria and the federal capital territory. The area highlighted in blue holds about 60% of entire maize planted area in Nigeria. Source: Constructed in ArcGIS by TAMASA project team.

Average yield has rather stagnated over the same period, moving from 0.8 tons per ha in 1961 to 1.6 tons per ha in 2017, and has been lagging behind average yield in the rest of the world (Fig. 1.3). While Nigeria ranked high in maize area harvested and the production volume in 2017, yield is much lower than in several other countries in Africa (FAOSTAT, 2018). The substantial increase in production volume over the years is due to extensification, which may be limited by population pressure and declining per capita farm size. There is the need for intensification of maize production to close the yield gap, which in turn can contribute substantially to food security (Smith et al., 1994; Gil et al., 2019). Low and inappropriate use of nutrients plays a crucial role in limiting yields. Apart from the soil fertility-related constraints, other notable biophysical constraints include drought and pest infestation, such as *Striga hermonthica*, particularly in the savannas, and poor agronomic practices, such as improper planting density (Kamara et al., 2014).

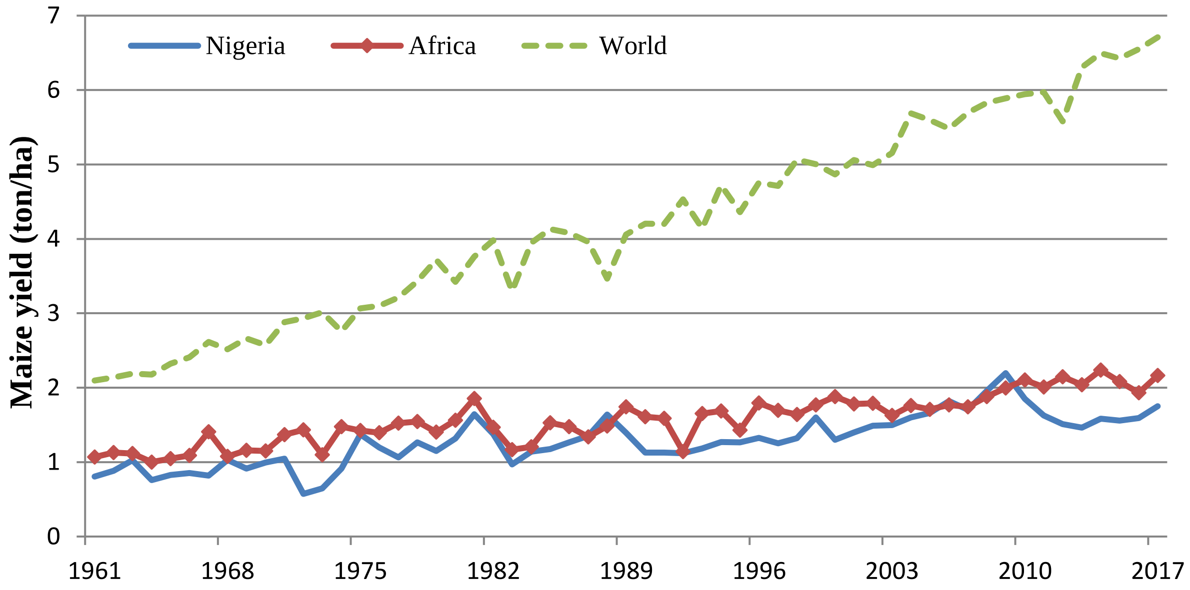

Fig. 1.3: Maize yield trend in Nigeria, Africa and the World, 1961 – 2017. Source: Author's computation based on data from FAOSTAT.

3.2 Fertilizer use in Nigeria

There is a long history of fertilizer use in Nigeria: experimental trials were conducted as far back as 1937 (Tarfa et al., 2017; Amapu et al., 2018). The promotion efforts for farmers to use fertilizer date back to the 1970s (Liverpool-Tasie et al., 2017; Wossen et al., 2017). While the share of farmers using fertilizer in SSA is generally considered low, the share of farmers applying fertilizer on maize is relatively high, particularly in Nigeria (Sheahan and Barrett, 2017; Liverpool-Tasie et al., 2017). The use of fertilizer is more widespread in northern Nigeria, where more than 90% of cultivated plots receive fertilizer (Manyong et al., 2001; Maiangwa et al., 2007; Sanni and Droppler, 2007). A number of factors, including relatively active agricultural extension services – mainly driven by donor support, more investment in fertilizer subsidy, and lower inherent fertility of soils in the region – compared to southern Nigeria have been put forward to explain this (Mustapha, 2003; Liverpool-Tasie and Takeshima, 2013).

Despite the seemingly widespread and long tradition of fertilizer use, the application rates are generally low on average. The annual average nutrient application rates on arable land in Nigeria over the years lag behind the average rates in Africa, which in turn lags far behind the rest of the world (Fig. 1.4). In 2016, the application rate was 5.5 kg per hectare of arable land – lower than the average of 16.2 kg per hectare of arable land for SSA (FAOSTAT, 2018). Given such low fertilizer application rates, it is not surprising that Nigeria also has considerable crop yield gaps. Application rates for maize are generally higher than for other cereals – 40 to 50 kg N per hectare – but are still far below the rates which are generally recommended for the region, i.e. 120 kg N per hectare (Sanni and Droppler, 2007; Liverpool-Tasie et al., 2017; Abdoulaye et al., 2018).

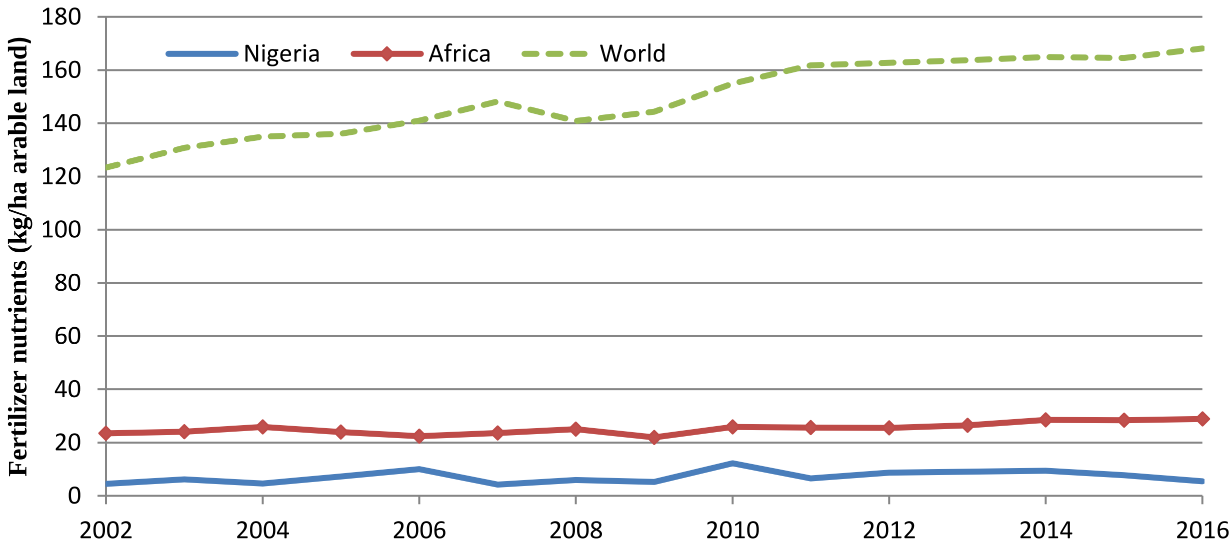

Fig. 1.4: Fertilizer application trend in Nigeria, Africa and the World, 2002 – 2016. Source: Author’s computation based on data from FAOSTAT.

Fertilizer use has been stimulated directly through different fertilizer subsidy programs by successive national (Federal) and subnational (States) governments in Nigeria (Liverpool-Tasie, 2014). This evolved from the traditional government-led procurement and distribution of subsidized fertilizer (1970 to 2011) to an e-voucher scheme where procurement and distribution of subsidized fertilizer is led by the private sector (2012 to 2015) (Takeshima and Nkonya, 2014; Wossen et al., 2017). Other indirect measures that have been taken include programs on extension services for soil fertility management and improvement of farmers' access to credit (Liverpool-Tasie et al., 2017). In recent years, there have been increased policy interventions to induce farm-level investments in fertilizer, raise productivity and improve farmer welfare. This follows the 2006 African fertilizer summit in Nigeria, where African countries committed to increasing fertilizer use to 50 kg nutrients per ha by 2015, and reinvigorated by the Malabo declaration in 2014 (Vanlauwe et al., 2015b, Sheahan and Barrett, 2017). Yet, on-farm fertilizer use rates have not substantially improved – fall short of the 2015 target in Nigeria and many other countries, and are on average below economically optimal rates (Sheahan et al., 2013; Ragada and Chapato, 2017; Theriault et al., 2018).

Starting from 2017, the Federal Government of Nigeria stopped the direct provision of subsidized fertilizer, i.e. smallholder farmers no longer receive 50% subsidy on two 50 kg bags of fertilizer (one NPK and one urea) per farmer per annum. This is largely connected to the huge financial burden of the subsidy program. The government has shifted focus on improving availability and affordability of quality fertilizer by providing an enabling environment for local blending and distribution of fertilizer in the country via a fertilizer policy 'Presidential Initiative on Fertilizer (PFI)' flagged-off in December 2016. Overall, the PFI seeks to end the importation of fully blended fertilizer into Nigeria, which has been the norm over the years, reduce the retail price of fertilizer, improve fertilizer use by smallholder farmers and in turn enhance their productivity and welfare. The expected reduction in fertilizer prices aligns with Smale et al. (2013) and Liverpool-Tasie and Takeshima (2013) who document that the cost of fertilizer importation into SSA contributes substantially to the high price of fertilizer.

The strong emphasis on increased application of fertilizer is based on the assumption that the marginal return to fertilizer is very high, but this is not always the case as yield response is often low and highly variable (Xu et al., 2009; Liverpool-Tasie, 2017; Burke et al., 2017; Koussoube and Nauges, 2017; Theriault et al., 2018; Macours, 2019). This holds in particular for maize production in Nigeria, where yield response to fertilizer (marginal physical product of applied N or agronomic efficiency of applied N) is even lower than in other parts of SSA. Empirical findings show that the maize yield response to fertilizer is on average 8 kg maize per kg of N for Nigeria (Liverpool-Tasie et al., 2017), 16 kg for Zambia (Xu et al., 2009), 17 to18 kg for Kenya (Marenya and Barrett, 2009; Sheahan et al., 2013), 21 to 25 kg for Uganda (Matsumoto and Yamano, 2013), 22 to 26 kg for Ghana (Ragasa and Chapoto, 2017) and 19 to 24 kg for Burkina Faso (Koussoube and Nauges, 2017; Theriault et al., 2018)[6]. The low yield response to applied N can contribute to explain the low profitability and low fertilizer use rates widely observed in the literature (Jayne et al., 2019). In fact, a low response rate can be more important in some cases than market-related constraints, and a focus on improving efficient fertilizer use, which requires better nutrient management extension services, can be more rewarding (Jayne et al., 2018; ten Berge et al., 2019).

3.3 TAMASA project

This thesis is undertaken within the framework of the Taking Maize Agronomy to Scale in Africa (TAMASA) project. TAMASA is a 4-year project with an overall objective of improving productivity and profitability of maize for smallholder farmers in Nigeria, Tanzania and Ethiopia by using innovative approaches to transform agronomy. It is funded by the Bill and Melinda Gates foundation and led by the International Maize and Wheat Improvement Centre (CIMMYT) across the three countries and supported in Nigeria by the International Institute of Tropical Agriculture (IITA) and the Centre for Dry land Agriculture (CDA), Bayero University Kano, Nigeria. It focuses on four gaps necessary to transform agronomy at scale: data gap, knowledge gap, adoption gap and capacity gap (Fig. 1.5). In line with its specific objectives: use available geospatial soil, climate and socioeconomic datasets, work with service providers (government and private extension organizations, input suppliers and agro-dealers) to co-develop systems that transform the available dataset into products and build capacity in national programs, the co-development of a nutrient management DST known as Nutrient Expert was put forward at the outset of the project.

The co-development of the tool was led by the International Institute of Plant Nutrition (IPNI) in collaboration with CIMMYT and the national partners, including service providers and farmers. The tool development process essentially consists of data collection phase (multi-location nutrient omission trials), model development (algorithm, decision rules and programming) and field validation (on-farm model testing and refining). This leads to packaging of the SSNM paradigm into the nutrient management software, i.e. Nutrient Expert tool. The final version of the tool is a tablet- or smartphone-based DST that allows extension

[6]These are survey-based estimates, i.e. based on survey data from farmer-managed plots and not potential yield responses from on-farm or research-station trials. Also, these are average yield responses, which are likely to mask substantial heterogeneity in responses across plots due to variation in management, soil and microclimate (Jayne et al., 2018). Hence, the response rates for individual plots can be much lower or higher than the averages.

agents to generate fertilizer recommendations tailored to the specific situation of an individual farmer's field. It is based on the SSNM: 4R principles of nutrient management – the right rate, the right fertilizer source, the right placement and the right time of application, and allows adjusting fertilizer application based on crop-, plot- and season-specific conditions (Pampolino et al., 2012; Johnston and Bruulsema, 2014). In the use of the tool by an extension agent to provide advice to a farmer, the inputs required include farmer-supplied information about his previous season's crop management practices on the plot (use of inorganic fertilizer and organic resources, seed type, cropping system, yield, etc.), characteristics of the growing environment (water availability, incidence of drought, flood, etc.), a target maize yield and the prices of inputs and maize. Additional information on soil characteristics (color, texture, etc.) is elicited through physical observation of the soil in the plot by the extension agent, and a Geographical Positioning System (GPS)-based plot area is recorded. A target yield is defined as the attainable or optimal yield for a farmer's specific location estimated by the tool using the information on the farmer's current crop management practices and characteristics of the growing environment. The tool can allow a farmer to choose a yield lower than the attainable yield as the target yield – in this way it can take into account the financial situation of farmers by allowing the fertilizer rate to be adjusted according to the farmer's available budget. The outputs of the tool include SSNM information – plot-specific optimal nutrient rates and fertilizer sources that supply these nutrients as well as general advice on nutrient management practices, such as timing of fertilizer application (in particular on splitting the nitrogen application to match nutrient demands at different stages in the maize growth cycle) and fertilizer application method (in particular spot application is recommended as this reduces nutrient losses and ensures optimal nutrient uptake by the plant). The tool recommends a site-specific nutrient rate for an individual farmer's plot based on the farmer's target yield and the expected yield responses, and it relies on the QUEFTS (Quantitative Evaluation of the Fertility of Tropical Soils) model to predict maize yield responses (Pampolino et al., 2012). The model was calibrated for the study area using nutrient omission trials data collected in two seasons, 2015 and 2016. In addition, the tool provides a simple profit analysis to compare farmers' current practice and the recommended practices.

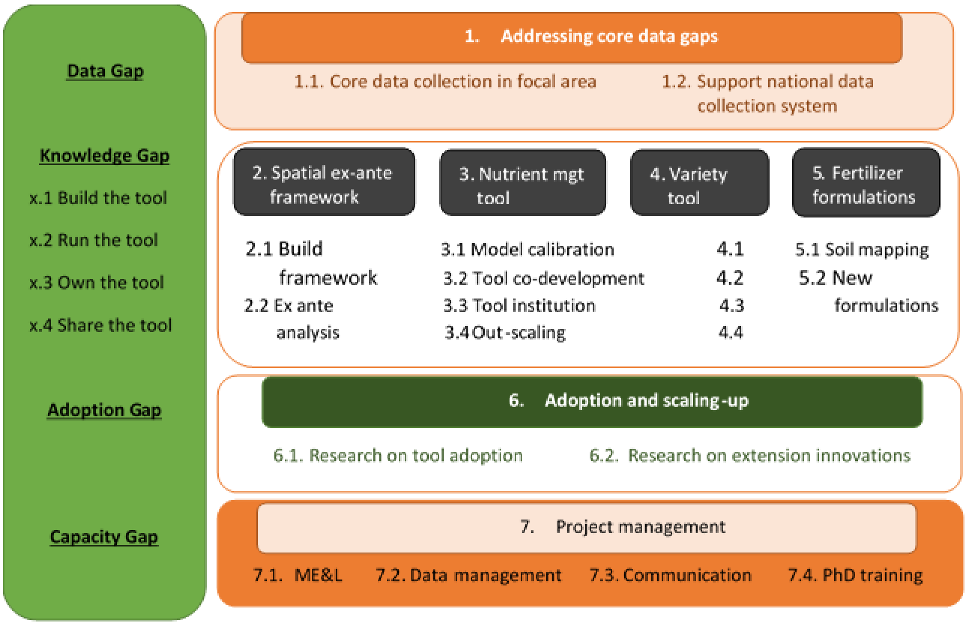

Fig. 1.5: Overview of the gaps addressed by TAMASA. Source: TAMASA project

3.4 Research area

The research area covers three states in northern Nigeria (Fig. 1.6), where maize is grown in a smallholder rainfed system under different agro-ecological conditions. More specifically, the states are in the north-west geopolitical zone – the zone with the highest percentage of extreme poor out of the six zones in Nigeria (World Bank, 2016; Otekunrin et al., 2019). The states are Kaduna, Kano and Katsina, and the agro-ecological zones of the specific research locations are southern Guinea, northern Guinea and Sudan savannas. Rainfall pattern is uni-modal across the agro-ecologies but the amount and distribution varies. On average, the amount of annual rainfall and the length of the growing season in southern Guinea savanna are 1200 to 1500 mm and 181 to 210 days respectively. In northern Guinea savanna, it is 900 to 1200 mm and 151 to 180 days respectively, and it is 500 to 900 mm and 91 to 150 days respectively in the Sudan savanna (Manyong et al., 2001; Akpa et al., 2016). The three agro-ecologies and two others (i.e. derived and Sahel savannas) constitute the Nigeria savanna, which covers about 700,000 km^2 of its total land area of 923,768 km^2 (Tarfa et al., 2017). Soils in the area have a large sand content – sandy loam to loam – a low organic carbon and a low water retention capacity (Ekeleme et al., 2014; Shehu et al., 2018). The estimated populations of Kaduna, Kano and Katsina States in 2018 are 8.4, 12.7 and 7.9 million people respectively based on the Nigeria population census of 2006 and the annual population growth rates (World Bank, 2018b). In addition, their population densities are high – 182, 640 and 329 people per km^2 respectively.

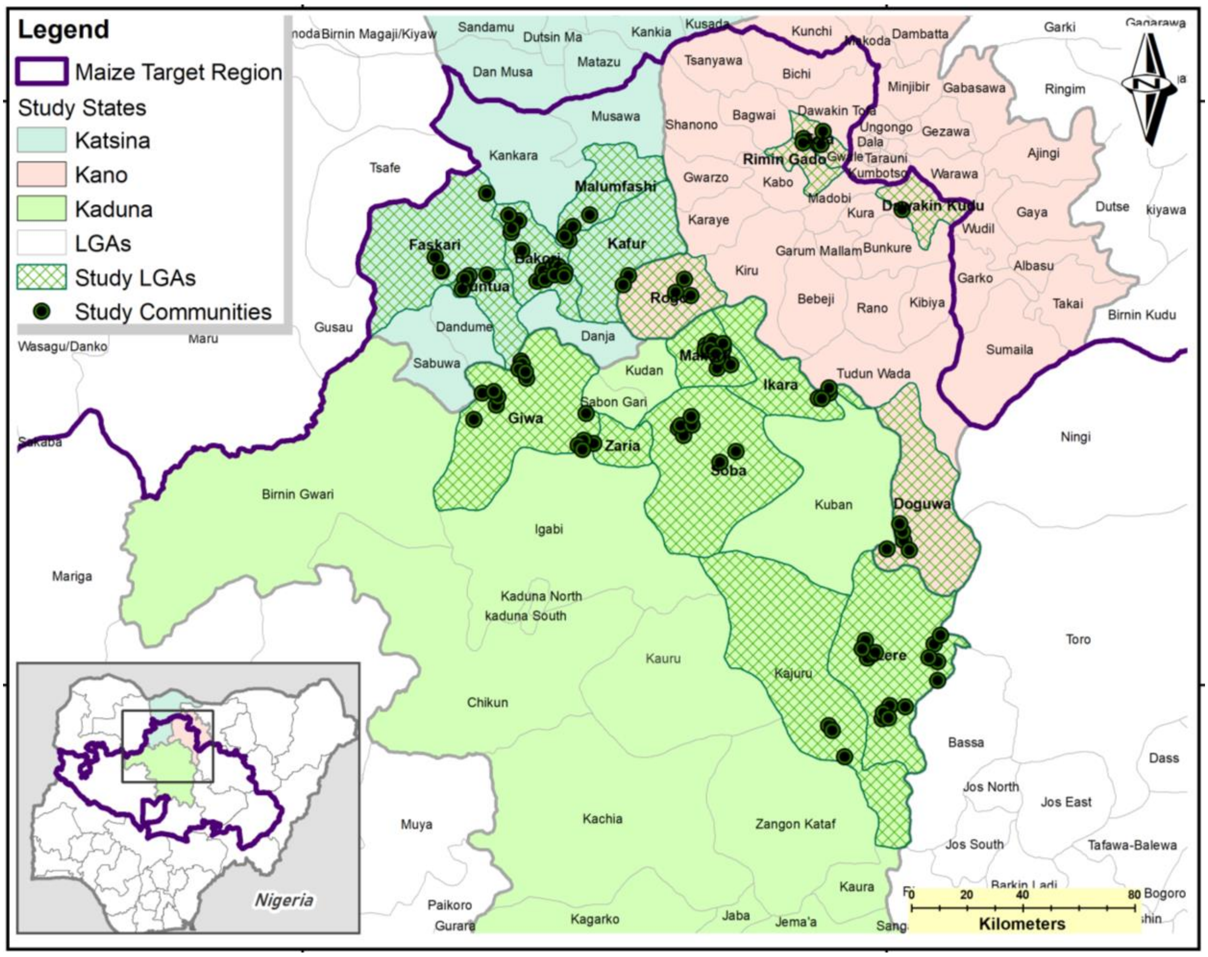

Fig. 1.6: Map of the study area showing the study states and communities. Source: Constructed in ArcGIS by TAMASA project team

The predominant cropping system in this area is a cereal-legume system with maize, sorghum and millet as the main cereal crops and cowpea, groundnut and soybean as the main legumes. The legumes are sometimes intercropped with cereals and sometimes grown in rotation. In light of the N-fixation capacity of these legumes and the fact that N is the most limiting nutrient for maize, their cultivation is increasingly promoted in the area and elsewhere in SSA as a way of improving soil fertility in cereal-dominated farming systems (Vanlauwe et al., 2019b). Other crops cultivated in the area include vegetables, such as tomatoes, pepper, onion and cabbage, and roots and tubers, such as yam and sweet potatoes. Livestock production is also common in the cropping system, including cattle, sheep, goat, chicken, duck and rabbit production. Farm-households who own cattle often use them for agricultural purposes – for animal traction, for transportation and as a source of manure.

Low soil fertility is one of the major constraints to crop production in the area. The cropping system is characterized by low levels of external input use, especially inorganic fertilizer and low yields. The use of organic fertilizer, such as animal manure and compost is common but the application rates are often too low to supply considerable nutrients (Manyong et al., 2001; Chianu and Tsujii, 2005). Hence, the large majority of farmers apply only inorganic fertilizer or both inorganic and organic fertilizer (Akinola et al., 2010). On-farm retention of crop residues, which helps in improving soil organic matter is not a very common practice, as farmers often use the residues for livestock feed and/or fuel (Akinola et al., 2015). The practice of fallow system, a traditional way of restoring soil fertility has become very rare, which may be due to an increase in land pressure (Sanni and Droppler, 2007). Apart from nutrient-related constraints, pest infestation is an important biotic constraint that farmers face in the cropping system. The parasitic witchweed, *Striga hermonthica* is a common pest in maize fields (Baiyegunhi et al., 2018). There is an emerging infestation of fall army worm, *Spodoptera frugiperda* in maize fields in the area following the outbreak of the pest in 2016 (Goergen et al., 2016). Drought stress is an important abiotic constraint to rainfed crop production, such as maize, in the area (Kamara et al., 2019).

The dominant ethnic group of the farm-households in the area is Hausa, and the large majority of them are Muslims. Polygamy is very common in the area and the household members often live in the same compound. Cultural norms of the dominant ethnic group limits the active participation of women in on-farm activities, particularly in rural communities where seclusion of married women is still strongly adhered to, and their role is mainly reproductive (Baba and van der Horst, 2018). Men are predominantly responsible for the productive activities of their households, particularly crop production while women are largely engaged in crop processing activities within the compound of their households. The men also engage in off-farm business activities, including petty trading, carpentry, tricycle and motorcycle transportation, meat processing, and tailoring among others.

There are several agricultural research institutes and centres in the area, including Institute for Agricultural Research (IAR), National Agricultural Extension and Rural Liaison Services (NAERLS), Centre for Dryland Agriculture (CDA), International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and IITA. Extension service providers in the area are mainly the public extension system – Kaduna State Agricultural Development Agency (KADA), Katsina State Agricultural and Rural Development Authority (KTARDA) and Kano State Agricultural and Rural Development Authority (KNARDA). Extension coverage by the public extension system is relatively low due to a gross inadequacy of extension personnel (1 extension agent for about 5,000-10,000 farmers) in the area (Davis et al., 2019). This contributes to limiting farmers' access to extension services, and in particular one-on-one extension agent-farmer interaction in the area. This situation has given rise to other extension service providers, including non-governmental organizations, such as Sasakawa-Global 2000, and private sector extension providers, such as input suppliers and agro-dealers in recent years. The extension service providers often work in close collaboration with research institutes and donor-funded projects, especially in on-farm testing of technologies and management practices. In addition, they are responsible for the dissemination of agronomic advice stemming from such collaborations. For instance, the general fertilizer use recommendations that the extension system disseminates to farmers were derived from fertilizer trials conducted over three decades ago and the recommendations are made for the sub-national levels – i.e. agro-ecological zones (Chude et al., 2012; Amapu et al., 2018).

4. Data collection

The data for this thesis were collected in four phases over the period of 2016 to 2018. I was personally involved in all the data collection phases and I was equally the main responsible person for coordinating and supervising the data collection. In this thesis, I use three main sources of data: 1/ primary data from a discrete choice experiment (CE) among farmers, 2/ primary data from a CE among extension agents, and 3/ primary data from a three-period panel survey associated to a randomized controlled trial (RCT)[7]. I implemented all the data collection activities by means of digital data collection using the Open Data Kit (ODK) software on tablets.

The first phase had two components, a CE and a baseline survey, which includes plot-, household- and village-level surveys that were conducted in September to October 2016 using a structured quantitative questionnaire. The CE was implemented first and lasted on average 20 minutes per interview. Then, the baseline survey was implemented and took about 3 hours, depending on the distance of maize plots from the homestead. Prior to this, in July 2016, I conducted three focus group discussions with farmers in two villages that did not belong to the selected sample. This was done to identify attributes and attribute levels for the design of the CE. In addition, I implemented a pilot version of the CE among 30 farmers in a village that was not sampled for the survey in August 2016. The pilot survey was

[7] In TAMASA project implementation across the three countries, the panel survey is referred to as Agronomy Panel Survey (APS).

implemented to help fine-tune the setup of the CE and generate priors to improve the efficiency of the CE design.

I used a two-stage sampling design to sample the maize-producing farm-households. In the first stage, I randomly generated 22 sampling grids of 10 by 10 km across the primary maize-producing areas in the three states to ensure spatial representativeness of the areas (Fig. 1.7). These grids include 99 randomly selected communities across 17 local government areas (LGAs) – the administrative units below the state. In this stage, I worked very closely with the post-doctoral research fellow (geospatial analyst) in the project who assisted me with the construction of the sampling grids, compilation of the GPS coordinates of the selected communities and all the maps used in this thesis. With the GPS coordinates, I was able to make my first visit to all the communities, and explain the purpose of the research to all the community heads. In the second stage, I constructed a sampling frame of maize-producing farm households in the communities with the assistance of the community heads and the extension agents operating the areas. I randomly selected eight households from each selected village, which results in a final sample of 792 households.

The data collection was implemented by 32 enumerators and 8 supervisors (4 teams of 8 enumerators with each team headed by 2 supervisors). All the enumerators had a minimum of bachelor degree and majority of them studied an agriculture-related course. The supervisors had a minimum of MSc. degree in a field of agriculture, and were mostly staff of a university in the area. I intensively trained the enumerators and the supervisors at IITA, Kano-station for one week with the support of Jordan, and we had pre-test sessions during the training in two communities that are not part of the survey sample. All the enumerators and the supervisors are fluent in the local language – Hausa, and majority of them had prior experience in digital data collection. Each enumerator was only allowed to interview two households in a day to allow of better data quality control. I am also very fluent in the local language and this enabled me to participate actively in the survey and render technical support to the enumerators and the supervisors across the 4 teams of the survey.

For the plot survey, detailed data were collected for the focal maize plot cultivated by the household – which is the plot the household head considers to be most important for the household food security and/or income generation. The structured questionnaire that I used had different modules on: plot size measurement – farmer self-reported estimate and GPS-based estimate by a mobile app ‘UTM area measure app’, soil samples at two depths and crop cut where possible on the plot. The modules of the questionnaire for the household survey include household demographic characteristics, farm-level crop production and input investment, land market, household assets, fertilizer availability, fertilizer recommendations, social capital, extension, credit, income sources, food security, fertilizer use and crop management on the focal plot. The data were mostly collected for the last 12 months prior to the survey. The data were generally collected at the household level except for household demographic characteristics which were collected at individual level. For the community survey, the questionnaire had modules on community demographics, prices of inputs and outputs, access to institutions and services, and the respondent was usually the community head or the leader of farmers in the community. GPS coordinates of the focal maize plots, homesteads and central locations of all the communities were recorded.

In the second phase, a discrete choice experiment was implemented among extension agents (EAs) in November 2016 and was accompanied by a survey. I sampled EAs from both public and private extension service providers who directly advise farmers, and are in turn the expected users of extension DSTs. I randomly selected 278 EAs from the public extension service providers – KADA, KTARDA and KNARDA, and 42 EAs affiliated to private extension providers, which results in a final sample of 320 EAs. For the survey, I used a structured quantitative questionnaire, comprising of modules on: demographic characteristics of the EAs, work environment of EAs, fertilizer recommendations, income sources, time and risk preferences. The data collection was implemented by a team of 8 enumerators and 3 supervisors from the survey team that participated in the first phase of data collection. I trained the enumerators and the supervisors at IITA, Kano-station for three days, including a pre-test of the questionnaire with some EAs. The data collection was much easier because most of the EAs were educated and the survey team had good experience about CE implementation from the first phase.

In the third phase, the second round of the panel survey, i.e. first follow-up survey was conducted in September to October 2017. This survey follows the first implementation of SSNM information interventions using Nutrient Expert DST in April to May 2017 in the area. For the survey, I used the same structured questionnaire that was used in the first round but I made some modifications to the questionnaire in response to the randomized controlled trial, and I dropped some variables that are time-invariant. The data collection was implemented by 24 enumerators and 6 supervisors, i.e. 3 teams of 8 enumerators and 2 supervisors per team and about 90% of them participated in the first survey round. I trained the enumerators and the supervisors at IITA, Kano-station for five days, including a pre-test of the questionnaire in a community outside the survey sample. I collected data from 788 households out of the survey sample of 792 households, which results in an attrition rate of 0.5%. The households who cultivated maize on their focal plot were 690 households, which results in a balanced panel of 690 households who cultivated maize on their focal plot for the 2016-2017 period.

In the fourth phase, I implemented the third round of the three-period panel data collection – second follow-up survey in September to October 2018. This is a follow up to the second implementation of the SSNM information interventions in April to May 2018. In addition, a CE was implemented in this phase to assess farmers' willingness to pay for agronomic advice in response to the debate for a market-led extension but this is not part of this thesis. The structured questionnaire that was used in the first follow-up survey was used for the survey with some little changes. The survey was implemented by a team of 24 enumerators and 6 supervisors and all of them participated in the first or second round except one enumerator and one supervisor. The training of the survey team was at the Centre for Dryland Agriculture, Bayero University Kano for five days. At the end of the survey, the attrition rate was 0.8% because data were only collected from 786 households out of the original sample, and I had a balanced panel of 666 households who cultivated maize on their focal plot for the 2016-2018 period.

The summary of the different data collection activities, databases and the outputs produced is presented in Fig. 1.8. While the baseline survey data were associated with the RCT and also complemented the CE data from the farmers in the first phase, data from the first and second follow-up surveys were only associated with the RCT in this thesis. I provide an overview of the RCT setup in Fig. 1.9. The advantage of the CE method is that it allows us to *ex-ante* quantify the respondents' preferences regarding specific features of nutrient management DSTs and of extension advice from such DSTs to support maize intensification, before introducing the DSTs into the extension systems. In this way, the use of CE in agricultural economics can help to provide insights to better inform the design, fine-tuning and delivery of technologies, extension initiatives or policy interventions to improve the efficiency and efficacy of extension systems. The major limitation of the CE method is that it is susceptible to hypothetical bias because of its hypothetical nature (Loomis, 2014). Yet, there are different approaches to mitigate this, including the use of a cheap talk script, honesty priming and opt-out reminder. The advantage of the RCT (often regarded as the 'gold standard' of impact evaluation) is that it allows us to clearly identify the causal effects of site-specific nutrient management advice with or without complementary information on variability of fertilizer investment returns by virtue of the randomization mechanism. In this way, the use of RCT in agricultural and development economics allows to rigorously test the effectiveness of interventions and provide evidence-based information to development and policy interventions[8]. One of the criticisms on the use of RCTs is the issue of limited external validity, which is still open to debate in the literature (Deaton and Cartwright, 2018).

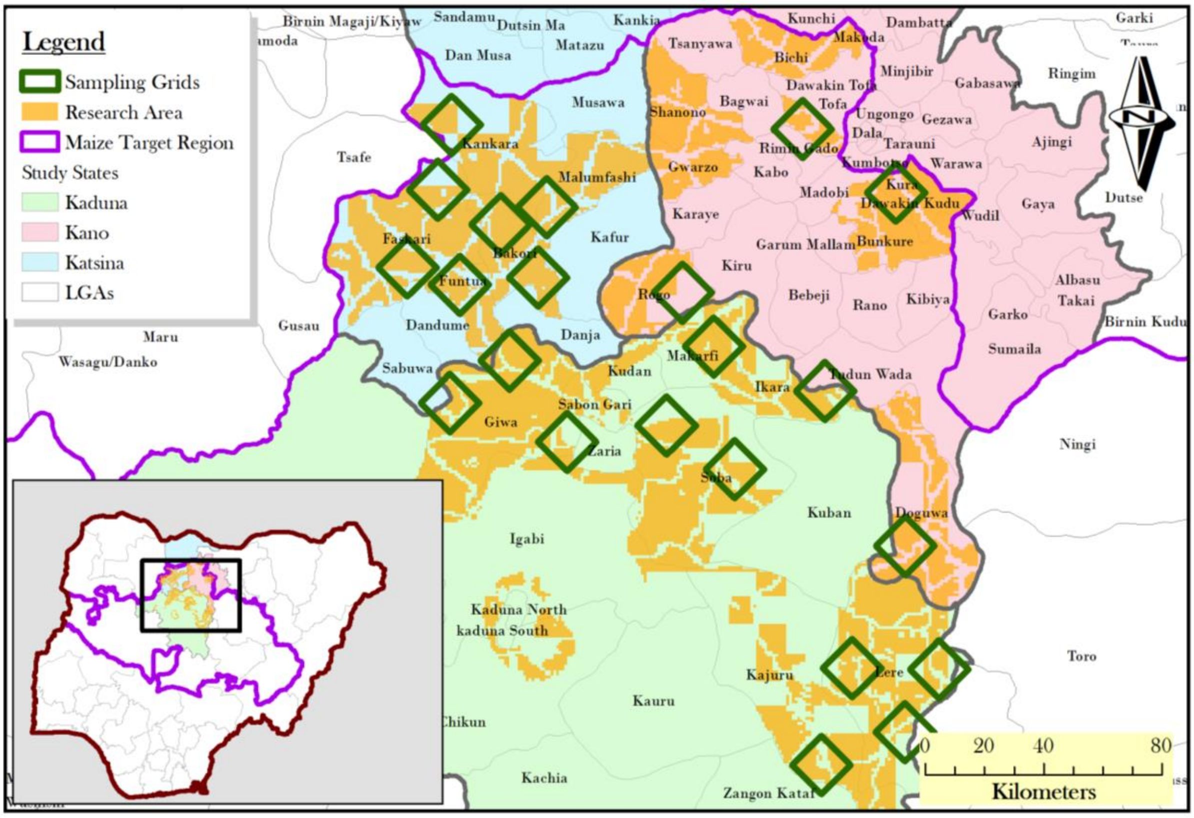

Fig. 1.7: Map of the study area showing the 10 by 10 km sampling grids. Source: Constructed in ArcGIS by TAMASA project team.

[8]This line of experimental approach in development economics earned the trio, Professors Abhijit Banerjee, Esther Duflo and Michael Kremer the 2019 Nobel Prize for economics.

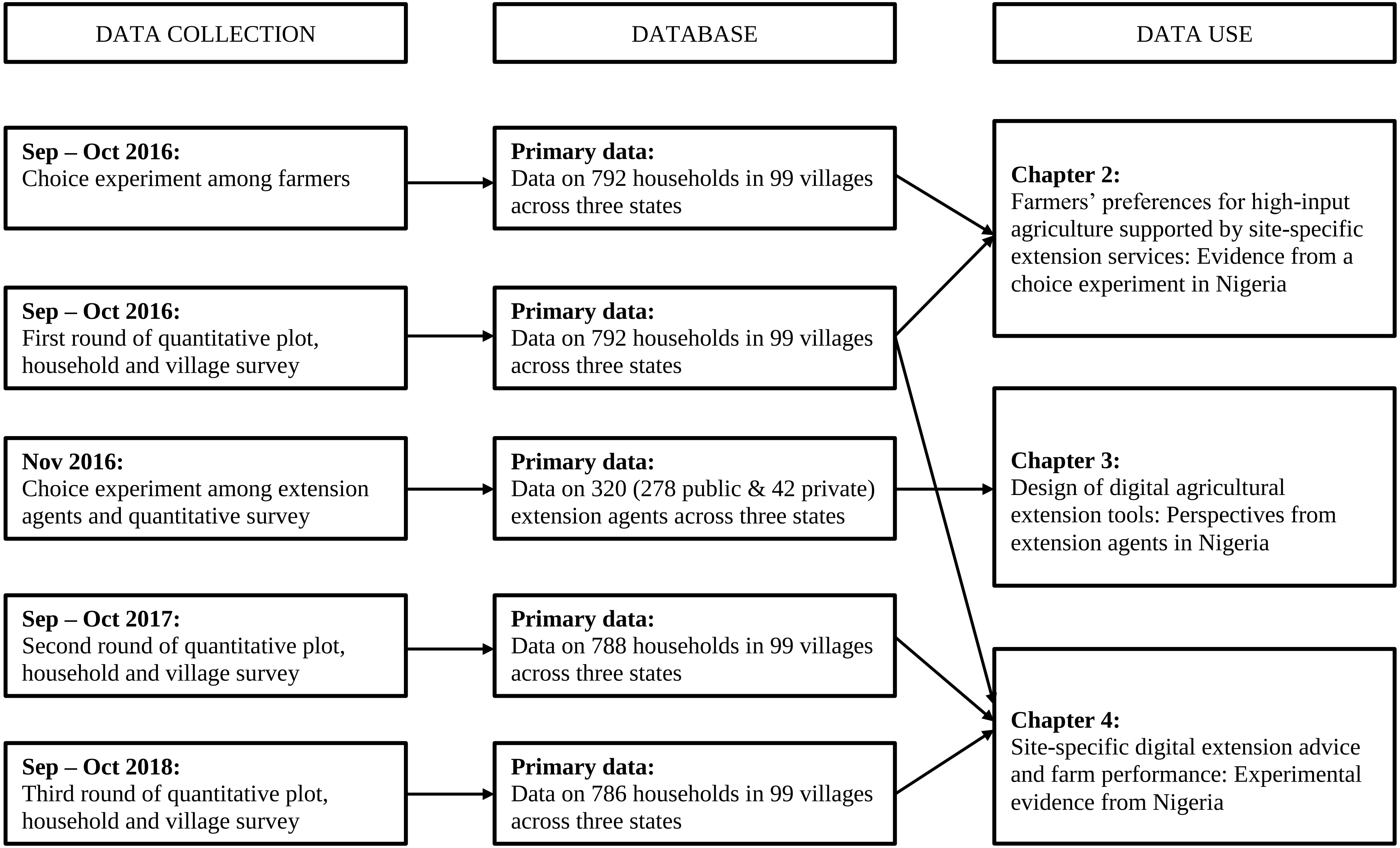

Fig. 1.8: Schematic overview of data collection. Source: Author's own sketch

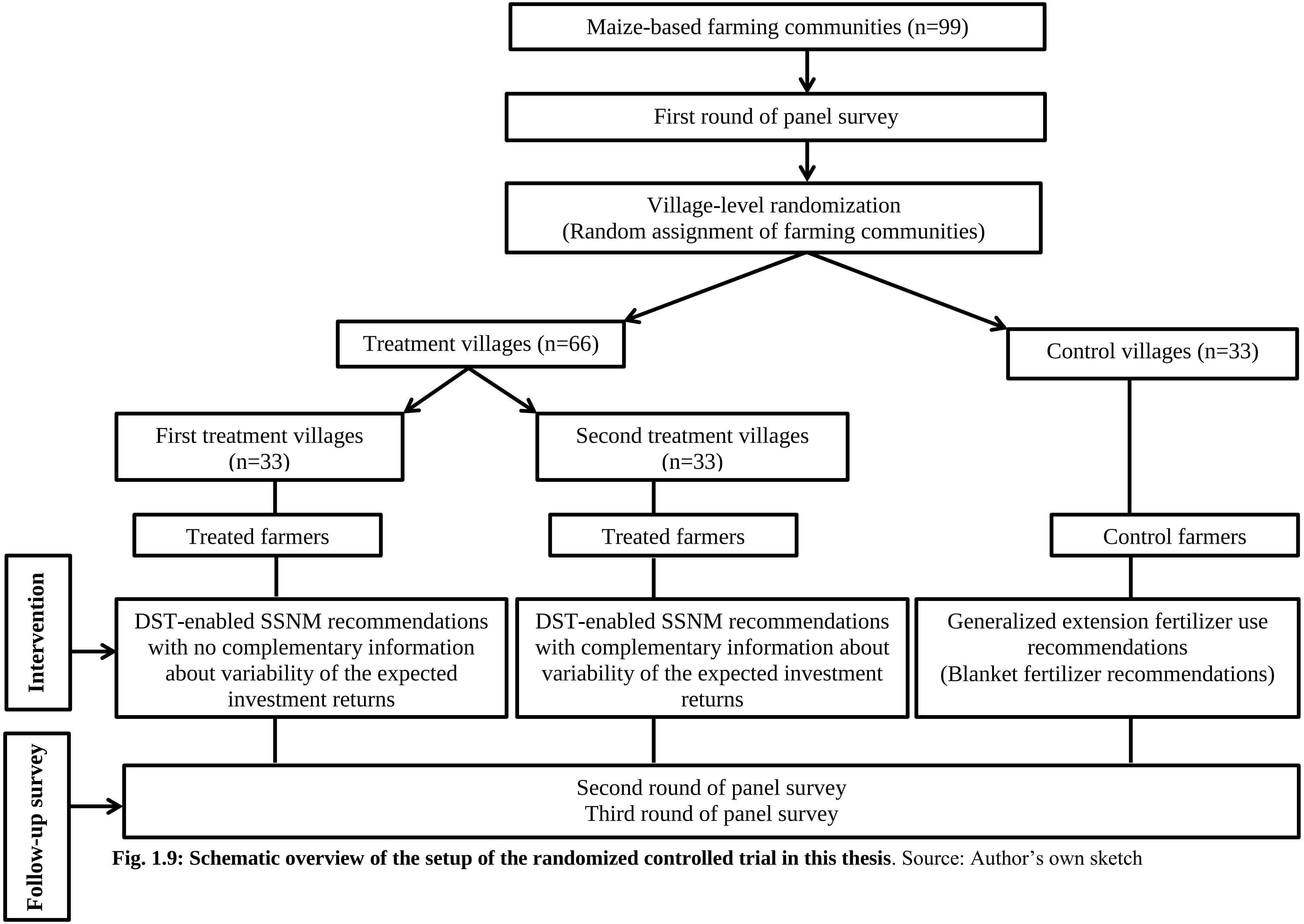

Fig. 1.9: Schematic overview of the setup of the randomized controlled trial in this thesis. Source: Author’s own sketch

5. Outline of the dissertation

In chapter 2, I analyze farmers' preferences for intensification of maize production supported by DST-enabled site-specific nutrient management recommendations in the maize belt of Nigeria in an *ex ante* quantitative way. To do this, I implement a discrete choice experiment among farmers in the research area. I use different econometric models to control for attribute non-attendance and account for preference as well as scale heterogeneity. In chapter 3, I *ex-ante* assess preferences of extension agents for the design of a nutrient management DST for extension services, and their willingness to use such tool. I implement a discrete choice experiment among extension agents in the design stage of a new DST for site-specific nutrient management recommendations for maize, the Nutrient Expert in northern Nigeria. I estimate conventional and validation attribute non-attendance models that allow us to account for attribute non-attendance. In addition, I estimate mixed logit and latent class models to account for preference heterogeneity for the design features of a nutrient management DST. In chapter 4, I rigorously evaluate the impact of farmers' access to DST-enabled site-specific nutrient management recommendations on fertilizer use rates, take-up of fertilizer use management practices, yield and revenue. I implement a randomized controlled trial with two treatment groups and a control group. Using three-period panel data, I estimate the causal effects of the site-specific nutrient management interventions with a difference-in-difference (DiD) estimation. I perform several robustness checks, including estimation of DiD with and without baseline controls, robustness checks to potential attrition bias, and to alternative statistical inference and to corrections for multiple hypotheses testing. In addition, I explore heterogeneity of treatment effects across the outcome distribution and across seasons. Finally in chapter 5, I conclude by summarizing the main findings of the thesis and put forward the research and policy implications of the thesis.

Chapter 2

Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria[9]

[9] This chapter is published as Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, A.Y., Craufurd, P. & Maertens, M. (2019). Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria. *Agricultural Systems*, 173, 12-26.

1. Introduction

The yields of major food crops, such as maize, in Sub-Saharan Africa (SSA) are lagging behind yields in other parts of the world, and are often far below their potential (Tittonell and Giller, 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., 2016a) 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., 2016a; 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 this argument does not always hold and that it is not always profitable for farmers to increase their application rates of inorganic fertilizer in maize production, primarily because of a low maize yield response to fertilizer application in some areas. 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. Extension services on soil fertility management that are adapted to the local context of individual farmers may contribute to improving the yield response to fertilizer and the marginal physical product of applied fertilizer (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 and Giller, 2013; Kihara et al., 2016a; 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., 2016a). 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 (Njoroge et al., 2017).

In this chapter, we analyze farmers' preferences for high-input production systems supported by site-specific nutrient management (SSNM) recommendations for maize provided by an ICT-based extension tool called Nutrient Expert (Pampolino et al., 2012). The Nutrient Expert 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 optimize 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 (e.g. Kragt, 2013; Coffie et al., 2016; Dalemans et al., 2018; Campbell et al., 2018; Caputo et al., 2018).

The remainder of the chapter 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. 2.1).

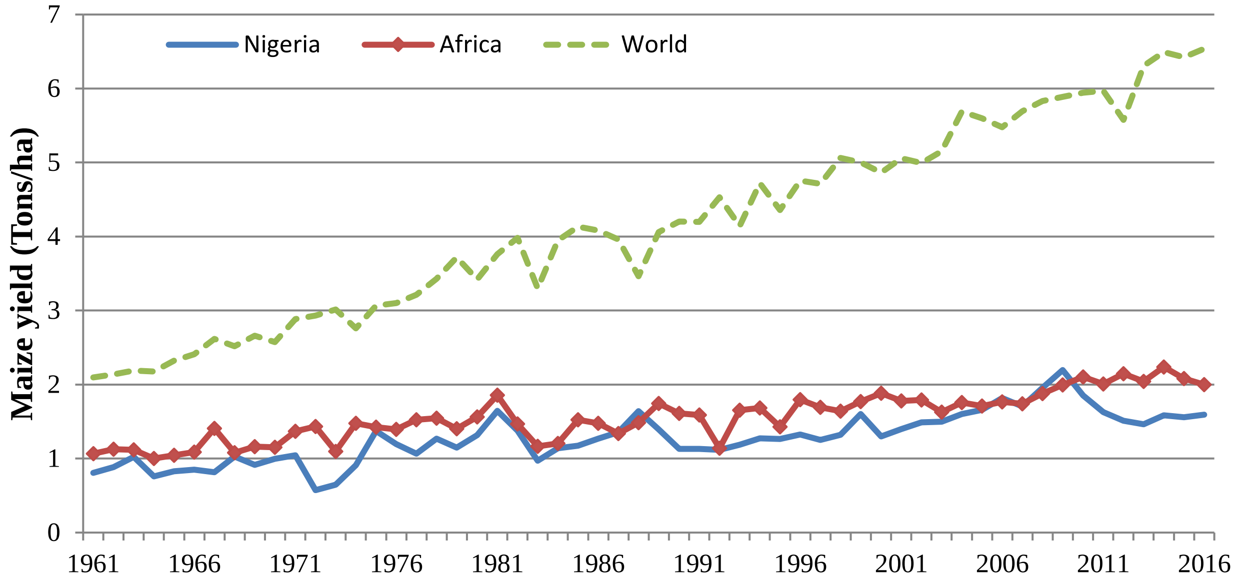

Fig. 2.1: Maize yield trend in Nigeria, Africa and the world at large (FAOSTAT, 2018).

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, high cost of fertilizer, low access to credit, high transportation costs, behavioral constraints such as risk and time preferences, poor knowledge of fertilizer use, as well as to a poor yield responses to fertilizer applications (Chianu and Tsuji, 2005; Sanni and Droppler, 2007; 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, about 15 kg P_2O_5 per ha and 15 kg K_2O 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). In addition, general recommendations may result in fertilizer rates that are sub-optimal from an economic point of view because (expected) marginal returns to fertilizer application are not the same across farmers and fields. Site-specific recommendations may result in fertilizer application rates that allow to better align marginal costs and benefits of fertilizer application, and better account for farmers risk preferences.

2.3 Nutrient Expert tool

The project 'Taking Maize Agronomy to Scale in Africa (TAMASA)' is co-developing a user-friendly, scalable nutrient management extension tool, known as Nutrient Expert, with the aim of providing site-specific soil fertility management recommendations to maize farmers in Nigeria, Tanzania and Ethiopia[10]. This effort is expected to result in a mobile phone-based, easy-to-use and interactive tool that will be used by 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 placement of fertilizer) (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 (Janssen et al., 1990). 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 prevailing market prices of inputs and maize. A target yield is the attainable yield for a farmer's location estimated by the tool using the information on current crop management practices and characteristics of the growing environment provided by the farmer. However, a farmer has the option of choosing a yield lower than the attainable yield as the target yield. The outputs of the tool include information on SSNM (N, P, K application guide and associated crop

[10] The development of the Nutrient Expert tool is a collaborative effort of International Plant Nutrition Institute (IPNI), International Maize and Wheat Improvement Centre (CIMMYT), International Institute of Tropical Agriculture (IITA), extension service providers, national institutes, government agencies, input dealers and farmers with IPNI leading the process.

management practices) to achieve the target maize yield and a simple profit analysis to compare farmers' current practice and the recommended practices. The tool can take into account the financial situation of farmers by allowing recommendations to be adjusted 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 high-input maize production that is supported by site-specific extension recommendations. This allows to analyze how farmers trade off specific attributes of a high-input, -output, -investment and -risk production system, and generates insights for optimizing the design of the Nutrient Expert tool.

3. Methodology

3.1 Research area and sampling

The research was conducted in the maize belt of northern Nigeria which covers the northern Guinea, southern Guinea and Sudan savannas, and where agro-ecological conditions are diverse. In this region maize is mainly grown under a smallholder rain-fed cereal-legume cropping system. The predominant cropping system in this area is a cereal-legume system with maize and sorghum as main cereal crops and cowpea, soybean and other legumes often intercropped with cereals and sometimes in rotation. The tillage practice in the system is mostly traditional tillage that involves the use of a hoe and animal traction. Retention of crop residues on fields is not very common because residues are often used as livestock feed and fuel (Manyong et al., 2001; Akinola et al., 2015). The cropping system is characterized by low levels of external input use, such as inorganic fertilizer, and low yields. For example, the application rate of fertilizer is on average less than 50 kg N per ha for maize, which is low in comparison with the general recommendation of 120 kg N per ha. Yields are on average around 2 tons per ha while the potential maize yield in this area has been estimated to be more than 5 tons per ha (Manyong et al., 2001; Sanni and Droppler, 2007; Liverpool-Tasie et al., 2017; Abdoulaye et al., 2018). The low-input low-output cropping systems relates to a low yield response to fertilizer and to constraints faced by farmers, including information constraints on optimal input use, high cost of fertilizer, low access to credit, and high transaction costs in acquiring inputs (Manyong et al., 2001; Chianu and Tsuji, 2005; Sanni and Droppler, 2007; Liverpool-Tasie et al., 2017).

For this study, the states of Kaduna, Katsina and Kano (Fig. 2.2) were purposively selected because of their strategic position in maize production and to pilot research activities for the development of the Nutrient Expert 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. All the selected farm-households are male-headed. Crop production activities in the research area are predominantly carried out by men while women are largely engaged in crop processing activities. Cultural norms such as seclusion of married women among the dominant Hausa ethnic group in most rural communities of the research area is one of the main factors that limit the active participation of women in on-farm activities (Baba and van der Horst, 2018). Also women’s poor access to and control over productive resources hinders an active participation and leading role of women in crop production. There is a general believe in the research area that women do not farm (Manyong et al., 2001). The focus on male-headed households limits a detailed consideration of gender issues in this study.

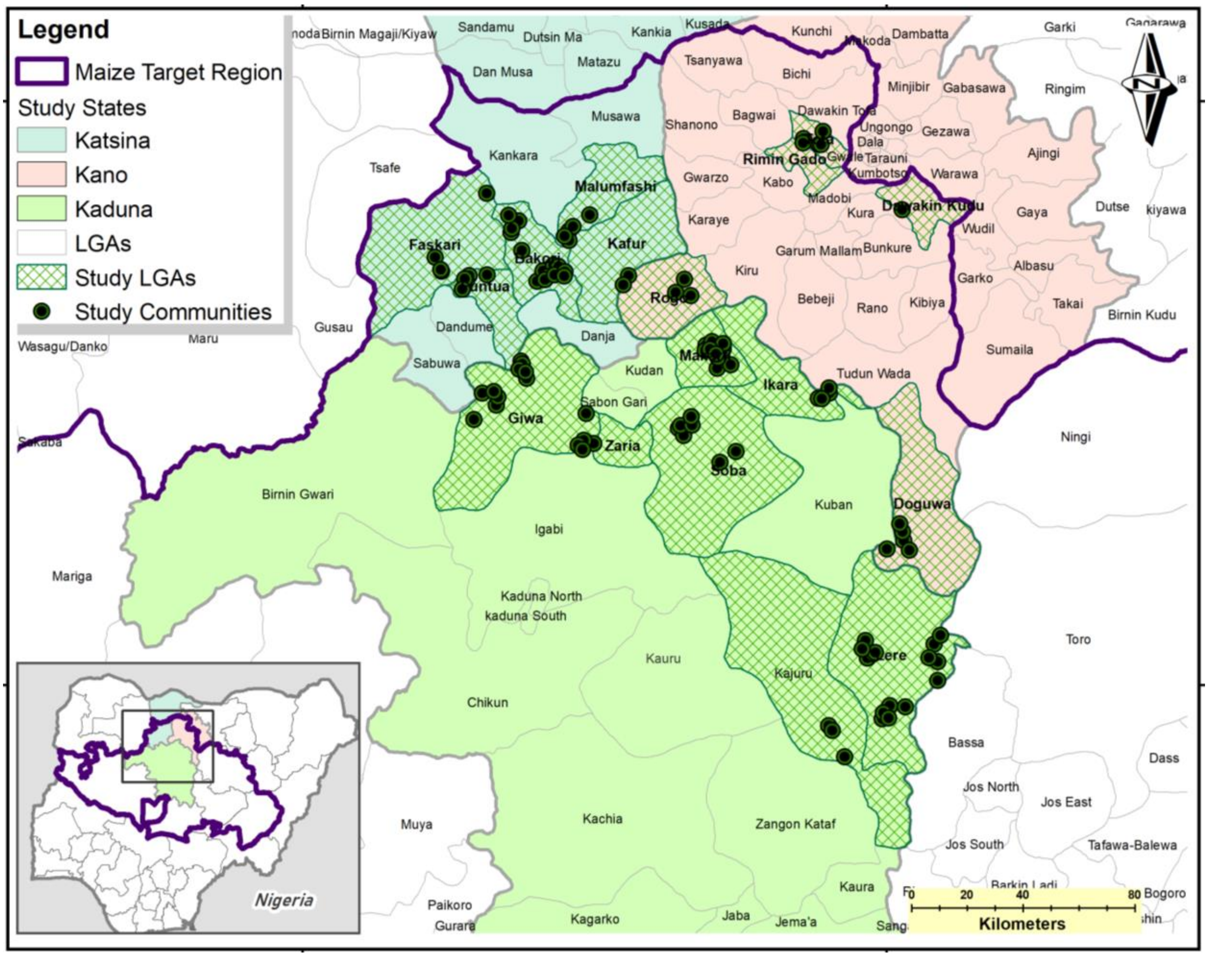

Fig. 2.2: Map of the study area

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 high-input agriculture supported by SSNM recommendations prior to the development of the Nutrient Expert 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 several scientists within and outside the project team and conducted three focus group discussions with farmers[11]. Ten relevant attributes were identified namely fertilizer application rate, fertilizer application method, fertilizer application timing, fertilizer sources, fertilizer quality, seed type, planting density, expected yield, yield variability, cost of fertilizer and seed. A clear description of these attributes and the range of possible levels of the attributes to be included in the CE were elicited from review of soil fertility management literature and during the consultations. However, only the six most important attributes, as revealed from a ranking of attributes during the focus group discussion and the consultations with scientists, were included in the CE in order to reduce the complexity of the choice tasks from inclusion of too many attributes and limit the occurrence of random non-deterministic choices by farmers (Beck et al., 2013). The attributes and their levels are summarized in table 2.1. 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 farmer's 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

[11] This includes personal communication with a scientist from IPNI who is leading the tool development activities in Nigeria and four other scientists who are working in the research area. During focus group discussions, farmers were asked about fertilizer use in general (e.g. questions on whether they use fertilizer, at what rate, how often, with what method, awareness/use of fertilizer recommendations, yield with and without fertilizer, fertilizer use constraints etc.) and the range of attributes they consider relevant for soil fertility management.

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 (115 to 279 USD) 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 2.1: 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

Based on the selected attributes and attribute levels, the choice experimental design was implemented in Ngene 1.1.2 software to combine the various attribute levels into different pairs of mutually exclusive hypothetical options of soil fertility management (i.e. choice sets or situations) that will be evaluated by farmers. For the experimental design we use a fractional factorial design to allocate the attribute levels into choice sets; more specifically a Bayesian D-efficient design which minimizes the D-error and improves efficiency of the design. As proposed by Scarpa et al. (2013), and to improve efficiency, we conducted a pilot version of the CE with 30 farmers prior to the actual design. For this pilot CE we used an orthogonal design in which priors are fixed to zero. 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 such that each farmer can easily evaluate six choice sets. The blocking facilitates the implementation among farmers as it reduces the cognitive burden of evaluating too many choice sets and improves the quality of responses.

Twelve laminated choice cards were constructed for the 12 paired choice sets – see an example in Fig. 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 or alternatives (options A and B) of SSNM recommendations. Each option is defined by six attributes but differs in some attribute levels. 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 for options A and B (Lancsar et al., 2017).

3.2.3 CE and survey implementation

In the CE implementation, the experimentally designed hypothetical options of fertilizer recommendations were provided to each farmer in the form of choice cards. Farmers were asked to carefully evaluate the options on each choice card and to choose the most preferred option for each choice card. Each farmer was presented six distinct choice cards and each choice card had three options of fertilizer recommendations (options A, B and C). Within the set of six choice cards presented to each farmer, options A and B vary within and between the cards but option C which represents the farmer's current practice is fixed. The choice of one option (e.g. option B) over the others (options A and C) on a choice card implies that the expected utility of the chosen option exceeds the utility of the other options. Prior to the CE, there was an introductory session in which farmers were sensitized on its purpose, contents and how to correctly participate. As part of the introduction, 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. The text that was used in this cheap talk script is included in Appendix. After the introductory session, the six choice cards were presented one after the other to each farmer by an enumerator and each farmer was specifically asked to carefully examine the three options on each card, and freely make a choice between the three options on each of the six cards. This is on the premise that the technology option that offer the largest expected utility for the farmer will be chosen among the different options available.

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 access to 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:

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

Where U_{ijs} is the i^{th} farmer's indirect or latent utility, V_{ijs} is the systematic part of the utility function, $\boldsymbol{x}_{ijs}$ is a vector of six attributes describing alternative j with associated preference parameters $\boldsymbol{\beta}_i$, 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 $\boldsymbol{\beta}_c$. 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.

$$Pr_{ijs}|c = \frac{\exp(\boldsymbol{\beta}'_c \boldsymbol{x}_{ijs})}{\sum_{t=1}^{J} \exp(\boldsymbol{\beta}'_c \boldsymbol{x}_{its})} \tag{2}$$

The class membership probability is modeled using a multinomial logit specification as a function of farmer-specific characteristics[12] 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).

$$Pr_{ijs}|c = \frac{\exp(\boldsymbol{\gamma}'_c \boldsymbol{z}_i)}{\sum_{q=1}^{C} \exp(\boldsymbol{\gamma}'_q \boldsymbol{z}_i)} \tag{3}$$

Where $\boldsymbol{z}_i$ is a vector of farmer-specific characteristics and $\boldsymbol{\gamma}'_c$ is a vector of parameters of $\boldsymbol{z}_i$. 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 for the current practice and 0 otherwise. A negative coefficient for the ASC implies a positive utility of moving away from the current practice to

[12] 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.

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.

$$Pr_{ijs}|c,d = \frac{\exp(\lambda_d \boldsymbol{\beta}'_c \boldsymbol{x}_{ijs})}{\sum_{t=1}^{J} \exp(\lambda_d \boldsymbol{\beta}'_c \boldsymbol{x}_{its})} \tag{4}$$

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, i.e. all information about the alternatives are taken into account by respondents in making their choices (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).

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

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 considered or ignored 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).

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

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 2.2 describes individual-, household- and farm-level characteristics of sampled farmers. Farmers are on average 44.7 years old and have an average of 5.2 years of schooling. Farm-households include on average 1.7 adult men, 1.9 adult women and 5.6 children. 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, 16% produce maize under a contract-farming arrangement and 37% have extension experience from government and/or non-government extension service providers. 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 (128 USD) 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. Farm-households live on average 4.08 km from the nearest tarmac road and the large majority (81%) is located in the northern guinea savanna agro-ecological zone.

Fig. 2.3 shows the distributions of fertilizer application and maize yield of sampled farmers. The distributions are rather skewed, with a long tail towards larger values of fertilizer application rates and maize yields, especially for NPK fertilizer application rates. In addition, the distributions suggest considerable variation in farmers' fertilizer application rates and associated maize yields. Fig. 2.4 shows that there is a positive correlation between NPK fertilizer application rates and maize yield, and between urea fertilizer application rates and maize yield.

Table 2.2: Summary statistics of farmers' characteristics (N=792)

	Description of variable	Mean	SD
Age (years)	Age of household head	44.70	12.03
Education (years)	Years of schooling attained by household head	5.16	6.01
Health of head (%)[1]	Health status of household head	96.43	
Male adults (no.)	Number of male adults in a household	1.70	1.02
Female adults (no.)	Number of female adults in a household	1.87	1.22
Children (no.)	Number of children in a household	5.88	4.49
Credit (%)	Household have access to agricultural credit	20.7	0.40
Member of association (%)	Household belong to a farmer association	33.71	
Maize contract farming (%)	Household produce maize under contract-farming	16.37	
Extension (%)[2]	Household have access to extension services	37.28	
Farming experience (years)	Years of maize farming attained by household	19.11	0.43
Off-farm income (%)	Household have access to off-farm income	94.98	
Farm assets[3] (1,000 NGN)	Value of farm assets a household owns	51.36	11.45
Transport assets (1,000 NGN)	Value of transport assets a household owns	201.85	459.05
Livestock assets (1,000 NGN)	Value of livestock assets a household owns	394.51	586.67
Durable assets[4] (1,000 NGN)	Value of durable assets a household owns	22.66	52.86
Annual income[5] (1,000 NGN)	Income earned during the past one year	177.63	221.35
Total farm area (ha)	Size of household total farmland	3.23	3.63
Maize focal plot area[6] (ha)	Size of household maize focal plot	0.82	1.04
Use improved seed (%)	Household cultivate improved maize seed	28.04	
NPK fertilizer (kg/ha)	Quantity of NPK fertilizer applied per hectare	126.96	102.84
Urea fertilizer (kg/ha)	Quantity of urea fertilizer applied per hectare	88.79	95.09
Input cost/ha[7] (1,000 NGN)	Cost of fertilizer and seed	38.61	25.11
Maize-legume intercrop (%)	Maize plot intercropped with a legume	30.15	
Maize yield (tons/ha)	Output of maize per hectare	2.05	0.91
Distance to tarmac road (km)	Distance from homestead to nearest tarmac road	4.08	5.15
Northern guinea savanna (%)	Northern guinea savanna agro-ecological zone	80.71	
Southern guinea savanna (%)	Southern guinea savanna agro-ecological zone	3.40	
Sudan savanna (%)	Sudan savanna agro-ecological zone	15.88	

[1] Percentage of farmers who self-report to be healthy during the past one year,
[2] Extension experience through a face-to-face contact with extension agents, on-farm trials, field demonstrations or any extension-related training from both government and non-government extension services in the last three years,
[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.

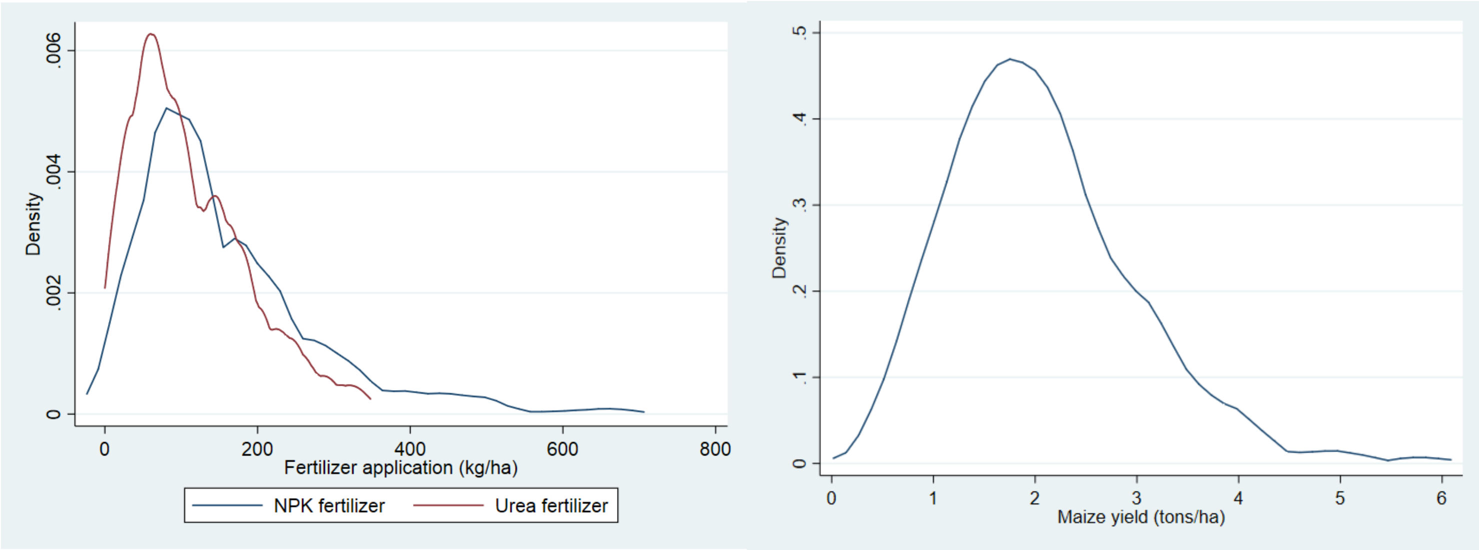

Fig. 2.3: Kernel density distributions of fertilizer application and maize yield

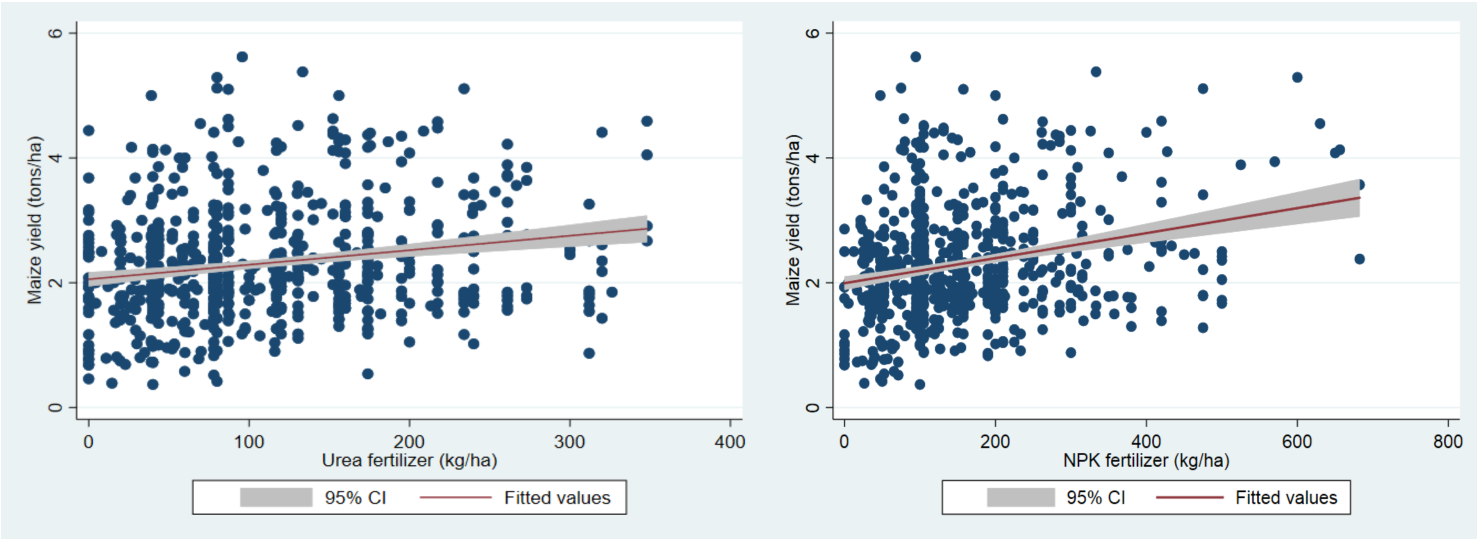

Fig. 2.4: Correlation between fertilizer application and maize yield

4.2. Econometric results

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. 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 2.3 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 2.3: 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

The results of the estimated LCMs with two latent classes are presented in table 2.4, 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)[13], 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. Only in 3% of the choices farmers chose the opt-out, implying they prefer the current practice over the site-specific scenarios of soil fertility management. Both classes have significant positive preferences for site-specific fertilizer application rates. Latent class one farmers (LC1) have a significant positive preference for a site-specific fertilizer rate that is above their current fertilizer application rate, which indicates a preference for moving to a high-input high-output production system. Latent class two farmers (LC2) have a significant positive preference for a site-specific fertilizer rate that is below their current application rate, which indicates a low willingness to move to a high-input high-output production system. 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 input demand curve. The former is not and may seem counterintuitive. This results likely stems from the failure to account for the quality of inputs in the design of the choice experiment, and the intuitive association farmers make between cost and quality of inputs while eliciting their choices during the implementation of the choice experiment. The positive preference for a higher input cost is consistent with a willingness to pay more for higher quality farm inputs. This is in line with Palma et al. (2016) and Lambrecht et al. (2015) who note that a positive cost preference can represent a cue for quality in choice modeling. 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

[13] 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.

recommendations that result in higher and more stable yields, which is in line with the *a priori* expectations and with farmers being risk averse.

Table 2.4: Results of different latent class models estimating farmers' preferences for ICT-based site-specific 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	14256		14256		14256		14256			
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 a 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 2.5 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 2.5: 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. Yet, the estimates of the membership function do not imply causal relationship. Table 2.6 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 statistically 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 income and different types of assets) and access to services and institutions such as credit, farmer associations, contract farming arrangements, and extension services. This is in line with a large part of the technology adoption literature pointing to more-endowed farmers being more likely to adopt improved farm technologies and to the importance of association membership and extension services in driving technology adoption (Kuehne et al., 2017; Lambrecht et al., 2014). Farmers in LC2 appear better-off in terms of education and access to roads. Education is often (but not always) associated with a higher likelihood of adopting new technologies – it is not in our case. 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. Access to roads is often observed to benefit technology adoption because of reduced transport costs in input purchase but it may have no effect for technologies that are less input intensive. In terms of 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 2.6: Farmer characteristics by preference classes

	Latent class 1 (N=507)		Latent class 2 (N=285)		
	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		
Male adults	1.70	1.15	1.68	0.71	
Female adults	1.89	1.31	1.81	1.04	
Children	6.02	4.72	5.62	3.99	***
Access to credit	26.68		9.72		***
Member of association	40.40		21.30		***
Maize contract farming	17.96		13.43		***
Farming experience	19.12	10.48	19.10	10.68	
Extension experience	39.65		32.87		***
Access to off-farm income	96.51		92.13		***
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	**
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 described 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 that their production conditions are heterogeneous and that they are open to soil fertility management recommendations that are tailored to their specific growing conditions and derived from 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, are more willing to invest in a high-input maize production system, and have no aversion for more labor-intensive production techniques with higher expected returns. 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 (or able) 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 is likely related to the observation that weak potential adopters have less resources such as income and assets, and a lower access to services such as credit and extension services. They are therefore likely less able to accept riskier recommendations compared to the strong potential adopters. This implies that the adoption behavior of farmers and their fertilizer investment decisions are not only influenced by expected profits, which is determined by an increased input cost and an expected yield response to fertilizer, but also by the expected risk exposure associated with high-input high-output production systems. 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 indicate their willingness to invest in high-input high-output production systems. 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 are more likely to follow extension advice that follows a high-input high-output logic.

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 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 Nutrient Expert 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 the expected yields for farmers. Most importantly, our results strongly indicate the need to optimize design of tools to allow of 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. This is especially the case for farmers who are more risk averse, are less resource-endowed, are not associated in farmer groups, and have no access to credit and other services. 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 recommendations, and high-investment high-risk 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 information 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 chapter, we analyze farmers' preferences for high-input maize production supported by site-specific nutrient management recommendations provided by ICT-based extension tools such as Nutrient Expert that is being developed for extension services in the maize belt of Nigeria. We use a discrete choice experiment to provide *ex-ante* insights on the adoption potentials of ICT-based site-specific extension services on soil fertility management from the perspective of farmers and with the aim to inform the design of DSTs. 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 and ability of farmers to invest in high-input production systems and take risk, and inform farmers correctly on expected yield and returns as well as on the variability in yield and potential losses.

Appendix

Script for implementation of choice experiment

Dear farmer,
In a bid to serve you with SITE-SPECIFIC extension services in which recommendations are tailored to your field-specific conditions instead of the conventional GENERAL extension recommendations, your inputs are highly needed to optimize the design of an ICT-enabled extension tool ‘‘Nutrient Expert” that is being developed. This tool will enable extension service providers easily deliver site-specific nutrient management (SSNM) recommendations to you which will help you make better informed decisions on soil fertility and crop management. I will guide you through an exercise in which you will have the opportunity to choose soil fertility management options for your maize production. These options are defined using six attributes namely fertilizer application rate, fertilizer application method, expected yield, yield variability, seed type and cost of fertilizer and seed. (At this point, kindly show the farmer a card containing the six attributes and attribute levels and also, sample of a choice card with explanations to ensure that the farmer fully understands the choice experiment). I will now offer you six distinct choice cards one after the other and each choice card contains two hypothetical scenarios of SSNM (options A and B) and your current practice (option C). The aim is for you to choose one option that you prefer from the three options on each card and this will require you to objectively reflect on the attribute levels of the two hypothetical scenarios of SSNM in comparison with your current practice. You are to carefully go through and evaluate the options on each card that I will present to you and indicate the option you prefer between the three options on each of the cards. Even though this exercise entails hypothetical options of soil fertility management, kindly make very truthful choices as if these were real choices that have real cost implications. This is to ensure that the choices an individual makes in this hypothetical exercise are not different from the actual choices if such individual were exposed to real site-specific recommendations from the extension tool being developed.

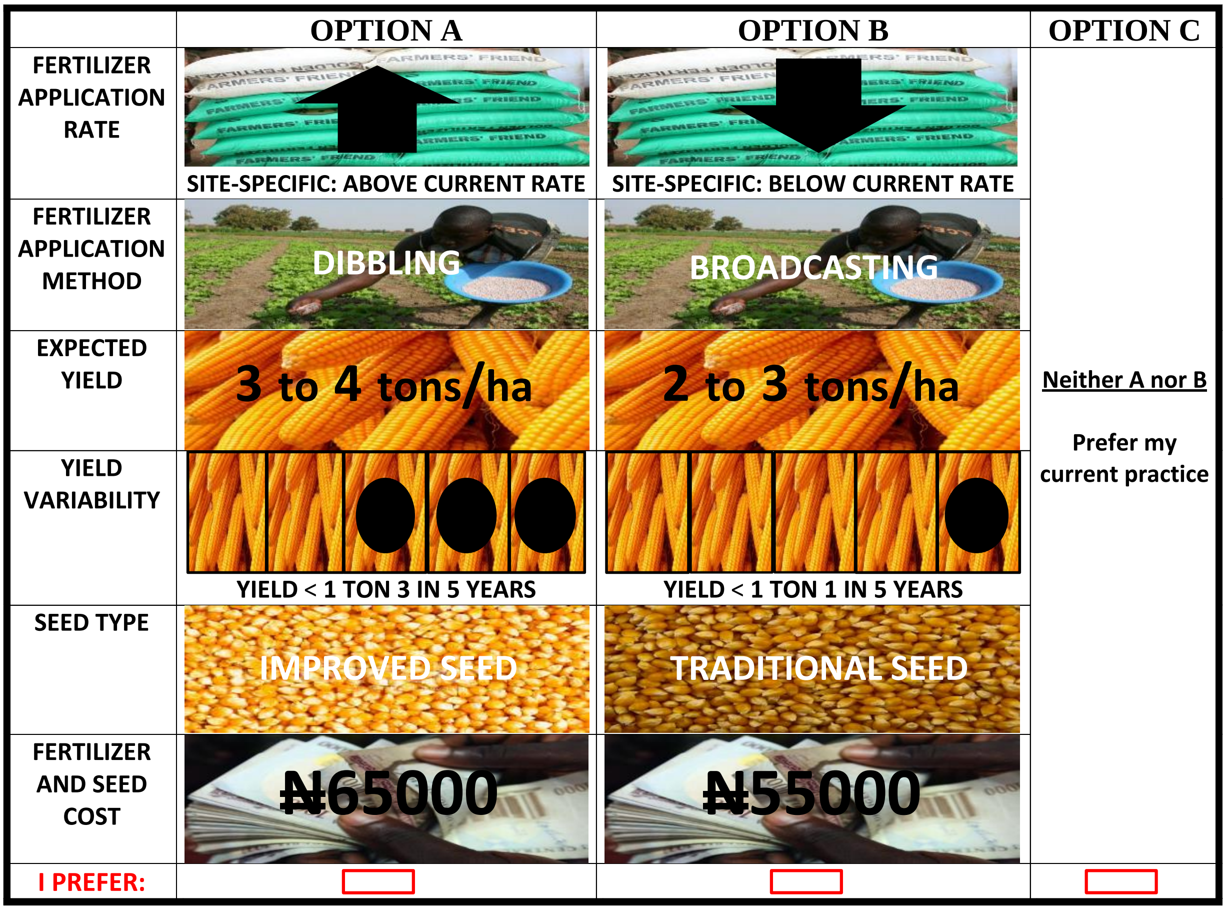

Fig. A1: Example of a choice card

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

	LCM		SALCM		conventional ANA		validation 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 14256,

SALCM has two scale classes. Scale class 1 has 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.

Chapter 3

Design of digital agricultural extension tools: Perspectives from extension agents in Nigeria[14]

[14] This chapter is based on Oyinbo, O., Chamberlin, J. & Maertens, M. (2019). Design of digital agricultural extension tools: Perspectives from extension agents in Nigeria. Revised and resubmitted to Journal of Agricultural Economics.

1. Introduction

Traditional extension systems in Sub-Saharan African (SSA) provide very general agronomic advice, such as fertilizer use recommendations, across wide and highly heterogeneous environments (Theriault et al., 2018; Shehu et al., 2018). Such information fails to take into account the spatial and temporal variability in biophysical and socio-economic conditions within a given national or regional context (MacCarthy et al., 2018; Jayne et al., 2019). The use of digital decision support tools (DSTs), enabled by modern information and communication technology such as smartphones and tablets, is increasingly promoted for more effective delivery of agronomic information tailored to the site-specific conditions of individual farmers (Bernet et al., 2001; Kragt and Llewellyn, 2014; MacCarthy et al., 2018). A growing number of DSTs are being developed or have recently been developed in SSA, including tools specific for maize ('Maize-Variety-Selector', 'Maize-Seed-Area'), for rice ('RiceAdvice', 'WeedManager'), for cassava ('Akilimo'), for cocoa ('CanOvaLator') and for crops in general ('Farmbook', Fertilizer Optimizer', 'FAMEWS').

Despite the potential of DSTs to improve information delivery, their use at scale is low (Rose et al., 2016). Constraints are posed not only by farmers who might be reluctant to take up extension advice delivered through such tools, but also by extension agents who might be reluctant to use such tools to provide extension advice to farmers (Hochman and Carberry, 2011; Ravier et al., 2016; Rose et al., 2016). While farmers are the ultimate recipients of DST-supported extension advice, extension agents are most often (in SSA and elsewhere) the actual users of DSTs. Some advocate that encouraging uptake of DSTs would require design of DSTs to be driven by user-defined preferences via a co-design approach (Botha et al., 2017; Ditzler et al., 2018; Rose et al., 2018).

In this paper, we analyze the preferences of extension agents for the design of DSTs and their willingness to use such tools. We implement a discrete choice experiment (CE) among 320 extension agents in northern Nigeria, at the design stage of a new DST for site-specific nutrient management recommendations for maize, the 'Nutrient Expert' tool. This allows us to have an *ex ante* understanding of the potential uptake of DSTs and the specific practical and effectiveness-related design features that are more (or less) appealing to extension agents. In addition, it allows us to gain insights on the heterogeneous preferences for the design of DSTs, and the underlying sources of heterogeneity.

The contribution of this paper to the literature is twofold. First, to the best of our knowledge, there is only one quantitative *ex ante* study of extension agents' preferences for DSTs (Kragt and Llewellyn, 2014). A main contribution of our paper is the extension and application of this type of research. While Kragt and Llewellyn (2014) provide evidence on a DST for weed management in Australia, we build on this with evidence on a DST for nutrient management in maize farming systems in Nigeria. In particular, the developing country context is innovative. Extension agents in developing countries are likely more constrained in the uptake of DSTs, e.g. because of a lower level of education and ICT skills among extension agents; a lower level of education among recipient farmers, resulting in difficulties or more time needed to explain more detailed and more complicated extension advice to farmers. Farming conditions are very heterogeneous in our research area, which makes nutrient management more challenging, especially for maize – a major staple crop in Nigeria and in most SSA countries. The specific application of DSTs for nutrient management advice for maize in Nigeria is different from the application of DSTs for weed management in a developed country context. Extension agents' preferences for DSTs might also vary across locations and contexts. In addition, in comparison with Kragt and Llewellyn (2014), we use more recent data and a larger sample of respondents (about 200% larger). Other studies on DSTs such as Rose et al. (2016, 2018) analyze the uptake of DSTs among farmers and extension agents in an *ex post* qualitative way, and Ditzler et al. (2018) put forward a theoretical framework to assess extension tools. Our paper complements this literature through an *ex-ante* quantitative assessment of the preferences of extension agents for the design of DSTs.

Second, this study contributes to the CE literature by adding to the scant empirical studies that implement CEs among extension agents instead of the more common use of CEs for farmers and food consumers in agricultural economics. CE studies are gaining importance in agricultural economics; they are increasingly used to assess farmers' preferences for agricultural technologies prior to the spread of new technologies, and inform agricultural research (Breustedt et al., 2008; Asrat et al., 2010; Jaeck and Lifran, 2014; Lambrecht et al., 2015; Coffie et al., 2016; Van den Broeck et al., 2017; Dalemans et al., 2018; Geussens et al., 2019). Yet, the use of CEs to inform agricultural extension *ex ante* is still very limited. Some studies use CEs to assess farmers' preferences for extension advice from DSTs (Oyinbo et al., 2019) but none specifically focus on extension agents except for Kragt and Llewellyn (2014). Yet the latter did not account for attribute non-attendance (ANA), a phenomenon where respondents do not consider all attributes in a CE, i.e. they make incomplete trade-offs which may lead to biased estimates (Caputo et al., 2018). Our study extends the application of CE among extension agents and considers ANA, and can potentially open up further digital extension-related CE research.

2. Research background and methods

2.1 Research area

The study area includes three states in northern Nigeria – Kaduna, Katsina and Kano – where maize is an important staple crop (Fig. 3.1). It is grown across the northern Guinea, southern Guinea and Sudan savanna agro-ecological zones under a smallholder rain-fed cropping system. Maize yields on farmers' fields in the area are low, on average 1 to 2 tons per hectare despite potential yields of 5 tons per hectare and above (Shehu et al., 2018; ten Berge et al., 2019). A low and inappropriate use of fertilizer and other management practices contribute to low yield, and information constraints play a role in this (Shehu et al., 2018). Traditionally, provision of extension services rests on the public sector extension systems, implemented at the state level (Naswem and Ejembi, 2017). In our study area, these are the Kaduna state agricultural development agency (KADA), the Katsina state agricultural and rural development authority (KTARDA) and the Kano state agricultural and rural development authority (KNARDA). The relatively low extension coverage of the public extension systems has given rise to other non-governmental extension providers in recent years. Examples include increased private sector participation in the provision of advisory services (e.g. from input suppliers, agro-dealers, etc.) as well as non-governmental organizations such as Sasakawa-Global 2000 (Davis and Spielman, 2017; Gizaki and Madukwe, 2019). The extension system largely provides generalized agronomic recommendations across heterogeneous locations in our study area, and in Nigeria at large. Such a system might be inefficient as it fails to address site-specific information constraints (Naswem and Ejembi, 2017). A typical example is the provision of a general recommended fertilizer application rate of 120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha for maize in much of northern Nigeria (Shehu et al., 2018), which may be sub- or supra-optimal for the site-specific conditions of individual farmers. The development of DSTs such as the Nutrient Expert and similar tools could enhance the capacity of the extension system, and allow of the provision of site-specific agronomic recommendations.

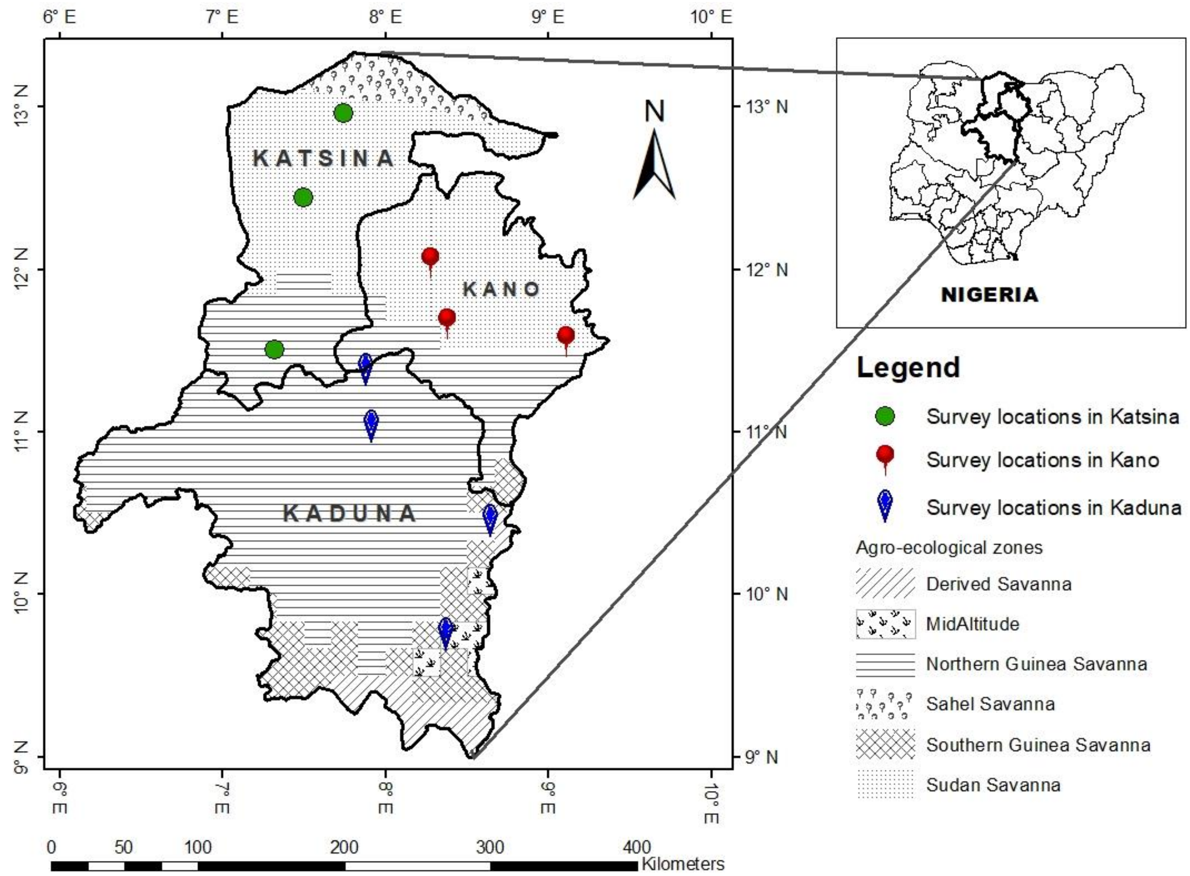

Fig. 3.1: Map of the study area

2.2 Data collection and sampling

Data were collected through a discrete choice experiment (CE) and an accompanying survey among individual extension agents in November 2016. A structured questionnaire was developed for the survey, with modules on extension agent demographics, work environment, experience with ICT, fertilizer recommendations and income sources. The CE and survey were implemented using computer assisted personal interviewing, face-to-face with individual extension agents. Prior to this implementation, the aim of the interview and the set-up of the CE were explained to extension agents in introductory group sessions, including all sampled extension agents in a specific survey location. The CE is explained in the next section. We used a one-stage random sampling design to select 320 extension agents. The study area comprises three extension institutions, including 10 governmental zonal extension offices (4 from KADA, 3 from KTARDA and 3 from KNARDA) and one major private extension provider. We randomly selected 30% of the extension agents from each of these institutions, based on a full list of frontline extension agents – i.e. extension agents who directly advise farmers in the field – provided by each of the extension offices.

2.3 Choice experiment design and implementation

We use a discrete CE as a stated preference elicitation method to *ex-ante* assess extension agents' preferences and willingness to use DSTs, before introducing the Nutrient Expert tool in the extension systems. Respondents were presented with a sequence of choice sets, each having two discrete hypothetical alternatives of a nutrient management DST, and asked to choose their most preferred alternative. The hypothetical alternatives are described by different attributes of the DST with levels that vary over the alternatives.

Based on consultations with a number of scientists involved in the development of the Nutrient Expert tool for Nigeria, a detailed review of DST design literature and a series of meetings with extension agents, we identified six relevant attributes (table 3.1). These include practical attributes – level of user-friendliness, delivery platform, delivery language and time cost – and attributes related to the content and effectiveness of the extension advice – level of detailed output and predictive power. The first attribute 'level of user-friendliness', relates to the interface ease-of-use of a DST, i.e. the ease of navigating through tool modules to generate an extension output. The second attribute, level of detailed output, relates to the number of different recommendations that result from the DST and that should be explained by the extension agent to the farmers as different options. Both are described by three levels: low, moderate, and high levels of user-friendliness and detailed output. The third attribute 'predictive power' relates to the accuracy of a DST in formulating fertilizer recommendations for a farmer to achieve a certain yield. It is expressed as the percentage of farmers that actually achieve expected yields after applying the DST-enabled fertilizer recommendations received from extension agents. We include five levels ranging from less than 31% to more than 90%. The fourth attribute 'delivery platform' relates to the format or platform in which extension recommendations are delivered. This is defined by three levels: non-mobile platforms (desktops/laptops), quick guides (paper-based) and mobile platforms (smartphones/tablets). The fifth attribute 'delivery language' relates to the operating language of the tool and the recommendation output. The levels are: English only, native only and both English and native. The sixth attribute 'time cost' describes the amount of time needed for an extension agent to generate a fertilizer recommendation with the DST. This attribute is defined by four levels, ranging from 15 to 60 minutes per farmer. These levels were chosen based on a possible range of time that some agents expressed as acceptable during a meeting with the extension providers.

Table 3.1: Attributes and attribute levels used in the choice experiment

Attributes	Attribute levels
User-friendliness	Low, Moderate, High
Detailed output	Low, Moderate, High
Predictive power[a]	< 31%, 31 – 50%, 51 – 70%, 71 – 90%, > 90%
Delivery platform	Non-mobile (desktops/laptops), Quick guides (paper-based version), Mobile (smartphones/tablets)
Delivery language	English only, Native only, English + native
Time cost	15, 30, 45, 60 minutes per recommendation

Note: [a]we use midpoints of the attribute level ranges in the estimation,
A more detailed description of the attributes and attribute levels is given in the script used to introduce and explain the CE to respondents (see appendix).

We use a D-efficient design, which minimizes the number of choice sets, compared to a full factorial design, and improves the efficiency of parameter estimates (Hensher et al., 2015). Where a pilot is not feasible, prior information, such as the expected signs, can be obtained from the empirical literature, from theory and/or from expert judgement (Rose and Bliemer, 2009). If the expected size is completely unknown, taking small priors (close to zero) with the expected signs can still allow of a more efficient design over the use of null priors (Bliemer et al., 2016; van Cranenburgh and Collin, 2019). Based on this reasoning and on empirical applications (e.g. Van den Broeck et al., 2017; Dalemans et al., 2018; Meyerhoff et al., 2019) we use small positive and negative priors (0.001 and -0.001) depending on whether we expect a positive or negative sign. These expectations informed by discussions with some extension agents and by a review of the literature. We use Ngene software to generate the design, resulting in 12 paired choice sets randomly blocked into two blocks of six choice sets (D-error = 0.058, A-error = 0.255). The number of choice sets was informed by practical considerations on reducing the cognitive burden of evaluating several choice sets and allowing a minimal number of blocks to facilitate the CE implementation. From the choice sets, we constructed 12 laminated choice cards (an example is given in Fig. 3.2) each consisting of two unlabeled hypothetical options of a nutrient management DST (options A and B) and an opt-out (option C). An opt-out option is included to avoid forcing the extension agents to accept the use of a DST, which corresponds to the reality of holding onto the use of the current traditional extension methods (Hensher et al., 2015). As described in Scarpa and Rose (2008) and implemented in Caputo et al. (2018), we report *ex-post* efficiency measures of our design using the true parameter estimates – D-error = 0.063, A-error = 0.280. Taking the *ex-ante* and *ex-post* measures together, our design performs well with an efficiency of 92% and 91% for D- and A-errors respectively.

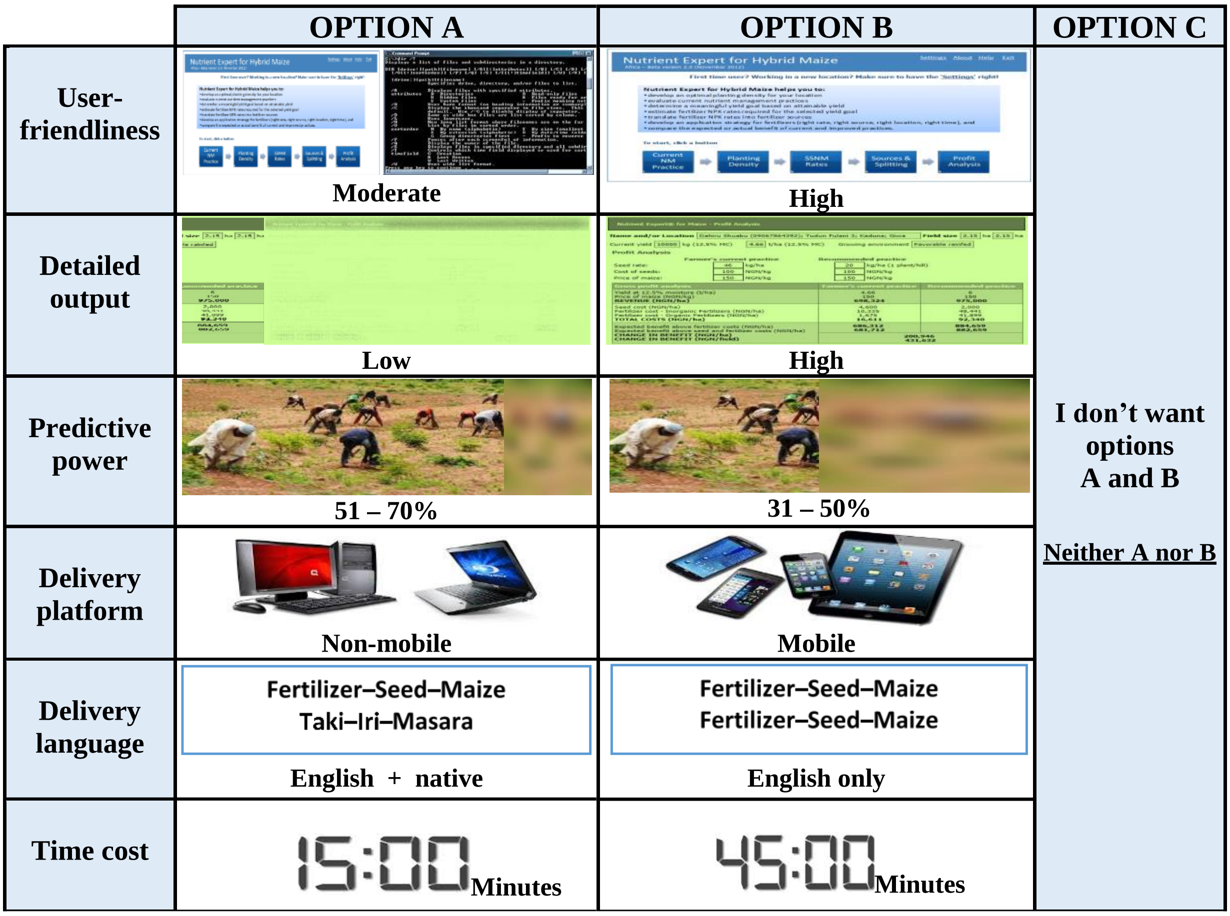

Fig. 3.2. Example of a choice card used in the choice experiment

In the CE implementation, we started with an introductory session in group to explain the purpose of the CE, the attributes and attribute levels and the hypothetical set-up. A cheap talk script was used to stress the need to give truthful responses and to minimize hypothetical bias (Cummings and Taylor, 1999). The same script was used for all group sessions to allow of a uniform explanation across extension agents and avoid informational bias. The script is included in the appendix. Questions were allowed after the introduction but we made sure our answers were only for clarification about the CE and did not prime their responses. Subsequently, each agent separately was presented six choice cards in a random order by an enumerator, and was asked to choose the most preferred option. At the end of the CE, respondents were questioned about which attributes they ignored, which corresponds to serial-based attribute non-attendance, and about individual-specific and work-related characteristics.

3. Econometric analysis

Choice experiments are rooted in random utility theory; the rationale is that utility is derived from the underlying attributes of a good or service rather than from the good or service *per se* (Lancaster, 1966) and that respondents choose those alternatives that offer the largest expected utility (McFadden, 1974). Hence, the utility U_{ijs} of extension agent i choosing alternative j in choice set s is given by an indirect utility consisting of a deterministic and a random component:

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

The vector of attributes $\boldsymbol{x}_{ijs}$ describes alternatives j with associated individual-specific parameters $\boldsymbol{\beta}_i$. The idiosyncratic error term ε_{ijs} is assumed to be independently and identically distributed (iid). ASC is an alternative-specific constant to capture preferences for the opt-out option.

First, we estimate a mixed logit (MXL) model to account for preference heterogeneity across extension agents (Train, 2009). All parameters are specified to be random with a normal distribution. The ASC is coded as 1 for the opt-out option and 0 for all hypothetical DST options, which implies that a negative parameter for the ASC corresponds to a willingness to adopt DSTs. For ease of interpretation, all categorical variables are dummy-coded.

Second, we estimate two models to account for attribute non-attendance (ANA) – i.e. a situation where respondents ignore some attributes when making choices – which can be an important source of bias in the parameter estimates (Kragt, 2013; Alemu et al., 2013; Coffie et al., 2016). With serial stated ANA data, derived from the respondents at the end of the CE, we account for ANA in the MXL models by estimating a conventional ANA model and a validation ANA model as described in Caputo et al. (2018). In the conventional ANA method, the parameters of attributes that are reported as ignored by respondents are constrained to zero. The utility function can then be expressed as:

$$U_{ijs} = ASC + \sum_{k=1}^{6-\tau} \beta_{ik} x_{ijks} + \varepsilon_{ijs} \tag{2}$$

where τ are attributes self-reported as ignored. In the validation method, two parameters are estimated for each attribute depending on whether the attribute is reported to be ignored or not by respondents (Alemu et al., 2013; Scarpa et al., 2013; Caputo et al., 2018; Oyinbo et al., 2019). This helps to validate the stated ANA responses and the conventional ANA model. The utility function is expressed as:

$$U_{ijs} = ASC + \sum_{k=1}^{6-\tau} \beta_{ik}^{1} x_{ijks} + \sum_{k=1}^{\tau} \beta_{ik}^{0} x_{ijks} + \varepsilon_{ijs} \tag{3}$$

where the utility coefficients conditional on attendance are indicated with the superscript 1 (β^1) and those conditional on non-attendance with superscript 0 (β^0).

Third, we estimate a latent class model (LCM) to further unravel preference heterogeneity and to better explain the potential sources of heterogeneity. A LCM assumes that a heterogeneous population of extension agents consists of a discrete number of preference classes (latent classes) (Hensher et al., 2015). Preferences are assumed to be homogeneous within each latent class c but heterogeneous across classes. The probability of extension agent i choosing alternative j in choice set s is conditional on the agent's membership of latent class c:

$$P_{ijs}|c = \prod_{s=1}^{S} \frac{\exp(\boldsymbol{\beta}_c' \boldsymbol{x}_{ijs})}{\sum_{t=1}^{J} \exp(\boldsymbol{\beta}_c' \boldsymbol{x}_{its})} \tag{4}$$

where $\boldsymbol{\beta}_c'$ is the vector of class-specific parameter estimates. The class membership probabilities are modeled using a multinomial logit with class-specific constant terms and no respondent-specific characteristics:

$$P_{ic} = \frac{\exp(z_i)}{\sum_{c=1}^{C} \exp(z_i)} \tag{5}$$

This implies that class membership probabilities are estimated solely taking into account the sequence of choices made by the extension agents. Respondents are then allocated to the preference classes for which they have the largest probabilities[15]. We characterize the preference classes through a comparison of means of a large set of individual- and work-related characteristics of the extension agents. We follow recent empirical CE applications (e.g. Van den Broeck et al., 2017; Dalemans et al., 2018; Guessens et al., 2019) and opt for a LCM without inclusion of respondent-specific covariates in the membership function. This allows of better inferences about heterogeneous preference classes, conditioned only by the observed choice patterns, and avoids a potential bias in selecting relevant covariates in the

[15] This is implemented using STATA estimation and post-estimation commands, *lclogit* and *lclogitpr* with the *cp* option (Pacifico and Yoo, 2013).

membership function that explain observed preferences. Given that limited information is available in the literature on the preferences of extension agents and the underlying characteristics explaining these, this method suits our CE.

The joint probability of observing a sequence of choices (y_{ijs}) over all classes is the product of (4) and (5), and the panel formulation of the model is:

$$P_{y_{ijs}} = \sum_{c=1}^{C} \left[\frac{\exp(z_i)}{\sum_{c=1}^{C} \exp(z_i)} \right] \left[\prod_{s=1}^{S} \frac{\exp(\boldsymbol{\beta}'_c \boldsymbol{x}_{ijs})}{\sum_{t=1}^{J} \exp(\boldsymbol{\beta}'_c \boldsymbol{x}_{its})} \right] \tag{6}$$

We estimate LCMs with two to five latent classes in order to sufficiently represent preference heterogeneity in our data. Selection of the optimal number of classes is based on the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) (Boxall and Adamowicz, 2002).

Fourth, to meaningfully compare the relative importance of the different attributes we need to take into account differences in scale (Greene and Hensher, 2003). To this end, we estimate marginal rates of substitution (MRS) between time cost and other attributes using Krinsky-Robb method with 2000 draws (Krinsky and Robb, 1986). The MRS is interpreted as the willingness to accept a higher time cost and by extension, more effort in the use of a DST for an increase in the utility of another attribute. The MRS estimation is based on the results of the LCM, as this model allows of a better interpretation in terms of differences in the magnitude of trade-offs between time costs and other attributes across the classes of extension agents.

4. Results

Table 3.2 describes the individual- and work-related characteristics of the extension agents, which are used to explain observed preference heterogeneity (as described later in this section). The large majority (95%) of the extension agents are male. Their age is on average 40 years, and they had on average 18.9 years of schooling. About three fourths of the extension agents report to be proficient in the use of smartphones and/or tablets but only 44% owns a smartphone and only 2% owns a tablet. Also, the majority (87%) is affiliated to the public extension system. The average extension experience is 12.7 years in the sample. About 30% of the extension agents have ICT-based extension experience and 72% report to be aware of site-specific nutrient management advice. Respectively 72% and 21% report to have received training on respectively soil fertility issues and ICT aspects in the last 12 months prior to the survey. Only 48% of the extension agents have access to a vehicle, motorcycle or bicycle to carry out their extension work. More than 90% of the extension agents agree that they receive adequate supervision and timely remuneration, and more than 80% agree to receive regular promotion.

Table 3.2: Summary statistics of extension agents' characteristics

Variables	Description of variables	Mean	Std. Dev.
Individual-specific characteristics			
Male (yes=1)	Gender of extension agent	0.95	0.35
Age (years)	Age of extension agent	39.58	10.48
Married (yes=1)	Marital status of extension agent	0.82	0.39
Education (years)	Years of schooling attained	18.88	1.82
Engage in agriculture (yes=1)	Self-reported engagement in agriculture	0.88	0.32
Proficient in the use of a smartphone/tablet (yes=1)	Self-assessed proficiency in the use of a smartphone/tablet	0.74	0.44
Own a smartphone (yes=1)	Ownership of a smartphone	0.44	0.50
Own a tablet (yes=1)	Ownership of a tablet	0.02	0.15
Work-related characteristics			
Affiliated to public extension (yes=1)	Affiliation of extension agent	0.87	0.34
Extension experience (years)	Years of working in the extension system attained by extension agent	12.74	10.27
ICT-based extension experience (yes=1)	Self-reported experience on the use of digital technologies, such as smartphones and tablets for extension purpose	0.29	0.45
Soil fertility-related training (yes=1)	Self-reported access to training on soil fertility the past one year	0.72	0.45
ICT-related training (yes=1)	Self-reported access to training on ICT the past one year	0.21	0.41
Access to transport facilities (yes=1)	Self-reported access to transport facilities, such as bicycle, motorcycle or vehicle for extension purpose	0.48	0.49
Receive adequate supervision (yes=1)	Self-assessed adequacy of supervision	0.95	0.22
Receive regular promotion (yes=1)	Self-assessed regularity of promotion	0.83	0.38
Receive timely remuneration (yes=1)	Self-assessed timeliness of remuneration	0.96	0.20
Perceive job to be secure (yes=1)	Self-assessed job security	0.93	0.25
% of working time devoted to soil fertility-related issues (%)	Self-estimated share of time devoted to soil-fertility related issues	63.22	
Aware of site-specific nutrient management (yes=1)	Self-reported awareness of site-specific nutrient management	0.72	0.45
Farmers often request for soil fertility-related advice (yes=1)	Self-reported farmers' request for soil fertility-related advice	0.98	0.16
Observations		320	

Table 3.3 reports the results of the mixed logit (MXL) models, including the standard MXL without controlling for ANA, the conventional ANA and validation ANA models. Thirty three percent of the extension agents report to have ignored at least one attribute, which supports the estimation of ANA models. The estimated conventional ANA model is

qualitatively similar to the standard MXL model in terms of expected signs of the coefficients. Also the model fit using the AIC and BIC information criteria is similar across the models. This implies that results are robust to potential ANA bias[16]. This is corroborated by the results of the validation ANA model, which show that coefficients for ignored attributes are not significantly different from zero – except for predictive power. This implies that the choice behavior of the extension agents is consistent with their stated ANA information, and that hence the conventional ANA and the MXL results are not biased due to ANA (Scarpa et al., 2013; Caputo et al., 2018). Overall, the ANA models do not clearly outperform the MXL model. A plausible explanation for this relates to the fact that individual respondents ignore only a few attributes and the ignored attributes vary in the sample (table A1 in appendix). This may also reflect limitations related to 'measurement errors' in serial ANA models, as mentioned by Caputo et al. (2018). Therefore we base our discussion on the MXL results.

The ASC coefficient estimate is significantly negative, which indicates that the extension agents generally prefer the use of DSTs for site-specific extension advice on nutrient management. This supports the ongoing efforts to develop such DSTs for maize in the research area. In general, the extension agents prefer DSTs with a higher level of user-friendliness, more detailed output, and a higher predictive power. In addition, they prefer a mobile platform in the native or a combination of English and the native language. DSTs that have a higher time demand per output and paper-based DST platforms are disliked by the extension agents. The standard deviations are statistically significant for most of the attributes. This implies that there is preference heterogeneity across extension agents – e.g. the large majority prefer DSTs with lower time demand (84%), with moderate user-friendliness (81%), with higher predictive power (84%), with both English and the native language (68%), and dislike paper-based platforms (61%). We observe that the preferences between agents with and without access to smartphones only vary slightly (table A2). Also, we find no major differences in preferences between agents across the three study states (table A3). Yet, to allow better insights into preference heterogeneity and infer practical implications for DST design and targeting, we look beyond the general findings and consider distinct sub-groups of agents defined by their choice behavior via a LCM.

[16] One cannot compare the magnitude of coefficients between models because of scale differences (Greene and Hensher, 2003), and so we make no claim about similarity in terms of magnitude of coefficients

Table 3.3: Results of mixed logit models, with and without control for attribute non-attendance (ANA)

	MXL		Conventional ANA		Validation ANA			
					Considered attributes		Ignored attributes	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
ASC	-3.41***	1.37**	-3.78***	1.55***	-3.59***	1.60***		
	(0.61)	(0.54)	(0.64)	(0.51)	(0.69)	(0.59)		
Time cost (minutes/output)	-0.01**	-0.01*	-0.01***	0.01***	-0.01**	0.01**	-0.01	0.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
User-friendliness: moderate	0.48***	0.55***	0.56***	0.58***	0.49***	0.60***	0.53	0.09
	(0.12)	(0.17)	(0.12)	(0.18)	(0.13)	(0.18)	(0.36)	(0.59)
User-friendliness: high	0.47***	0.28	0.55***	0.26	0.50***	0.25	0.29	0.47
	(0.11)	(0.39)	(0.11)	(0.32)	(0.12)	(0.39)	(0.39)	(0.69)
Detailed output: moderate	0.34***	-0.03	0.28***	0.24	0.37***	0.26	-0.13	0.06
	(0.10)	(0.47)	(0.10)	(0.33)	(0.11)	(0.34)	(0.45)	(0.63)
Detailed output: high	0.28***	0.29	0.29***	0.30	0.28**	0.41*	0.57	0.14
	(0.10)	(0.33)	(0.10)	(0.31)	(0.11)	(0.24)	(0.46)	(1.51)
Predictive power	0.01***	-0.01***	0.01***	0.00	0.01***	0.01*	0.01***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Platform: paper	-0.20**	0.71***	-0.21*	0.80***	-0.23**	0.90***	0.06	0.02
	(0.10)	(0.17)	(0.11)	(0.17)	(0.11)	(0.17)	(0.37)	(0.37)
Platform: mobile	0.40***	-0.36	0.38***	0.31**	0.41***	0.40*	0.53	0.58
	(0. 09)	(0.22)	(0.09)	(0.26)	(0.09)	(0.23)	(0.36)	(0.57)
Language: native	0.19*	-0.20	0.20*	0.22	0.23*	0.15	-0.25	0.40
	(0.10)	(0.29)	(0.10)	(0.27)	(0.11)	(0.36)	(0.35)	(0.68)
Language: English + native	0.36***	0.79***	0.32**	0.84***	0.43***	0.92***	-0.09	0.00
	(0.14)	(0.17)	(0.13)	(0.16)	(0.15)	(0.17)	(0.38)	(0.70)
N	5,760		5,760		5,760			
Log likelihood	-1348.12		-1354.12		-1333.95			
AIC	2740.25		2752.20		2751.90			
BIC	2886.75		2874.60		2985.40			

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

Table 3.4 presents the results of a latent class model, which allows to further explore heterogeneity in preferences, and gain better insights on how the extension agents trade off the attributes of DSTs. We selected a model with two latent classes based on a comparison of the information criteria across models with two up to five classes (table A4). Preference class one (PC1) includes 52% of the sampled extension agents and preference class 2 (PC2) 48%. In both classes, extension agents are in general willing to accept the use of DSTs, and have strong preferences for DSTs that limit the time demand per recommendation output and that have a moderately to highly user-friendly interface. Yet, we observe substantial heterogeneity in preferences between the two classes for the other attributes. Extension agents of PC1 prefer DSTs with highly detailed output and a strong predictive power while those in PC2 are indifferent to these attributes. Extension agents of PC2 prefer DSTs on mobile devices that use the native language or a combination of the native language and English, and dislike paper-based tools while those in PC1 are indifferent to these attributes.

Table 3.4: Results of latent class models

	Preference class 1 = 52%		Preference class 2 = 48%	
	Coefficient	Std. error	Coefficient	Std. error
ASC	-2.15***	0.40	-3.66***	0.93
Time cost (minutes/output)	-0.01*	0.00	-0.01*	0.01
User-friendliness: moderate	0.39**	0.18	0.67***	0.25
User-friendliness: high	0.19	0.18	1.02***	0.31
Detailed output: moderate	0.26	0.18	0.35	0.25
Detailed output: high	0.45***	0.16	-0.12	0.28
Predictive power	0.01***	0.00	0.00	0.00
Platform: paper	0.21	0.19	-0.66*	0.35
Platform: mobile	0.15	0.15	0.59***	0.15
Language: native	0.15	0.16	0.46*	0.25
Language: English + native	-0.19	0.27	1.14**	0.56
N	5,760			
Log likelihood	-1344.04			
AIC	2734.07			
CAIC	2910.23			
BIC	2887.22			

Notes: Asterisks ***, **, and * denote any variable significant at 1%, 5%, and 10% levels respectively.

To explore the sources of preference heterogeneity, we compare individual- and work-related characteristics of extension agents between the two PCs (table 3.5). The results show that PC2 extension agents have a significantly higher education, a lower likelihood to engage in agriculture, and a higher likelihood to be proficient in the use of smartphones and/or tablets, to have experience with ICT-based extension, to receive regular promotion and to be paid timely. This might explain their strong preferences for DSTs with mobile platforms. Yet, they appear to care less about the level of detail and accuracy of extension advice, which suggests that the appeal for these attributes is not necessarily correlated with education and ICT proficiency of extension agents, and with receipt of timely remuneration and regular promotion. Overall, the differences in observed characteristics between the two PCs are significant but very small, which implies that unobservable characteristics, such as motivation and ability, likely play a role as well in determining preference heterogeneity.

Table 3.5: Profile of extension agents characteristics across latent preference classes

	PC1 = 52%		PC2= 48%		
	Mean	Std. Dev.	Mean	Std. Dev.	Sig.
Individual-specific characteristics					
Male	0.95		0.95		
Age	39.64	10.49	39.51	10.49	
Married	0.79	0.41	0.85	0.36	
Education	18.71	1.88	19.06	1.73	*
Engage in agriculture	0.91	0.29	0.85	0.36	*
Proficient in the use of a smartphone/tablet	0.70	0.46	0.78	0.41	*
Own a smartphone	0.40	0.49	0.48	0.50	
Own a tablet	0.01	0.11	0.03	0.18	
Work-related characteristics					
Affiliated to public extension	0.87	0.33	0.86	0.35	
Extension experience	12.78	10.45	12.69	10.09	
ICT-based extension experience	0.23	0.42	0.35	0.48	**
Soil fertility-related training	0.75	0.44	0.69	0.46	
ICT-related training	0.19	0.39	0.24	0.42	
Access to transport facilities	0.49	0.50	0.46	0.50	
Receive adequate supervision	0.95	0.23	0.95	0.22	
Receive regular promotion	0.80	0.40	0.87	0.34	*
Receive timely remuneration	0.93	0.25	0.98	0.14	**
Perceive job to be secure	0.94	0.24	0.93	0.26	
% of working time devoted to soil fertility-related issues	63.0		63.5		
Aware of site-specific nutrient management	0.74	0.44	0.69	0.46	
Farmers often request for soil fertility-related advice	0.98	0.13	0.97	0.18	

Notes: Two-sided t-tests of mean differences between extension agents in PC 1 and 2, asterisks ***, **, and * denote significant differences at 1%, 5%, and 10% levels respectively, Variables are as described in table 3.2.

Table 3.6 reports the estimated MRS between time cost and other attributes. The MRS estimates show that in both classes extension agents are willing to accept a higher time cost for a more user-friendly interface, but this trade-off is on average larger in PC2. In addition, extension agents in PC1 are willing to accept a higher time cost for a more detailed and more accurate output while extension agents in PC2 are not. The latter are willing to accept a higher time cost for a mobile delivery platform in the native language, or a combination of English and the native language. This is plausible as some of the extension agents may have a low English language proficiency.

Table 3.6: Marginal rate of substitution (MRS) between time cost and other attributes[a]

	Preference class 1	Preference class 2
	Mean (95% confidence interval)	Mean (95% confidence interval)
User-friendliness: moderate	66.86 (-313.20 – 498.99)	74.31 (-203.49 – 360.52)
User-friendliness: high	33.37[b] (-92.89 – 283.70)	113.42 (-193.98 – 465.70)
Detailed output: moderate	45.19[b] (-123.32 – 256.86)	38.78[b] (-55.37 – 144.69)
Detailed output: high	78.84 (-254.35 – 489.48)	-13.10[b] (-144.38 – 93.13)
Predictive power	1.45 (-7.20 – 10.55)	0.02[b] (-1.37 – 1.49)
Platform: paper	36.75[b] (-164.65 – 316.66)	-73.51 (-295.43 – 91.49)
Platform: mobile	26.28[b] (-82.00 – 180.73)	65.50 (-147.91 – 288.33)
Language: native	26.48[b] (-110.71 – 203.32)	51.20 (-52.04 – 204.79)
Language: English + native	-32.54[b] (-349.82 – 203.83)	126.41 (-106.89 – 467.53)

Notes: [a]Estimated based on coefficients in the latent class model in table 3.4, [b]Not discussed as coefficients are insignificant

5. Discussion and conclusion

We find that extension agents in the maize belt of Nigeria are in general willing to accept the use of DSTs for site-specific extension services on nutrient management for maize. While extension agents in the sample prefer DSTs with a more user-friendly interface that require less time to generate an output, we observe substantial preference heterogeneity for the other design features of DSTs, and identify two groups of extension agents with a different preference pattern. Extension agents in PC1 (52%) care more about attributes related to the effectiveness of the extension advice resulting from a DST, such as a more detailed and more accurate output. These extension agents can more likely be motivated to use DSTs through a careful explanation of the underlying science and evidence-base aspects of DSTs. Extension agents in PC2 (48%) care more about the practical attributes of DSTs such as the platform, the language and the user-friendliness of the interface. These extension agents are likely more easily convinced about the use of DSTs if the practical and operational aspects of DSTs are taken care of. Reflecting on the sources of heterogeneous preferences, the role of observed characteristics is quite small and hence, unobservable characteristics, e.g. motivation and ability, likely play a role in explaining the differences in preferences. Yet, we cannot analyze the role of motivation and ability more in-depth as we do not have proxy variables for these typically unobservable characteristics in our data.

Our finding that extension agents prefer DSTs with a user-friendly interface and a lower time requirement is partly consistent with Kragt and Llewellyn (2014), who report preferences for low time cost in a weed management DST in a developed country context but did not consider interface ease-of-use. In addition, our results are in line with the extant literature on the design of user-friendly interfaces to stimulate the use of such tools (Bernet et al., 2001; Hochman and Carberry, 2011; Rose et al., 2016). Our finding of a strong preference by the extension agents PC2 for DSTs on mobile devices such as smartphones and tablets contrasts with Kragt and Llewellyn (2014), who find that extension agents prefer a spreadsheet-based platform. The result that some extension agents prefer the use of native or a combination of native and English language is consistent with Tata and McNamara (2016), who opine that the use of local languages in the design of '*farmbook'*, an ICT-based extension tool, is more beneficial to farmers. This will likely facilitate better communication with the majority of farmers who do not understand English, and reduce the likelihood of misinterpreting the inputs and outputs of DSTs. Our findings on the strong preferences of extension agents for DSTs that provide a more accurate and more detailed output are consistent with some studies that considered these attributes. For example, Kragt and Llewellyn (2014) find that a DST that generates more accurate output is strongly desired across the groups of extension agents identified in their study, whereas we find this only to be the case for the extension agents in PC1. Qualitatively, Hochman and Carberry (2011) find that the use of DSTs that allow of the provision of a wide range of options to farmers is keenly considered by tool users in a developed country setting. The fact that the sources of observed heterogeneous preferences in our study appear to derive from unobservable characteristics is consistent with Kragt and Llewellyn (2014) who find that observed demographic characteristics were not significant in explaining preferences.

We provide some specific policy implications of our findings. Our results imply that there is high potential demand for ICT-enabled DSTs for site-specific extension services in our study area – a finding which aligns with the currently widespread interest and investments in site-specific and ICT-enabled extension tools for agricultural applications in developing countries. Our results imply that a user-friendly interface and a reduced time effort needed to generate extension advice are important to pay attention to in the design process of a DST. To stimulate uptake and facilitate better targeting, a more effective design will likely require DSTs to be differentiated along dimensions of their practical attributes such as the platform and the language. Yet, differentiating DSTs according to effectiveness attributes is in our view unacceptable as this would result in quality differentiation among farmers of the extension advice they receive. The effectiveness of the advice should be strongly considered in the design stages of DSTs to allow of higher-quality agronomic advice to all farmers. Extension agents who are indifferent to DSTs that can offer a more accurate and more detailed output – i.e. those in PC2 – may need to be better disposed to the quality of extension advice from DSTs beyond the practical features of DSTs. This may require improved capacity building for such agents (Davis and Spielman, 2017; Makate and Makate, 2019). In terms of methodological reflections, there is a growing scholarly interest on ANA in the CE literature. While we account for ANA using a serial stated ANA approach and do not find significant improvements in model fit, future CEs among extension agents in developing countries can explore other approaches less prone to measurement errors, such as choice task stated ANA, eye tracking and inferred ANA.

Finally, our empirical findings have direct implications for the development of the nutrient management DST for maize 'Nutrient Expert' in Nigeria[17]. Our findings have contributed to informing the choice of delivery language and selection of the tool delivery platform among propositions for a paper-based platform, quick guides and other possible platforms. Our results show that the tool user-friendliness and time required to generate farm-specific advice are actually important for extension agents. The practical implication is that DST development should consider time optimization – for example through tweaking the color-text-image combinations of the interface of the tool and directly engaging extension agents in testing of interface alternatives, and identifying the specific amount of time that is acceptable for the use of the tool in a given context. In addition, the engagement of extension agents is required in testing variants of DST outputs with varying levels of detail in the output to optimize a DST in line with extension agents' preferences. An attractive DST should not only optimize the output in terms of accurate nutrient management advice but also balance this with optimizing user- and convenience-related features.

[17] The institution responsible for developing the tool in this project – the International Plant Nutrition Institute (IPNI) – ceased operations in April 2019. A new institution – the African Plant Nutrition Institute (APNI) – has been created to build on the IPNI's plant nutrition research and education in Africa. It is not yet clear to what extent or how APNI will continue development of the Nutrient Expert tool for maize in Nigeria.

Appendix

Appendix A: Script for implementation of choice experiment among extension agents

In a bid better serve farmers with SITE-SPECIFIC extension services in which recommendations are tailored to site-specific conditions of individual farmers instead of the conventional GENERAL extension recommendations, your inputs are highly needed to optimize the design of a nutrient management decision support tool for maize ‘‘Nutrient Expert”. The design is expected to result in an extension tool that can enable you to provide site-specific nutrient management (SSNM) recommendations to farmers, which will help them make better informed decisions on soil fertility and crop management. We (referring to supervisors and enumerators) will guide you through an exercise in which you will have the opportunity to choose different hypothetical options of nutrient management decision support tools for maize, and the options will be presented in the form of a card called choice card. These options are defined using six features called attributes, namely level of user-friendliness, level of detailed output, predictive power, delivery platform, delivery language and time cost. Each of the six attributes has different levels called attribute levels (At this point, the attributes and attribute levels are described in detail).

Description of attributes

1. **Level of user-friendliness**

This attribute relates to the user-interface of a nutrient management DST and the ease of navigating through tool modules (i.e. the necessary steps) to generate an extension output for a farmer. In other words, it describes the ease with which an extension agent can interact with a tool via the interface. This is defined by three levels, namely low, moderate and high levels of user-friendliness where a high level of user-friendliness is rated above a moderate level, and a moderate level is rated above a low level. To distinguish between the three levels in a choice card, an image showing only a command-line interface, a combination of command-line and graphical user interfaces and only a graphical user interface will be used to depict low, moderate and high levels of interface ease-of-use respectively. At this point, a sample of a card that shows the three levels is presented to the extension agents to enable them see in practice how the attribute levels will be depicted in the choice cards.

2. **Level of detailed output**

This attribute relates to the number of different recommendations that result from a nutrient management DST and that should be explained by an extension agent to a farmer as different options of fertilizer use recommendations. In other words, the level of information set that can be produced from a DST for a farmer. This is described by three levels, namely low, moderate and high levels of detailed output where a high level of detailed output is rated above a moderate level, and a moderate level is rated above a low level. To distinguish between the three levels in a choice card, an image with a larger portion being blurred (smaller portion with text), halfway blurred and halfway with text, and all portion with text will be used to depict low, moderate and high levels of interface detailed output from a DST respectively. At this point, a sample of a card that shows the three levels is presented to the extension agents to enable them see in practice how the attribute levels will be depicted in the choice cards.

3. **Predictive power**

This attribute relates to the accuracy of a DST in formulating fertilizer recommendations for a farmer to achieve a certain yield. It is expressed as the percentage of farmers that actually achieve expected yields after applying the DST-enabled fertilizer recommendations received from extension agents. This is defined by three five levels, < 31%, 31 – 50%, 51 – 70%, 71 – 90% and > 90% where < 31% indicates the % of farmers who realize the expected yields associated with a fertilizer use recommendation from a DST. The same interpretation apples to 31 – 50%, 51 – 70%, 71 – 90% and > 90%. To distinguish between the five levels in a choice card, different versions of an image of a group of farmers with different extent of blurry portions as a sign of differences in realizing the expected yields will be used to depict the different levels of the predictive power of a DST. At this point, a sample of a card that shows the five levels is presented to the extension agents to enable them see in practice how the attribute levels will be depicted in the choice cards.

4. **Delivery platform**

This attribute relates to the format or platform in which extension recommendations are delivered to farmers from a nutrient management DST. This is defined by three five levels, including the use of non-mobile platforms, such as desktop and laptop computers, the use of quick guides, i.e. paper-based platforms, and the use of mobile platforms, such as smartphones and tablets. To distinguish between the three levels in a choice card, an image of desktop and laptop computers, an image of a paper extension guide and an image of smartphones and tablets will be used to depict the three levels of a delivery platform. At this point, a sample of a card that shows the three levels is presented to the extension agents to enable them see in practice how the attribute levels will be depicted in the choice cards.

5. Delivery language

This attribute relates to the operating language of a nutrient management DST and the recommendation output of the DST. This is defined by three five levels, namely the use of English language only, the use of native language only, and a combination of English and native language. To distinguish between the three levels in a choice card, an image showing some text in only English language, in only native language and in both English and native languages will be used to depict the three levels of a DST delivery language. At this point, a sample of a card that shows the three levels is presented to the extension agents to enable them see in practice how the attribute levels will be depicted in the choice cards.

6. Time cost

This attribute describes the amount of time needed for an extension agent to generate a fertilizer recommendation with a nutrient management DST. This is defined by six levels, namely 15, 30, 45, 60 minutes per recommendation from a DST. To distinguish between the four levels in a choice card, an image showing the different amount of time in minutes will be used to depict the four levels of time cost of using a nutrient management DST to offer extension advice to a farmer. At this point, a sample of a card that shows the four levels is presented to the extension agents to enable them see in practice how the attribute levels will be depicted in the choice cards.

After the group introductory session, we will have a face-to-face interview with each extension agent. In the interview, each agent will be offered six distinct choice cards one after the other and each choice card contains two hypothetical scenarios of nutrient management decision support tools (options A and B) and a third option (option C) that reflects your current extension approach. The aim is for you to choose one option that you prefer from the three options on each card, and this will require you to objectively reflect on the attribute levels of the two hypothetical scenarios of nutrient management decision support tools in comparison with your extension approach. You are to carefully go through the cards and evaluate the options on each card that we will present to you, and then select the option you prefer between the three options on each of the cards. Even though this exercise entails hypothetical options of nutrient management decision support tools, you are expected to kindly make very truthful choices as if these were real choices that have real cost implications. This is to ensure that the choices you make in this hypothetical exercise are not different from the actual choices if you were exposed to real nutrient management decision support tools. At this point, a sample of a choice card is shown to the extension agents with a description of the rows and columns of the card.

Table A1: Self-reported information on ANA – serial stated ANA

# of ignored attributes	Share of extension agents (%)	Ignored attributes	Share of extension agents (%)
0	67.5	Level of user-friendliness	6.9
1	22.2	Level of detailed output	3.8
2	9.4	Predictive power	13.7
3	0.9	Delivery platform	5.6
		Delivery language	6.6
		Time cost	7.2

Table A2: Results of MXL models showing heterogeneity in preferences for DST features by access to smartphones

	Agents with smartphones		Agents without smartphones	
	Mean	Std. Dev.	Mean	Std. Dev.
ASC	-4.93***	2.46**	-2.7***	-0.86
	(1.44)	(1.08)	(0.73)	(0.86)
Time cost (minutes/output)	-0.01***	0.02**	-0.00	-0.00
	(0.00)	(0.01)	(0.00)	(0.00)
User-friendliness: moderate	0.81***	0.99***	0.38**	0.62***
	(0.27)	(0.34)	(0.16)	(0.21)
User-friendliness: high	0.91***	-0.37	0.28*	-0.50*
	(0.24)	(0.37)	(0.15)	(0.27)
Detailed output: moderate	0.39*	1.01***	0.39***	-0.11
	(0.22)	(0.39)	(0.14)	(0.37)
Detailed output: high	0.34*	-0.41	0.26*	-0.37
	(0.20)	(0.36)	(0.15)	(0.34)
Predictive power	0.01**	0.01***	0.01***	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)
Platform: paper	-0.60**	0.97***	-0.07	0.74***
	(0.24)	(0.32)	(0.14)	(0.23)
Platform: mobile	0.60***	-0.61*	0.40***	0.47*
	(0.20)	(0.33)	(0.12)	(0.24)
Language: native	0.07	-0.82**	0.28**	0.12
	(0.20)	(0.29)	(0.14)	(0.34)
Language: English+ native	0.25	1.21***	0.51***	-0.78***
	(0.26)	(0.04)	(0.19)	(0.21)
N	2520		3240	
Log likelihood	-571.81		-763.52	
AIC	1187.61		1571.03	
BIC	1315.92		1704.86	

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

Table A3: Results of MXL models showing heterogeneity in preferences for DST features by the states where extension agents work in the research area

	Agents in Kaduna		Agents in Katsina		Agents in Kano	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
ASC	-3.52***	-0.72	-2.15***	0.19	-4.12***	-2.04***
	(0.76)	(0.94)	(0.66)	(1.36)	(1.11)	(0.69)
Time cost (minutes/output)	-0.02***	0.02**	-0.00	0.01	-0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
User-friendliness: moderate	0.67**	0.66	0.52**	0.57	0.45**	0.71***
	(0.26)	(0.42)	(0.26)	(0.37)	(0.19)	(0.24)
User-friendliness: high	0.44*	-0.88**	0.72***	0.05	0.49***	0.49*
	(0.25)	(0.35)	(0.25)	(0.48)	(0.17)	(0.29)
Detailed output: moderate	0.30	0.83**	0.04	0.07	0.59***	0.04
	(0.22)	(0.34)	(0.23)	(0.60)	(0.17)	(0.41)
Detailed output: high	0.27	0.46	0.37	0.42	0.31*	-0.11
	(0.22)	(0.45)	(0.24)	(0.46)	(0.17)	(0.39)
Predictive power	0.01	-0.00	0.01	-0.00	0.01***	0.01***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Platform: paper	-0.15	1.37***	-0.22	0.16	-0.29*	0.65**
	(0.23)	(0.33)	(0.22)	(0.92)	(0.16)	(0.28)
Platform: mobile	0.63***	0.95***	0.40**	0.47	0.42***	-0.22
	(0.22)	(0.32)	(0.20)	(0.37)	(0.13)	(0.43)
Language: native	-0.15	0.94***	0.51**	-0.12	0.30*	0.11
	(0.23)	(0.30)	(0.22)	(0.56)	(0.16)	(0.31)
Language: English+ native	0.31	1.12***	0.59**	0.61	0.39*	0.73***
	(0.28)	(0.35)	(0.30)	(0.39)	(0.21)	(0.25)
N	2196		1080		2484	
Log Likelihood	-511.85		-245.15		-564.492	
AIC	1067.71		534.31		1172.99	
BIC	1192.99		643.97		1300.97	

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

Table A4: Criteria for the selection of optimal number of preference classes (N=5760)

Classes	Log-likelihood (LL)	# of parameters (k)	Akaike information criterion (AIC)	Consistent Akaike information criterion (CAIC)	Bayesian information criterion (BIC)
2	-1344.04	23	2734.08	2910.23	2887.23
3	-1321.49	35	2712.99	2981.03	2946.03
4	-1308.49	47	2710.98	3070.94	3023.94
5	-1293.10	59	2704.20	3156.06	3097.06

Notes: N is the number of observations on choice responses from 320 extension agents (3 alternatives × 6 choice sets × 320). The AIC is calculated as −2LL + 2k, the CAIC as −2LL + k ln(N+1), and the BIC as −2LL + k ln(N).

Chapter 4

Site-specific digital extension advice and farm performance: Experimental evidence from Nigeria[18]

[18] In preparation for submission to a Journal as: Oyinbo, O., Chamberlin, J., Abdoulaye, T. & Maertens, M. (2019). Site-specific digital extension advice and farm performance: Experimental evidence from Nigeria.

1. Introduction

Crop yields in Sub-Saharan Africa (SSA) are far below attainable yields and below yields in other regions (Tittonell and Giller, 2013; Benson and Mogues, 2018; ten Berge et al., 2019). Depletion of soil fertility contributes to this situation (Sanchez, 2002; Barrett and Bevis, 2015; Theriault et al., 2018). Yet the use of fertilizer is low in most parts of SSA (Xu et al., 2009; Harou et al., 2017; Burke et al., 2017), which partially relates to information constraints (Marenya and Barrett, 2009; Benson and Mogues, 2018; Jayne et al., 2019). Traditional agricultural extension systems typically provide general or 'blanket' fertilizer recommendations across wide and heterogeneous areas (Shehu et al., 2018; Theriault et al., 2018; Burke et al., 2019). Such recommendations are not tailored to the site-specific conditions of individual farmers and do not account for spatio-temporal variation in biophysical and socioeconomic conditions (Vanlauwe et al., 2015b; Jayne et al., 2019). In addition, they are based on average expected returns and do not provide information on the variability in returns stemming from yield and/or market risk and uncertainty.

In this article, we analyze the impact of farmers' access to site-specific nutrient management (SSNM) recommendations for maize production in Nigeria, provided through an ICT-enabled decision support tool (DST) or Nutrient Expert tool, on fertilizer use, fertilizer management practices, maize yield and revenue. We analyze the impact of SSNM versus blanket nutrient management recommendations, and the impact of providing complementary information about variability of expected returns. We implement a cluster randomized controlled trial (RCT) among 792 households in the maize belt of northern Nigeria. The RCT includes two treatment groups of farmers who are exposed to SSNM information interventions, the first group without and the second group with additional information on variability of expected returns, and a control group of farmers who do not receive an SSNM information intervention. We use three-period panel data to estimate the immediate (after 1 year) and longer-term (after 2 years) effects of the interventions on farmers' investment and management decisions and the outcomes in terms of yields and revenue. We relate the empirical findings to a conceptual framework to explain causal pathways.

We contribute to the general literature on agricultural extension and return to fertilizer use in Africa, which includes non-experimental studies (e.g. Marenya and Barrett, 2009; Liverpool-Tasie et al., 2017; Burke et al., 2017; Theriault et al., 2018) as well as experimental studies (e.g. Duflo et al., 2008; Beaman et al., 2013; Harou et al., 2017). Our specific focus on the impact of SSNM recommendations reveals what part traditional extension approaches with general fertilizer recommendations play in limiting the profitability of fertilizer use in Africa. We provide innovative evidence on how DST-enabled delivery of plot-specific technical recommendations affects investments and management decisions of smallholder farmers in a developing country setting. Our research complements on-farm evaluations of nutrient expert tool for maize under researcher-managed trial conditions (Pampolino et al., 2012; Xu et al., 2016). In addition, we add new insights on the role of relaxing uncertainty in the uptake of agronomic recommendations (Feder et al., 1985; Saha et al., 1994; Koundouri et al., 2006; Genius et al., 2014). We provide evidence on how information about the variability of expected returns to fertilizer investment influences the uptake of fertilizer recommendations. Finally, in contrast to most agriculture-related RCTs that rely on a single post-intervention round, we use multiple rounds of post-intervention data to evaluate impact (c.f. Beaman et al., 2013; de Brauw et al., 2018; Vandercasteelen et al., 2018; Hossain et al., 2019; Omotilewa et al., 2019). With this approach, we are able to observe effects and outcomes under different weather realizations over time, and to describe inter-temporal heterogeneity in treatment effects.

2. Theoretical framework

We present a simple graphical theoretical framework that explains how relaxing information constraints through DST-enabled site-specific agronomic advice changes farmers' fertilizer investment decisions and associated yields and revenues. The framework is based on Magruder (2018), who uses a two-period model in which fertilizer use decisions at planting time are subjected to uncertainty about the return to fertilizer at harvest time. The framework fits the situation of our research area with smallholder farmers who market their output, but use fertilizer in a suboptimal way and attain yields which are low relative to potential yields.

In Fig. 4.1 we depict an initial situation in which a farmer does not reach technical efficiency because of sub-optimal fertilizer management practices[19]. Given the marginal

[19] Technical efficiency refers to the maximum attainable level of maize output for a given level of farm inputs, such as fertilizer, given the range of altervative technologies available to a farmer. This reflects the highest possible production frontier that a farmer can operate on. Other related efficiency measures include allocative and economic efficiency. The former refers to the adjustment of inputs (e.g. fertilizer) and output (e.g. maize) to reflect their relative prices (i.e. fertilizer-maize price ratio), the technology of production already chosen while the latter refers to the simultaneous achievement of both technical and allocative efficiency (Ellis, 1998; Coelli et al., 2005).

factor cost of inputs (i.e. the market price of fertilizer), the farmer operates on a lower production function TVP_{SP} (total value of production with sub-optimal fertilizer management practices), either in point X_0 corresponding to allocative efficiency[20] and total value Y_0 or in point X_0' corresponding to sub-optimal fertilizer input and total value Y_0'. The latter situation may emerge due to cash constraint – associated with low savings and/or limited access to credit. Providing extension information about optimal fertilizer management practices – including information on the right nutrient sources, the right timing of application, and the right application method – enables farmers to move to a higher production function TVP_{OP} that corresponds to optimal management practices and technical efficiency (Anderson and Feder, 2007; Ellis, 1998; Pan et al., 2018). This will result in an increase in yield and revenue, either from Y_0' to Y_1' for the cash constrained farmer or from Y_0 to Y_1 for the allocative efficient farmer. In the latter case, the farmer has an immediate incentive to expand fertilizer use from X_0 to X_1, which is associated with a further increase in revenue to Y_2 and with economic efficiency. The cash constrained farmer may not be able to immediately expand fertilizer use to an allocative efficient level but the increase in revenue to Y_1' may allow the farmer to gradually expand fertilizer use from X_0' to a higher level.

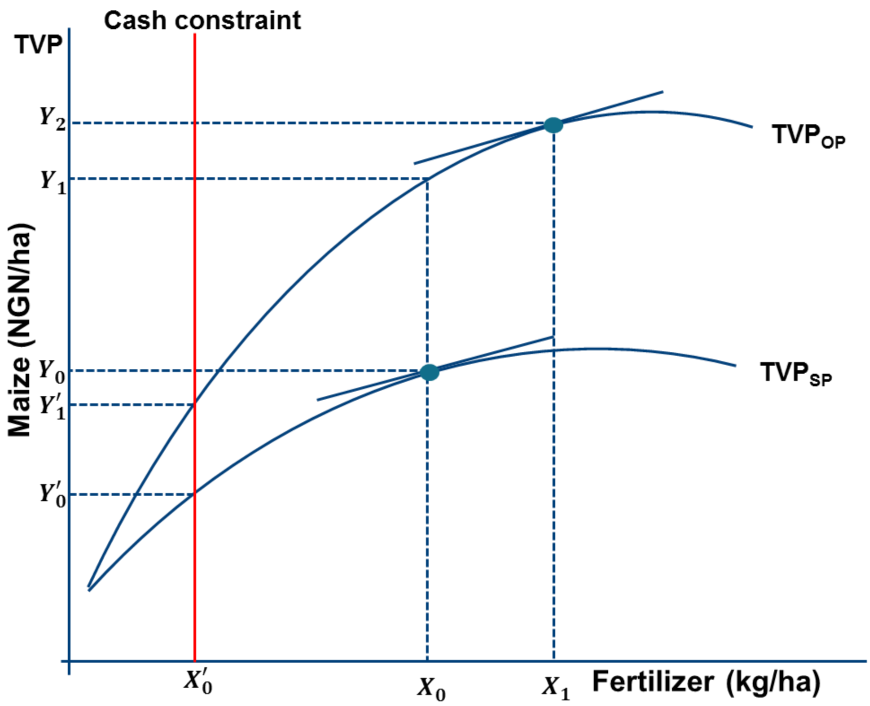

Fig. 4.1: The effect of relaxing information constraints about optimal fertilizer management practices on fertilizer use, yield and revenue

[20] Allocative efficieny is depicted in Fig. 4.1, 4.2 and 4.3 as the points of tangency of the parallel lines and the TVP curves, which corresponds to the points where the marginal value product of applied fertilizer (i.e. slope of TVP) equals the marginal factor cost/price of fertilizer. In other words, the points where the marginal physical product of applied fertilizer equals the fertilizer-maize price ratio.

In Fig. 4.2 we depict a situation in which farmers use fertilizer inputs either according to a general fertilizer recommendation rate X_{0A} used by extension agents in a wide area – such as the general extension recommendation to use 120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha for maize in northern Nigeria (Shehu et al., 2018) – or according to cash constraints that limit fertilizer inputs to X_0'. Agro-ecological conditions may vary across farms and plots, which causes TVP to vary as well. This variation is depicted through an upper TVP_H, a lower TVP_L and an average TVP_A function. This aligns with the findings of Suri (2011) on substantial heterogeneity in returns to improved technologies across farmers, and the underlying mechanism, such as plot-level soil variation, in explaining marginal returns to fertilizer (Marenya and Barrett, 2009). In Fig. 4.2 the general fertilizer recommendation rate X_{0A} corresponds to economic efficiency on TVP_A or an optimal fertilizer level for the average farm or plot. Revenues will vary between Y_{0L} and Y_{0H}, depending on how conducive agro-ecological conditions are, or between Y_{0L}' and Y_{0H}' if cash constraints are binding. Farmers face site-specific technical uncertainty if they are uncertain about the production function that corresponds to their site- and management-specific context (Magruder, 2018; Burke et al., 2019). General recommendations, based on an average response rate, result in sub-optimal fertilizer application rates for many farmers (Giller et al., 2011; Vanlauwe et al., 2015b; Kihara et al., 2016b). Providing site-specific fertilizer recommendations that correspond to allocative efficiency of the specific plot can reduce this uncertainty for farmers. Such site-specific rates may be below, at or above the general recommendation, and vary between X_{1L} and X_{1H}. If agro-ecological conditions are good (TVP_H), the site-specific recommendation will induce farmers to increase fertilizer use from X_{0A} to X_{1H}, which will be associated with a substantial increase in yield and revenue from Y_{0H} to Y_{1H}. Under less conducive agro-ecological conditions (TVP_L), site-specific recommendations may result in a decrease in fertilizer use from X_{0A} to X_{1L}, and be associated with a small decrease in yield and revenue from Y_{0L} to Y_{1L}. The average effect of site-specific recommendations on fertilizer use may be zero because the positive response of farmers operating under good conditions (X_{1H} - X_{0A}) and the negative response (X_{1L} - X_{0A}) of farmers operating under less suitable conditions may cancel each other out. However, the average effect on yields and revenue is likely positive because the loss from decreasing fertilizer use for farmers operating on TVP_L (Y_{0L} - Y_{1L}) is smaller than the gain from increasing fertilizer use for farmers operating on TVP_H (Y_{0H} - Y_{1H}). If binding cash constraints limit fertilizer use to X_0', providing site-specific fertilizer recommendation (without lifting cash constraints) will not immediately change farmers' fertilizer use nor their yield or revenue which remains between Y'_{0L} and Y'_{0H} depending on agro-ecological conditions.

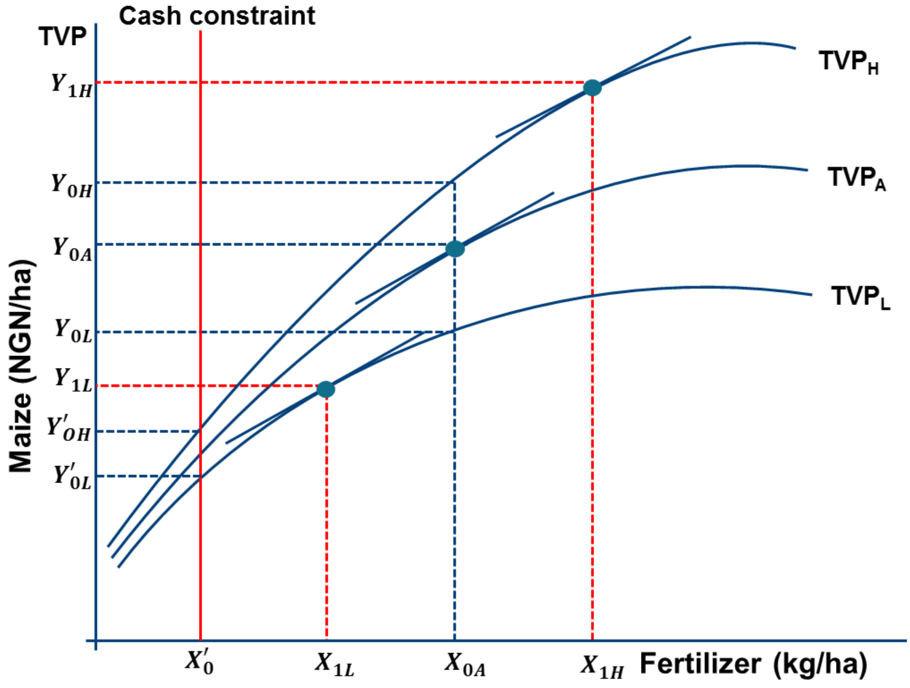

Fig. 4.2: The effect of site-specific fertilizer recommendations on fertilizer use, yield and revenue

In Fig. 4.3 we build on the situation depicted in Fig. 4.2 by adding seasonal variation in climate and/or market conditions. We only depict the situation for farmers for whom the recommended site-specific fertilizer rate X_{1H} is above the average or general recommendation rate X_{0A}. In Fig. 4.3 the fertilizer rates X_{1H} and X_{OA} corresponds to allocative efficient outcomes on $TVP_{H,average}$ and $TVP_{A,average}$, which represent production outcomes in an average year in terms of market prices or climate conditions for farmers operating under respectively good and average agro-ecological conditions. Market (output) prices or climate conditions may vary across seasons, which causes TVP_H to vary between $TVP_{H,good}$ and $TVP_{H,bad}$. This seasonal variation in return is uncertain to a farmer lacking experience with high fertilizer levels. A farmer who increases fertilizer use from a general recommendation X_{OA} to a higher site-specific recommendation X_{1H} will experience a large increase in revenue, from an average level of $Y_{0,average}$ to $Y_{1,good}$ in case market and climate conditions are good. This large revenue increase likely motivates the farmer to continue producing at higher fertilizer levels in line with the site-specific recommendations. Yet, when market and climate conditions are bad (e.g. low output price or local weather shocks – early-, mid- and/or late-season drought) after the farmer expands fertilizer use from X_{OA} to X_{1H}, the change in revenue from $Y_{0,average}$ to $Y_{1,bad}$ will be much smaller (as depicted in Fig. 4.3) or could even be negative (not depicted in Fig. 4.3). This might cause disappointment with the realized outcome and the fertilizer recommendation, and result in dis-adoption of the site-specific recommendation. Dis-adoption of fertilizer use or agricultural practices and technology in general, is often observed (Moser and Barrett, 2006; Kijima et al., 2011; Lambrecht et al., 2014). Relaxing uncertainty about the return to high fertilizer levels by providing information on the seasonal variation in expected returns might prevent such disappointment and dis-adoption and ensure a continued adoption of a site-specific and more efficient fertilizer level in subsequent years, even if the initial return from higher fertilizer use is low. Relaxing this uncertainty allows farmers to make better-informed fertilizer use decisions (Saha et al., 1994; Koundouri et al., 2006). In addition, provision of more information about the expected variability of economic returns may signal greater credibility of the extension information to farmers. A larger information set might be perceived to be more accurate, and/or because the acknowledgement of uncertainty around returns to site-specific recommendations might be perceived as an indicator of honesty of the extension agent.

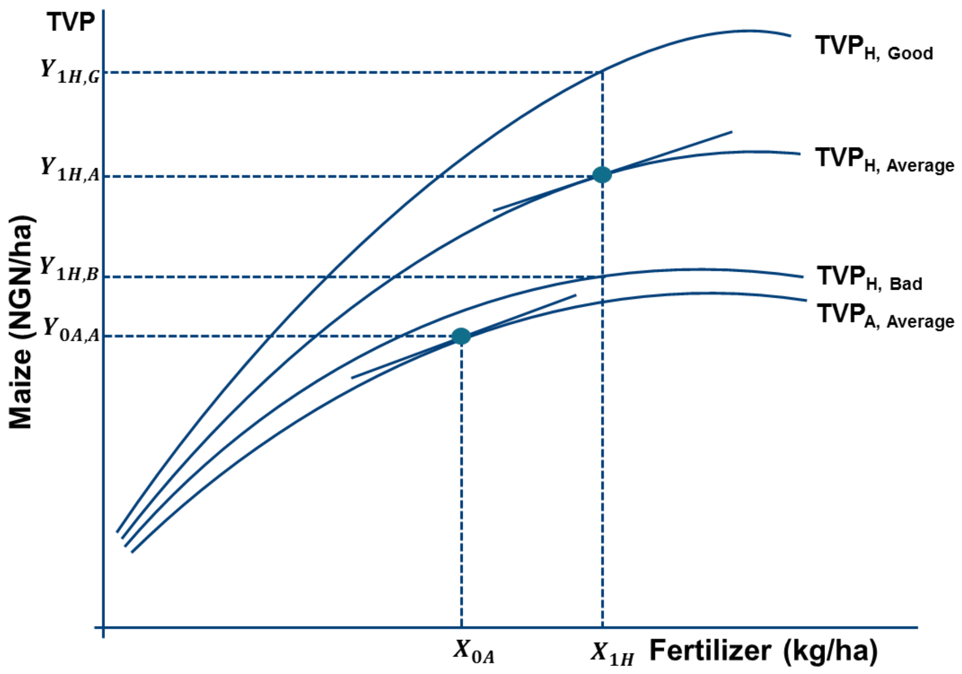

Fig. 4.3: The effect of relaxing information constraints about variability of the expected returns to investments on fertilizer use, yield and revenue

Based on this conceptual discussion, we formulate three hypotheses. First, relaxing information constraints about optimal fertilizer management practices improves technical efficiency and results in higher yield and revenue, and can be associated with an immediate or a gradual expansion of fertilizer use (Fig. 4.1). Second, site-specific fertilizer recommendations reduce technical uncertainty and only result in an expansion of fertilizer use and associated higher yields and revenue for farmers operating in conducive agro-ecological conditions and may not have much effect on average (Fig. 4.2). Third, additional information on variability of expected returns can motivate continued adoption of site-specific recommendations and result in higher yield and revenue in the longer run (Fig. 4.3).

3. Methods

3.1 Research area and background

The research is conducted in three states in northern Nigeria (Fig. A1 in appendix), where maize is grown in a smallholder rainfed system under different agro-ecological conditions. Fertilizer use is low in this area, and maize yields amount to 1 or 2 tons per hectare (ha) despite a yield potential of over 5 tons per ha (Liverpool-Tasie et al., 2017; Shehu et al., 2018; ten Berge et al., 2019). Despite heterogeneous conditions in the area, the extension system relies on a general fertilizer recommendation of 120 kg N, 60 kg P_2O_5 and 60 kg K_2O per ha maize (Shehu et al., 2018). Within this context the project 'Taking Maize Agronomy to Scale in Africa (TAMASA)' co-developed a locally calibrated version of a Nutrient Expert tool to provide SSNM recommendations to farmers. This is a tablet- or smartphone-based DST that allows extension agents to generate fertilizer recommendations tailored to the specific situation of an individual farmer's field (Pampolino et al., 2012).

The Nutrient Expert tool is based on the 4R principles of nutrient management – the right fertilizer source, the right rate, the right placement and the right time of application (Pampolino et al., 2012; Johnston and Bruulsema, 2014) – and should allow to adjust fertilizer application based on crop-, plot- and season-specific conditions. The tool uses farmer-supplied information on plot management history, growing conditions and target yield as inputs and produces SSNM information based on the QUEFTS (Quantitative Evaluation of the Fertility of Tropical Soils) model to predict maize yield responses (Pampolino et al., 2012). This includes plot-specific information on optimal nutrient rates and fertilizer sources that supply these nutrients as well as general advice on nutrient management practices, such as timing of fertilizer application (in particular on splitting the nitrogen application to match nutrient demands at different stages in the maize growth cycle) and fertilizer application method (in particular spot application is recommended as this reduces nutrient losses and ensures optimal nutrient uptake by the plant). The model was calibrated for the study area using data from nutrient omission trials in two seasons – 2015 and 2016.

3.2 Experimental design

A two-stage sampling design was used to sample maize farmers in the research area. In the first stage, 99 villages were randomly selected in the three states[21] by generating 22 sampling grids of 10 by 10 km across the primary maize-producing areas in the three states to ensure spatial representativeness. In the second stage, we constructed a sampling frame of maize-producing farm households and randomly selected eight from each selected village, which results in a sample of 792 households. We randomly assigned the 99 villages to one control (C) and two treatment groups (T1 and T2, described below), resulting in 33 villages and 264 households in each group[22]. For each household a maize focal plot was selected, which is the plot the household head perceives to be most important for food security or income generation. All treatment interventions were done for this focal plot.

Farmers in T1 were exposed to SSNM information including a site-specific fertilizer application rate to obtain a target yield, optimal fertilizer management practices (sources, timing and placement), the rationale behind the recommendations and a detailed explanation on how to implement them as well as the expected return from uptake of the recommendations. The latter is a naïve estimate based on the prevailing maize market price at the time of providing the information, before planting. This is akin to most agronomic recommendations and to the uncertainty farmers face due to the time lag between planting decisions and outcomes at harvest time. Farmers in T2 were exposed to the same information as T1 farmers but received additional information on the variability of expected returns. This is a more robust estimate based on the 25th, 50th and 75th percentiles of the distribution of the monthly real maize price during post-harvest months over the last eight years in the research area[23]. The treatments represent situations as described in Fig. 4.1 and 4.2 (T1) and in Fig. 4.1, 4.2 and 4.3 (T2). Farmers in C are exposed to general recommendations prevailing in the traditional extension systems.

[21] These 99 villages are located in 17 Local Government Areas, the administrative unit below the state.
[22] We prefer a village-level randomization over a household-level randomization to avoid unintended behavioral and spillover effects that can interfere with causal identification – violation of SUTVA (Athey and Imbens, 2017).
[23] Price data are derived from weekly nominal maize price data collected from grain markets in the study area by the National Agricultural Extension and Rural Liaison Services (NAERLS), Ahmadu Bello University, Nigeria.

The SSNM information was provided to farmers using the Nutrient Expert tool prior to planting in the 2017 and 2018 farming seasons (April to May) by public extension agents. These extension agents were trained intensively to ensure a proper understanding of how to use the tool, to generate recommendations and to interpret the results to farmers; and supervised in the field to ensure that recommendation protocols were correctly followed. The use of the Nutrient Expert tool requires farmers to provide information on previous crop management practices on the plot (use of inorganic and organic fertilizer, seed type, cropping system, yield, etc.), on characteristics of the growing environment (water availability, incidence of drought, flood, etc.), and on input and maize prices; and extension agents to obtain additional information on soil characteristics (color, texture, etc.) through physical observation and record the plot location and size by GPS. The output generated by the Nutrient Expert tool includes fertilizer use guidelines (amount, type, timing and placement), crop management practices and a simple profit analysis to compare returns from current and recommended practices. Extension agents explain the details of the output to the farmer and provide a summary of the recommendations in a report sheet in the local language to serve as a reminder for the farmer.

3.3 Data collection

We implement three rounds of a farm-household survey among T1, T2 and C households (HHs); a baseline survey conducted in 2016 before any SSNM intervention and two follow-up surveys in 2017 and 2018, after a first and a second SSNM intervention. The surveys were conducted during the maize harvest season (September to October). The questionnaire includes general household information, production data and detailed agronomic data for the focal plot, and community-level information on prices and access to institutions and services. At baseline, data were collected from the full sample of 792 HHs while this dropped to 788 and 786 HHs in the first and second follow-up rounds. This implies a very low attrition of 0.5% and 0.8%. An additional attrition of 13 and 16% arises due to HHs not cultivating maize on their focal plot in 2017 and 2018 respectively. For both types of attrition, we test for possible differential attrition across treatment groups and baseline observable characteristics (appendix tables A1 and A2). We find no strong evidence of non-random attrition, apart from attrition due to not cultivating maize being correlated with T1 in the first follow-up (table A2). We check for possible imbalances in baseline characteristics that could arise from attrition (Athey and Imbens, 2017). We find no pairwise differences between treatment groups, which indicates that attrition does not undermine the randomization (table 4.1 and A3). Finally, we perform a robustness check for possible attrition bias using the non-parametric bounds approach of Lee (2009) as in other randomized evaluations (de Brauw et al., 2018; Omotilewa et al., 2019). In our model estimation, we use a balanced panel of 690 HHs who cultivate maize for the first 2016-2017 panel period, which we refer to as panel A and contains one year of treatment, and a balanced panel of 666 HHs who cultivate maize for the second 2016-2018 panel period, which we refer to as panel B and contains two years of treatment.

3.4 Estimation strategy

We estimate the intent-to-treat (ITT) effect using the difference-in-difference (DiD) estimation in equation 1, which compares the average change in outcomes over time for the treated and control groups. It accounts for possible imbalances in pre-treatment outcomes and time-invariant unobserved heterogeneity not controlled for by randomization. In an alternative specification in equation 2, we include baseline controls for plot, farmer and household characteristics that are potentially correlated with outcomes of interest to improve the precision of the estimates.

$$y_{ijt} = \beta_0 + \beta_1 \mathrm{T1}_{iJt} + \beta_2 \mathrm{T2}_{iJt} + \beta_3 \mathrm{Post}_t + \beta_4 \mathrm{T1}_{iJt} * \mathrm{Post}_t + \beta_5 \mathrm{T2}_{iJt} * \mathrm{Post}_t + \varepsilon_{ijt} \quad (1)$$

$$y_{ijt} = \beta_0 + \beta_1 \mathrm{T1}_{iJt} + \beta_2 \mathrm{T2}_{iJt} + \beta_3 \mathrm{Post}_t + \beta_4 \mathrm{T1}_{iJt} * \mathrm{Post}_t + \beta_5 \mathrm{T2}_{iJt} * \mathrm{Post}_t + \beta_6 \mathrm{X}_{iJ} + \varepsilon_{ijt} \quad (2)$$

Various outcome variables y_{ijt} for the focal plot of HH i in village j in year t are used: 1/ adoption of optimal fertilizer management practices, including binary variables for combined application of inorganic and organic fertilizer, split N application, application at sowing time, and spot application or dibbling; 2/ fertilizer application rates (kg/ha), including N, P_2O_5 and K_2O rates and the overall rate; 3/ maize yield (ton/ha); and 4/ production costs, and gross and net revenue (NGN/ha). The variables $\mathrm{T1}_{iJt}$ and $\mathrm{T2}_{iJt}$ are binary indicators for farmers in T1 and T2 respectively, and Post_t for observations in the follow-up year (2017 or 2018). X_{iJ} is a vector of baseline control variables and ε_{ijt} is a random error term clustered at the village level. The coefficients β_4 and β_5 capture the ITT effects T1 and T2 respectively while β_0 is the average outcome value for the control group at baseline. Two sets of estimations are reported for the first one-year treatment, panel A (using baseline and 2017 data) and for a second two-year treatment, panel B (using baseline and 2018 data). This allows to explore immediate and more gradual effects. For binary outcome variables, a linear probability model is used. Consistent with Fig. 4.2 in the theoretical framework, we only expect an increase in fertilizer application rates for farmers whose baseline application rate is below the SSNM recommendation. Therefore we estimate conditional ITT effects on fertilizer application for this subgroup of farmers. In addition, we estimate quantile regressions for continuous outcome variables (fertilizer rate, yield, revenue) to explore heterogeneity in treatments effects across the outcome distribution.

In addition to the robustness checks for attrition bias mentioned above, we perform multiple hypothesis corrections using False Discovery Rate (FDR) sharpened *q*-values to control for the proportion of false treatment effects due to multiple outcomes and treatments (Anderson, 2008). These *q*-values are computed following Benjamin et al.'s (2006) and Anderson (2008), and empirical implementations (Omotilewa et al., 2018; Hossain et al., 2019). Moreover, we perform hypotheses tests using randomization inference *p*-values as a robustness check to conventional inference *p*-values. Although statistical inference in RCT is commonly done by sampling-based (asymptotic) inference, it is recommended to use randomization-based inference to test the sharp null hypothesis of no treatment effect for all respondents (Athey and Imbens, 2017; Heß, 2017; Young, 2019; Hossain et al., 2019). This yields consistent estimates solely based on the randomization assumption and is not sensitive to the number of clusters or observations.

4. Results

4.1 Baseline characteristics and recommendations

In the overall sample, farmers are on average 44 years old, have about 5 years of formal schooling and 19 years of maize farming experience (table 4.1). Their maize focal plot is on average 0.9 ha, most (97%) of the plots are cultivated with inorganic fertilizer, and the plots produce an average yield of around 2 tons per ha. We perform randomization checks by testing equality of means of the baseline characteristics between the three groups (T1=C, T2=C and T1=T2). The *p*-values of the pairwise comparisons in columns 5, 6 and 7 show that there are no significant differences in almost all the baseline characteristics between the groups. Only in two cases out of the 69 orthogonality tests (23 variables for each group) across the three groups we find significant differences: for livestock holdings and assets for T2=C comparison. Overall, the *p*-values for the chi-squared tests of joint orthogonality between the groups fail to reject the null hypothesis that the baseline observables are orthogonal to the treatment status.

Table 4.1: Baseline household and plot characteristics and balance tests

	Overall sample (1)	Treatment one (T1) (2)	Treatment two (T2) (3)	Control (C) (4)	T1=C *p*-value (5)	T2=C *p*-value (6)	T1=T2 *p*-value (7)
Age of head (years)	44.28	44.20	44.23	44.41	0.856	0.871	0.984
	(0.45)	(0.79)	(0.78)	(0.77)			
Education of head (years)	5.23	5.34	4.93	5.42	0.881	0.385	0.462
	(0.23)	(0.39)	(0.40)	(0.41)			
Household size	9.27	8.93	9.87	9.01	0.863	0.105	0.086
	(0.21)	(0.34)	(0.44)	(0.31)			
Group membership (1/0)	0.31	0.35	0.30	0.291	0.208	0.912	0.245
	(0.02)	(0.03)	(0.03)	(0.03)			
Access to credit (1/0)	0.23	0.22	0.25	0.23	0.698	0.692	0.425
	(0.02)	(0.03)	(0.03)	(0.03)			
Maize experience (years)	18.80	19.14	18.24	19.01	0.885	0.431	0.356
	(0.39)	(0.67)	(0.71)	(0.66)			
Access to extension (1/0)	0.40	0.43	0.40	0.36	0.180	0.429	0.583
	(0.02)	(0.03)	(0.03)	(0.03)			
Maize contract farming (1/0)	0.19	0.19	0.18	0.20	0.735	0.640	0.892
	(0.02)	(0.03)	(0.03)	(0.03)			
Livestock holding (TLU)[1]	1.94	1.80	2.29	1.73	0.751	0.041	0.067
	(0.10)	(0.15)	(0.22)	(0.16)			
Number of plots cultivated	2.70	2.73	2.69	2.67	0.602	0.865	0.730
	(0.04)	(0.08)	(0.08)	(0.08)			
Total farm area (hectare)	3.15	3.08	3.37	3.00	0.800	0.277	0.384
	(0.13)	(0.22)	(0.27)	(0.21)			
Assets (1,000 NGN)[2]	534.09	516.46	608.36	475.67	0.503	0.096	0.225
	(29.58)	(40.75)	(64.47)	(45.52)			
Annual income (1,000 NGN)[3]	188.51	182.49	206.50	176.26	0.820	0.377	0.420
	(12.44)	(15.90)	(25.46)	(22.70)			
Off-farm income (1/0)	0.88	0.86	0.90	0.87	0.859	0.367	0.272
	(0.01)	(0.02)	(0.02)	(0.02)			
Focal plot area (hectare)	0.82	0.84	0.82	0.81	0.688	0.898	0.813
	(0.04)	(0.06)	(0.08)	(0.07)			
Plot ownership (1/0)	0.96	0.94	0.97	0.96	0.200	0.928	0.165
	(0.01)	(0.02)	(0.01)	(0.01)			
Plot distance (minutes) [4]	15.11	14.33	16.05	14.96	0.604	0.536	0.277
	(0.63)	(0.70)	(1.44)	(1.00)			
Use organic fertilizer (1/0)	0.78	0.76	0.77	0.80	0.396	0.580	0.770
	(0.02)	(0.03)	(0.03)	(0.03)			
Use improved seed (1/0)	0.29	0.27	0.33	0.27	0.884	0.218	0.159
	(0.02)	(0.03)	(0.03)	(0.03)			
Use mineral fertilizer (1/0)	0.97	0.96	0.97	0.97	0.401	0.647	0.698
	(0.01)	(0.01)	(0.01)	(0.01)			
NPK fertilizer (kg/ha)	130.89	131.83	132.89	127.77	0.697	0.627	0.920
	(4.29)	(7.40)	(7.53)	(7.34)			
Urea fertilizer (kg/ha)	87.25	83.35	91.61	86.94	0.677	0.612	0.343
	(3.60)	(5.77)	(6.55)	(6.44)			
Maize yield (ton/ha)	2.07	2.01	2.09	2.12	0.217	0.711	0.390
	(0.04)	(0.06)	(0.06)	(0.06)			
Joint orthogonality test *p*-value					0.985	0.648	0.398
N	690	240	230	220			

p-values in columns 5, 6, 7 are from t-tests of equality of means except the joint test *p*-values from chi-squared tests, [1]One tropical livestock unit (TLU) is equivalent to 250 kg (cattle=0.7, sheep/goat=0.1, pig=0.2, chicken=0.01, duck=0.02, rabbit=0.01), [2]Value of household assets, [3]Per-adult equivalent household annual income from all sources, [4] Time to walk from homestead to the plot, Standard errors are reported in parentheses, NGN: 305 NGN (Nigerian Naira) is equivalent to 1 USD at the survey time

We examine farmers' baseline fertilizer application rates and maize yields, and compare these with the recommended rates and corresponding expected yield level from the treatments (table 4.2). In the 2016-2017 panel period, farmers in T1 apply on average 93 kg of nutrients (including N, P_2O_5 and K_2O per ha) at baseline while the average recommended site-specific rate is 242 kg per ha. This results in an average nutrient gap of 149 kg (or 61%) and 95% of farmers initially (at baseline) using less fertilizer than recommended for their plot specific situations. This is associated with a low initial average yield (2 ton per ha) and a yield gap of an average of 3.3 tons per ha (or 63%). The comparison of baseline and recommended nutrient applications and of baseline and attainable yields is very similar for T2 farmers and for the 2016-2018 panel period.

Table 4.2: Descriptive statistics on farmers' baseline and recommended fertilizer application rates and yields

	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	All (kg/ha)	Yield (ton/ha)	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	All (kg/ha)	Yield (ton/ha)
	Panel A (one year): 2016-2017					Panel B (two years): 2016-2018				
<u>*Treatment one (T1)*</u>										
Baseline (2016) nutrient rates	57.77	17.41	17.41	92.58	2.01	59.58	17.58	17.58	94.73	1.96
and yields[1]	(48.00)	(14.65)	(14.65)	(65.27)	(0.92)	(49.90)	(14.60)	(14.60)	(67.07)	(0.90)
Recommended nutrient rates and	128.96	56.50	56.18	241.64	5.28	132.07	59.40	59.40	250.88	5.88
expected yields[2]	(23.31)	(25.84)	(25.89)	(72.23)	(1.07)	(22.21)	(18.62)	(18.62)	(56.46)	(1.33)
Nutrient gap and yield gap	71.19	39.09	38.77	149.06	3.27	72.49	41.83	41.83	156.15	3.92
	(50.12)	(27.93)	(27.96)	(88.79)	(1.52)	(55.71)	(23.89)	(23.89)	(89.48)	(1.70)
Nutrient gap and yield gap (%)	55	69	69	61	62	55	70	70	62	67
Farmers (%) applying nutrients below the recommended rate	92	95	95	95		90	95	95	95	
<u>*Treatment two (T2)*</u>										
Baseline (2016) nutrient rates	58.76	18.81	18.81	96.40	2.09	60.03	19.50	19.50	99.04	2.11
and yields[1]	(46.93)	(16.71)	(16.71)	(67.15)	(0.95)	(49.46)	(18.33)	(18.33)	(75.04)	(0.95)
Recommended nutrient rates and	128.56	53.19	53.03	234.79	5.35	134.80	56.13	56.13	247.05	5.90
expected yields	(19.53)	(22.16)	(22.24)	(60.82)	(1.10)	(24.28)	(21.71)	(21.71)	(62.77)	(1.19)
Nutrient gap and yield gap	69.80	34.38	34.21	138.39	3.27	74.76	36.62	35.08	148.01	3.78
	(50.92)	(28.54)	(28.68)	(92.49)	(1.45)	(57.90)	(29.51)	(29.26)	(104.34)	(1.64)
Nutrient gap and yield gap (%)	54	65	65	59	61	55	65	65	60	64
Farmers (%) applying nutrients below the recommended rate	90	91	91	92		90	93	93	93	

The macronutrients are based on the fertilizer blends used by farmers, which include NPK 15:15:15 (contains 15% N, 15% P and 15% K), NPK 20:10:10 (20% N, 10% P and 10% K), urea (46% N) and SSP (18% P).

[1] Baseline values refer to 2016 for both panel periods and differ for the two panel periods because of differences in the balanced sample size. [2] Values refer to 2017 (first year of treatment) for panel A and to 2018 (second year of treatment) for panel B.

N = 240 and 230 in T1 and T2 respectively for 2017; N = 225 and 220 in T1 and T2 respectively for 2018.

Standard deviations are reported in parentheses.

4.2 Treatment effects

In table 4.3, we report the ITT effects of farmers' access to SSNM interventions on adoption of optimal fertilizer management practices. Estimates are based on models including baseline control variables (equation 2) and are extremely similar to estimates from models without baseline control variables (equation 1 and results reported in table A4 in appendix), which is indication of the robustness of the results. The results show that the treatments increase the likelihood of adopting combined use of inorganic fertilizer and manure with on average 15 to 17 percentage points (pp), the likelihood of using a split N application with 13 to 17 pp, the likelihood of applying fertilizer at sowing time with 17 to 20 pp, and the likelihood of using a spot fertilizer application with 15 to 21 pp. Given that baseline adoption is around 77 to 79 percent for combined inorganic-organic fertilizer application and for split N application, the estimated effects translate into absolute increases of around 11 to 13 percent. Baseline use of fertilizer at sowing and of spot application is much lower, and estimated effects translate into absolute increases of around 3% for the former and around 5 to 7 percent of the latter. There is no statistically significant difference between estimated ITT effects for T1 and T2. Differences in estimated effects over the two panel periods are small with most effects larger in the two-year panel period but not statistically significant.

Table 4.3: ITT effects on fertilizer management practices

	Inorganic-organic fertilizer (1/0)	Split N application (1/0)	Fertilizer at sowing (1/0)	Spot fertilizer application (1/0)
Panel A: 2016 - 2017				
Treatment one (T1)	0.147***	0.135*	0.170***	0.149*
	(0.053)	(0.076)	(0.056)	(0.077)
Treatment two (T2)	0.164***	0.173**	0.187***	0.202***
	(0.052)	(0.068)	(0.061)	(0.073)
Baseline control mean (C)	0.77	0.79	0.14	0.36
N	1380	1380	1380	1380
Panel B: 2016 - 2018				
Treatment one (T1)	0.170***	0.148**	0.199***	0.155**
	(0.056)	(0.073)	(0.057)	(0.066)
Treatment two (T2)	0.145**	0.141**	0.196***	0.214***
	(0.058)	(0.068)	(0.055)	(0.060)
Baseline control mean (C)	0.76	0.78	0.14	0.35
N	1332	1332	1332	1332
p-values:				
$T1_{2017} = T2_{2017}$	0.757	0.542	0.761	0.507
$T1_{2018} = T2_{2018}$	0.684	0.902	0.943	0.335
$T1_{2017} = T1_{2018}$	0.683	0.857	0.597	0.943
$T2_{2017} = T2_{2018}$	0.752	0.664	0.876	0.872

Estimates with baseline control variables as specified in equation (2).
Standard errors clustered at the village level reported between parentheses.
Significant coefficients at * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 4.4 shows the ITT effects of farmers' access to SSNM interventions on fertilizer application rates. Estimates for overall macronutrients application are positive but very small with increases of on average 6 to 10 kg per ha for T1 and 12 to 19 kg per ha for T2. Only the effect of T2 in the 2016-2018 panel period is statistically significant and is mainly driven by an increased application of nitrogen. Table 4.5 shows the ITT effects on fertilizer application rates but only including those farmers for whom baseline application rates are below SSNM recommendations. These conditional ITT effects are slightly above the unconditional ITT effects in table 4.4. We find statistically significant effects of T2 in both periods – but without significant differences between the periods – and for all nutrients. Yet, also these conditional effects remain rather small. An increase of 26 kg of nutrient per ha is a small impact, which is only about one fourth of the average baseline application rate. Estimates in tables 4.4 and 4.5 are derived from models including baseline control variables (equation 2) but are robust to excluding the control variables (equation 1; table A5 & A6 in appendix).

Table 4.4: ITT effects on farmers' fertilizer application rates (unconditional estimates)

	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	Overall (kg/ha)
Panel A: 2016 - 2017				
Treatment one (T1)	0.976	2.360	2.398	5.736
	(6.661)	(2.476)	(2.468)	(9.903)
Treatment two (T2)	8.200	2.153	2.054	12.405
	(5.659)	(2.473)	(2.445)	(8.920)
Baseline control mean (C)	62.19	20.35	20.35	102.88
N	1380	1380	1380	1380
Panel B: 2016 - 2018				
Treatment one (T1)	3.868	3.141	2.918	9.927
	(5.440)	(2.271)	(2.070)	(8.680)
Treatment two (T2)	13.524**	2.661	3.305	19.490**
	(5.458)	(2.396)	(2.320)	(8.882)
Baseline control mean (C)	62.13	19.97	19.97	102.09
N	1332	1332	1332	1332
p-values:				
$T1_{2017} = T2_{2017}$	0.296	0.924	0.873	0.499
$T1_{2018} = T2_{2018}$	0.104	0.831	0.857	0.290
$T1_{2017} = T1_{2018}$	0.633	0.763	0.828	0.669
$T2_{2017} = T2_{2018}$	0.366	0.839	0.602	0.440

Estimates with baseline control variables as specified in equation (2).
Standard errors clustered at the village level reported between parentheses.
Significant coefficients at * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 4.5: ITT effects on farmers' fertilizer application rates (conditional estimates)

	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	Overall (kg/ha)
Panel A: 2016 - 2017				
Treatment one (T1)	3.733	2.491	2.524	8.750
	(6.381)	(2.550)	(2.536)	(10.111)
Treatment two (T2)	13.251**	4.494*	4.370*	22.114***
	(5.420)	(2.353)	(2.316)	(8.438)
Baseline control mean (C)	62.19	20.35	20.35	102.88
N	1312	1312	1312	1312
Panel B: 2016 - 2018				
Treatment one (T1)	5.921	3.592	3.332*	12.845
	(5.083)	(2.202)	(1.990)	(7.934)
Treatment two (T2)	16.517***	4.330*	4.971**	25.818***
	(5.480)	(2.217)	(2.148)	(8.449)
Baseline control mean (C)	58.53	19.62	19.62	97.77
N	1268	1268	1268	1268
p-values:				
$T1_{2017} = T2_{2017}$	0.119	0.336	0.371	0.141
$T1_{2018} = T2_{2018}$	0.060	0.717	0.401	0.116
$T1_{2017} = T1_{2018}$	0.716	0.671	0.735	0.675
$T2_{2017} = T2_{2018}$	0.586	0.945	0.794	0.685

Estimates with baseline control variables as specified in equation (2)
Standard errors clustered at the village level reported between parentheses.
Significant coefficients at * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

Table 4.6 shows the ITT effects of farmers' access to SSNM interventions on maize yields, production costs, gross and net revenues. Estimates are based on models including baseline control variables (equation 2) but are again extremely similar to estimates from models without baseline control variables (equation 1; table A7 in appendix). The results show that the interventions lead to statistically significant increases in maize yield. We find that T1 increases maize yield with 0.2 ton per ha for panel A and with 0.3 ton for panel B while T2 increases yield with 0.3 and 0.4 ton per ha in respectively panel A and B. These are moderately important effects which correspond to increases of 10 to 18% from the average baseline yield. The estimated yield effects of T2 are larger than the effects of T1, and the estimated effects for panel B larger than for panel A, but differences in estimated effects are not significant. A potential confounder to the observed effects is the incidence of fall army worm (FAW) infestation during the 2017 and 2018 seasons in Nigeria and other parts of SSA (Nagoshi et al., 2018). The incidence of FAW infestation in our sample is 17% and 8% in 2017 and 2018 respectively. Column 2 of table 4.6 shows that the results are robust to controlling for FAW infestation.

The results in table 4.6 further show that the yield increase associated with T1 and T2 translates into a significant increase in gross revenue after one year (panel A) and a significant increase in net revenue after two years (panel B). The economic importance of these revenue increases is rather modest, with effects amounting to 9 to 16% of baseline revenue values. Both treatments result in significantly higher production costs but only after two years of treatment, which points to gradual investments by farmers. After two years (panel B), production costs increase on average with 9,870 NGN per ha or 13% for T1 farmers and with 13,426 NGN per hectare or 18% for T2 farmers. None of the estimated effects on yield, production costs, gross and net revenue differs significantly between T1 and T2, or between panel A and panel B.

Table 4.6: ITT effects on maize yields, production costs, gross revenue and net revenue

	Yield (ton/ha)		Production costs (NGN/ha)	Gross revenue (NGN/ha)	Net revenue (NGN/ha)
Panel A: 2016 - 2017					
Treatment one (T1)	0.205*	0.201*	6457.705	20602.54*	14144.83
	(0.120)	(0.120)	(6784.210)	(12353.58)	(14312.15)
Treatment two (T2)	0.257**	0.256**	9324.822	25776.22**	16451.39
	(0.121)	(0.121)	(5897.551)	(12521.2)	(14011.51)
FAW (1/0)		0.024			
		(0.077)			
Baseline control mean (C)	2.12	2.12	75052.94	222394.8	147341.8
N	1380	1380	1380	1380	1380
Panel B: 2016 - 2018					
Treatment one (T1)	0.310***	0.310***	9870.715*	30413.34***	20542.63*
	(0.104)	(0.103)	(5477.933)	(10361.2)	(10548.44)
Treatment two (T2)	0.389***	0.389***	13426.04***	35290.05***	21864.02*
	(0.102)	(0.102)	(4938.405)	(10451.88)	(11220.75)
FAW (1/0)		-0.047			
		(0.102)			
Baseline control mean (C)	2.13	2.13	75118.16	223364.9	148246.8
N	1332	1332	1332	1332	1332
p-values:					
$T1_{2017} = T2_{2017}$	0.636	0.636	0.320	0.640	0.863
$T1_{2018} = T2_{2018}$	0.451	0.451	0.508	0.643	0.905
$T1_{2017} = T1_{2018}$	0.223	0.223	0.594	0.264	0.488
$T2_{2017} = T2_{2018}$	0.153	0.153	0.524	0.294	0.568

Estimates with baseline control variables as specified in equation (2).

Net revenue is the gross revenue (value of output) less the variable costs of production, which include cost of inorganic fertilizer, seed, organic fertilizer, labor and agrochemicals such as herbicides and insecticides.

Standard errors clustered at the village level reported between parentheses.

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

4.3 Robustness checks

The results of the Lee (2009) bounds estimator as robustness check for potential attrition bias show that all the point estimates of our outcomes of interest lie within the lower and upper treatment-effect bounds (tables 4.7 to 4.9). This implies that the treatment effects we observe are robust to attrition bias, particularly for T1 in 2017 where we have differential attrition rates in relation to households who did not cultivate maize on the focal plot in 2017 and/or 2018. Tables 4.10 to 4.12 show the results of statistical hypothesis testing using the conventional inference *p*-values and the randomization inference *p*-values. The former relies on the assumption of a random draw of the sample from an infinite population and is thus sensitive to the experimental sample size, which is not the case for the latter that takes the sample as fixed and considers only the treatment assignment as a random draw. The tests using randomization inference *p*-values are consistent with those of the conventional inference *p*-values. This implies that the significant treatment effects we find are robust to the somewhat small number of villages or observations at hand and are unlikely due to chance (Heß, 2017). In table 4.13, we report the results of correction for multiple hypotheses testing arising from the fact that we have multiple outcomes (fertilizer management practices, fertilizer application rates, yield and revenue) and treatment groups (T1, T2, C) in the RCT setting and thus more prone to Type I error, i.e. higher likelihood of false positive inference. Using the approach exemplified in Anderson (2008), the false discovery rates-adjusted *q*-values indicate that all the statistically significant treatment effects we find are robust to accounting for multiple hypothesis tests. In general, our results are robust to potential attrition bias, to alternative statistical inference and to corrections for multiple hypotheses testing.

Table 4.7: Results of Lee bounds estimates for fertilizer management practices

	Inorganic-organic fertilizer (1/0)	Split N application (1/0)	Fertilizer at sowing (1/0)	Spot fertilizer application (1/0)
Panel A: 2016 - 2017				
Treatment one (T1)	0.147***	0.135*	0.170***	0.149*
Lower bound	0.064	0.050	0.095	0.068
	(0.067)	(0.068)	(0.059)	(0.073)
Upper bound	0.245***	0.232***	0.277***	0.250***
	(0.070)	(0.070)	(0.067)	(0.077)
Treatment two (T2)	0.164***	0.173**	0.187***	0.202***
Lower bound	0.123*	0.132**	0.150***	0.164**
	(0.066)	(0.064)	(0.058)	(0.072)
Upper bound	0.214***	0.223***	0.241***	0.255
	(0.070)	(0.068)	(0.067)	(0.079)
N	1380	1380	1380	1380
Panel B: 2016 - 2018				
Treatment one (T1)	0.170***	0.148**	0.199***	0.155**
Lower bound	0.154**	0.131*	0.186***	0.140**
	(0.069)	(0.076)	(0.058)	(0.063)
Upper bound	0.190***	0.167**	0.222***	0.176**
	(0.072)	(0.079)	(0.069)	(0.071)
Treatment two (T2)	0.145**	0.141**	0.196***	0.214***
Lower bound	0.141**	0.136*	0.191***	0.205***
	(0.067)	(0.075)	(0.065)	(0.066)
Upper bound	0.150**	0.177	0.200***	0.214***
	(0.071)	(0.188)	(0.063)	(0.064)
N	1322	1322	1322	1322

Table 4.8: Results of Lee bounds estimates for fertilizer application rates

	N (kg/ha)		P_2O_5 (kg/ha)		K_2O (kg/ha)		Overall (kg/ha)	
Panel A: 2016 - 2017								
Treatment one (T1)	0.976	3.733	2.360	2.491	2.398	2.524	5.736	8.750
Lower bound	-9.903	-6.237	-2.0391	-1.581	-1.997	-1.551	-12.140	-8.097
	(7.177)	(6.829)	(2.509)	(2.565)	(2.472)	(2.514)	(10.994)	(10.874)
Upper bound	13.216*	13.474**	6.189**	6.266**	6.204**	6.278**	22.107**	23.018**
	(6.922)	(6.466)	(2.505)	(2.528)	(2.500)	(2.523)	(10.277)	(10.230)
Treatment two (T2)	8.200	13.251**	2.153	4.494*	2.054	4.370*	12.405	22.114***
Lower bound	2.281	6.516	-.463	1.519	-.579	1.373	3.073	11.733
	(7.543)	(6.177)	(2.677)	(2.591)	(2.678)	(2.592)	(11.347)	(10.902)
Upper bound	15.349**	20.189***	4.502*	6.684***	4.387	6.538***	22.136*	31.726***
	(7.544)	(7.061)	(2.741)	(2.518)	(2.727)	(2.505)	(11.673)	(10.480)
N	1380	1312	1380	1312	1380	1312	1380	1312
Panel B: 2016 - 2018								
Treatment one (T1)	3.868	5.921	3.141	3.592	2.918	3.332*	9.927	12.845
Lower bound	1.212	4.278	1.843	2.640	1.879	2.647	6.136	10.797
	(6.828)	(6.687)	(2.743)	(2.836)	(2.675)	(2.736)	(10.282)	(11.328)
Upper bound	7.426	7.567	4.013	4.0618	3.767	3.787	14.478	15.080
	(7.525)	(7.363)	(2.509)	(2.552)	(2.412)	(2.450)	(11.315)	(11.093)
Treatment two (T2)	13.524**	16.517***	2.661	4.330*	3.305	4.971**	19.490**	25.818***
Lower bound	12.835	16.517	2.402	4.318	3.050	4.960	18.560	25.753*
	(8.094)	(10.377)	(3.105)	(3.116)	(3.053)	(3.109)	(11.886)	(15.728)
Upper bound	14.281*	16.548**	2.982	4.342	3.630	4.984	20.780	25.860**
	(8.417)	(8.472)	(3.369)	(3.363)	(3.380)	(3.329)	(13.552)	(12.099)
N	1322	1268	1322	1268	1322	1268	1322	1268

Table 4.9: Results of Lee bounds estimates for maize yield, production costs, gross and net revenues

	Yield (ton/ha)	Production costs (NGN/ha)	Gross revenue (NGN/ha)	Net revenue (NGN/ha)
Panel A: 2016 - 2017				
Treatment one (T1)	0.201*	6457.705	20602.54*	14144.83
Lower bound	-0.011	-8767.822	-921.136	-7561.754
	(0.134)	(7252.44)	(13736.13)	(14768.27)
Upper bound	0.420***	16846.38**	43349.55***	38259.85***
	(0.132)	(75758.14)	(13507.23)	(14489.51)
Treatment two (T2)	0.256**	9324.822	25776.22**	16451.39
Lower bound	0.142	960.885	14260	5554.082
	(0.135)	(7659.079)	(13747.17)	(14826.65)
Upper bound	0.394***	15717.35**	40105.45***	31769.56**
	(0.140)	(8002.4)	(14460.20)	(15685.12)
N	1380	1380	1380	1380
Panel B: 2016 - 2018				
Treatment one (T1)	0.310***	9870.715*	30413.34***	20542.63*
Lower bound	0.264**	6977.707	26051.81**	15843.1
	(0.125)	(7319.879)	(12375.62)	(13944.07)
Upper bound	0.362***	12809.74*	35682.35**	25808.53*
	(0.141)	(7401.317)	(14084.11)	(14681.18)
Treatment two (T2)	0.389***	13426.04***	35290.05***	21864.02*
Lower bound	0.375**	12567.68	33908.18**	20298.46
	(0.151)	(9061.317)	(15038.08)	(17301.93)
Upper bound	0.404**	14705.86	36711.82**	23419.88
	(0.161)	(11657.82)	(15551.47)	(16470.75)
N	1322	1322	1322	1322

Table 4.10: ITT effects on farmers' fertilizer management practices using conventional inference (C.I) and randomization inference (R.I) *p*-values

	Inorganic-organic fertilizer (1/0)	Split N application (1/0)	Fertilizer at sowing (1/0)	Spot fertilizer application (1/0)
Panel A: 2016 - 2017				
Treatment one (T1)	0.147	0.135	0.170	0.149
C.I *p*-value	(0.006)	(0.078)	(0.003)	(0.057)
R.I *p*-value	(0.008)	(0.074)	(0.003)	(0.070)
Treatment two (T2)	0.164	0.173	0.187	0.202
C.I *p*-value	(0.002)	(0.013)	(0.003)	(0.007)
R.I *p*-value	(0.004)	(0.017)	(0.006)	(0.008)
Panel B: 2016 - 2018				
Treatment one (T1)	0.170	0.148	0.199	0.155
C.I *p*-value	(0.003)	(0.044)	(0.001)	(0.021)
R.I *p*-value	(0.006)	(0.048)	(0.001)	(0.024)
Treatment two (T2)	0.145	0.141	0.196	0.214
C.I *p*-value	(0.015)	(0.042)	(0.001)	(0.001)
R.I *p*-value	(0.024)	(0.049)	(0.001)	(0.000)

Conventional inference (C.I) and randomization inference (R.I) *p*-values reported between parentheses

Table 4.11: ITT effects on farmers' fertilizer application rates using conventional inference (C.I) and randomization inference (R.I) *p*-values

	N (kg/ha)		P_2O_5 (kg/ha)		K_2O (kg/ha)		Overall (kg/ha)	
Panel A: 2016 - 2017								
Treatment one (T1)	0.976	3.733	2.360	2.491	2.398	2.524	5.736	8.750
C.I *p*-value	(0.884)	(0.560)	(0.343)	(0.256)	(0.334)	(0.322)	(0.564)	(0.389)
R.I *p*-value	(0.871)	(0.584)	(0.319)	(0.331)	(0.320)	(0.325)	(0.543)	(0.404)
Treatment two (T2)	8.200	13.251	2.153	4.494	2.054	4.370	12.405	22.114
C.I *p*-value	(0.151)	(0.016)	(0.386)	(0.059)	(0.403)	(0.062)	(0.167)	(0.010)
R.I *p*-value	(0.159)	(0.022)	(0.396)	(0.068)	(0.417)	(0.068)	(0.166)	(0.010)
Panel B: 2016 - 2018								
Treatment one (T1)	3.868	5.921	3.141	3.592	2.918	3.332	9.927	12.845
C.I *p*-value	(0.479)	(0.247)	(0.170)	(0.106)	(0.162)	(0.097)	(0.256)	(0.109)
R.I *p*-value	(0.473)	(0.245)	(0.166)	(0.107)	(0.149)	(0.094)	(0.242)	(0.114)
Treatment two (T2)	13.524	16.517	2.661	4.330	3.305	4.971	19.490	25.818
C.I *p*-value	(0.015)	(0.003)	(0.269)	(0.054)	(0.158)	(0.023)	(0.031)	(0.003)
R.I *p*-value	(0.014)	(0.004)	(0.280)	(0.062)	(0.167)	(0.027)	(0.034)	(0.004)

Conventional inference (C.I) and randomization inference (R.I) *p*-values reported between parentheses,
Estimates in columns 1, 3, 5 and 7 (results for unconditional estimates in table 4.4), estimates in columns 2, 4, 6 and 8 (results for conditional estimates in table 4.5)

Table 4.12: ITT effects on maize yields, production costs, gross revenue and net revenue using conventional inference (C.I) and randomization inference (R.I) *p*-values

	Yield (ton/ha)		Production costs (NGN/ha	Gross revenue (NGN/ha)	Net revenue (NGN/ha)
Panel A: 2016 - 2017					
Treatment one (T1)	0.205	0.201	6457.705	20602.540	14144.830
C.I *p*-value	(0.098)	(0.096)	(0.344)	(0.099)	(0.325)
R.I *p*-value	(0.107)	(0.107)	(0.339)	(0.107)	(0.330)
Treatment two (T2)	0.257	0.256	9324.822	25776.220	16451.390
C.I *p*-value	(0.037)	(0.036)	(0.117)	(0.042)	(0.243)
R.I *p*-value	(0.034)	(0.034)	(0.128)	(0.042)	(0.246)
Panel B: 2016 - 2018					
Treatment one (T1)	0.310	0.310	9870.715	30413.340	20542.630
C.I *p*-value	(0.003)	(0.003)	(0.075)	(0.004)	(0.054)
R.I *p*-value	(0.005)	(0.005)	(0.073)	(0.006)	(0.057)
Treatment two (T2)	0.389	0.389	13426.040	35290.050	21864.020
C.I *p*-value	(0.000)	(0.000)	(0.008)	(0.001)	(0.054)
R.I *p*-value	(0.000)	(0.001)	(0.011)	(0.003)	(0.063)

Conventional inference (C.I) and randomization inference (R.I) *p*-values reported between parentheses

Table 4.13: Robustness check for multiple hypothesis testing

	Outcomes	Panel A: 2016 - 2017		Panel B: 2016 - 2018	
		p-value	*q*-value	*p*-value	*q*-value
Table 4.3					
T1	Inorganic-organic fertilizer (1/0)	0.006	0.019	0.003	0.006
	Split N application (1/0)	0.078	0.076	0.044	0.031
	Fertilizer at sowing (1/0)	0.003	0.017	0.001	0.004
	Spot fertilizer application (1/0)	0.057	0.061	0.021	0.022
T2	Inorganic-organic fertilizer (1/0)	0.002	0.017	0.015	0.018
	Split N application (1/0)	0.013	0.023	0.042	0.031
	Fertilizer at sowing (1/0)	0.003	0.017	0.001	0.004
	Spot fertilizer application (1/0)	0.007	0.019	0.001	0.004
Table 4.4					
T1	Overall fertilizer (kg/ha)	0.564	0.214	0.256	0.069
T2	Overall fertilizer (kg/ha)	0.167	0.113	0.031	0.029
Table 4.5					
T1	Overall fertilizer (kg/ha)	0.389	0.167	0.109	0.053
T2	Overall fertilizer (kg/ha)	0.010	0.023	0.003	0.006
Table 4.6					
T1	Yield (ton/ha)	0.098	0.080	0.003	0.006
T2	Yield (ton/ha)	0.037	0.044	0.000	0.001
T1	Net revenue (NGN/ha)	0.325	0.162	0.054	0.035
T2	Net revenue (NGN /ha)	0.243	0.143	0.063	0.038

The false discovery rate adjusted *q*-values are estimated from the *p*-values of estimates in tables 4.3, 4.4, 4.5, and 4.6.

5. Discussion

We find small but significant improvements in fertilizer management practices and associated yield and gross revenue for T1 after one year, but with no immediate change in fertilizer use rates in response to DST-enabled site-specific nutrient management recommendations. This suggests that the latter can improve uptake of optimal fertilizer management practices, which may not represent much additional investments, but improve yields by reducing technical inefficiencies stemming from the use of inappropriate fertilizer management practices. This is consistent with our theoretical predictions about technical efficiency gains associated with take-up of optimal management practices. We know this because there is no significant effect on fertilizer use rates for T1 but an effect on yield, which comes from the effect on management practices. This aligns with other calls to address variability in yield response to fertilizer through better targeted management practices (Tittonell and Giller, 2013; Jayne et al., 2019; Burke et al., 2019), and should be the starting point for extension interventions on promoting fertilizer use. This is important because the benefits of ICT-enabled tools are often framed in terms of benefitting from spatially explicit information and targeting, i.e. location-specific information. While this very well may be the case, our finding suggests that even delivery of non-targeted management information may be an important role for such platforms.

We find that fertilizer use rates for T1 do not increase after one year while for T2 they do but the estimated yield and revenue gains are quite similar for the two groups, which suggests that increase in fertilizer application improves yield but the considerable increase by T2 over T1 does not result in substantial yield gains over T1. In other words, both types of information content (T1 and T2) are likely to have similar yield and revenue impacts. A possible explanation for this is that the yield response to higher fertilizer levels is relatively low and further support the finding that much of the yield gains accrue via management practices. This is consistent with empirical studies that find low and variable maize yield responses to fertilizer in Nigeria and elsewhere in SSA (Marenya and Barrett, 2009; Harou et al., 2017; Liverpool-Tasie et al., 2017; Burke et al., 2017; Theriault et al., 2018). Our observed fertilizer increasing effect of 26 kg per ha and the associated yield effect of 0.4 ton per ha, i.e. 16 kg maize per kg nutrient is twice the survey-based estimate of 8 kg maize per kg N documented in previous empirical findings for Nigeria (Liverpool-Tasie et al., 2017). Yet, this is still far below the potential of up to or more than 40 kg maize per kg nutrient under researcher-managed farm trials (Vanlauwe et al., 2011, 2015b; Ichami et al., 2019), and below survey-based estimates in other parts of SSA even without site-specific recommendations, e.g. 17 to18 kg maize per kg N for Kenya (Marenya and Barrett, 2009; Sheahan et al., 2013), 21 to 25 kg for Uganda (Matsumoto and Yamano, 2013), 22 to 26 kg for Ghana (Ragasa and Chapoto, 2017) and 19 to 24 kg for Burkina Faso (Koussoube and Nauges, 2017; Theriault et al., 2018). Overall the magnitude of the yield effects, a 10 to 18% increase in relation to the yield gap of over 60% (i.e. the gap between farmers' baseline yields and the yields expected under optimal management), suggests that the progress towards closing the yield gap is rather modest. In addition, given the market prices of inputs and output, the yield gains did not translate into substantial revenue gains but rather a small and gradual improvement.

We find that for T2 management practices improve after one year, fertilizer use and outcomes in terms of yield and gross revenue also improves after one year and increases further after two years, while net revenue only improves after two years. This finding is similar for T1 except for fertilizer use rates. This suggests that provision of plot-specific recommended fertilizer application rates, combined with additional information on the distribution of expected returns, appears to incentivize more fertilizer use after one year and foster continued fertilizer investment after two years. This is consistent with our conceptual framework on the role of reducing farmers' uncertainty about fertilizer investment outcomes, and with other literature which argues that farmers may not adopt technologies if they are uncertain about the returns to investments (Koundouri et al., 2006; Genius et al., 2014; Magruder, 2018). Also, the limited fertilizer effect for T1 is weakly consistent with our theoretical model's illustration of how fertilizer use may be increased by reducing plot-specific technical uncertainties. The fact that T2 had generally larger and more significant impacts on all outcomes than T1, including management outcomes which do not necessarily imply larger cash investments suggests that reducing uncertainty may also induce greater investments of time or attention. The emergence of net revenue effects only after two years suggests that the gradual improvements in revenue effects of site-specific recommendations requires a continued investment in nutrient management over time, and for the latter, information about fertilizer investment returns can play a crucial role. In addition, despite the expectation of an immediate or gradual expansion in fertilizer use from improvements in technical efficiency and in turn yields and revenue as indicated in our theoretical framework, we observe that this does not really hold for T1 – fertilizer use did not significantly change after one and two years.

In our specific context, the observed increase in fertilizer use is economically small relative to the general and the site-specific recommended fertilizer rates despite the incentive created by relaxing technical inefficiency, site-specific technical uncertainty and uncertainty in investment returns as put forward in the conceptual discussion. Yet, the marginal increase in fertilizer could be due to low fertilizer responsiveness of some plots and hence, an expanded use of fertilizer may not be expected in line with our theoretical insights. Again, as fertilizer is capital intensive, a binding cash constraint may also play a role in limiting substantial expansion in the use of fertilizer as highlighted in our theoretical framework, and in empirical fertilizer adoption literature (Croppenstedt et al., 2003; Lambrecht et al., 2014; Koussoube and Nauges, 2017). Although, we do not test whether cash constraint matter for farmers' responses to site-specific recommendations, descriptive evidence suggests that it is likely a key challenge for some farmers given the high cost of fertilizer (table A15 in appendix). In a broader sense, the modest increase in fertilizer use by 26 kg nutrients per ha after two years can be considered important relative to the low application of less than on average 10 kg nutrients per ha of arable land for Nigeria, and less than 20 kg for SSA for over a decade (World Bank, 2018c). In addition, the gradual fertilizer investment and net revenue effects is somewhat worthwhile given the high fertilizer acquisition cost in the area. To this end, the small and modest increase over time, i.e. persistence of effects can allow of further increase in fertilizer use and returns in the longer run, which in a way makes our observed effects moderately important.

Our results entail some general policy implications and some direct policy advice for improving agricultural extension systems for maize production in Nigeria. For the specific context of our research area, our results imply that a focus on information about optimal fertilizer management practices (i.e. beyond fertilizer type and amount) should be the first priority for extension agencies in promoting fertilizer use as this can lead to efficiency gains, improved returns and gradual increase in fertilizer use. Hence, traditional extension systems could benefit from low-cost agronomic DSTs which allow them to better inform farmers about optimal fertilizer use and crop management practices beyond focusing only on site-specific fertilizer application rates, especially when the DSTs are learning tools for extension officers. Second, our results imply that giving advice on site-specific fertilization application rates is an effective instrument to induce fertilizer use – but its impacts on yield and revenue gains are small. Therefore, intensifying fertilizer use in our research area without corresponding efforts at improving yield responses is unlikely to generate substantial profitable maize production. This is consistent with empirical studies (Marenya and Barrett, 2009; Burke et al., 2017; Liverpool-Tasie et al., 2017; Jayne et al., 2019; ten Berge et al., 2019; Burke et al., 2019), on the need for complementary measures to improve fertilizer use efficiency and returns. To this end, more research is needed to unpack the underlying causes of low yield response to fertilizer – possible areas include issues of fertilizer quality, micronutrient deficiencies, etc. Third, for the development of nutrient management and other agronomic DSTs in our research area and more broadly, our results imply that farmers are not only interested in agronomic recommendations and the associated average expected returns, but are also interested in variability of the expected returns. Providing information about the expected variability of economic returns (in addition to the expected value) may signal greater credibility of the information to farmers (Silehi et al., 2010; Vanlauwe et al., 2019a). The use of weather data such as rainfall should be explored to simulate possible distribution of expected yields and returns, which will be more informative, particularly for risk-averse farmers. Lastly and in general, despite the marginal potentials of agronomic advisory tools, such as Nutrient Expert, the use of the tools requires physical contact of extension agents with farmers, which may limit farmers' access given the poor extension coverage due to low agents-to-farmers ratio in our research area. In this sense, investments in DST development should not be seen as substitutes for investments in extension systems and other modes of scaling advisory services. Possible alternative low-cost options include the increased use of community-based contact farmers and agro-dealers to provide extension information using such tools.

We acknowledge that this study is associated with some methodological limitations. First, information on optimal fertilizer management practices was not included as a separate treatment. This would have allowed stronger conclusions about the role of fertilizer management practices. Second, uncertainty about seasonal variation in return to fertilizer was only captured by price variation and not by yield variation. Some farmers may be aware of variation in prices or have subjective expectations about this but they may be more uncertain about yield variation when applying new practices or expanding input use. Third, including three seasons in the analysis is an important improvement in comparison with other RCT impact studies and resulted in insights on a very gradual expansion of fertilizer use. Yet, to really understand farmers' fertilizer use decisions and the impact of SSNM extension, studies should look at even longer periods. Lastly, we estimate only direct effects. Yet, there could be indirect effects, e.g. environmental benefits (through reduced soil nutrient mining/degradation/nutrient losses to the environment in response to SSNM) which if quantified can amount to substantial effects. More research may clarify some of these limitations.

6. Conclusion

Our study contributes to the nascent empirical literature on emerging digital agronomy tools targeting smallholders in developing countries, with an experimental study of ICT-enabled plot-specific fertilizer recommendations for smallholder farmers in northern Nigeria. We find that the provision of site-specific nutrient management recommendations results in small but statistically significant increases in the use of inorganic fertilizer and related improved management practices, and results in related impacts on maize yields and gross farm revenue. In addition, we show that there are only gradual increases in investment, fertilizer use and net revenue after two years, particularly for farmers exposed to site-specific recommendations, combined with information on the distribution of expected returns. The persistence of effects in year two may allay concern about a novelty effect, i.e. that the ICT-enabled tool induced greater behavioral changes simply because it was new. Yet, the observed effects are economically small and only emerge gradually, which may create some doubt about site-specific extension recommendations but again, a slow and steady increase is worthwhile. In this regard, lending a stronger credence for scaling up the use of nutrient management DSTs in the traditional extension systems of SSA, particularly in northern Nigeria will require a much more longer-term research while explicitly taking into consideration the underlying issues of yield response to fertilizer, and complementary roles of management practices, and market-related factors, such as cash or credit constraints.

Appendix

A1. Heterogeneous treatment effects

We consider inter-temporal heterogeneity in treatment effects using the *p*-values of the tests of equality of treatment effects ($T1_{2017}$=$T1_{2018}$ and $T2_{2017}$ =$T2_{2018}$) reported in tables 3 to 6 in the main text. The results indicate that we cannot reject the null of equality of treatment effects over time for all outcomes of interest. This suggests that the observed impacts of the interventions that we find are persistent or stable over time. In other words, the treatment effects we find do not significantly increase or decrease for the two treatment groups over the two post-intervention periods. We present the distributions of treatment effects on fertilizer application rates for T1 and T2 in Fig. A2, and the distributions on maize yields and net revenue in Fig. A3. The observed effects are positive across the entire distributions for the two treatment groups and the two post-intervention years except for fertilizer and net revenue effects in 2017, and are not significantly different from zero in some quantiles of the distributions. In addition, they are not systematically concentrated in the upper or lower tails of the distributions. The effects for T2 farmers across most quantiles of the distributions dominate that of T1 farmers except for the effects on net revenue, where we observe considerable variability in distribution of net revenue effects between the two groups. Overall, the figures suggest that heterogeneity in treatment effects is rather limited. This is consistent with Duflo et al. (2008) who find limited evidence for considerable heterogeneity in returns to fertilizer across plots.

Table A1: Results of tests for differential attrition (attrition- HHs who dropped out)

	First follow-up: 2017			Second follow-up: 2018		
	Attrition dummy	Attrition dummy	Attrition dummy	Attrition dummy	Attrition dummy	Attrition dummy
Treatment one (T1)	-0.004	-0.003	0.060	-0.011	-0.012	-0.138
	(0.004)	(0.004)	(0.054)	(0.008)	(0.008)	(0.154)
Treatment two (T2)	0.008	0.008	0.111	-0.011	-0.011	-0.136
	(0.009)	(0.009)	(0.100)	(0.008)	(0.008)	(0.154)
Age of farmer		-0.000	0.000		0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.001)
Education of farmer		0.001	0.002		0.002*	0.002
		(0.001)	(0.002)		(0.001)	(0.002)
Household size		0.000	0.002		0.001	0.005
		(0.000)	(0.002)		(0.001)	(0.003)
Access to credit		-0.006	-0.003		0.005	-0.001
		(0.004)	(0.005)		(0.009)	(0.017)
Group membership		-0.008*	-0.015		-0.001	-0.018
		(0.005)	(0.014)		(0.007)	(0.023)
Maize contract farming		-0.004	-0.000		0.002	0.015
		(0.003)	(0.003)		(0.008)	(0.020)
Access to off-farm income		0.005	0.004		-0.004	-0.020
		(0.004)	(0.004)		(0.011)	(0.028)
ln (assets)		-0.000	0.002		-0.001	-0.002
		(0.002)	(0.002)		(0.002)	(0.003)
Plot ownership		0.004	-0.002		-0.025	-0.113
		(0.004)	(0.005)		(0.028)	(0.105)
Plot distance		0.000	0.001		-0.000	0.000
		(0.000)	(0.001)		(0.000)	(0.001)
_cons	0.004	-0.000	-0.060	0.015**	0.023	0.109
	(0.004)	(0.032)	(0.054)	(0.007)	(0.053)	(0.151)
Baseline controls x treatment dummies[1]	No	No	Yes	No	No	Yes
[2]F-tests of :						
a. baseline controls		0.991			0.838	
b. interaction terms with T1			0.920			0.880
c. interaction terms with T2			0.928			0.758
Observations	792	792	792	792	792	792

[1]Interaction terms of all baseline controls with treatment dummies for T1 and T2 are all statistically insignificant but not reported for brevity,
[2]*p*-values of the joint F-tests of baseline controls and interaction terms to check for non-random attrition,
Standard errors clustered at the village level reported between parentheses.
Significant coefficients at * p < 0.1, ** p < 0.05 and *** p < 0.01

Table A2: Results of tests for differential attrition (attrition - HHs who did not cultivate maize on focal plots + HHs who dropped out)

	First follow-up: 2017			Second follow-up: 2018		
	Attrition dummy	Attrition dummy	Attrition dummy	Attrition dummy	Attrition dummy	Attrition dummy
Treatment one (T1)	-0.076**	-0.076**	-0.471	-0.015	-0.013	0.137
	(0.032)	(0.032)	(0.368)	(0.035)	(0.034)	(0.351)
Treatment two (T2)	-0.038	-0.036	0.013	0.004	0.004	0.173
	(0.036)	(0.037)	(0.347)	(0.036)	(0.035)	(0.343)
Age of farmer		0.001	-0.001		-0.002	-0.001
		(0.001)	(0.003)		(0.001)	(0.002)
Education of farmer		-0.001	-0.002		0.002	0.004
		(0.002)	(0.003)		(0.003)	(0.005)
Household size		-0.006**	-0.017***		0.003	0.003
		(0.002)	(0.006)		(0.003)	(0.005)
Access to credit		0.006	0.058		0.043	0.058
		(0.028)	(0.068)		(0.033)	(0.068)
Group membership		-0.013	-0.033		-0.027	-0.033
		(0.024)	(0.045)		(0.027)	(0.045)
Maize contract farming		-0.022	0.014		-0.059**	0.014
		(0.030)	(0.058)		(0.029)	(0.058)
Access to off-farm income		0.016	-0.049		-0.042	-0.049
		(0.037)	(0.081)		(0.045)	(0.081)
ln (assets)		0.011	0.015		-0.005	-0.000
		(0.009)	(0.014)		(0.010)	(0.015)
Plot ownership		0.006	0.049		0.020	0.049
		(0.057)	(0.104)		(0.060)	(0.104)
Plot distance		0.001	0.001		-0.000	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
_cons	0.167***	0.043	0.121	0.163***	0.292**	0.183
	(0.026)	(0.145)	(0.287)	(0.022)	(0.142)	(0.236)
Baseline controls x treatment dummies[1]	No	No	Yes	No	No	Yes
[2] *p*-values of :						
a. baseline controls		0.388			0.502	
b. interaction terms with T1			0.066			0.972
c. interaction terms with T2			0.225			0.708
Observations	792	792	792	792	792	792

[1]Interaction terms of all baseline controls with treatment dummies for T1 and T2 are statistically insignificant (except for the interactions of T1 and T2 with household size in 2017 and T2 with maize contract farming in 2018) but not reported for brevity,

[2]*p*-values of the joint F-tests of baseline controls and interaction terms to check for non-random attrition,

Standard errors clustered at the village level reported between parentheses.

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

Table A3: Baseline characteristics and balance test - based on HHs who cultivated maize in 2018

	Overall sample (1)	Treatment one (T1) (2)	Treatment two (T2) (3)	Control (C) (4)	T1=C p-value (5)	T2=C p-value (6)	T1=T2 p-value (7)
Age of head (years)	44.5	44.91	44.35	44.23	0.555	0.916	0.628
	(0.47)	(0.84)	(0.81)	(0.80)			
Education of head (years)	5.08	5.07	4.93	5.25	0.752	0.573	0.800
	(0.23)	(0.40)	(0.41)	(0.40)			
Household size	9.09	8.96	9.71	8.62	0.476	0.040	0.185
	(0.21)	(0.36)	(0.44)	(0.29)			
Group membership (1/0)	0.31	0.35	0.3	0.29	0.235	0.893	0.294
	(0.02)	(0.03)	(0.03)	(0.03)			
Access to credit (1/0)	0.22	0.21	0.24	0.22	0.831	0.715	0.562
	(0.02)	(0.03)	(0.03)	(0.03)			
Maize experience (years)	19.02	19.72	18.03	19.29	0.669	0.200	0.097
	(0.41)	(0.72)	(0.72)	(0.68)			
Access to extension (1/0)	0.38	0.40	0.37	0.36	0.358	0.816	0.494
	(0.02)	(0.03)	(0.03)	(0.03)			
Maize contract farming (1/0)	0.20	0.19	0.21	0.20	0.741	0.981	0.723
	(0.02)	(0.03)	(0.03)	(0.03)			
Livestock holding (TLU)[1]	2.14	2.22	2.26	1.93	0.514	0.287	0.932
	(0.17)	(0.39)	(0.22)	(0.22)			
Number of plots cultivated	2.68	2.76	2.62	2.67	0.434	0.675	0.233
	(0.05)	(0.08)	(0.08)	(0.08)			
Total farm area (hectare)	3.19	3.19	3.40	2.99	0.515	0.253	0.570
	(0.14)	(0.22)	(0.28)	(0.23)			
Assets (1,000 NGN)[2]	537.75	556.8	584.53	471.77	0.197	0.145	0.736
	(30.76)	(50.60)	(64.94)	(41.86)			
Annual income (1,000 NGN)[3]	186.05	174.4	196.97	187.06	0.650	0.775	0.454
	(12.64)	(15.69)	(25.90)	(23.14)			
Off-farm income (1/0)	0.88	0.88	0.9	0.87	0.831	0.306	0.415
	(0.01)	(0.02)	(0.02)	(0.02)			
Focal plot area (hectare)	0.82	0.87	0.84	0.75	0.141	0.342	0.751
	(0.04)	(0.07)	(0.08)	(0.05)			
Plot ownership (1/0)	0.96	0.93	0.97	0.96	0.146	0.800	0.090
	(0.01)	(0.02)	(0.01)	(0.01)			
Plot distance (minutes)[4]	15.41	14.7	16.11	15.45	0.566	0.716	0.399
	(0.66)	(0.78)	(1.49)	(1.04)			
Use organic fertilizer (1/0)	0.77	0.75	0.76	0.8	0.212	0.347	0.762
	(0.02)	(0.03)	(0.03)	(0.03)			
Use improved seed (1/0)	0.29	0.27	0.32	0.28	0.825	0.334	0.233
	(0.02)	(0.03)	(0.03)	(0.03)			
Use mineral fertilizer (1/0)	0.97	0.96	0.98	0.97	0.482	0.365	0.113
	(0.01)	(0.01)	(0.01)	(0.01)			
NPK fertilizer (kg/ha)	127.46	126.44	131.95	124.05	0.811	0.451	0.591
	(4.17)	(6.88)	(7.60)	(7.20)			
Urea fertilizer (kg/ha)	86.92	82.39	90.38	88.09	0.513	0.804	0.349
	(3.60)	(5.65)	(6.40)	(6.64)			
Maize yield (ton/ha)	2.07	1.96	2.11	2.13	0.054	0.832	0.095
	(0.04)	(0.06)	(0.06)	(0.06)			
Joint orthogonality test *p*-value					0.872	0.648	0.180
N	666	225	220	221			

p-values in columns 5, 6, 7 are from t-tests of equality of means except the joint test *p*-values from chi-squared tests

Table A4: ITT effects on farmers' fertilizer management practices[1]

	Inorganic-organic fertilizer (1/0)	Split N application (1/0)	Fertilizer at sowing (1/0)	Spot fertilizer application (1/0)
Panel A: 2016 - 2017				
Treatment one (T1)	0.147***	0.135*	0.170***	0.149*
	(0.052)	(0.076)	(0.056)	(0.077)
Treatment two (T2)	0.164***	0.173**	0.187***	0.202***
	(0.052)	(0.068)	(0.061)	(0.073)
Baseline control mean (C)	0.77	0.79	0.14	0.36
N	1380	1380	1380	1380
Panel B: 2016 - 2018				
Treatment one (T1)	0.170***	0.148**	0.199***	0.155**
	(0.056)	(0.072)	(0.056)	(0.066)
Treatment two (T2)	0.145**	0.141**	0.196***	0.214***
	(0.058)	(0.068)	(0.054)	(0.060)
Baseline control mean (C)	0.76	0.78	0.14	0.35
N	1332	1332	1332	1332
p-values:				
$T1_{2017} = T2_{2017}$	0.756	0.540	0.760	0.505
$T1_{2018} = T2_{2018}$	0.683	0.901	0.943	0.333
$T1_{2017} = T1_{2018}$	0.682	0.857	0.596	0.943
$T2_{2017} = T2_{2018}$	0.752	0.664	0.875	0.871

[1]Estimates with no baseline control variables

Table A5: ITT effects on farmers' fertilizer application rates[1] (unconditional estimates)

	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	Overall (kg/ha)
Panel A: 2016 - 2017				
Treatment one (T1)	0.976	2.360	2.398	5.736
	(6.637)	(2.467)	(2.459)	(9.867)
Treatment two (T2)	8.200	2.153	2.054	12.405
	(5.638)	(2.465)	(2.436)	(8.888)
Baseline control mean (C)	62.19	20.35	20.35	102.88
N	1380	1380	1380	1380
Panel B: 2016 - 2018				
Treatment one (T1)	3.868	3.141	2.918	9.927
	(5.420)	(2.263)	(2.062)	(8.647)
Treatment two (T2)	13.524**	2.661	3.305	19.490**
	(5.437)	(2.387)	(2.311)	(8.849)
Baseline control mean (C)	62.13	19.97	19.97	102.09
N	1332	1332	1332	1332
p-values:				
$T1_{2017} = T2_{2017}$	0.294	0.924	0.873	0.497
$T1_{2018} = T2_{2018}$	0.103	0.830	0.857	0.288
$T1_{2017} = T1_{2018}$	0.632	0.762	0.828	0.668
$T2_{2017} = T2_{2018}$	0.365	0.839	0.602	0.439

[1]Estimates with no baseline control variables

Table A6: ITT effects on farmers' fertilizer application rates[1] (conditional estimates)

	N (kg/ha)	P_2O_5 (kg/ha)	K_2O (kg/ha)	Overall (kg/ha)
Panel A: 2016 - 2017				
Treatment one (T1)	3.733	2.491	2.524	8.750
	(6.357)	(2.541)	(2.526)	(10.073)
Treatment two (T2)	13.251**	4.494*	4.370*	22.114***
	(5.400)	(2.344)	(2.308)	(8.406)
Baseline control mean (C)	62.19	20.35	20.35	102.88
N	1312	1312	1312	1312
Panel B: 2016 - 2018				
Treatment one (T1)	5.921	3.592	3.332*	12.845
	(5.063)	(2.194)	(1.982)	(7.902)
Treatment two (T2)	16.517***	4.330*	4.971**	25.818***
	(5.458)	(2.209)	(2.140)	(8.416)
Baseline control mean (C)	58.53	19.62	19.62	97.77
N	1268	1268	1268	1268
p-values:				
$T1_{2017} = T2_{2017}$	0.118	0.334	0.369	0.140
$T1_{2018} = T2_{2018}$	0.059	0.716	0.400	0.115
$T1_{2017} = T1_{2018}$	0.716	0.670	0.735	0.674

[1]Estimates with no baseline control variables

Table A7: ITT effects on maize yields, production costs, gross revenue and net revenue[1]

	Yield (ton/ha)		Production costs (NGN/ha)	Gross revenue (NGN/ha)	Net revenue (NGN/ha)
Panel A: 2016 - 2017					
Treatment one (T1)	0.201*	0.201*	6457.705	20602.54*	14144.83
	(0.120)	(0.120)	(6759.477)	(12308.54)	(14259.97)
Treatment two (T2)	0.256**	0.256**	9324.822	25776.22**	16451.39
	(0.121)	(0.121)	(5876.050)	(12475.56)	(13960.43)
FAW (1/0)		0.019			
		(0.075)			
Baseline control mean (C)	2.12	2.12	75052.94	222394.8	147341.8
N	1380	1380	1380	1380	1380
Panel B: 2016 - 2018					
Treatment one (T1)	0.310***	0.310***	9870.715*	30413.34***	20542.63*
	(0.103)	(0.103)	(5457.238)	(10322.05)	(10508.59)
Treatment two (T2)	0.389***	0.389***	13426.04***	35290.05***	21864.02*
	(0.102)	(0.102)	(4919.749)	(10412.4)	(11178.36)
FAW (1/0)		-0.053			
		(0.101)			
Baseline control mean (C)	2.13	2.13	75118.16	223364.9	148246.8
N	1332	1332	1332	1332	1332
p-values:					
$T1_{2017} = T2_{2017}$	0.635	0.635	0.260	0.669	0.863
$T1_{2018} = T2_{2018}$	0.445	0.449	0.506	0.642	0.905
$T1_{2017} = T1_{2018}$	0.223	0.223	0.593	0.263	0.488
$T2_{2017} = T2_{2018}$	0.152	0.152	0.523	0.293	0.567

[1]Estimates with no baseline control variable

Table A15: Treated farmers' stated constraints associated with the use of site-specific fertilizer recommendations

Constraints	Share of farmers (%)		
	T1 & T2	T1	T2
2017 treatment			
High cost of fertilizer	53.1	46.9	60.4
Lack of trust/confidence in the recommendations	34.3	34.4	34.2
Fertilizer unavailability when needed	7.9	7.0	9.0
Poor knowledge/understanding of the details of the recommendations	15.9	18.0	13.5
Poor quality of fertilizer available in the market	3.8	4.7	2.7
Others	5.4	4.7	6.3
2018 treatment			
High cost of fertilizer	47.7	47.7	47.8
Lack of trust/confidence in the recommendations	16.8	22.1	10.1
Fertilizer unavailability when needed	15.5	8.1	24.6
Poor knowledge/understanding of the details of the recommendations	11.6	5.8	18.8
Poor quality of fertilizer available in the market	1.3	1.2	1.4
Others	38.7	44.2	31.9
2017 & 2018 treatments			
High cost of fertilizer	51.0	47.2	55.6
Lack of trust/confidence in the recommendations	27.4	29.4	25.0
Fertilizer unavailability when needed	10.9	7.5	15.0
Poor knowledge/understanding of the details of the recommendations	14.2	13.1	15.6
Poor quality of fertilizer available in the market	2.8	3.3	2.2
Others	18.5	20.6	16.1

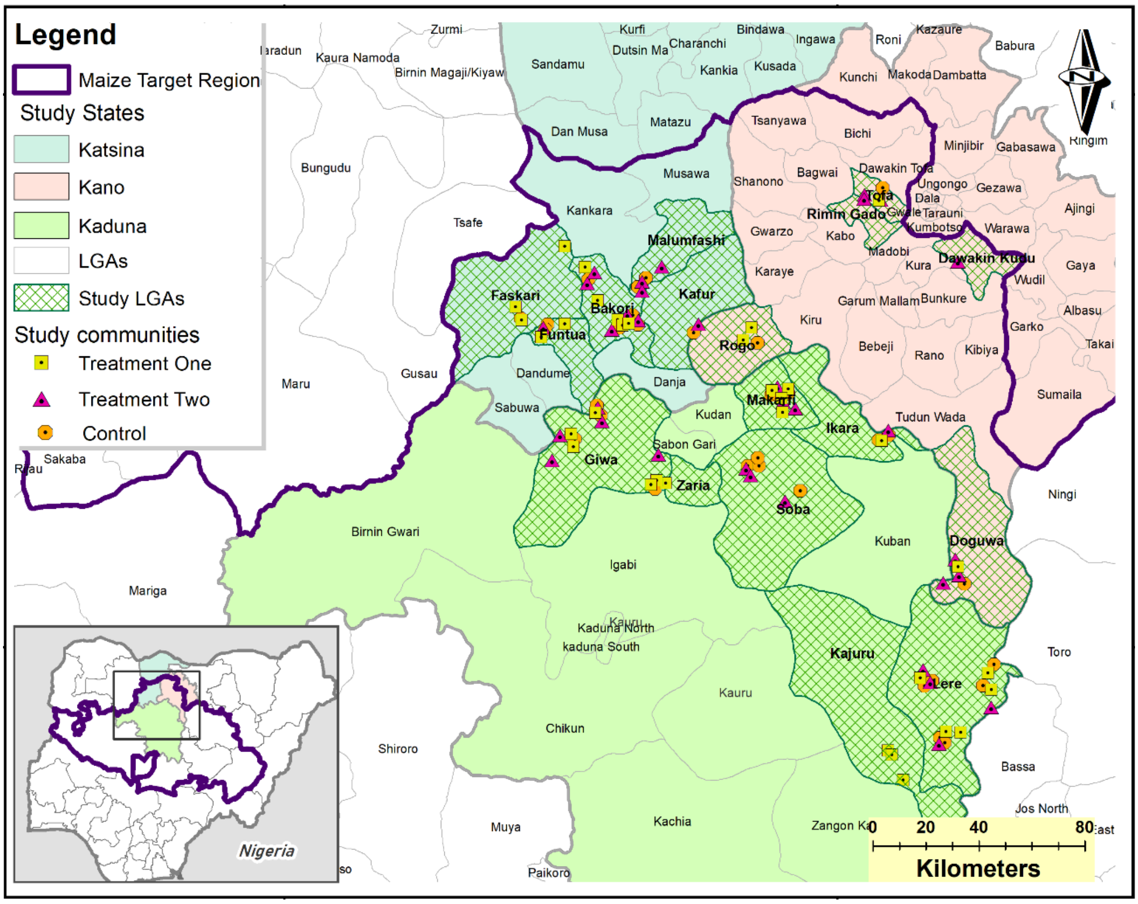

Fig. A1: Map of the research area showing the treatment (T1 and T2) and control villages

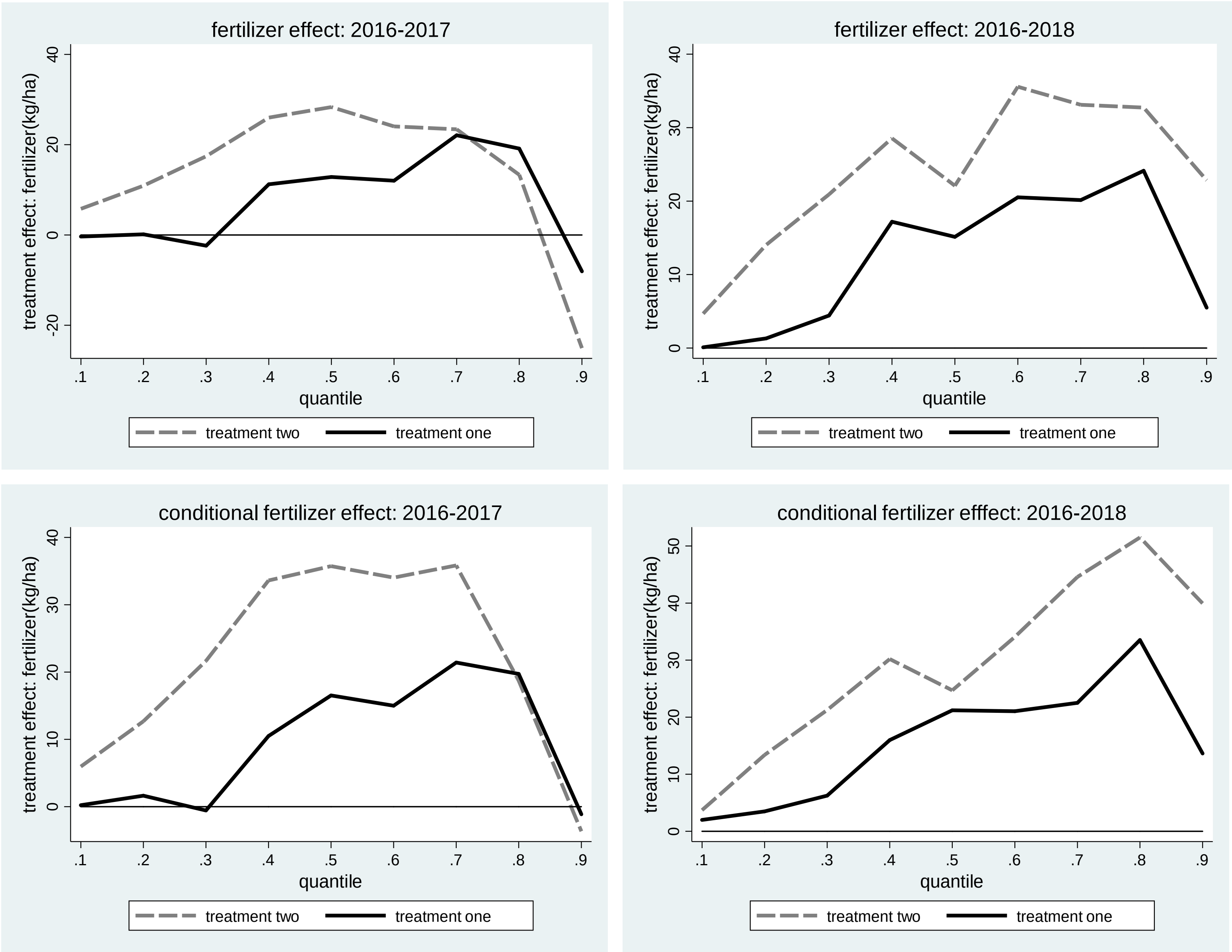

Fig. A2: Quantile treatment effects on unconditional and conditional fertilizer application rates

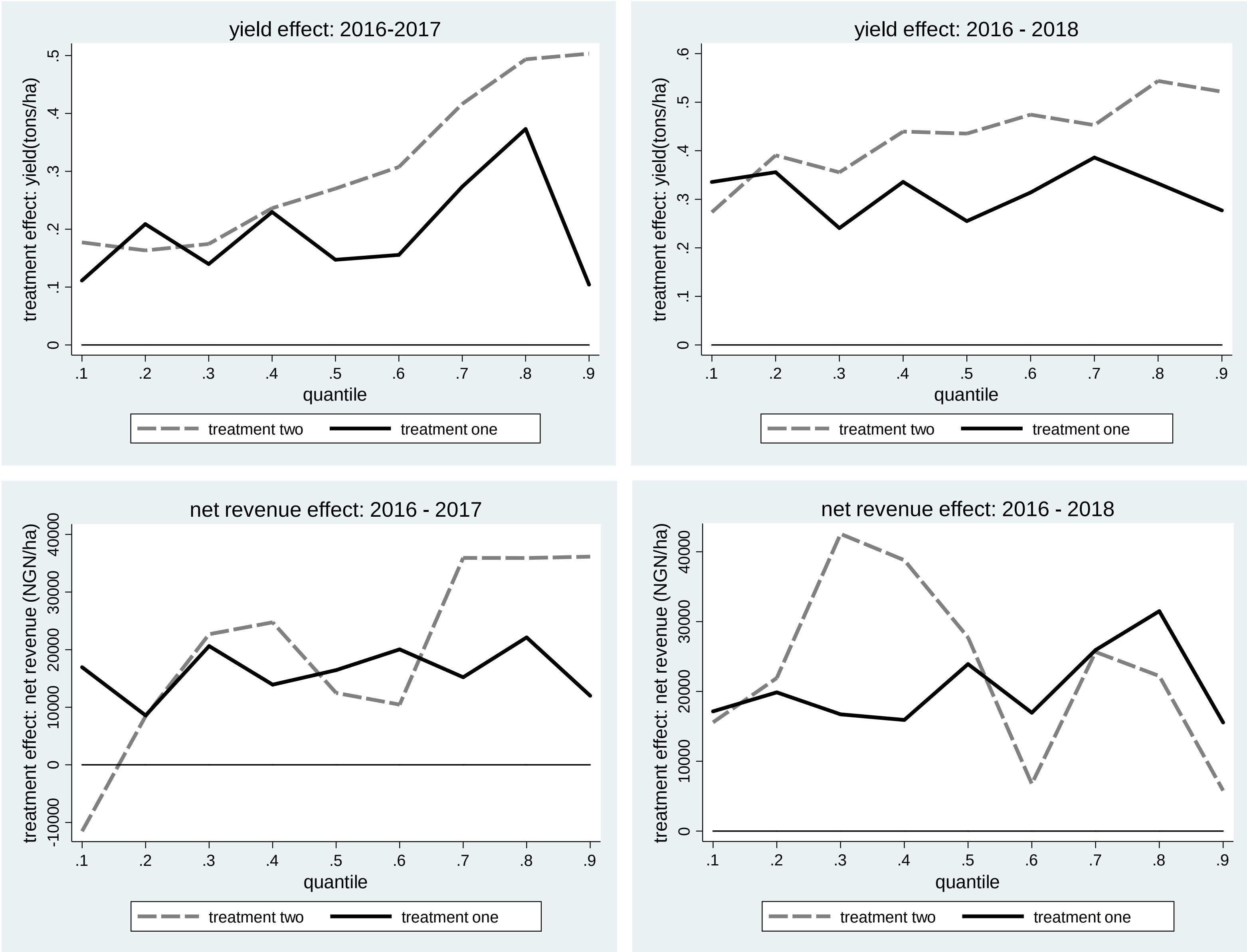

Fig. A3: Quantile treatment effects on maize yield and net revenue

Chapter 5

General Discussion and Conclusion

The focus of this PhD thesis on Nigeria, specifically northern Nigeria, on maize and on ICT-enabled agricultural extension is important for several reasons. First, Nigeria has the largest number of extreme poor and out-of-school children in the world, and a large number of hungry people – is among the eight countries who suffer high levels of acute hunger. More importantly, northern Nigeria accounts for a larger share of these developmental challenges amidst a high population pressure, a rising food demand and a declining per capita land. Productivity growth in agriculture can substantially contribute to address the challenges because a larger share of the rural population depends on agriculture, directly and/or indirectly. Yet, agricultural productivity is on average low, which may be connected with low adoption of external inputs and improved crop management practices. Despite, the large body of theoretical and empirical studies that try to explain agricultural technology adoption in the area and in SSA in general, the literature is yet to adequately reveal why adoption of potentially relevant technologies is still low.

Second, maize is the most important staple food crop in northern Nigeria, and a source of income for smallholder farmers in light of its increasing industrial demand. Yet, its yield on farmers' fields has remained low – around 1 to 2 tons/ha despite the potential for high yield of over 7 tons/ha. Depletion of soil fertility associated with low and inappropriate use of nutrients is a primary biophysical factor that strongly contributes to low maize yield. While intensifying the use of fertilizer is necessary in the area because the use of fallow system to replenish soil fertility is limited resulting to a continuous cropping system, its use is still low. Information constraints may contribute to explain in part the limited use of fertilizer to offset the declining soil fertility, and in turn the returns to fertilizer investment. Intensifying fertilizer use in maize production is based on the assumption of substantial marginal return to fertilizer investment, which is not always the case due to low and variable maize yield response to fertilizer. Good nutrient management can help to improve the yield response, which calls for better extension services.

Third, agricultural extension interventions are expected to produce positive outcomes but do not always result in the intended effects, which may be connected with the highly diverse smallholder farming systems in the area. Yet, the extension systems in the area still provide general fertilizer use recommendations, which do not account for the substantial variation in production conditions, such as soil quality and microclimate. In addition, the general fertilizer use recommendations do not provide additional information about variability of the expected fertilizer investment returns – associated with variation in climate and/or market conditions. Moving forward, these limitations in the extension systems need to be addressed, and a potential intervention in this regard is SSNM, which can play a crucial role in sustainable intensification of maize. In light of the rapid transformation in digital technologies in recent times, digital DSTs can be deplored in the extension system to allow of provision of SSNM advice.

There are specific research gaps in the existing theoretical and empirical literature on design, adoption and impact of DST-enabled site-specific extension services, and in the broader agricultural technology adoption literature related to fertilizer use in maize production. This PhD thesis focuses on a nutrient management DST for maize 'Nutrient Expert tool' in northern Nigeria, and addresses some of the research gaps.

1. Main findings

In the second chapter, I assess farmers' preferences for intensification of maize production supported by DST-enabled SSNM advice *ex-ante*, i.e. before introducing nutrient management DSTs for maize in the area. The findings show that farmers are in general favorably disposed to switch from general fertilizer use recommendations to DST-enabled SSNM recommendations. This suggests that farmers are aware that their production conditions are heterogeneous, and are open to site-specific extension advice that are better tailored to their crop-, site- and season-specific conditions, and enabled by digital technologies. Also, the findings show heterogeneity in preferences, and the observed preference patterns relate to farmers resource endowments and access to services. The findings show that a first group of farmers can be described as strong potential adopters of site-specific extension recommendations for more intensified maize production and a second group of farmers as weak potential adopters. The two groups of farmers are willing to accept some yield variability for a higher average yield, but this trade-off is on average larger for the first group. The findings imply that improving the design of advisory tools to enable provision of information on the riskiness of expected investment returns and flexibility in switching between low-input, -risk and -return and high-input, -risk, and -return recommendations will help farmers to make better informed input use decisions.

In the third chapter, the preferences of extension agents for the design of nutrient management DSTs for maize and their willingness to use the tools are analyzed *ex-ante*. The findings show that the extension agents generally prefer the use of DSTs for site-specific extension advice on nutrient management, which lends credence to the emerging policy interest in design of extension DSTs for maize in the area. The findings also show that they prefer a DST with a more user-friendly interface that requires less time to generate an output but that their preferences for other design features of DSTs are substantially heterogeneous. The findings also show two preference groups of extension agents. The first group includes the extension agents, who prioritize the attributes related to the effectiveness of the extension advice resulting from a DST, such as a more detailed and more accurate output. The second group includes the extension agents, who care more about practical features, such as the platform, the language and the user-friendliness of the interface. The differences in observed characteristics between the two groups are small, which implies that unobservable characteristics, such as motivation and ability, likely play a role in explaining preference heterogeneity. The findings imply that recognizing and accommodating preference differences may facilitate the take-up of DSTs by extension agents and thus enhance the scope for such tools to influence the farm investment decisions of farmers.

In chapter four, the causal effects of SSNM extension recommendations enabled by a DST, ‘Nutrient Expert tool’ on fertilizer use, management decisions and associated maize yield and revenue are analyzed. The findings show that SSNM extension recommendations bring about improvements in fertilizer management practices, yield and gross revenue after one-year treatment but not in fertilizer use for one of the extension treatments. This suggests that optimal fertilizer management practices can improve yield and revenue at current nutrient application by reducing technical inefficiencies associated with the use of sub-optimal fertilizer management practices. The findings also show that fertilizer use rates for one of the two extension treatments did not increase after one year, i.e. for T1 while for the other extension treatment, i.e. for T2, it increased but the estimated yield and revenue gains are quite similar for the two groups. This suggests that increase in fertilizer application rates can improve yield but the considerable increase by T2 over T1 does not result in substantial yield gains over T1, which may be connected to low yield responses to higher fertilizer levels. The findings also show that SSNM recommendations, combined with additional information on the distribution of expected returns, appears to induce more fertilizer use after one year and foster continued fertilizer investment after two years via reduction in farmers’ uncertainty about fertilizer investment outcomes. In addition, I show that there are only gradual increases in investment, fertilizer use, maize yield and especially net revenue after two years. Overall, the economic importance of the observed effects is rather modest.

Overall, the findings of the different chapters are closely related – deals with different aspects of nutrient management DSTs for maize, including the design and adoption potential, *ex-ante* and testing the effectiveness on-farm, *ex-post* and considers two key actors in the use of DSTs, farmers and extension agents. The findings point to favorable adoption potential of nutrient management DSTs for maize from the perspective of extension agents, and of extension advice from such DSTs from the perspective of farmers. The findings also point to the role of risk and uncertainty in the take-up of extension recommendations for intensification of maize production, *ex-ante* insights (chapter 2) and *ex-pos*t insights (chapter 4). In the same vein, the findings show that majority of extension agents are favorably disposed to offering a wide range of options or recommendation alternatives, which can potentially meet farmers demand for information on distribution of expected outcomes of recommendations (chapter 3). Despite the potentials of agronomic advisory DSTs in the literature, and also from the findings of chapters 2 and 3, the findings of chapter 4 show economically small but significant effects of the DST-enabled site-specific extension recommendations on intensification of maize production. A brief summary of some of the findings of chapter 4 is presented in Fig. 5.1.

Fig. 5.1: Treatment effects on fertilizer management practices, nutrient application rate (conditional estimates), maize yield, production cost and net revenue. Errors bars are 95% confidence intervals.

2. Policy implications

The findings of this PhD thesis have some important policy implications for agricultural research, development and extension, including digitalizing extension in developing countries. The first policy implication is related to the importance of variability or riskiness of expected investment returns to DST-enabled SSNM recommendations. Stimulating (continued) fertilizer investment is more effective if farmers are better informed about variability of expected fertilizer returns beyond the expected value (i.e. greater parameterization of returns likelihood) given the time lag between planting decisions and outcomes at harvest time. This implies that provision of information about the expected variability of economic returns stemming from seasonal variation in climate and market conditions may allow of better informed farm investment decisions of smallholder farmers. Yet, extension interventions and in particular advisory tools are designed to only provide information about average expected investment returns associated with agronomic recommendations. The direct implication of this for optimizing the design of digital agronomic advisory tools is that tool developers should strongly consider designing tools in a way that data on variation in rainfall and output price – climate and market uncertainty can be accommodated to better inform farmers about variability of expected investment returns. In a similar vein, optimizing the design of DSTs to allow of flexibility in switching between low-input, -risk and -return and high-input, -risk, and -return recommendations will help targeting of extension advice by risk taking ability of farmers.

The second policy implication is related to the fact that in the presence of substantial technical inefficiency, optimal fertilizer management practices can improve maize yields and revenue without an increase in fertilizer application rate by reducing the inefficiency. This implies that the entry point for traditional extension systems in trying to promote expanded use of fertilizer is to pursue widespread diffusion of information about optimal fertilizer management practices, such as the right fertilizer sources, the right timing of application and the right method of application. This will help to improve technical efficiency, returns at current fertilizer investment outlay and allow of immediate or gradual increase in fertilizer investments depending on whether cash constraint is binding. While most agronomic tools are promoted to allow of site-specific agronomic advice, the underlying mechanism for much of the observed impact seems to be through the optimal fertilizer use management practices, which are not necessarily site-specific issues. To this end, low-cost agronomic advisory tools that allow extension agents to learn about optimal fertilizer and crop management practices –

as learning tools, and thus to better advise farmers about management practices beyond advice on site-specific fertilizer rates can be more beneficial for extension agents and farmers. In this way, extension agents can leverage advisory tools for self-study to improve their capacity, and be in a better position to properly inform farmers about fertilizer management practices in detail – both site- and non-specific aspects. The idea of using DSTs as leaning tools has been slightly highlighted in the literature (e.g. Evans et al., 2017; Lundstrom and Lindlbom, 2018).

The third policy implication is related to the effectiveness of DST-enabled SSNM recommendations in improving fertilizer use but with no substantial impact on yields and gross revenue while net revenue only emerges gradually. On the one hand, a low yield response to fertilizer can play a crucial role in this, and have been highlighted in empirical fertilizer use literature (e.g. Marenya and Barrett, 2009; Xu et al., 2009; Liverpool-Tasie et al., 2017; Burke et al., 2017, 2019). This implies that policy interventions to stimulate expanded use of fertilizer to drive intensification of staple food crops, such as maize without associated efforts aimed at improving yield response to fertilizer may only produce limited impact – low fertilizer use and returns. A focus on improving nutrient use efficiency can help to improve returns to higher fertilizer levels and encourage sustainable fertilizer use. This may require a shift from emphasis on fertilizer alone to broader nutrient and non-nutrient management practices, such as variety type, timeliness of planting, planting density, weeding, etc. (Otsuka and Muraoka, 2017; Jayne et al., 2018, 2019; ten Berge et al., 2019). For instance, the use of a sub-optimal planting density can substantially lower nutrient use efficiency as demonstrated by Xu et al. (2017)[24]. Therefore, a more holistic approach that involves a strong focus on both socioeconomic, soil- and non-soil agronomic considerations in fertilizer use can be more rewarding for farmers. On the other hand, a better understanding of the impact of DST-enabled SSNM recommendations will require a longer-term research while accounting for the role of low and variable yield response, which will allow of a stronger support for massive investment in scaling the use of nutrient management DSTs.

The fourth policy implication is related to the fact that extension agents in general prefer digital agronomic advisory tools with a more user-friendly interface that require less time to generate an output but have substantial heterogeneous preferences for other design

[24] This line of thought contributed in informing the development of a tool 'Maize-Seed-Area App' by the TAMASA project to support the provison of farm-specific agronomic advice on optimal planting density, and the tool was piloted in Kenya in 2018.

features. This implies that optimization of a DST regarding interface ease-of-use and time effort should be given strong attention while also accommodating other preference differences to allow a good balance of content- and convenience-related features. This is important for user-centered design of DSTs to induce the adoption and the sustained use of such DSTs by extension agents, and in turn enhance the provision of targeted extension advice at scale. This may help to address the low use of DSTs at scale reported in some studies (Hochman and Carberry, 2011; Ravier et al., 2016; Rose et al., 2016). In practice, optimizing the design of DSTs to facilitate better targeting will require more work and engagement of extension agents in testing alternative interfaces, e.g. variants of color-text-image combinations, and platforms, such as mobile- and web apps, excel- and ODK-based interfaces as well as other practical features of a DST. The engagement of extension agents is required in testing DST information sets with varying levels of detail in the output to optimize a DST. In addition, for the subgroup of extension agents who are appear to care less about the quality of extension messages from a DST. This implies that beyond the practical features of DSTs, such extension agents should be well disposed to effectiveness-related features of DSTs and in turn, to provision of higher-quality extension advice. Improved capacity building for extension agents may play a role in this (Makate and Makate, 2019).

The fifth policy implication is related to the fact that the use of most agronomic advisory tools, such as Nutrient Expert tool requires a face-to-face contact of an extension agent with a farmer, which may have contributed to the observed impact of the nutrient management advice. Such one-on-one interaction can be very effective but not cost-effective (Lambrecht et al., 2014). It may limit impact at scale, as a lot of farmers may not have access to DST-enabled extension advice due to poor extension coverage, i.e. low agent-farmer ratio of about 1:5000-10000 in Nigeria (Ande et al., 2017; Davis and Spielman, 2017). This implies that agronomic advisory tools that require one-to-one interaction may face scalability constraints. The rising policy interest on increasing investment in development of agronomic advisory tools should only complement investment in traditional extension systems and not be considered as substitute for it. Moving forward, low-cost options should be explored, including the use of agro-dealers, contact farmers, farmer group officials, etc. for scaling advisory services using DSTs. The latter have to be competent to avoid misinforming farmers. In addition, the provision of SSNM recommendations without the need for a face-to-face contact can be explored by leveraging the use of mobile phones to facilitate communication between agent and farmer – via phone calls, SMS, IVR, and allow of a wider reach. This is often the premise for promoting the use of digital tools in providing agronomic advice at scale without a one-on-one contact. Yet, this will require making more realistic approximations about certain input data for Nutrient Expert tool, such as plot size that should be measured by an extension agent, and may not allow farmers to adequately engage with an extension agent. Alternatively, a fee-for-service extension model, i.e. a market-led extension approach, where private extension service providers make available one-on-one tailored advisory services to farmers for a fee may be explored in the research area. Yet, the latter may not be beneficial to highly resource-poor farmers (Anderson and Feder, 2007; Davis, 2008).

The sixth implication is related to the impressive adoption potential of nutrient management DSTs for maize from the perspective of extension agents, and of extension advice from such DSTs from the perspective of farmers. This supports the transition from general to digitally-supported site-specific extension services in the maize belt of Nigeria. In a broader sense, it lends credence to the emerging interest on how to leverage recent digital transformation in improving provision of advisory and related agricultural services, such as credit and insurance in developing countries (Janssen et al., 2017; Verma and Sinha, 2018). This calls for more public policy interventions, particularly digital inclusion policies to close the digital gap in the traditional extension systems and allow of improved efficiency of extension services in lifting information constraints and supporting the process of agricultural intensification.

Lastly, from a public policy perspective, this thesis carefully reflects on the economically small impact of SSNM extension recommendations mediated by DSTs. The small impact that I find may create some doubt about the potentials of nutrient management advisory tools in contributing substantially to maize intensification, and in turn to addressing the key development challenges of SSA – hunger and extreme poverty. The limited fertilizer use effects of the DST-enabled SSNM recommendations may also be connected with high acquisition cost of fertilizer and the role of binding cash or credit constraints. While I explicitly address the role of information constraints, alternative policy interventions may consider provision of SSNM advice with a complementary intervention to relax cash constraint, which may induce immediate and sustained expansion in fertilizer use and associated yield and revenue, but this remains an open question. In addition, since farmers likely face multiple constraints, policy interventions that address multiple constraints –

provision of SSNM advice combined with well-targeted input subsidy and/or insurance, etc. can be explored as a potential way to achieve economically large impact but this remains an empirical question. Overall, all these will require rigorous testing of the cost-effectiveness of alternative policy interventions, and are areas for further research. In a broader perspective, i.e. looking at the observed effects, such as the fertilizer increasing effect of 26 kg nutrient per ha after two years relative to the application of less than 20 kg nutrients per ha of arable land in Nigeria and SSA in general for over a decade, the short-term effects are quite worthwhile. In this sense, a slow and steady increase in net revenue may allow further increase in fertilizer investment and returns to support intensification of maize and improvement in farmer welfare. While it is likely more effective to target SSNM advice at the plot level, as reported in this thesis, it may not be practically feasible to provide crop-, plot- and season-specific SSNM advice to every farmer in light of the limitations (e.g. shortage of manpower) of the traditional extension systems. Alternatively, targeting of nutrient management advice may be considered at a level above the plot level – e.g. recommendations at the village level or for a group of farmers that share similar production conditions within a village. This is more feasible especially for non-site specific aspects of the recommendations and given the possibility of positive spill-over effects. Yet, this is only suggestive and open to further research.

3. Research contributions

This thesis makes several contributions to the scientific literature. First, it adds to the extant literature on agricultural technology adoption choices, particularly in relation to soil fertility management and intensification of staple food crops, such as maize in SSA. A large body of *ex-post* studies has explained farmers' adoption of intensification technologies, such as inorganic fertilizer, soil- and non-soil management practices, etc. in relation to farm(er) characteristics (Chianu and Tsuji, 2005; Sanni and Droppler, 2007; Lambrecht et al., 2014; Mponela et al., 2016; Morello et al., 2018). Few studies have taken a different approach, which is to assess the technology adoption choices of farmers *ex ante* by explicitly taking into account the specific technology traits (Lambrecht et al., 2015; Dalemans et al., 2018; Gamboa et al., 2018; Tarfasa et al., 2018). So far, no study has specifically analyzed farmers' preferences for maize intensification in the context of DST-enabled site-specific extension services *ex ante* in SSA. Using data from a CE among farmers, this thesis adds to the literature by providing empirical evidence on how farmers trade off specific attributes of a high-input, -output, -investment and -risk maize production system supported by site-specific extension in the design stage of a nutrient management DST for maize. The results show that in general farmers are favorably disposed to the adoption of nutrient management extension advice from DSTs to support intensification of maize, but with substantial heterogeneous preferences related to their resource endowments and access to services. More resource-endowed and less risk-averse farmers are more willing to invest in maize intensification in response to sit-specific extension advice.

Second, this thesis adds to the emerging literature on digitalizing agricultural extension services, particularly in the design of nutrient management advisory tools for maize in SSA. Several studies have documented the potentials of the rising digital revolution in transformation of extension services and agricultural systems in general (e.g. Aker et al., 2011; Nakasone et al., 2014; Beuermann, 2015; Aker and Ksoll, 2016; Janssen et al., 2017; Verma and Sinha, 2018; Camacho and Conover, 2019). Yet, empirical literature in the design of digital DSTs for locally-tailored extension is rather scant and most of the literature is based on case studies of DSTs in developed country settings (Kragt and Llewellyn, 2014; Small et al., 2015; Lacoste and Powles, 2016; Lundstrom et al., 2017; Oliver et al., 2017; Rose et al., 2016, 2018). In addition, with the exception of Kragt and Llewellyn (2014) none of the previous studies documented the preferences of extension agents for the design of agronomic advisory DSTs in an *ex-ante* quantitative fashion. This thesis builds on the existing literature by providing empirical evidence on the preferences of extension agents for the design features of nutrient management DSTs for maize using data from a CE among extension agents in Nigeria. In this way, this thesis provides *ex ante* insights on the potential uptake of DSTs, the practical and the content-related features of DSTs that are more (less) appealing, and the preference heterogeneity for such design features. As adoption of DSTs is relatively low despite their potential benefits, *ex ante* insights can help to optimize the design of DSTs and potentially stimulate uptake and sustained adoption of such tools.

Third, this thesis contributes to the literature on agricultural extension in relation to SSNM paradigm and intensification of maize under widely varying production conditions in SSA. Some authors argue that general fertilizer use recommendations do not account for spatio-temporal diversity in biophysical and socioeconomic conditions of smallholder farmers, and may result in sub-optimal fertilizer use (Vanlauwe et al., 2015b; Kihara et al., 2016a; Njoroge et al., 2017; MacCarthy et al., 2018). Others show that the use of SSNM can bring about substantial improvement in nutrient use efficiency and returns, and also reduce negative environmental impact, but such findings are from researcher-managed trial conditions, and mainly in Asia (Dobermann et al., 2002; Pampolino et al., 2007; Xu et al., 2014; Buresh et al., 2019). These may not reflect real-world farm settings, where conditions are quite different, and farmers have full control over their resource allocations and management decisions (Barrett et al., 2004; Duflo et al., 2008; Beaman et al., 2013; Vandercasteelen et al., 2018; Jayne et al., 2019; Macours, 2019). Empirical findings on smallholder farmers' fertilizer investment decisions and returns in SSA do not consider the potential role of general extension recommendations on fertilizer use in the traditional extension systems. These findings are from non-experimental studies (e.g. Marenya and Barrett, 2009; Ragasa and Chapoto, 2017; Koussoube and Nauges, 2017; Liverpool-Tasie et al., 2017; Burke et al., 2017; Theriault et al., 2018), and experimental studies (e.g. Duflo et al., 2008; Beaman et al., 2013; Harou et al., 2017). This thesis adds to the existing literature by providing empirical evidence on impact of DST-enabled SSNM advice to reveal the role of information constraint, i.e. what part general fertilizer use recommendations play in explaining the on average low use of fertilizer and returns in SSA. This thesis relies on data from an RCT, and specifically provides a conceptual model to explain the underlying mechanisms for expected immediate and longer-term effects – changes in fertilizer investment, management decisions and returns in response to SSNM advice. The results show that provision of SSNM extension recommendations results in small but statistically significant increases in fertilizer investment and related management practices, as well as the associated yield and gross revenue. Also, the results show that there are only gradual increases in the outcomes, particularly net revenue, and the observed yield and revenue increasing effects are mainly driven by optimal fertilizer management practices.

Fourth, this thesis contributes to the theoretical and empirical literature on agricultural technology adoption under uncertainty and the pivotal role of information on this in developing countries. Previous studies argue that farmers are more likely to give up productivity gains for stability in returns to investments, and also may be unwilling to adopt or may delay adoption in the face of uncertainty about the expected returns (e.g. Feder et al., 1985; Asrat et al., 2010; Dercon and Christiaensen, 2011; Musaka, 2018; Oliva et al., 2019). Some advocate that acquisition of information about the use of a technology, especially via learning-by-doing can reduce uncertainty about the expected outcomes, and enhance adoption decisions (e.g. Just and Zilberman, 1983; Feder and Umali, 1993; Saha et al., 1994; Marra et al., 2003; Koundouri et al., 2006; Abdulai et al., 2008; Genius et al., 2014). None of these studies looked at how relaxing uncertainty about expected returns to high fertilizer levels affects investment decisions – whether to intensify fertilizer use and/or whether to continue to use higher fertilizer levels despite the sunk cost. This thesis builds on the literature by providing empirical evidence on how provision of information about the variability of expected fertilizer investment returns stemming from variation in market (output price) conditions influences the take-up and sustained use of fertilizer recommendations. In addition, this thesis provides a theoretical model to explain the causal pathways. Using data from an RCT, the results show that provision of SSNM recommendations combined with information about the variability of expected investment returns increases fertilizer use after one year and motivates the continued use of fertilizer after two years. In addition, the results show that the observed fertilizer increasing effects are statistically significant but economically small, and do not result in substantial yield and revenue increasing effects over farmers who did not have access to information about uncertainty in expected fertilizer investment returns.

4. Strengths and weaknesses

The novelty in this PhD thesis lies in its focus on ICT-enabled advisory tools in an era where digitalization of extension is gaining policy interest in developing countries, on a crop notable for food security in SSA – maize and on a key factor that limits crop productivity in SSA – depletion of soil fertility. Although, there is a large body of agronomic and socioeconomic studies on soil fertility management and extension services in SSA (e.g. Vanlauwe et al., 2015a, Lambrecht et al., 2016a, 2016b; ten Berge et al., 2019; Burke et al., 2019), the focus of most of them is not related to digital innovations for nutrient management to improve the efficiency of traditional extension systems. Given the highly diverse farming conditions in SSA, and the rapid digital transformation in recent years, there is increasing interest in the use of digital advisory tools to adapt agronomic advice to site-specific conditions of individual farmers. Yet, empirical literature on design, adoption and impact of agronomic advisory tools is thin, particularly in relation to nutrient management for maize. This thesis uses data from smallholder farmers and extension agents in the maize belt of northern Nigeria to build on the nascent literature on emerging digital advisory tools for farmers in developing countries and SSA in particular.

From a methodological point of view, this PhD thesis makes several contributions. First, this thesis relies on a large and unique database, including primary data from a sample of 792 farmers and 320 extension agents, and panel data from three household survey rounds. Second, I implement a CE among farmers to analyze their preferences for tailored extension advice from nutrient management DSTs. I also implement a CE among extension agents to assess their preferences for the design of nutrient management DSTs. The use of CE in this thesis allows us to provide *ex ante* insights on adoption potential and optimizing the design of nutrient management DSTs from the perspectives of farmers and extension agents. The application of CE to study farmers' technology adoption choices in an *ex ante* quantitative way to better inform agricultural research and development initiatives is becoming popular in agricultural economics (e.g. Mahadevan and Asafu-Adjaye, 2015; Lambrecht et al., 2015; Kassie et al., 2017). However, the use of CE among extension agents to inform extension initiatives is very limited. In fact, no published study has applied CE among extension agents except for Kragt and Llewellyn (2014) but for a weed management DST and in a developed country setting. The use of CE in this thesis, especially among extension agents should inspire other extension-related studies to consider applying CEs among extension agents beyond the conventional use of CEs for farmers and consumers in agricultural economics.

Third, I implement an RCT to allow of consistent estimates of the causal effects of SSNM extension interventions with and without complementary information about variability of expected investment returns to uptake of the SSNM recommendations. Using an RCT in this thesis, I am able to overcome the identification challenge in impact evaluation, which arises from self-selection or unobserved farm(er) heterogeneity, and often poses a threat to internal validity of observational or non-experimental studies. This allows us to control for confounding effects of farm- and farmer-specific characteristics, and precisely attribute the observed effects to the extension interventions. This thesis contributes to the growing impact evaluation literature on the application of RCTs, especially in development economics to establish causal effects of soil fertility-related interventions (e.g. Duflo et al., 2008; Beaman et al., 2013) and ICT-enabled information interventions (e.g. Fu and Akter, 2016; Larochelle et al., 2019).

Fourth, I rely on multiple rounds of post-intervention data to estimate causal effects, which is an advancement in comparison with most agriculture-related randomized evaluations that use a single post-intervention round (c.f. Beaman et al., 2013; Bulte et al., 2014; de Brauw et al., 2018; Vandercasteelen et al., 2018; Abate et al., 2018; Hossain et al., 2019; Omotilewa et al., 2019). In this regard, we are able to observe effects (e.g. yield effect) under different weather realizations over time, and to show whether the treatment effects persist over time. In addition, I administer the extension interventions in two years – 2017 and 2018 maize production seasons. Overall, the set-up of the RCT allows us to estimate immediate effects (after one-year treatment) and more gradual or longer-term effects (after two-year treatment) of the SSNM extension recommendations.

Fifth, I use different econometric models to explicitly take into account both scale heterogeneity and attribute non-attendance (ANA), which are potential sources of bias in CE studies. I estimate scale-adjusted latent class model to account for scale heterogeneity, and also estimate two models to account for ANA, i.e. conventional and validation stated ANA models. This is an improvement over previous CE studies that address only one of these issues (e.g. Kragt, 2013; Coffie et al., 2016; Dalemans et al., 2018; Campbell et al., 2018; Caputo et al., 2018), and several others that do not consider any of these issues (e.g. Asrat et al., 2010; Jaeck and Lifran, 2014; Mahadevan and Asafu-Adjaye, 2015; Lambrecht et al., 2015; Van den Broeck et al., 2017; Tarfasa et al., 2018). In general, our results are consistent across all the estimated models, which suggest that any possible bias from scale and ANA issues is relatively small. Yet, this may not always be the case for other studies that do not account for these issues.

Sixth, I consider heterogeneous effects in this thesis beyond average effects to allow better insights about the estimated effects. In chapter 2, I use latent class model to analyze heterogeneity in farmers' preferences for maize intensification in the context of site-specific extension advice. I also analyze heterogeneous preferences of extension agents for the design of nutrient management DST using mixed logit and latent class models in chapter 3. The estimation of heterogeneous preferences in chapters 2 and 3 allows for better insights that can help to optimize the design of nutrient management DSTs and of tailored extension advice for farmers. In addition, it can allow of better targeting of specific subgroups of farmers and extension agents, and in turn potentially improve uptake and impacts of DSTs in service delivery to farmers. In chapter 4, I use quantile regressions to analyze heterogeneity in treatment effects across the outcome distribution for continuous outcome variables, i.e. fertilizer application rate, maize yield and net revenue. This provides additional information about the observed effects of SSNM extension recommendations by showing the effects at different quantiles of the outcome distribution, and whether the effects are systematically concentrated in the lower or upper tails of the outcome distribution. This adds to the empirical agriculture-related RCT studies that estimate quantile regressions to explore heterogeneous effects (e.g. Vandercasteelen et al., 2018; Hossain et al., 2019). Also, I estimate inter-temporal heterogeneity in the observed effects of SSNM extension recommendations. This provides additional insights on whether the observed impacts of the extension interventions are stable over time, i.e. further insights about inter-temporal external validity as explained in Rosenzweig and Udry (2019).

Seventh, I employ more rigorous empirical estimation in analyzing the impact of SSNM extension recommendations as robustness checks in chapter four. I estimate Lee (2009) bounds estimator as robustness check for potential attrition bias, and the results show that all point estimates of the outcomes of interest lie within the lower and upper bounds, which suggests that the observed treatment effects are robust to attrition bias. I perform statistical hypothesis testing using the increasingly recommended randomization inference *p*-values as a robustness check to conventional (sampling-based) inference *p*-values (Bruhn and McKenzie, 2009; Athey and Imbens, 2017, Heß, 2017; Young, 2019). The tests using randomization inference *p*-values are consistent with those of the conventional inference *p*-values, which implies that the observed treatment effects are robust to the number of clusters or observations at hand and are unlikely due to chance. I perform corrections for multiple hypotheses testing using False Discovery Rate (FDR) sharpened *q*-values to control for the proportion of false treatment effects due to multiple outcomes and treatments in the RCT implemented in this thesis (Anderson, 2008). The FDR *q*-values show that all the observed treatment effects are robust to accounting for multiple hypotheses tests.

I end this sub-section by highlighting some limitations of this thesis and prospects for further research. Although this PhD thesis has made some relevant contributions to different strands of literature, it has some shortcomings, which entails general and specific limitations. The general limitation stems from the fact that this thesis is based on one case study, comprising of farmers and extension agents in the maize belt of northern Nigeria, specifically to Kaduna, Kano and Katsina States. While the narrow focus on this case study allows for an in-depth analysis, it can limit generalization of the findings of this thesis to other parts of Nigeria and SSA, especially in relation to external validity of the impact of SSNM advice. This is despite the fact that I use a spatial sampling framework to allow spatially representative maize-based areas, and to improve external validity of the findings of the RCT. Therefore, further research can consider expanding the coverage to include other states and regions in Nigeria, as well as other parts of SSA to make additional contribution to the literature. The specific limitations of this thesis are as follows.

First, in chapter 2, I do not account for the quality of inputs in the design of the CE, which may have contributed to the observed positive preference for a higher fertilizer and seed cost attribute by a subgroup of farmers. This is because of a possible intuitive association farmers make between cost attribute and quality of inputs while eliciting their choices during the CE implementation. This is in line with empirical CE studies (Lambrecht et al., 2015; Palma et al., 2016), who note that such a positive preference for a higher cost can indicate a cue for quality in choice modeling. This suggests that future CE studies should consider inclusion of quality of inputs as a separate attribute to control for this, and allow of stronger claim about farmers preferences for technology traits and trade-offs in relation to input price attribute. While I make an attempt to account for attribute non-attendance (ANA) in chapters 2 and 3 using serial stated ANA models, the results show that the respondents did not completely ignore some of the attributes self-reported as ignored. This suggests that some respondents assign a lower weight to the attributes self-reported as ignored and/or may be due to measurement errors, which is the major limitation of stated ANA approach (Hess and Hensher, 2010; Scarpa et al., 2013; Caputo et al., 2018). While there is no consensus in the CE literature on how best to account for ANA *ex-post*, more agricultural economics research in developing country contexts may explore other approaches, such as choice task stated ANA, inferred ANA and eye tracking.

Second, in chapter 4, provision of information on variability of expected economic returns to fertilizer investment to treatment two farmers in the RCT was captured by seasonal maize price variation without inclusion of climate-induced yield variation. As expected, farmers may face uncertainty about expected yield variability when applying new practices or expanding input use, especially due to the rainfed nature of agriculture in SSA. I made effort to include information on variability of yields as determined by different possible weather realizations but could not accommodate spatially explicit data on rainfall variation (as proxy for weather conditions) in defining the distribution of expected yields in the present design of Nutrient Expert tool. This is a possible area for improving Nutrient Expert tool, and an area worth considering in the design of other agronomic DSTs to allow of estimating uncertainty in investment returns from both variations in climate and market conditions. In practice, this will require high quality geospatial datasets. While I use three-period panel data to estimate the immediate and longer-term effects of SSNM extension recommendations, a research with longer periods is necessary to really understand the impact of the interventions, and allow of stronger claim to support up-scaling of nutrient management DSTs. More research may be needed to provide additional long term impact and cover welfare variables, such as poverty, food and nutrition security. While I explicitly consider the 'right rate' as one of the 4Rs of nutrient stewardship, the site-specific fertilizer rate is limited to primary macronutrients and did not consider the possible role of secondary macro- and micronutrients deficiencies. In addition, the role of substandard fertilizer may be important in explaining the observed yield responses following the empirical findings of Bold et al. (2017) in Uganda. I did not measure the quality of fertilizer applied by farmers, which may allow of stronger conclusion on the role of fertilizer quality in fertilizer investments and returns to SSNM. More research may help to clarify these issues.

Lastly, I estimate only direct effects, including fertilizer investment, management decisions and associated maize yield and revenue in response to the SSNM recommendations. However, there are possible indirect effects drawing from agronomic literature about SSNM (e.g. Dobermann et al., 2002; Pampolino et al., 2007; Satyanarayana et al., 2011; Xu et al., 2014; Sapkota et al., 2014; Banayo et al., 2018). Such indirect effects include environmental benefits stemming from the notion of balanced nutrient application that underpin SSNM paradigm, which forms the basis for its potential in reducing soil nutrient mining and nutrient losses to the environment. In practice and under farmers' conditions and management, this remains an open question for further research to empirically test whether and to what extent SSNM advice can really reduce negative environmental externalities associated with input intensification in maize. This is in line with Stevenson et al. (2019) and Macours (2019) who note that consideration of environmental outcomes of interventions beyond yield and income gains is important to better understand the effectiveness of agricultural interventions.

References

Abay, K. A., Berhane, G., Taffesse, A. S., Abay, K. & Koru, B. (2018). Estimating input complementarities with unobserved heterogeneity: Evidence from Ethiopia. *Journal of Agricultural Economics*, 69, 495-517.

Abdoulaye, T. & Sanders, J.H. (2005). Stages and determinants of fertilizer use in semiarid African agriculture: The Niger experience. *Agricultural Economics*, 32, 167-179.

Abdoulaye, T., Wossen, T. & Awotide, B. (2018). Impacts of improved maize varieties in Nigeria: Ex-post assessment of productivity and welfare outcomes. *Food Security*, 10, 369-379.

Abdulai, A., Monnin, P. & Gerbere, J. (2008). Joint estimation of information acquisition and adoption of new technologies under uncertainty. *Journal of International Development*, 20, 437-451.

Adebayo, K., Babu, S.C., Sanusi, R. & Sofola, M. (2015). Private sector participation in agricultural extension for cocoa farming in Nigeria: The case of multi-trex integrated foods. In Y. Zhou & S.C. Babu (Eds.), *Public policy and global development, knowledge driven development* (pp. 141-162). Academic Press.

Aker, J. (2011). Dial "A" for agriculture: Using ICTs for agricultural extension in developing countries. *Agricultural Economics*, 42(6), 631-47.

Aker, J.C. & Ksoll, C. (2016). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy*, 60, 44-51.

Akinola, A.A., Alene, A.D., Adeyemo, R., Sanogo, D., Olanrewaju, A.S., Nwoke, C. & Nziguheba, G. (2010). Determinants of adoption and intensity of use of balance nutrient management systems technologies in the northern Guinea savanna of Nigeria. *Quarterly Journal of International Agriculture*, 49 (1), 25-45.

Akinola, A.A., Ayedun, B., Abubakar, M., Sheu, M. & Abdoulaye, T. (2015). Crop residue usage and its determinants in Kano State, Nigeria. *Journal of Development & Agricultural Economics*, 7(4), 162-173.

Akpa, I.C., Odeh, I.O.A., Bishop, T.F.A., Hartemink, A.E. & Amapu, I.Y. (2016). Total soil organic carbon and carbon sequestration potential in Nigeria. *Geoderma*, 271, 202-215.

Alemu, M.H., Mørkbak, M.R., Olsen, S.B. & Jensen, C.L. (2013). Attending to the reasons for attribute non-attendance in choice experiments. *Environmental & Resource Economics*, 54(3), 333-359.

Alwang, J., Gotor, E., Thiele, G., Hareau, G., Jaleta, M. & Chamberlin, J. (2019). Pathways from research on improved staple crop germplasm to poverty reduction for smallholder farmers. *Agricultural Systems*, 172, 16-27.

Amapu, I.Y., Chude, V.O. & Tarfa, B.D. (2018). Fertilizer recommendation for maize, sorghum, millet, cowpea, soybean and cotton in Nigeria. In A. Bationo et al. (Eds.), *Improving the profitability, sustainability and efficiency of nutrients through site specific fertilizer recommendations in West Africa agro-ecosystems* (pp. 221-240). Springer International Publishing.

Ande, O.T., Huising, J., Ojo, A.O., Azeez, J., Are, K.S. Olakojo, S.A., Fademi, I.O. & Ojeniyi, S.O. (2017). Status of integrated soil fertility management (ISFM) in southwestern Nigeria. *International Journal of Sustainable Agricultural Research*, 4(2), 28-44.

Anderson, J. & Feder, G. (2007). Agricultural extension. In R. Evenson & P. Pingali (Eds.), *Handbook of Agricultural Economics* (vol. 3, pp. 2343-2378).

Anderson, M.L. (2008). Multiple inference and gender differences in the effects of early intervention: A Reevaluation of the Abecedarian, Perry preschool, and early training projects. *Journal of the American Statistical Association*, 103(484), 1481-1495.

Antonopoulou, E., Karetsos, S., Maliappis, M. & Sideridis, A. (2010). Web and mobile technologies in a prototype DSS for major field crops. *Computers & Electronics in Agriculture*, 70, 292-301.

Arora, A., Bansal, S. & Ward, P.S. (2019). Do farmers' value rice varieties tolerant to droughts and floods? Evidence from a discrete choice experiment in Odisha, India. *Water Resources & Economics*, 25, 27-41.

Asfaw, A. & Admassie, A. (2004). The role of education on the adoption of chemical fertilizer under different socioeconomic environments in Ethiopia. *Agricultural Economics*, 30(3), 215-228.

Asrat, S., Yesuf, M., Carlsson, F. & Wale, E. (2010). Farmers' preferences for crop variety traits: Lessons for on-farm conservation and technology adoption. *Ecological Economics*, 69, 2394-2401.

Athey, S. & Imbens, G.W. (2017). The econometrics of randomized experiments. In A. V. Banerjee, & E. Duflo (Eds.), *Handbook of Economic Field Experiments* (vol. 1, pp. 73-140).

Baba, S.U. & van der Horst, D. (2018). Intrahousehold relations and environmental entitlements of land and livestock for women in rural Kano, northern Nigeria. *Environments*, 5(26), 1-19.

Badu-Apraku, B., Menkir, A., Ajala, S. O., Akinwale, R. O., Oyekunle, M. & Obeng-Antwi, K. (2011). Performance of tropical early maturing maize cultivars in multiple stress environments. *Canadian Journal of Plant Science*, 90, 831-852.

Badu-Apraku, B., Yallou, C.G. & Oyekunle, M. (2013). Genetic gains from selection for high grain yield and Striga resistance in early maturing maize cultivars of three breeding periods under Striga-infested and Striga-free environments. *Field Crops Research*, 147, 54-67.

Badu-Apraku, B., Talabi, A.O., Ifie, B.E., Chabi, Y., Obeng-Antwi, K., Haruna, A. & Asiedu, R. (2018). Gains in grain yield of extra-early maize during three breeding periods under drought and rain-fed conditions. *Crop Science*, 58(6), 2399-2412.

Baiyegunhi, L.J.S., Hassan, M.B. & Ortmann, G.F. (2018). Impact of integrated Striga management (ISM) technology on maize productivity in northern Nigeria: A treatment effect approach. *African Journal of Science, Technology, Innovation & Development*, 10(3), 335-344.

Bamire, A.S. & Manyong, V.M. (2003). Profitability of intensification technologies among smallholder maize farmers in the forest-savanna transition zone of Nigeria. *Agriculture, Ecosystems & Environment*, 100(2-3), 111-118.

Banayo, N.P.M.C, Haefele, S.M., Desamero, N.V. & Kato, Y. (2018). On-farm assessment of site-specific nutrient management for rainfed lowland rice in the Philippines. *Field Crops Research*, 220, 88-96.

Barrett, C. B., Moser, C. M., McHugh, O. V. & Barison, J. (2004). Better technology, better plots, or better farmers? Identifying changes in productivity and risk among Malagasy rice farmers. *American Journal of Agricultural Economics*, 86(4), 869-888.

Barrett, C.B. & Bevis, L.E.M. (2015). The self-reinforcing feedback between low soil fertility and chronic poverty. *Nature Geoscience*, 8, 907-912.

Barrett, C.B., Christiaensen, L., Sheahan, M. & Shimeles, A. (2017). On the structural transformation of rural Africa. *Journal of African Economies*, 26(1), 11-35.

Barrett, C.B., Christian, P. & Shimeles, A. (2018). The processes of structural transformation of African agriculture and rural spaces. *World Development*, 105, 283-285.

Beaman, L., Karlan, D., Thuysbaert, B. & Udry, C. (2013). Profitability of fertilizer: Experimental evidence from female rice farmers in Mali. *American Economic Review*, 103(3), 381-86.

Beaman, L. & Dillon, A. (2018). Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali. *Journal of Development Economics*, 133, 147-161.

Beck, M.J., Rose, J.M. & Hensher, D.A. (2013). Consistently inconsistent: The role of certainty, acceptability and scale in choice. *Transportation Research Part E*, 56, 81-93.

Benjamini, Y., Krieger, A. & Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, 93, 491-507.

Benson, T. & Mogues, T. (2018). Constraints in the fertilizer supply chain: Evidence for fertilizer policy development from three African countries. *Food Security*, 10(6), 1479-1500.

BenYishay, A. & Mobarak, A.M. (2019). Social learning and incentives for experimentation and communication. *The Review of Economic Studies*, 86(3), 976-1009.

Berazneva, J., McBride, L., Sheahan, M. & Güereña, D. (2018). Empirical assessment of subjective and objective soil fertility metrics in east Africa: Implications for researchers and policy makers. *World Development*, 105, 367-382.

Berazneva, J., Conrad, J.M., Güereña, D.T., Lehmann, J. & Woolf, D. (2019). Agricultural productivity and soil carbon dynamics: A bioeconomic model. *American Journal of Agricultural Economics*, 101 (4), 1021-1046.

Berkhout, E.D., Schipper, R.A., Van Keulen, H. & Coulibaly, O. (2011). Heterogeneity in farmers' production decisions and its impact on soil nutrient use: Results and implications from northern Nigeria. *Agricultural Systems*, 104(1), 63-74.

Bernet, T., Ortiz, O., Estrada, R.D., Quiroz, R. & Swinton, S.M. (2001). Tailoring agricultural extension to different production contexts: A user-friendly farm-household model to improve decision-making for participatory research. *Agricultural Systems*, 69(3), 183-198.

Beuermann, D.W. (2015). Information and communications technology, agricultural profitability and child labor in rural Peru. *Review of Development Economics*, 19(4), 988-1005.

Buehren, N., Goldstein, M., Molina, E. & Vaillant, J. (2019). The impact of strengthening agricultural extension services on women farmers: Evidence from Ethiopia. *Agricultural Economics*, 50, 407-419.

Binswanger-Mkhize, H.P., McCalla, A.F. & Patel, P. (2010). Structural transformation and African agriculture. *Global Journal of Emerging Market Economies*, 2(2), 113-152.

Binswanger-Mkhize, H.P. & Savastano, S. (2017). Agricultural intensification: The status in six African countries. *Food Policy*, 67, 26-40.

Bold, T., Kaizzi, K. C., Svensson, J. & Yanagizawa-Drott, D. (2017). Lemon technologies and adoption: Measurement, theory and evidence from agricultural markets in Uganda. *The Quarterly Journal of Economics*, 132, 1055-1100.

Botha, N., Turner, J. A., Fielke, S. & Klerkx, L. (2017). Using a co-innovation approach to support innovation and learning: Cross-cutting observations from different settings and emergent issues. *Outlook on Agriculture*, 46, 87-91.

Boxall, P.C. & Adamowicz, W.L. (2002). Understanding heterogeneous preferences in random utility models: A latent class approach. *Environmental Resource Economics*, 23, 421-446.

Breustedt, G., Müller-Scheeßel, J. & Latacz-Lomann, U. (2008). Forecasting the adoption of GM oilseed rape: Evidence from a discrete choice experiment in Germany. *Journal of Agricultural Economics*, 59, 237-256.

Bruhn, M. & McKenzie, D. (2009). In pursuit of balance: Randomization in practice in development field experiments. *American Economic Journal: Applied Economics*, 1(4), 200-232.

Bulte, E., Beekman, G., Di Falco, S., Hella, J. & Lei, P. (2014). Behavioral responses and the impact of new agricultural technologies: Evidence from a double-blind field experiment in Tanzania. *American Journal of Agricultural Economics*, 96(3), 813-830.

Buresh, R.J., Castillo, R.L., Torre, J.C.D., Laureles, E.V., Samson, M.I., Sinohin, P.J. & Guerra, M. (2019). Site-specific nutrient management for rice in the Philippines: Calculation of field-specific fertilizer requirements by Rice Crop Manager. *Field Crops Research*, 239, 56-70.

Burke, W.J., Jayne, T.S. & Black, T.J.R. (2017). Factors explaining the low and variable profitability of fertilizer application to maize in Zambia. *Agricultural Economics*, 48, 115-126.

Burke, W.J., Frossard, E., Kabwe, S. & Jayne, T.S. (2019). Understanding fertilizer adoption and effectiveness on maize in Zambia. *Food Policy*, 86, 101721.

Byerlee, D., de Janvry, A. & Sadoulet, E. (2009). Agriculture for development: Toward a new paradigm. *Annual Review of Resource Economics*, 1(1), 15-31.

Camacho, A. & Conover, E. (2019). The impact of receiving SMS price and weather information on small scale farmers in Colombia. *World Development*, 123, 104596.

Campbell, R.M., Venn, T.J. & Anderson, N.M. (2018). Heterogeneity in preferences for woody biomass energy in the US mountain West. *Ecological Economics*, 145, 27-37.

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

Carsky, R., Nokoe, S., Lagoke, S., & Kim, S. (1998). Maize yield determinants in farmer-managed trials in the Nigerian northern Guinea savanna. *Experimental Agriculture*, 34(4), 407-422.

Cerf, M., Jeuffroy, M.H., Prost, L. & Meynard, J.M. (2012). Participatory design of agricultural decision support tools: Taking account of the use situations. *Agronomy for Sustainable Development*, 32, 899-910.

Chianu J.N. & Tsujii, H. (2005). Determinants of farmers' decision to adopt or not adopt inorganic fertilizer in the savannas of northern Nigeria. *Nutrient Cycling in Agroecosystems*, 70, 293-301.

Chianu, J.N., Chianu, J.N. & Mairura, F. (2012). Mineral fertilizers in the farming systems of Sub-Saharan Africa. A review. *Agronomy for Sustainable Development*, 32, 545-566.

Christiaensen, L. & Kuhl, D.J. (2011). The (evolving) role of agriculture in poverty reduction—an empirical perspective. *Journal of Development Economics*, 96, 239-254.

Chude, V. O., Olayiwola, S. O., Osho, A. O., & Daudu, C. K. (2012). *Fertilizer use and management practices for crops in Nigeria*. Fouth edition. Abuja: Federal Ministry of Agriculture and Water Resources.

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J. & Battese, G.E. (2005). *An introduction to efficiency and productivity analysis*. Second edition. New York: Springer.

Coffie, R.O., Burton, P.B., Gibson, F.L. & Hailu, A. (2016). Choice of rice production practices in Ghana: A comparison of willingness to pay and preferences space estimates. *Journal of Agricultural Economics*, 67(3), 799-819.

Conley, T. G. & Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, 100(1), 35-69.

Cox, P. (1996). Some issues in the design of agricultural decision support systems. *Agricultural Systems*, 52, 355-381.

Croppenstedt, A., Demeke, M. & Meschi, M.M. (2003). Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia. *Review of Development Economics*, 7(1), 58-70.

Cummings, R.G. & Taylor, L.O. (1999). Unbiased value estimates for environmental goods: A cheap talk design for the contingent valuation method. *American Economic Review*, 89(3), 649-665.

Czajkowski, M., Hanley, N. & LaRiviere, J. (2015). The effects of experience on preferences: theory and empirics for environmental public goods. *American Journal of Agricultural Economics*, 97(10), 333-351.

Dalemans, F., Muys, B., Verwimp, A., Van den Broeck, G., Bohra, B., Sharma, N., Gowda, B., Tollens, E. & Maertens, M. (2018). Redesigning oilseed tree biofuel systems in India. *Energy Policy*, 115, 631-643.

Davis, K. (2008). Extension in Sub-Saharan Africa: Overview and assessment of past and current models and future prospects. *Journal of International Agricultural & Extension Education*, 15, 15-28.

Davis, K. & Spielman, D.J. (2017). Applying the best-fit framework to assess and strengthen national extension and advisory services. *Journal of International Agricultural & Extension Education*, 24, 80-90.

Davis, K., Lion, K. & Arokoyo, T. (2019). Organizational capacities and management of agricultural extension services in Nigeria: Current status. *South African Journal of Agricultural Extension*, 47(2), 118-127.

Dawson, N., Martin, A. & Camfield, L. (2019). Can agricultural intensification help attain sustainable development goals? Evidence from Africa and Asia. *Third World Quarterly*, 40(5), 926-946.

Deaton, A. & Cartwright, N. (2018). Understanding and misunderstanding randomized controlled trials. *Social Science & Medicine*, 210, 2-21.

de Brauw, A., Eozenou, P., Gilligan, D.O., Hotz, C., Kumar, N. & Meenakshi, J.V. (2018). Biofortification, crop adoption and health information: Impact pathways in Mozambique and Uganda. *American Journal of Agricultural Economics*, 100(3), 906-930.

de Janvry, A. & Sadoulet, E. (2002). World poverty and the role of agricultural technology: Direct and indirect effects. *The Journal of Development Studies*, 38, 1-26.

de Janvry, A. & Sadoulet, E. (2010). Agricultural development in sub-Saharan Africa: An update. *African Journal of Agricultural Resource Economics*, 5, 194-204.

de Janvry, A., Sadoulet, E. & Rao, M. (2016). Adjusting extension models to the way farmers learn. In A. de Janvry et al. (Eds.), *Learning for adopting: Technology adoption in developing country agriculture* (pp. 71-84). Fondation pour les études et recherches sur le développement international (Ferdi).

de Janvry, A., Sadoulet, E. & Suri, T. (2017). Field experiments in developing country agriculture. In A.V. Banerjee & E. Duflo (Eds.), *Handbook of Economic Field Experiments* (vol. 2, pp. 427-466).

Dercon, S., Gilligan, D., Hoddinott, J. & Woldehanna, T. (2009). The impact of agricultural extension and roads on poverty and consumption growth in fifteen Ethiopian villages. *American Journal of Agricultural Economics*, 91, 1007-1021.

Dercon, S. & Christiensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, 96(2), 159-173.

Dercon, S. & Gollin, D. (2014). Agriculture in African development: Theories and strategies. *Annual Review of Resource Economics*, 6(1), 471-492.

Diao, X., Hazell, P. & Thurlow, J. (2010). The role of agriculture in African development. *World Development*, 38, 1375-1383.

Ditzler, L., Klerkx, L., Chan-Dentoni, J., Posthumus, H., Krupnik, T.J., Ridaura, S.L., Andersson, J.A., Baudron, F. & Groot, J.C.J. (2018). Affordances of agricultural systems analysis tools: A review and framework to enhance tool design and implementation. *Agricultural Systems*, 164, 20-30.

Dobermann, A., Witt, C., Dawe, D., Abdulrachman, S., Gines, H.C., Nagarajan, R., Satawathananont, S., Son, T.T., Tan, P.S., Wang, G.H., Chien, N.V., Thoa, V.T.K., Phung, C.V., Stalin, P., Muthukrishnan, P., Ravi, V., Babu, M., Chatuporn, S., Sookthongsa, J., Sun, Q., Fu, R., Simbahan, G.C. & Adviento, M.A.A. (2002). Site-specific nutrient management for intensive rice cropping systems in Asia. *Field Crops Research*, 74, 37-66.

Droppelmann, K.J., Snapp, S.S. & Waddington, S.R. (2017). Sustainable intensification options for smallholder maze-based farming systems in sub-Saharan Africa. *Food Security*, 9, 133-150.

Duflo, E., Kremer, M. & Robinson, J. (2008). How high are the returns to fertilizer? Evidence from field experiments in Kenya. *American Economic Review*, 98(2), 482-88.

Duflo, E., Kremer, M. & Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review*, 101, 2350-2390.

Ekeleme, F., Jibrin, J.M., Kamara, A.Y., Oluoch, M., Samndi, A.M. & Fagge, A.A. (2014) Assessment of the relationship between soil properties, *Striga hermonthica* infestation and the on-farm yields of maize in the dry Savannas of Nigeria. *Crop Protection*, 66, 90-97.

Ellis, F. (1998). *Peasant economics: Farm households and agrarian development*. Second edition. Cambridge: Cambridge University Press.

Emerick, K., de Janvry, A., Sadoulet, E. & Dar, M.H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, 106(6), 1537-1561.

Evans, K. J., Terhorst, A., & Kang, B. H. (2017). From data to decisions: Helping crop producers build their actionable knowledge. *Critical Reviews in Plant Sciences*, 36(2), 71-88.

Evenson, R. & Gollin, D. (2003). Assessing the impact of the Green Revolution, 1960 to 2000. *Science*, 300(5620), 758-762

Fafchamps, M. & Minten, B. (2012). Impact of SMS-based agricultural information on Indian farmers. *World Bank Economic Review*, 26(3), 383-414.

FAOSTAT (2017). Food and agriculture organization of the United Nations. Fertilizers by nutrient domain. http://www.fao.org/faostat/en/#data/RFT

FAOSTAT (2018). Food and agriculture organization of the United Nations. Production dataset. http://faostat3.fao.

FAO (2019). The state of food security and nutrition in the World 2019. Safeguarding against economic slowdowns and downturns. Food and Agriculture Organization of the United Nations, Rome, 2019.

Feder, G., Just, R.E. & Zilberman, D. (1985). The adoption of agricultural innovations in developing countries-A survey. *Economic Development* & *Cultural Change*, 33, 255-98.

Feder, G. & Slade, R. (1986). The impact of agricultural extension: The training and visit system in India. *The World Bank Research Observer*, 1(2), 139-161.

Feder, G. & Umali, D.L. (1993). The adoption of agricultural innovations: A review. *Technological Forecasting & Social Change*, 43, 215-239.

Feder, G., Murgai, R. & Quizon, J.B. (2004). Sending farmers back to school: The impact of farmer field schools in Indonesia. *Review of Agricultural Economics*, 26, 45-62.

Foster, A.D. & Rosenzweig, M.R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy*, 103(6), 1176-1209.

Foster, A.D. & Rosenzweig, M.R. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, 2, 395-424.

Fu, X. & Akter, S. (2016). The impact of mobile phone technology on agricultural extension services delivery: Evidence from India. *Journal of Development Studies*, 52(11), 1-16.

Gars, J. & Ward, P.S. (2019). Can differences in individual learning explain patterns of technology adoption? Evidence on heterogeneous learning patterns and hybrid rice adoption in Bihar, India. *World Development*, 115, 178-189.

Genius, M., Koundouri, P., Nauges, C. & Tzouvelekas, V. (2014). Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *American Journal of Agricultural Economics*, 96(1), 328-344.

Gil, J.D.B., Reidsma, P., Giller, K., Todman, L., Whitmore, A. & van Ittersum, M. (2019). Sustainable development goal 2: Improved targets and indicators for agriculture and food security. *Ambio*, 48(7), 685-698.

Gilbert, C.L., Christiaensen, L. & Kaminski, J. (2017). Food price seasonality in Africa: Measurement and extent. *Food Policy*, 67, 119-132.

Giller, K.E., Tittonell, P., Rufino, M.C., van Wijk, M.T., Zingore, S., Mapfumo, P., Adjei-Nsiah, S., Herrero, M., Chikowo, R., Corbeels, M., Rowe, E.C., Baijukya, F., Mwijage, A., Smith, J., Yeboah, E., van der Burg, W.J., Sanogo, O.M., Misiko, M., de Ridder, N., Karanja, S., Kaizzi, C., K'ungu, J., Mwale, M., Nwaga, D., Pacini, C. & Vanlauwe, B. (2011). Communicating complexity: Integrated assessment of trade-offs concerning soil fertility management within African farming systems to support innovation and development. *Agricultural Systems*, 104(2), 191-203.

Gizaki, L.J. & Madukwe, M.C. (2019). Socioeconomic impact of SG 2000 quality protein maize (QPM) technology delivery on beneficiaries in Bauchi and Gombe States. *European Scientific Journal*, 15, 169-198.

Godfray, H.C.J. (2015). The debate over sustainable intensification. *Food security*, 7(2), 199-208.

Goergen, G., Kumar, P.L., Sankung, S.B., Togola, A. & Tamò, M. (2016). First report of outbreaks of the fall armyworm *Spodoptera frugiperda* (J E Smith) (Lepidoptera, Noctuidae), a new alien invasive pest in West and Central Africa. *PLoS ONE*, 11(10), e0165632.

Greene, W. & Hensher, D. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B: Methodological*, 37(8), 681-698.

Geussens, K., Van den Broeck, G., Vanderhaegen, K., Verbist, B. & Maertens, M. (2019). Farmers' perspectives on payments for ecosystem services in Uganda. *Land Use Policy*, 84, 316-327.

Guilpart, N., Grassini, P., van Wart, J. Yang, H., van Ittersum, M.K., van Bussel, L.G.J., Wolf, J., Claessens, L., Leenaars, J.G.B. & Cassman, K.G. (2017). Rooting for food security in Sub-Saharan Africa. *Environmental Research Letter*, 12, 114036.

Haggblade, S., Hazell, P.B., & Dorosh, P.A. (Eds.) (2007). Sectoral growth linkages between agriculture and the rural nonfarm economy. In *Transforming the rural nonfarm economy: Opportunities and threats in the developing world* (pp. 141-182). Baltimore: Johns Hopkins University Press.

Harou, A.P., Liu, Y., Barrett, C.B. & You, L., (2017). Variable returns to fertilizer use and the geography of poverty: Experimental and simulation evidence from Malawi. *Journal of African Economics*, 26, 342-371.

Hatzenbuehler, P.L., Abbott, P.C. & Abdoulaye, T. (2017). Price transmission in Nigerian food security crop markets. *Journal of Agricultural Economics*, 68(1), 143-163.

Heß, S. (2017). Randomization inference with Stata: A guide and software. *Stata Journal*, 3, 630-651.

Headey, D., Dereje, M. & Taffesse, A.S. (2014). Land constraints and agricultural intensification in Ethiopia: A village-level analysis of high-potential areas. *Food Policy*, 48, 129-141.

Hensher, D.A., Rose, J.M. & Greene, W.H. (2015). *Applied Choice Analysis*. Second edition. Cambridge: Cambridge University Press.

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

Hochman, Z. & Carberry, P.S. (2011). Emerging consensus on desirable characteristics of tools to support farmers' management of climate risk in Australia. *Agricultural Systems*, 104, 441-450.

Holden, S.T. (2018). Fertilizer and sustainable intensification in Africa. *Global Food Security*, 18, 20-26.

Hossain, M., Malek, M.A., Hossain, M.A., Reza, M. & Ahmed, M. (2019). Agricultural microcredit for tenant farmers: Evidence from a field experiment in Bangladesh. *American Journal of Agricultural Economics*, 101(3), 692-709.

Ibrahim, K., Shamsudin, M.D., Yacob, R. & Radam, A.B. (2014). Technical efficiency in maize production and its determinants: A survey of farms across agro ecological zones in northern Nigeria. *Trends in Agricultural Economics*, 7, 57-68.

Ichami, S.M., Shepherd, K.D., Sila, A.M., Stoorvogel, J.J. & Hoffland, E. (2019). Fertilizer response and nitrogen use efficiency in African smallholder maize farms. *Nutrient Cycling in Agroecosystems*, 133(1), 1-19.

Iken, J.E. & Amusan, N.A. (2004). Maize research and production in Nigeria. *African Journal of Biotechnology*, 3(6), 302-307.

Jaeck, M. & Lifran, R. (2014). Farmers’ preferences for production practices: A choice experiment study in Rhone river delta. *Journal of Agricultural Economics*, 65, 112-130.

Jama, B., Kimani, D., Harawa, R., Mavuthu, A.K. & Sileshi, G.W. (2017). Maize yield response, nitrogen use efficiency and financial returns to fertilizer on smallholder farms in southern Africa. *Food Security*, 9, 577-593.

Janssen, B.H., Guiking, F.C.T., van der Eijk, D., Smaling, E.M.A., Wolf, J. & van Reuler, H. (1990). A system for quantative-evaluation of the fertility of tropical soils (QUEFTS). *Geoderma*, 46, 299-318

Janssen, S.J.C., Porter, C.H., Moore, A.D., Athanasiadis, I.N., Foster, I., Jones, J.W. & Antle, J.M. (2017). Towards a new generation of agricultural system data, models and knowledge products: Information and communication technology. *Agricultural Systems*, 155, 200-212.

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

Jayne, T., Mason, N., Burke, W. & Ariga, J. (2018). Taking stock of Africa's second-generation agricultural input subsidy programs. *Food Policy,* 75, 1-14.

Jayne, T.S., Snapp, S., Place, F. & Sitko, N. (2019). Sustainable agricultural intensification in an era of rural transformation in Africa. *Global Food Security*, 20, 105-113.

Johnston, A.M. & Bruulsema, T.W. (2014). 4R nutrient stewardship for improved nutrient use efficiency. *Procedia Engineering*, 83, 365-370.

Just, R.E. & Zilberman, D. (1983). Stochastic structure, farm size and technology adoption in developing agriculture. *Oxford Economic Papers*, 35, 307-328.

Kamara, A.Y, Ewansiha, S.U. & Menkir, A. (2014). Assessment of nitrogen uptake and utilization in drought tolerant and Striga resistant tropical maize varieties. *Archives of Agronomy & Soil Science*, 60, 195-207.

Kamara, A.Y., Ewansiha, S.U. & Tofa, A.I. (2019). Yield, N uptake and N utilization of early maturing, drought and striga-tolerant maize varieties under low N conditions. *Communications in Soil Science & Plant Analysis*, 50(4), 373-387.

Karlan, D., Osei, R., Osei-Akoto, I. & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, 129, 597-652.

Kassie, T.G., Abdulai, A., Greene, W.H., Shiferaw, B., Abate, T., Tarekegne, A. & Sutcliffe, C. (2017). Modeling preference and willingness to pay for drought tolerance (DT) in maize in rural Zimbabwe. *World Development*, 94, 465-477.

Kihara, J., Huising, J., Nziguheba, G., Waswa, B.S., Njoroge, S., Kabambe, V., Iwuafor, E., Kibunja, C., Esilaba, A.O. & Coulibaly, A. (2016a). Maize response to macronutrients and potential for profitability in sub-Saharan Africa. *Nutrient Cycling in Agroecosystems*, 105, 171-181.

Kihara, J., Nziguheba, G., Zingore, S., Coulibaly, A., Esilaba, A., Kabambe, V., Njoroge, S., Palm, C. & Huising, J. (2016b). Understanding variability in crop response to fertilizer and amendments in sub-Saharan Africa. *Agriculture, Ecosystems & Environment*, 229, 1-12.

Kijima, Y., Otsuka, K. & Sserunkuuma, D. (2011). An inquiry into constraints on a green revolution in Sub-Saharan Africa: The case of NERICA rice in Uganda. *World Development*, 39(1), 77-86.

King, M.T., Hall, J., Lancsar, E., Fiebig, D., Hossain, I., Louviere, J., Reddel, H.K. & Jenkins, C.R. (2007). Patient preferences for managing asthma: Results from a discrete choice experiment. *Health Economics*, 16, 703-717.

Komarek, A.M., Drogue, S., Chenoune, R., Hawkins, J., Msangi, S., Belhouchette, H. & Flichman, G. (2017). Agricultural household effects of fertilizer price changes for smallholder farmers in central Malawi. *Agricultural Systems*, 154, 168-178.

Kondylis, F., Mueller, V. & Zhu, J. (2017). Seeing is believing? Evidence from an extension network experiment. *Journal of Development Economics*, 125, 1-20.

Koundouri, P., Nauges, C. & Tzouvelekas, V. (2006). Technology adoption under production uncertainty: theory and application to irrigation technology. *American Journal of Agricultural Economics*, 88, 657-670.

Koussoubé, E. & Nauges, C. (2017). Returns to fertilizer use: Does it pay enough? Some new evidence from Sub-Saharan Africa. *European Review of Agricultural Economics*, 44(2), 183-210.

Kragt, M.E. (2013). Stated and inferred attribute attendance models: A comparison with environmental choice experiments. *Journal of Agricultural Economics*, 64(3), 719-736.

Kragt, M.E. & Llewellyn, R.S. (2014). Using a choice experiment to improve decision support tool design. *Applied Economic Perspectives* & *Policy*, 36(2), 351-371.

Krinsky, I. & Robb, A. L. (1986). On approximating the statistical properties of elasticities. The *Review of Economics & Statistics*, 64, 715-719.

Kuehne, G., Llewellyn, R., Pannell, D.J., Wilkinson, R., Dolling, P. Ouzman, J. & Ewing, M. (2017). Predicting farmer uptake of new agricultural practices: A tool for research, extension and policy. *Agricultural Systems*, 156, 115-125.

Lacoste, M. & Powles, S. B. (2016). Beyond modelling: Considering user-centred and post development aspects to ensure the success of decision support system. *Computers & Electronics in Agriculture*, 121, 260-268.

Lambrecht, I., Vanlauwe, B., Merckx, R. & Maertens, M. (2014). Understanding the process of agricultural technology adoption: Mineral fertilizer in Eastern DR Congo. *World Development*, 59, 132-146.

Lambrecht, I., Vranken, L., Merckx, R., Vanlauwe, B. & Maertens, M. (2015). Ex ante appraisal of agricultural research and extension: A choice experiment on climbing beans in Burundi. *Outlook on Agriculture*, 44(1), 61-67.

Lambrecht, I., Vanlauwe, B. & Maertens, M. (2016a). Integrated soil fertility management: from concept to practice in Eastern DR Congo. *International Journal of Agricultural Sustainability*, 14(1), 100-118.

Lambrecht, I., Vanlauwe, B. & Maertens, M. (2016b). Agricultural extension in Eastern Democratic Republic of Congo: does gender matter? *European Review of Agricultural Economics*, 43(5), 841-874.

Lancaster, K.J. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2), 132-57.

Lancsar, E., Fiebig, D.G. & Hole, A.R. (2017). Discrete choice experiments: A guide to model specification, estimation and software. *Pharmacoeconomics*, 35(7), 697-716.

Larochelle, C., Alwang, J., Travis, E., Barrera, V.H. & Dominguez Andrade, J.M. (2019). Did you really get the message? Using text reminders to stimulate adoption of agricultural technologies. *The Journal of Development Studies*, 55(4), 548-564.

Lee, D.S. (2009). Training, wages, and sample selection: Estimating sharp bounds in treatment effects. *Review of Economic Studies*, 76(3), 1071-102.

Lindblom, J., Lundström, C., Ljung, M. & Jonsson, A. (2017). Promoting sustainable intensification in precision agriculture: Review of decision support systems development and strategies. *Precision Agriculture*, 18(3), 309-331.

Lundström, C. & Lindblom, J. (2018). Considering farmers' situated knowledge of using agricultural decision support systems (AgriDSS) to foster farming practices: The case of CropSAT, *Agricultural Systems*, 159, 9-20.

Ligon, E. & Sadoulet, E. (2018). Estimating the relative benefits of agricultural growth on the distribution of expenditures. *World Development*, 109, 417-428.

Liverpool-Tasie, L.S.O. & Takeshima, H. (2013). Input promotion within a complex subsector: fertilizer in Nigeria. *Agricultural Economics*, 44(6), 581-594.

Liverpool-Tasie, L.S.O. (2014). Fertilizer subsidies and private market participation: The case of Kano state, Nigeria. *Agricultural Economics*, 45, 663-678.

Liverpool-Tasie, L.S.O., Omonona, B.T., Sanou, A. & Ogunleye, W.O. (2017). Is increasing inorganic fertilizer use for maize production in SSA a profitable proposition? Evidence from Nigeria. *Food policy*, 67, 41-51.

Loomis, J.B. (2014). Strategies for overcoming hypothetical bias in stated preference surveys. *Journal of Agricultural & Resource Economics*, 39(1), 34-46.

Lopez-Ridaura, S., Frelat, R., van Wijk, M.T., Valbuena, D., Krupnik, T.J. & Jat, M.L. (2018). Climate smart agriculture, farm household typologies and food security: An ex-ante assessment from Eastern India. *Agricultural Systems*, 159, 57-68.

Louviere, J.J., Hensher, D.A. & Swait, J.D. (2000). *Stated choice methods, analysis and applications*. New York: Cambridge University Press.

Louviere, J. & Eagle, T. (2006). Confound it! That pesky little scale constant messes up our convenient assumptions. In sawtooth software conference proceedings: Sequim, WA. (pp. 211-228).

MacCarthy, D.S., Kihara, J., Masikati, P. & Adiku, S.G.K. (2018). Decision support tools for site-specific fertilizer recommendations and agricultural planning in selected countries in sub-Sahara Africa. *Nutrient Cycling in Agroecosystems*, 110, 343-359.

Macours, K. (2019). Farmers' demand and the traits and diffusion of agricultural innovations in developing countries. *Annual Review of Resource Economics*, 11, 483-499.

Magruder, J. (2018). An assessment of experimental evidence on agricultural technology adoption in developing countries. *Annual Review of Resource Economics*, 10(1), 299-316.

Mahadevan, R. & Asafu-Adjaye, J. (2015). Exploring the potential for green revolution: A choice experiment on maize farmers in Northern Ghana. *African Journal of Agricultural* & *Resource Economics*, 10(3), 207-221.

Maiangwa, M.G., Ogungbile, A.O., Olukosi, J.O. & Atala, T.K. (2007). Adoption of chemical fertilizer for land management in the north-west zone of Nigeria. *Tropical Agricultural Research & Extension*, 10, 34-46.

Makate, C. & Makate, M. (2019). Interceding role of institutional extension services on the livelihood impacts of drought tolerant maize technology adoption in Zimbabwe. *Technology in Society*, 56, 126-133.

Manyong, V.M., Makinde, K.O., Sanginga, N., Vanlauwe, B. & Diels, J. (2001). Fertilizer use and definition of farmer domains for impact-oriented research in the northern Guinea savanna of Nigeria. *Nutrient Cycling in Agroecosystems*, 59, 129-141.

Marenya, P.P. & Barrett, C.B. (2009). State-conditional fertilizer yield response on Western Kenyan farms. *American Journal of Agricultural Economics*, 91(4), 991-1006.

Marra, M., Pannell, D.J. & Ghadim, A.A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Agricultural Systems*, 75, 215-234.

Mason-D'Croz, D., Sulser, T.B., Wiebe, K., Rosegrant, M.W., Lowder, S.K., Nin-Pratt, A., Willenbockel, D., Robinson, S., Zhu, T., Cenacchi, N. & Dunston, S. (2019). Agricultural investments and hunger in Africa modeling potential contributions to SDG2–Zero Hunger. *World Development*, 116, 38-53.

Matsumoto, T. & Yamano, T. (2013). Maize, soil fertility, and the Green Revolution in East Africa. In K. Otsuka & D.F. Larson (Eds.), *An African green revolution: Finding ways to boost productivity on small farms* (pp. 197-221). Dordrecht: Springer.

Mcarthur, J. & Mccord, G. (2017). Fertilizing growth: Agricultural inputs and their effects in economic development. *Journal of Development Economics*, 127, 133-152.

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

Meyerhoff, J., Klefoth, T. & Arlinghaus, R. (2019). The value artificial lake ecosystems provide to recreational anglers: Implications for management of biodiversity and outdoor recreation. *Journal of Environmental Management*, 252, 109580.

Michler, J.D., Tjernström, E., Verkaart, S. & Mausch, K. (2019). Money matters: The role of yields and profits in agricultural technology adoption. *American Journal of Agricultural Economics*, 101(3), 710-731.

Minten, B., Koru, B. & Stifel, D. (2013). The last mile(s) in modern input distribution: pricing, profitability, and adoption. *Agricultural Economics*, 44(6), 629-646.

Mitra, S., Mookherjee, D., Torero, M. & Visaria, S. (2018). Asymmetric information and middleman margins: An experiment with Indian Potato farmers. *The Review of Economics & Statistics*, 100(1), 1-13.

Morello, T.F., Piketty, M., Gardner, T., Parry, L., Barlow, J., Ferreira, J. & Tancredi, N.S. (2018). Fertilizer adoption by smallholders in the Brazilian amazon: Farm-level evidence. *Ecological Economics*, 144, 278-291.

Moser, C.M. & Barrett, C.B. (2006). The complex dynamics of smallholder technology adoption: The case of SRI in Madagascar. *Agricultural Economics*, 35(3), 373-388.

Mponela, P., Tamene, L., Ndengu, G., Magreta, R., Kihara, J. & Mango, N. (2016). Determinants of integrated soil fertility management technologies adoption by smallholder farmers in the Chinyanja Triangle of Southern Africa. *Land Use Policy*, 59, 38-48.

Mukasa, A.N. (2018). Technology adoption and risk exposure among smallholder farmers: Panel data evidence from Tanzania and Uganda. *World Development*, 105, 299-309.

Mustapha, A.R. (2003). Colonialism and environmental perception in northern Nigeria. *Oxford Development Studies*, 31(4), 405-425.

Nagoshi, R.N., Goergen, G., Tounou, K.A., Agboka, K., Koffi, D. & Meagher, R.L. (2018). Analysis of strain distribution, migratory potential, and invasion history of fall armyworm populations in northern Sub-Saharan Africa. *Scientific Reports*, 8, Article number: 3710.

Nakano, Y., Tsusaka, T. W., Aida, T., & Pede, V. O. (2018). Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania. *World Development*, 105, 336-351.

Nakasone, E., Torero, M. & Minten, B. (2014). The power of information: The ICT revolution in agricultural development. *Annual Review of Resource Economics*, 6(1), 533-550.

Naswem, A.A. & Ejembi, S.A. (2017). Reviving agricultural extension for effective transition from subsistence to commercial agriculture in Nigeria. *Journal of Rural Social Sciences*, 32, 3-20.

Niu, C. & Ragasa, C. (2018). Selective attention and information loss in the lab-to-farm knowledge chain: The case of Malawian agricultural extension programs. *Agricultural Systems*, 165, 147-163.

Njoroge, S., Schut, G.T., Giller, K.E. & Zingore, S. (2017). Strong spatial-temporal patterns in maize yield response to nutrient additions in African smallholder farms. *Field Crops Research*, 214, 321-330.

Ogunti, E.O., Akingbade, F.K., Segun, A. & Oladimeji, O. (2018). Decision support system using mobile applications in the provision of day to day information about farm status to improve crop yield. *Periodicals of Engineering & Natural Sciences*, 6(2), 89-99.

Olaniyan, A. B. (2015). Maize: Panacea for hunger in Nigeria. *African Journal of Plant Science*, 9(3), 155-174.

Oliva, P., Jack, B.K., Bell, S., Mettetal, E. & Severen, C. (2019). Technology adoption under uncertainty: Take-up and subsequent investment in Zambia. *Review of Economics & Statistics*, https://doi.org/10.1162/rest_a_00823

Oliver, D.M., Bartie, P. J., Louise Heathwaite, A., Pschetz, L. & Quillam, R. S. (2017). Design of a decision support tool for visualising E. coli risk on agricultural land using a stakeholder driven approach. *Land Use Policy*, 66, 227-234.

Omotilewa, O.J., Ricker-Gilbert, J., Ainembabazi, J.H. & Shively, G.E. (2018). Does improved storage technology promote modern input use and food security? Evidence from a randomized trial in Uganda. *Journal of Development Economics*, 135, 176-198.

Omotilewa, O.J., Ricker-Gilbert, J. & Ainembabazi, J.H. (2019). Subsidies for agricultural technology adoption: Evidence from a randomized experiment with improved grain storage bags in Uganda. *American Journal of Agricultural Economics*, 101(3), 753-772.

Ortega, D.L, Waldman, K.B., Richardson, R.B., Clay, D.C. & Snapp, S. (2016). Sustainable intensification and farmer preferences for crop system attributes: Evidence from Malawi's Central and Southern Regions. *World Development*, 87, 139-151.

Otekunrin, O.A., Otekunrin, O.A., Momoh, S. & Ayinde, I.A. (2019). How far has Africa gone in achieving the zero hunger target? Evidence from Nigeria. *Global Food Security*, 22, 1-12.

Otsuka, K. & Muraoka, R. (2017). A green revolution for Sub-Saharan Africa: Past failures and future prospects. *Journal of African Economies*, 26(1), 73-98.

Oyinbo, O., Mbavai, J., Shitu, M., Kamara, A., Abdoulaye, T. & Ugbabe, O. (2019a). Sustaining the beneficial effects of maize production in Nigeria: Does adoption of short season maize varieties matter? *Experimental Agriculture*, 55, 885-897.

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, A.Y., Craufurd, P. & Maertens, M. (2019b). Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria. *Agricultural Systems*, 173, 12-26.

Pacifico, D. & Yoo, H. (2013). lclogit: A Stata command for fitting latent-class conditional logit models via the expectation-maximization algorithm. *The Stata Journal*, 13, 625-639.

Palma, D., Ortúzar, J.D., Rizzi, L.I., Guevara, C.A., Casaubon, G. & Ma, H. (2016). Modelling choice when price is a cue for quality: A case study with Chinese consumers. *The Journal of Choice Modelling*, 19, 24-39.

Pampolino, M.F., Manguiat, I.J., Ramanathan, S., Gines, H.C., Tan, P.S., Chi, T.T.N., Rajendran, R. & Buresh, R.J. (2007). Environmental impact and economic benefits of site-specific nutrient management (SSNM) in irrigated rice systems. *Agricultural Systems*, 93, 1-24.

Pampolino, M., Witt, C., Pasuquin, J.M., Johnston, A. & Fisher, M.J. (2012). Development approach and evaluation of the Nutrient Expert software for nutrient management in cereal crops. *Computers* & *Electronics in Agriculture*, 88, 103-110.

Pampolino, M. & Zingore, S. (2015). Nutrient expert for maize (Africa) – Nutrient expert for maize for Africa scientific principles and user guide. International Plant Nutrition Institute, Nairobi, Kenya.

Pan, Y., Smith, S.C. & Sulaiman, M. (2018). Agricultural extension and technology adoption for food security: Evidence from Uganda. *American Journal of Agricultural Economics*, 100(4), 1012-1031.

Pasuquin, J.M., Pampolino, M., Witt, C., Dobermann, A., Oberthüra, T., Fisher, M.J. & Inubushi, K. (2014). Closing yield gaps in maize production in Southeast Asia through site-specific nutrient management. *Field Crops Research*, 156, 219-230.

Pierre, G. & Kaminski, J. (2019). Cross country maize market linkages in Africa: Integration and price transmission across local and global markets. *Agricultural Economics*, 50, 79-90

Pingali, P.L. (2012). Green Revolution: Impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences*, 109(31), 12302-12308.

Pouta, E., Tienhaara, A. & Ahtiainen, H. (2014). Citizens' preferences for the conservation of agricultural genetic resources. *Frontiers in Genetics*, 5, 1-10.

Prost, L., Cerf, M. & Jeuffroy, M.H. (2012). Lack of consideration for end-users during the design of agronomic models. A review. *Agronomy for Sustainable Development*, 32, 581-594.

Ragasa, C. & Chapoto, A. (2017). Moving in the right direction? The role of price subsidies in fertilizer use and maize productivity in Ghana. *Food Security*, 9(2), 329-353.

Ragasa, C. & Mazunda, J. (2018). The impact of agricultural extension services in the context of a heavily subsidized input system: The case of Malawi. *World Development*, 105, 25-47.

Ravier, C., Jeuffroy, M. & Meynard, J. (2016). Mismatch between a science-based decision tool and its use: The case of the balance-sheet method for nitrogen fertilization in France. *NJAS -Wageningen Journal of Life Sciences*, 79, 31-40.

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P. & de Fraiture, C. (2017). Sustainable intensification of agriculture for human prosperity and global sustainability. *Ambio*, 46(1), 4-17.

Rose, D.C., Sutherland, W.J. Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffoulkes, C., Amano, T. & Dicks, L.V. (2016). Decision support tools for agriculture: Towards effective design and delivery. *Agricultural Systems*, 149, 165-174.

Rose, D., Parker, C., Fodey, J., Park, C., Sutherland, W. & Dicks, L. (2018). Involving stakeholders in agricultural decision support systems: Improving user-centred design. *International Journal of Agricultural Management*, 6, 80-89.

Rosenzweig, M.R. & Udry, C. (2019). External validity in a stochastic world: Evidence from low-income countries. *The Review of Economic Studies*, https://doi.org/10.1093/restud/rdz021

Rossi, F., Poni, S.S., Caffi, T. & Bettati, T. (2014). Addressing the implementation problem in agricultural decision support systems: The example of vite.net® *Computers & Electronics in Agriculture*, 100, 88-99.

Saha A., Love, A.H. & Schwart, R. (1994). Adoption of emerging technologies under output uncertainty. *American Journal of Agricultural Economics*, 76(4), 836-846.

Sanchez, P.A. (2002). Soil fertility and hunger in Africa. *Science*, 295(5562), 2019-2020.

Sanginga, N. & Woomer, P.L. (Eds.) (2009). Integrated soil fertility management in Africa: Principles, practices and developmental process. Tropical Soil Biology and Fertility Institute of the International Centre for Tropical Agriculture.

Sanni, S.A. & Doppler, W. (2007). Socio-economic determinants of household fertilizer use intensity for maize-based production systems in the northern Guinea savannah of Nigeria. *Journal of Applied Sciences*, 7, 1774-1779.

Sapkota, T.B., Majumdar, K., Jat, M.L., Kumar, A., Bishnoia, D.K. McDonald, A.J., & Pampolino, M. (2014). Precision nutrient management in conservation agriculture based wheat production of northwest India: Profitability, nutrient use efficiency and environmental footprint. *Field Crops Research*, 155, 233-244.

Satyanarayana, T., Majumdar, K. & Biradar, D.P. (2011). New approaches and tools for site-specific nutrient management with reference to potassium. *Karnataka Journal of Agricultural Sciences*, 24(1), 86-90.

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

Sheahan, M., Black, R. & Jayne, T.S. (2013). Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. *Food Policy*, 41, 39-52.

Sheahan, M., & Barrett, C.B. (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy*, 67, 12-25.

Shehu, B.M., Merckx, R., Jibrin, J.M., Kamara, A.Y. & Rurinda, J. (2018). Quantifying variability in maize yield response to nutrient applications in the northern Nigerian savanna. *Agronomy*, 8(2), 1-23.

Shikuku, K. M. (2019). Information exchange links, knowledge exposure, and adoption of agricultural technologies in northern Uganda. *World Development*, 115, 94-106.

Shikuku, K.M., Pieters, J., Bulte, E. & Läderach, P. (2019). Incentives and the diffusion of agricultural knowledge: Experimental evidence from northern Uganda. *American Journal of Agricultural Economics*, 101(4), 1164-1180.

Sileshi, G., Akinnifesi, F.K., Debusho, L.K., Beedy, T., Ajayi, O.C. & Mongomba S. (2010). Variation in maize yield gaps with plant nutrient inputs, soil type and climate across sub-Saharan Africa. *Field Crops Research*, 116, 1-13.

Singh S.P. (2019). Site specific nutrient management through nutrient decision support tools for sustainable crop production and soil health. In D. Panpatte & Y. Jhala (Eds.), *Soil fertility management for sustainable development* (pp. 13-23). Springer, Singapore.

Smale, M., Byerlee, D. & Jayne, T. (2013). Maize revolutions in Sub-Saharan Africa. In K. Otsuka & D.F. Larson (Eds.), *An African Green Revolution* (pp. 165-195). The Netherlands: Springer.

Small, I.M., Joseph, L. & Fry, W.E. (2015). Development and implementation of the BlightPro decision support system for potato and tomato late blight management. *Computers & Electronics in Agriculture*, 115, 57-65.

Stevenson, J., Vanlauwe, B., Macours, K., Johnson, N., Krishnan, L., Place, F., Spielman, D., Hughes, K. & Vlek, P. (2019). Farmer adoption of plot- and farm-level natural resource management practices: Between rhetoric and reality. *Global Food Security*, 20, 101-104.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1), 159-209.

Takahashi, K., Mano, Y. & Otsuka, K. (2019). Learning from experts and peer farmers about rice production: Experimental evidence from Cote d'Ivoire. *World Development*, 122, 157-169.

Takeshima, H. & Nkonya, E. (2014). Government fertilizer subsidy and commercial sector fertilizer demand: Evidence from the Federal Market Stabilization Program (FMSP) in Nigeria. *Food Policy*, 47, 1-12.

Tarfa, B.D., Amapu I.Y., Daudu, C.K., Arunah, U.L., Isah, A.S., Yakubu, A.A., Nafiu, A., Adeogun, T.T., Bakodo, P.R., Ugbaje, E.M., Dauda, H. & Ugbabe, O.O. (2017) Optimizing fertilizer use within the context of integrated soil fertility management in

Nigeria. In C.S. Wortmann, & K. Sones (Eds.), *Fertilizer use optimization in sub-Saharan Africa* (pp. 148-162). CAB International, Nairobi, Kenya.

Tarfasa, S., Balana, B.B., Tefera, T., Woldeamanuel, T., Moges, A., Dinato, M. & Black, H. (2018). Modeling smallholder farmers' preferences for soil management measures: A case study from South Ethiopia. *Ecological Economics*, 145, 410-419.

Tata, J.S. & Mcnamara, P.E. (2016). Social factors that influence use of ICT in agricultural extension in Southern Africa. *Agriculture*, 6, 1-10.

ten Berge, H.F.M., Hijbeek, R., Van Loon, M.P., Rurinda, J., Tesfaye, K., Zingore, S., Craufurd, P., Van Heerwaarden, J., Brentrup, F., Schröder, J.J., Boogaard, H.L., De Groot, H.L.E. & van Ittersum, M.K. (2019). Maize crop nutrient input requirements for food security in Sub-Saharan Africa. *Global Food Security*, 23, 9-21.

Theriault, V., Smale, M. & Haider, H. (2018). Economic incentives to use fertilizer on maize under differing agro-ecological conditions in Burkina Faso. *Food Security*, 10(5), 1263-1277.

Thiene, M., Meyerhoff, J. & De Salvo, M. (2012). Scale and taste heterogeneity for forest biodiversity: Models of serial nonparticipation and their effects. *Journal of Forest Economics*, 18(4), 355-369.

Tittonell, P., Muriuki, A., Shepherd, K.D., Mugendi, D., Kaizzi, K.C., Okeyo, J., Verchot, L., Coe, R. & Vanlauwe, B. (2010). The diversity of rural livelihoods and their influence on soil fertility in agricultural systems of East Africa – A typology of smallholder farms. *Agricultural Systems*, 103(2), 83-97.

Tittonell, P., Vanlauwe, B., Misiko, M. & Giller, K.E. (2011). Targeting resources within diverse, heterogeneous and dynamic farming systems: Towards a uniquely African green revolution. In A. Bationo et al. (Eds.), *Innovations as Key to the Green Revolution in Africa* (pp. 747-758). Springer Science + Business Media B.V.

Tittonell, P. & Giller, K.E. (2013). When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. *Field Crops Research*, 143, 76-90.

Tomich, T.P., Lidder, P., Coley, M., Gollin, D., Meinzen-Dick, R., Webb, P. & Carberry, P. (2019). Food and agricultural innovation pathways for prosperity. *Agricultural Systems*, 172, 1-15.

Train, K.E. (2009). *Discrete Choice Methods with Simulation*. Second edition. New York: Cambridge University Press.

Vandercasteelen, J., Dereje, M., Minten, B. & Taffesse, A.S. (2018). From agricultural experiment station to farm: The impact of the promotion of a new technology on farmers' yields in Ethiopia. *Economic Development & Cultural Change*, https://doi.org/10.1086/701234

Van Campenhout, B. (2019). The role of information in agricultural technology adoption: Experimental evidence from rice farmers in Uganda. *Economic Development & Cultural Change*, https://doi.org/10.1086/703868

Van den Broeck, G., Vlaeminck, P., Raymaekers, K., Vande Velde, K., Vranken, L. & Maertens, M. (2017). Rice farmers' preferences for fair trade contracting in Benin: Evidence from a discrete choice experiment. *Journal of Cleaner Production*, 165, 846-854.

van Ittersum, M.K., van Bussel, L.G.J., Wolfa, J., Grassini, P., van Wart, J., Guilpart, N., Claessens, L., de Groot, H., Wieb, K., Mason-D'Croz, D., Yang, H., Boogaard, H., van Oort, P.J.A., van Loon, M.P., Saito, K., Adimoh, O., Adjei-Nsiah, S., Agali, A., Bala, A., Chikowo, R., Kaizzi, K., Kouressy, M., Makoi, J.H.J.R., Ouattara, K., Tesfaye, K. & Cassman, K.G. (2016). Can sub-Saharan Africa feed itself? *Proceedings of the National Academy of Sciences*, 113(52), 1-6.

van Loon, M.P., Hijbeek, R., ten Berge, H. F., De Sy, V., ten Broeke, G., Solomon, D. & van Ittersum, M.K. (2019a). Impacts of intensifying or expanding cereal cropping in sub-Saharan Africa on greenhouse gas emissions and food security. *Global Change Biology*, 25(11), 3720-3730.

van Loon, M.P., Adjei-Nsiah, S., Descheemaeker, K., Akotsen-Mensah, C., van Dijk, M., Morley, T., van Ittersum, M.K. & Reidsma, P. (2019b). Can yield variability be explained? Integrated assessment of maize yield gaps across smallholders in Ghana, *Field Crops Research*, 236, 132-144.

Vanlauwe, B., Kihara, J., Chivenge, P., Pypers, P., Coe, R. & Six, J. (2011). Agronomic use efficiency of N fertilizer in maize-based systems in sub-Saharan Africa within the context of integrated soil fertility management. *Plant Soil*, 339, 35-50.

Vanlauwe, B., Six, J., Sanginga, N. & Adesina, A.A. (2015a). Soil fertility decline at the base of rural poverty in sub-Saharan Africa. *Nature Plants*, 1, 15101.

Vanlauwe, B., Descheemaeker, K., Giller, K.E., Huising, J., Merckx, R., Nziguheba, G., Wendt, J. & Zingore, S. (2015b). Integrated soil fertility management in sub-Saharan Africa: Unraveling local adaptation. *Soil*, 1, 491-508.

Vanlauwe, B., AbdelGadir, A.H., Adewopo, J., Adjei-Nsiah, S., Ampadu-Boakye, T., Asare, R., Baijukya, F., Baars, E., Bekunda, M., Coyne, D., Dianda, M., Dontsop-Nguezet, P.M., Ebanyat, P., Hauser, S., Huising, J., Jalloh, A., Jassogne, L., Kamai, N., Kamara, A., Kanampiu, F., Kehbila, A., Kintche, K., Kreye, C., Larbi, A., Masso, C., Matungulu, P., Mohammed, I., Nabahungu, L., Nielsen, F., Nziguheba, G., Pypers, P., Roobroeck, D., Schut, M., Taulya, G., Thuita, M., Uzokwe, V.N.E., van Asten, P., Wairegi, L., Yemefack, M. & Mutsaers, H.J.W. (2017). Looking back and moving forward: 50 years of soil and soil fertility management research in sub-Saharan Africa. *International Journal of Agricultural Sustainability*, 15(6), 613-631.

Vanlauwe, B., Coe, R. & Giller, K.E. (2019a). Beyond averages: New approaches to understand heterogeneity and risk of technology success or failure in smallholder farming. *Experimental Agriculture*, 55(S1), 84-106.

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

Verma, P. & Sinha, N. (2018). Integrating perceived economic wellbeing to technology acceptance model: The case of mobile based agricultural extension service. *Technological Forecasting & Social Change*, 126, 207-216.

Vermunt, J.K. & Magidson, J. (2014). *Upgrade manual for latent gold choice 5.0: Basic, advanced, and syntax*. Statistical Innovations Inc., Belmont Massachusetts.

Wang, G. H., Dobermann, A., Witt, C., Sun, Q. Z. & Fu, R. X. (2001). Performance of site-specific nutrient management for irrigated rice in southeast China. *Agronomy Journal*, 93, 869-878.

Welch, S.M., Jones, J.W., Brennan, M.W., Reeder, G. & Jacobson, B.M. (2002). PCYield: model-based decision support for soybean production. *Agricultural Systems*, 74(1), 79-98.

Wiredu, A.N., Zeller, M. & Diagne, A. (2015). What determines adoption of fertilizers among rice-producing households in Northern Ghana? *Quarterly Journal of International Agriculture*, 54(3), 261-281.

World Bank (2007). Agriculture for development, World development report, 2008, World Bank, Washington DC.

World Bank (2016). Poverty reduction in Nigeria in the last decade. World Bank, Washington, DC.

World Bank (2018a). Poverty and shared prosperity 2018: Piecing together the poverty puzzle. World Bank, Washington, DC.

World Bank (2018b). Population growth (annual %). https://data.worldbank.org/indicator/SP.POP.GROW?end=2018&locations=NG&start=2006

World Bank (2018c). Fertilizer consumption (kilograms per hectare of arable land). https://data.worldbank.org/indicator/AG.CON.FERT.ZS.

Wossen, T., Abdoulaye, T., Alene, A., Feleke, S., Ricker-Gilbert, J., Manyong, V. & Awotide, B. A. (2017). Productivity and welfare effects of Nigeria's e-voucher-based input subsidy program. *World Development*, 97, 251-265.

Wossen, T., Gatiso, T.T. & Kassie, M. (2019). Estimating returns to fertilizer adoption with unobserved heterogeneity: Evidence from Ethiopia. *Food & Nutrition Security*, 8(2), 1-9.

Xu, C., Huang, S., Tian, B., Ren, J., Meng, Q. & Wang, P. (2017). Manipulating planting density and nitrogen fertilizer application to improve yield and reduce environmental impact in Chinese maize production. *Frontier in Plant Sciences*, 8, 1234.

Xu, X., He, P., Pampolino, M.F., Li, Y., Liu, S., Xie, J., Hou, Y. & Zhou, W. (2016). Narrowing yield gaps and increasing nutrient use efficiencies using the Nutrient Expert system for maize in Northeast China. *Field Crops Research*, 194, 75-82.

Xu, Z., Guan, Z., Jayne, T.S. & Black, R. (2009). Factors influencing the profitability of fertilizer use on maize in Zambia. A*gricultural Economics*, 40(4), 437-446.

Young, A. (2019). Channeling Fisher: Randomization tests and the statistical insignificance of seemingly significant experimental results. *The Quarterly Journal of Economics*, 134, 557-598.

Zeng, D., Alwang, J., Norton, G.W., Shiferaw, B., Jaleta, M. & Yirga, C. (2015). Ex post impacts of improved maize varieties on poverty in rural Ethiopia. *Agricultural Economics*, 46(4), 515-526.

Zingore, S. & Johnston, A. (2013). The 4R Nutrient Stewardship in the context of smallholder Agriculture in Africa. In B. Vanlauwe et al. (Eds.), *Agro-ecological intensification of farming systems in the East and Central African highlands* (pp. 77-84). Oxon: Routledge.

General appendix: Modules of Nutrient Expert decision support tool

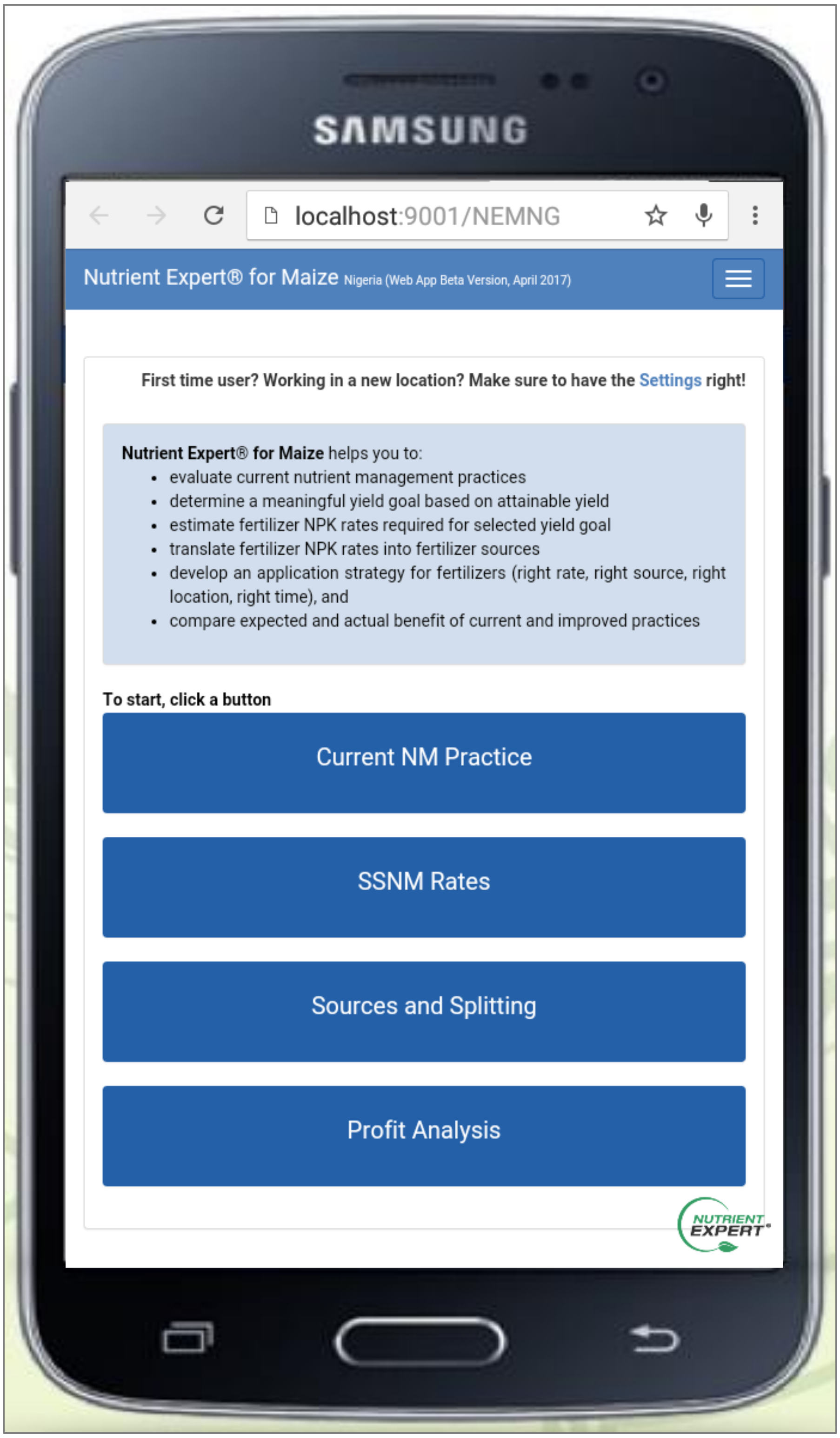

Fig. A1: Introductory screen of Nutrient Expert tool

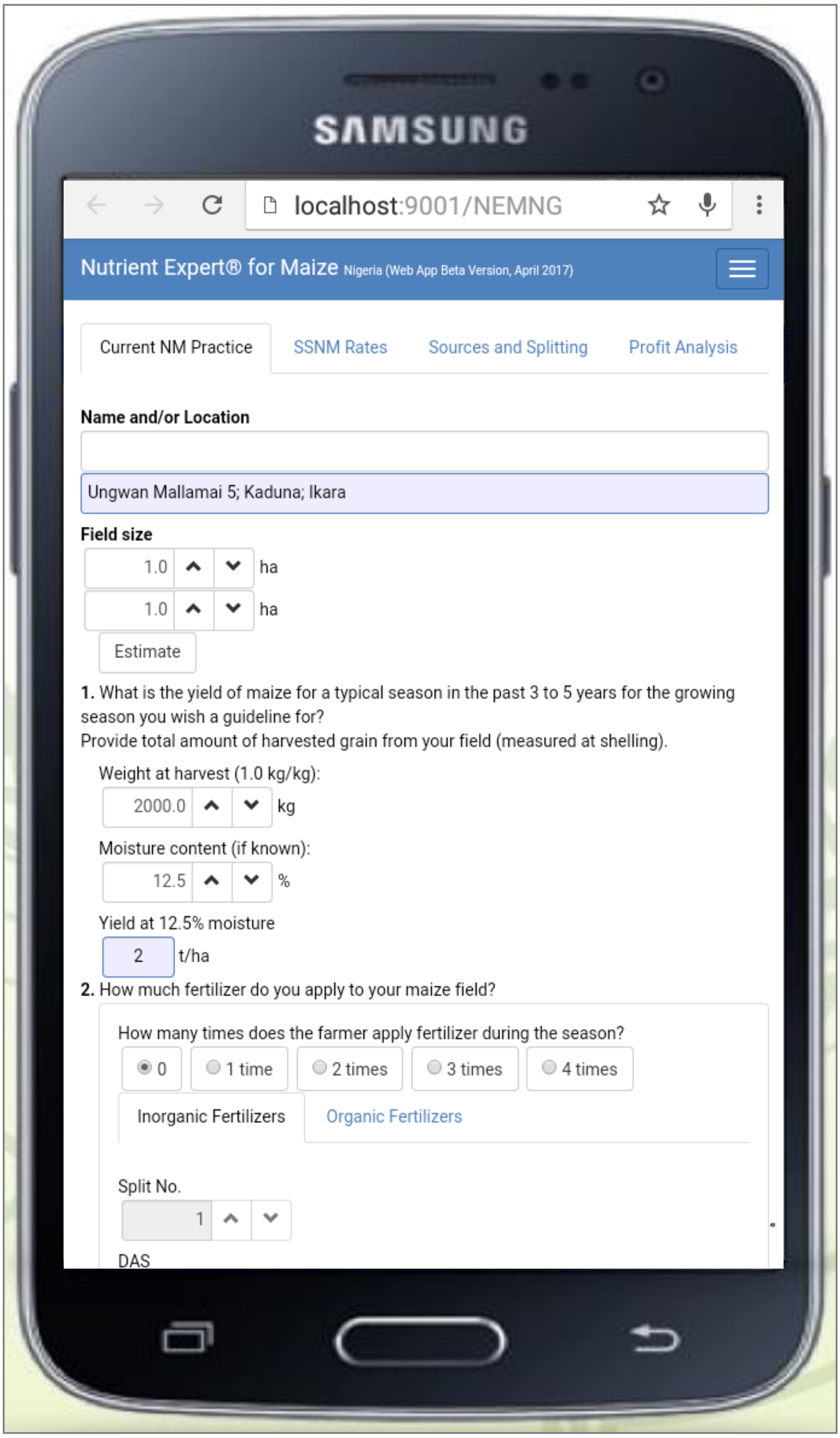

Fig. A2: Screen of the first module of Nutrient Expert tool. It only shows some portion of the module

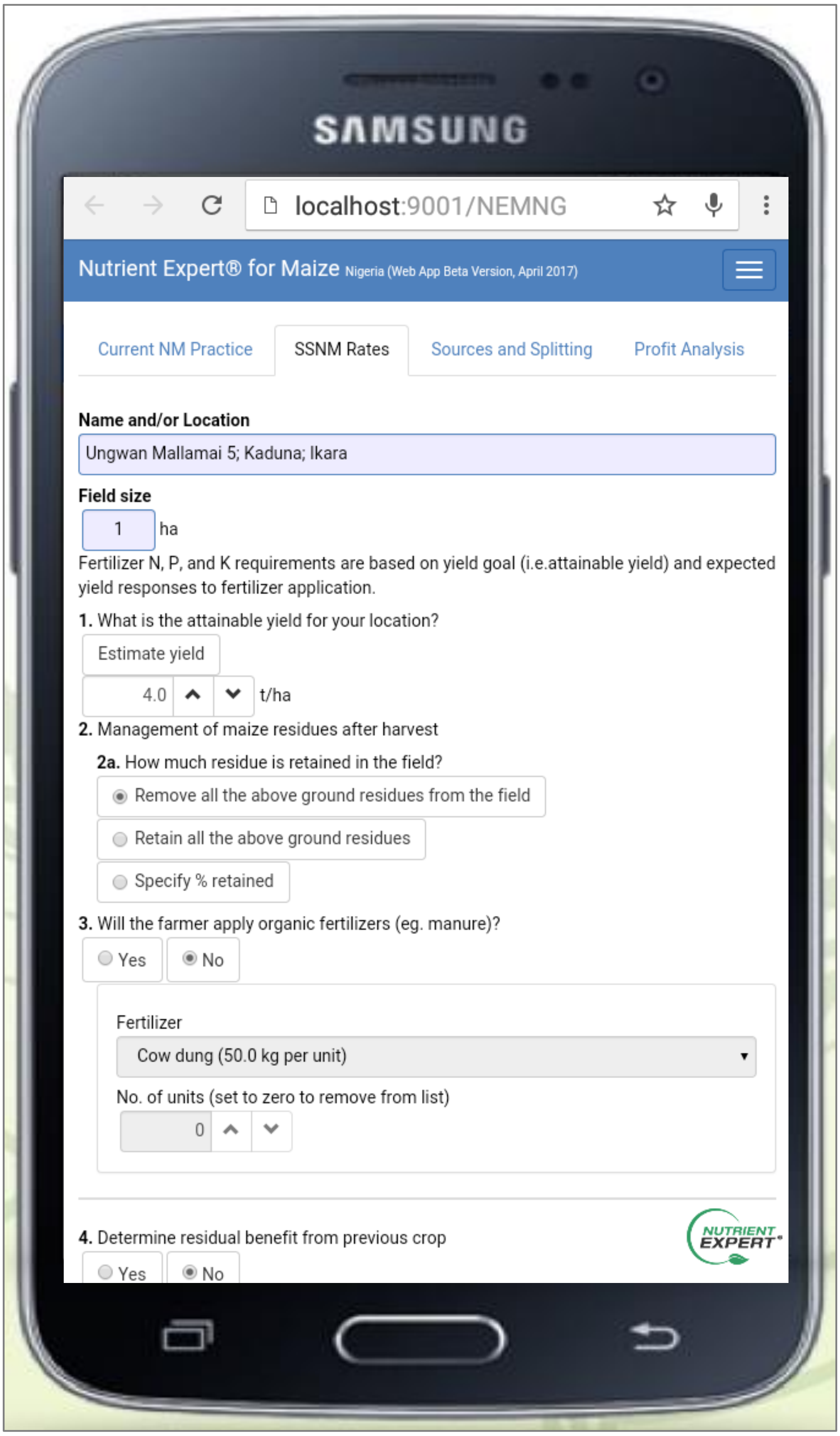

Fig. A3: Screen of the second module of Nutrient Expert tool. It only shows some portion of the module

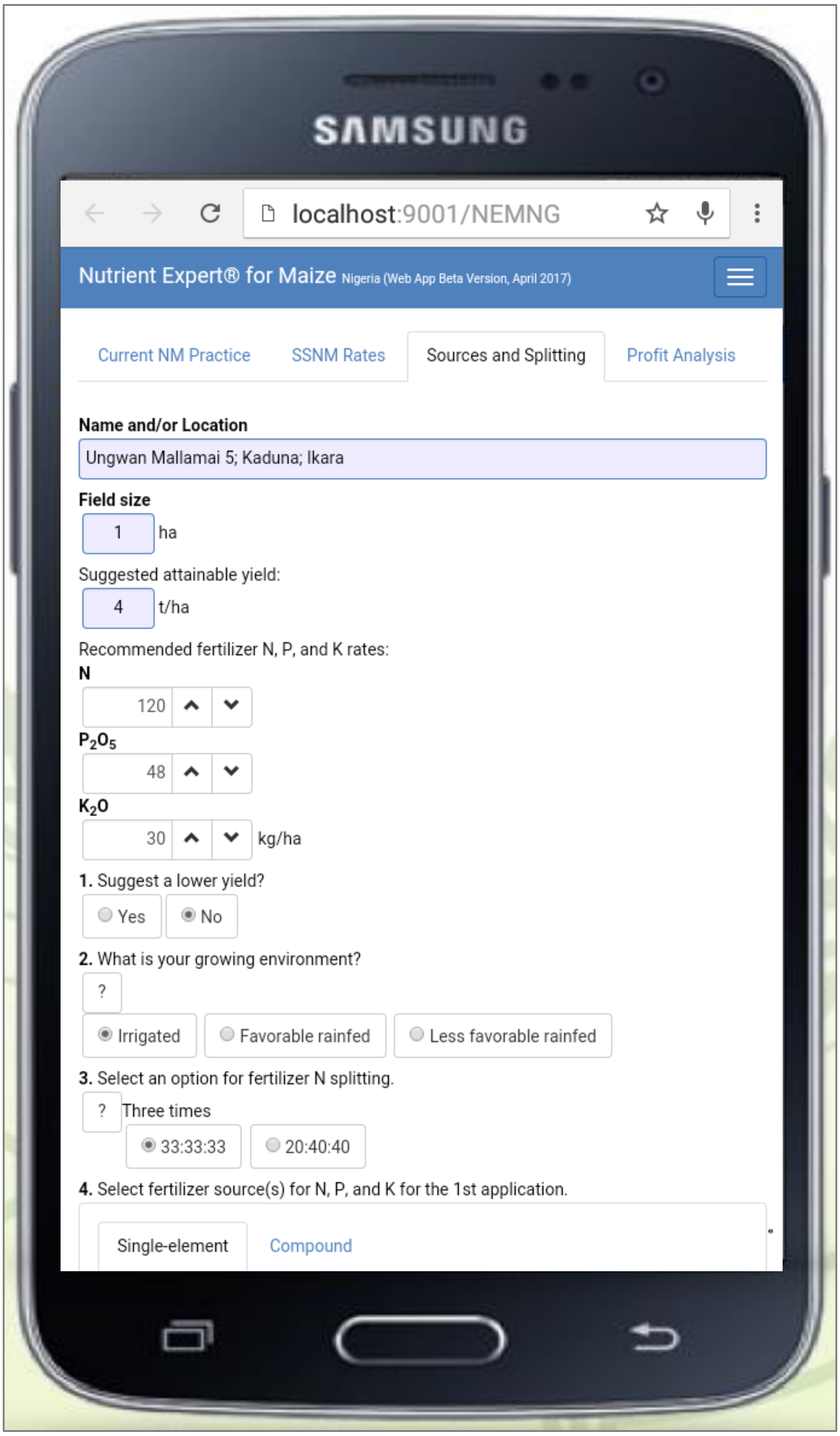

Fig. A4: Screen of the third module of Nutrient Expert tool. It only shows some portion of the module

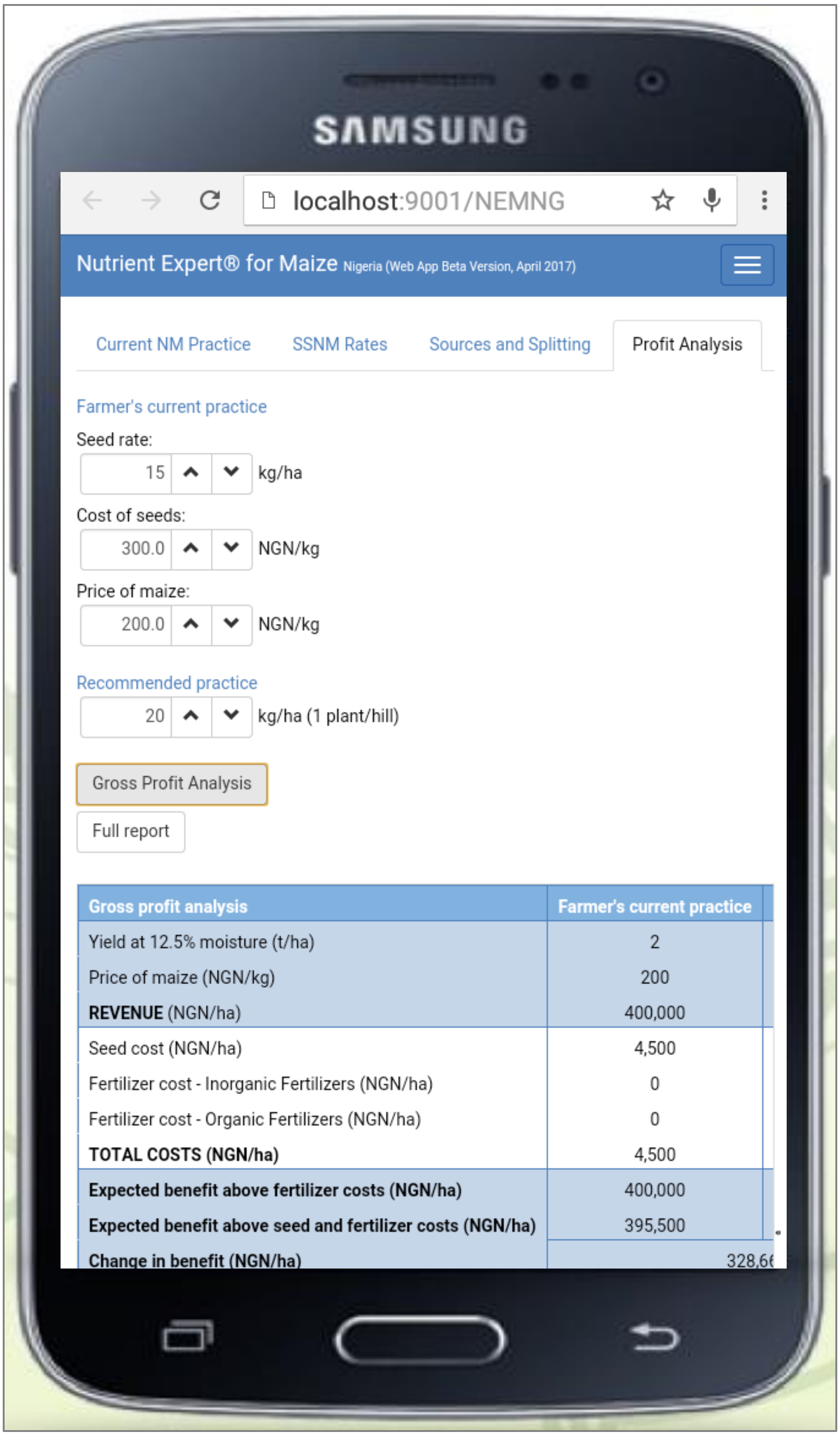

Fig. A5: Screen of the fourth module of Nutrient Expert tool. It only shows some portion of the module

Curriculum Vitae

Oyakhilomen Oyinbo

Gender	Male
Marital Status	Married
Date of Birth	04/02/1985
Nationality	Nigerian
Contact Address	Department of Agricultural Economics, Ahmadu Bello University, Zaria, Nigeria. Tel: +2348032779442 Email: ooyinbo@abu.edu.ng, ooyakhilomen@gmail.com Skype: saintoyas

EDUCATION

2015 – 2019	PhD in Agricultural and Development Economics, KU Leuven: "Site-Specific Nutrient Management Advice and Agricultural Intensification in Maize-Based Systems in Nigeria". Supervisors: Prof. Miet Maertens, Prof. Roel Merckx, Prof. Jan Diels, Dr. Jordan Chamberlin
2011 – 2014	MSc in Agricultural Economics: 4.66/5.00. Ahmadu Bello University, Zaria, Nigeria: "Household Demand Structure for Rice Consumption in Kaduna State, Nigeria". Supervisors: Prof. Raphael Omolehin, Prof. Abdulsalam Zakari.
2003 – 2009	Bachelor of Agriculture (Agricultural economics option): First class honors. Ahmadu Bello University, Zaria, Nigeria: "Economic Analysis of Cassava Production in Esan West Local Government Area of Edo State, Nigeria". Supervisor: Dr. Omadachi O. Ugbabe

PROFESSIONAL EXPERIENCE

Teaching and Research

2017 – date	Lecturer 1: Department of Agricultural Economics, Ahmadu Bello University, Zaria, Nigeria.
2014 – 2017	Lecture 2: Department of Agricultural Economics and Rural Sociology, Ahmadu Bello University, Zaria, Nigeria.
2011 – 2014	Assistant Lecturer: Department of Agricultural Economics and Rural Sociology, Ahmadu Bello University, Zaria, Nigeria.

Courses Taught

2013 – 2015	AGEX 204: Introductory Research Methods
2013 – 2015	AERS 302: Introductory Agricultural Marketing and Prices
2013 – 2015	AERS 502: Agricultural Marketing and Prices

Student Supervision

2011 – 2015	I supervised over ten undergraduate students and one postgraduate student

Field Engagement

2019 – 2020	Consultancy: Design and implementation of a discrete choice experiment on sustainable cereal-legume intensification in Ghana for the project 'The Africa Research in Sustainable Intensification for the Next Generation (Africa RISING)' led by the International Institute of Tropical Agriculture (IITA).
2016 – 2018	Activities managed during PhD: Three rounds of a farm-household panel survey, a discrete choice experiment among farmers, a discrete choice experiment among extension agents, and a randomized controlled trial for three years among 792 maize producing households as part of the Taking Maize Agronomy to Scale in Africa (TAMASA) project in Nigeria.
2017 – 2018	Resource person: Farm-household digital data collection using Open Data Kit (ODK) by the Taking Maize Agronomy to Scale in Africa (TAMASA) project in Nigeria.
2017	Resource person: Farm-household survey among 800 soybean producing households in Borno State, Nigeria by the N2Africa 'Putting Nitrogen fixation to work for smallholder farmers in Africa' project, Borno State, Nigeria.
2016	Resource person: Optimizing Fertilizer Recommendations in Africa (OFRA) project stakeholders engagement on Fertilizer Optimizer tool, Institute for Agricultural Research, Ahmadu Bello University, Zaria, Nigeria.
2014 – 2015	Resource person: Lecture series on market advisory service to farmers and agro dealers under the Alliance for a Green Revolution in Africa Soil Health Program (AGRA-SHP), Institute for Agricultural Research, Ahmadu Bello University, Zaria, Nigeria.

PROFESSIONAL HONOR AND AWARDS

2019	Best Contributed Paper Award – Second place, Sixth African Conference of Agricultural Economists.
2015 – 2019	Award of scholarship for a PhD program at KU Leuven, Belgium under the Taking Maize Agronomy to Scale (TAMASA) project funded by the Bill and Melinda Gates foundation.
2016 – 2019	Award of graduate research fellowship of the International Institute of Tropical Agriculture (IITA).
2014	Central Bank of Nigeria cash reward for a published article in the Central Bank of Nigeria Journal of Applied Statistics.
2009	ABUSRC Award of excellence for first class honors graduates of Ahmadu Bello University, Zaria, Nigeria.

MISCELLANEOUS

Computer and software skills	Stata, R (Basic), Ngene, Nlogit, Latent Gold, SPSS, OD software, Microsoft Office (Word, Excel, Powerpoint)

Short course certificates	Proficiency certificate in management (Chattered), Nigerian Institute of Management, Training course on linear programming by CABI under the Optimizing Fertilizer Recommendations in Africa (OFRA) project, International Livestock Research Institute (ILRI), Ethiopia, Effective graphical displays, Missing data and Introduction to R by the Flanders Training Network for Methodology and Statistics (FLAMES), Leuven, Belgium.

PUBLICATIONS

Articles in internationally peer-reviewed journals

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, A.Y., Craufurd, P. & Maertens, M. (2019). Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria. *Agricultural Systems*, 173, 12-26.

Oyinbo, O., Mbavai, J., Shitu, M., Kamara, A., Abdoulaye, T. & Ugbabe, O. (2019). Sustaining the beneficial effects of maize production in Nigeria: Does adoption of short season maize varieties matter? *Experimental Agriculture*, 55, 885-897.

Ugbabe, O.O., Tahirou, A., Kamara, A.Y., Mbavai, J.J. & Oyinbo, O. (2017). Profitability and technical efficiency of soybean production in northern Nigeria. *Tropicultura*, 35(3), 203-214.

Saleh, M.K. & Oyinbo, O. (2017). Rice production under different weed management technologies adopted by rice farmers in Katsina State, Nigeria. *Journal of Agricultural Extension*, 21(1), 1-15.

Oyinbo, O. & Rekwot, G.Z. (2014). Agricultural production and economic growth in Nigeria: Implication for rural poverty alleviation. *Quarterly Journal of International Agriculture*, 53(4), 207-223.

Oyinbo, O. & Rekwot, G.Z. (2014). Relationships of inflationary trend, agricultural productivity and economic growth in Nigeria. *Central Bank of Nigeria (CBN) Journal of Applied Statistics*, 5(1), 35-47.

Oyinbo, O., Omolehin, R.A. & Abdulsalam, Z. (2013). Analysis of demand for rice consumption in Kaduna State, Nigeria. *AGRIS Online Papers in Economics and Informatics*, 5(3), 45-52.

Oyinbo, O., Ugbabe O.O. & Rekwot Z.G. (2012). Assessment of the growth of maize production in the Pre-Sap, Sap and Post-Sap periods in Nigeria: Lessons for sustainable rural economy. *Journal of Sustainable Development in Africa*, 14(5), 17-24.

Working papers

Oyinbo, O., Chamberlin, J. & Maertens, M. (2019). Design of digital agricultural extension tools: Perspectives from extension agents in Nigeria. Bioeconomics working paper series, working paper 2019/1.

Conference presentations

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Tahirou, A., Kamara, A.Y., Craufurd, P. & Maertens, M. (2019). Site-specific digital extension advice and farm performance: Experimental evidence from Nigeria. Upgraded paper plenary session. 6th African Association of Agricultural Economists (AAAE) Conference, Abuja, Nigeria, 23-25th September, 2019.

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Tahirou, A., Kamara, A.Y., Craufurd, P. & Maertens, M. (2019). Can site-specific extension services improve fertilizer use and yields? Experimental evidence from Nigeria. 170th European Association of Agricultural Economists (EAAE) Seminar, Montpellier, France, 15-17th May, 2019.

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Tahirou, A., Kamara, A.Y., Craufurd, P. & Maertens, M. (2019). Can site-specific extension services improve fertilizer use and yields? Experimental evidence from Nigeria. 20th PhD symposium of the Belgian Association of Agricultural Economists, Brussels, Belgium, 24th April, 2019.

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, A.Y., Craufurd, P. & Maertens, M. (2019). Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria. LIFT project choice experiment workshop, Division of Bioeconomics, KU Leuven, 27th March, 2019.

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, A.Y., Craufurd, P. & Maertens, M. (2018). Farmers' preferences for site-specific extension services: Evidence from a choice experiment in Nigeria. 30th International Conference of Agricultural Economists (ICAE), Vancouver, Canada, 28th July - 2nd August, 2018.

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, A.Y., Craufurd, P. & Maertens, M. (2018). Farmers' preferences for ICT-based extension services: Evidence from a choice experiment in Nigeria. WOG choice experiment workshop, University of Antwerp, Belgium, 15th June, 2018.

Oyinbo, O., Kamsang, L., Kamara, A. & Kadafur, I.M. (2018). Farmers' preferences for technology-enabled climate smart agriculture: Evidence from Nigeria. International conference, climates and cultures: perspectives for the future, Brussels, Belgium, 23-24th May 2018.

Oyinbo, O., Chamberlin, J., Vanlauwe, B., Vranken, L., Kamara, A.Y., Craufurd, P. & Maertens, M. (2018). Farmers' preferences for ICT-based extension services: Evidence from a choice experiment in Nigeria. 19th PhD symposium of the Belgian Association of Agricultural Economists, Brussels, Belgium, 25th April, 2018.

Oyinbo O., Omolehin R.A. & Abdulsalam, Z. (2014). Household consumption preference for imported and domestic rice in Kaduna State, Nigeria: Implication for rice quality improvement. 24th annual conference of the International Food and Agribusiness Association (IFAMA), Cape Town, South Africa, 15-19th June, 2014.

FACULTY OF BIOSCIENCE ENGINEERING.
DEPARTMENT OF EARTH AND ENVIRONMENTAL SCIENCES.
DIVISION OF BIOECONOMICS
Celestijnenlaan 200e box 2411
B-3001 HEVERLEE, BELGIUM
tel. + 32 16 32 00800
oyakhilomen.oyinbo@kuleuven.be
https://ees.kuleuven.be/bioecon/