KU LEUVEN

FACULTY OF BIOSCIENCE ENGINEERING

Technology adoption in smallholder cassava production: insights from a choice experiment in Tanzania

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Promotors:
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Dissertation presented in
Fulfillment of the requirements
for the degree of Master of Bioscience Engineering:
Agro- and Ecosystems Engineering

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Scientific abstract

Ever since the onset of the Green Revolution, large efforts have been made towards spreading new agricultural technologies to sub-Saharan Africa, in order to increase crop productivity also in this part of the world. To improve the efficiency of such extension services, choice experiments are sometimes used as a tool to estimate the stated preferences of farmers on certain technology traits. As the African Cassava Agronomy Initiative (ACAI) is setting up decision support tools which recommend farmers on staggered planting and fertilizer use, we analyze farmers' preferences on six attributes related to these recommendations. The attributes are planting month, number of months leaving cassava in the field, fertilizer investment, average expected yield, yield variability, and the market type. As Tanzania is the first target country of ACAI together with Nigeria, the research is set in the rural areas of the Lake Zone, the Eastern Zone, and the Southern Zone of the Tanzanian mainland. The respondents are small-scale cassava farmers who are linked to an extension agent of ACAI or of one of its development partners. The ultimate goal of this paper is to ascertain whether certain recommendations should be adapted to the farmer due to heterogenous preferences among the target group, and, if necessary, how the adaptation should be done to increase adoption rates. A total of 333 farmers' responses have been collected from our choice experiment, and were linked with survey data and insights from group discussions. The data from the choice experiment are analyzed with a mixed multinomial logit model, followed by a latent class model. The socio-economic characteristics of the different classes are then compared using a two-sided t-test. The results show that there is significant preference heterogeneity for all attributes except planting month. The agronomic practice of staggered planting and harvesting does not necessarily need a personalized approach, but it is predicted that the highest adoption rates will be among the wealthiest farmers. The preference for fertilizer investment for cassava has shown to be very heterogenous. The largest aversion for fertilizer use is among the farmers who have the smallest cassava fields and the least experience with fertilizers on cassava. Yet, among the two other classes with a higher preference for fertilizer use, is the class of the least wealthy farmers. Hence, it is expected that these farmers will have low fertilizer adoption rates too, unless credit is made available for them. Considering that the preferences for a guaranteed market are the largest among the same least wealthy class, we recommend policy makers and large cassava buyers to look into the possibility of combining contracts with credit access. To conclude, it is clear that a certain degree of personalization is necessary to maximize the impact of extension services in general, and of ACAI's extension services in particular.

Wetenschappelijke samenvatting

Sinds de Groene Revolutie is er veel moeite gestoken in het verspreiden van nieuwe technologieën in sub-Saharaans Afrika, met het doel om de gewasproductiviteit ook in dit deel van de wereld te verhogen. Eén van de methoden om zulke *extension services* te verbeteren, is het gebruik van keuze-experimenten. Deze experimenten helpen de voorkeuren van boeren omtrent de karakteristieken van de te verspreiden technologieën in te schatten. Aangezien het *African Cassava Agronomy Initiative* (ACAI) technische ondersteuning zal verlenen aan cassave boeren over bepaalde agronomische praktijken zoals verspreid planten en het gebruik van kunstmest, worden de voorkeuren omtrent zes gerelateerde attributen onderzocht. Deze attributen zijn plantmaand, aantal maanden cassave in het veld houden, kunstmestgebruik, gemiddelde verwachte opbrengst, opbrengst variabiliteit, en markt type. Omdat Tanzania samen met Nigeria het eerste land is waarin ACAI te werk zal gaan, is dit onderzoek gevestigd in de *Lake Zone*, *Eastern Zone*, en *Southern Zone* van het Tanzaniaanse vasteland. De respondenten van dit onderzoek zijn kleinschalige boeren die cassave cultiveren, en gelinkt zijn aan *extension agents* van ACAI of ontwikkelingspartners van ACAI. Het doel is om te weten of en hoe advies aangepast moet worden aan verschillende types boeren om de implementatie te verhogen. In totaal hebben 333 boeren het keuze-experiment beantwoord, en deze data wordt gecombineerd met enquête-data en inzichten van groepsdiscussies. De data van het keuze-experiment wordt geanalyseerd met behulp van een *mixed multinomial logit* model en een *latent class* model. De socio-economische karakteristieken van de drie verschillende klassen boeren worden vervolgens onderling vergeleken met behulp van een tweezijdige t-test. De resultaten tonen aan dat er significante voorkeurheterogeniteit is voor alle attributen, behalve voor de plantmaand. Het advies om verspreid te planten en te oogsten hoeft geen personalisatie, maar een grotere implementatie wordt wel bij de welvarendere boeren verwacht. Voor kunstmestgebruik ligt de grootste aversie bij de boeren met het kleinste cassave veld en de minste ervaring met kunstmestgebruik voor cassave. De minst welvarende boeren tonen aan open te staan voor kunstmestgebruik. Er wordt echter voorspeld dat de implementatie bij hun ook laag zal zijn, tenzij ze toegang hebben tot krediet. Gezien dat ook een gegarandeerde markt het meest in smaak valt bij deze minst welvarende klasse, worden beleidsvormers en grote cassave kopers aangeraden om de mogelijkheid van contracten met kredietoegang te analyseren. Tot slot bevestigt dit onderzoek dat een zekere graad van personalisatie vereist is om de impact van *extension services*, meer specifiek die van ACAI, te maximaliseren.

List of abbreviations

ACAI = African Cassava Agronomy Initiative

ASC = Alternative Specific Constant

BIC = Bayesian Information Criterion

CAIC = Consistent Akaike Information Criterion

DCE = Discrete Choice Experiment

DRC = Democratic Republic of the Congo

EA = Extension Agent/Officer

EZ = Eastern Zone

IITA = International Institute of Tropical Agriculture

LZ = Lake Zone

MMNL = Mixed Multinomial Logit

MNL = Multinomial Logit

SSA = sub-Saharan Africa

SZ = Southern Zone

TARI = Tanzania Agricultural Research Institute

TSH = Tanzanian Shillings

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1 Introduction

While the rest of the world has seen a substantial increase in food security over the past 60 years, the food security levels in sub-Saharan Africa have remained constant or even decreased. This is among other factors due to the Green Revolution that did not penetrate (yet) for most crops in sub-Saharan Africa. Cassava is one of these crops for which new technologies were never adopted in small-scale cultivation, and thus an increase in productivity never came. However, a rise in production and yield of cassava is highly recommended in sub-Saharan Africa, both for its economic opportunities and for cushioning the impact of climate change on food security.

In order to stimulate technology adoption, and thus to install a Green Revolution in sub-Saharan Africa, much effort and money has gone to different extension service programs. For cassava we see that past extensions mainly focused on new technologies such as chemical fertilizers or improved varieties, but hardly ever on improved agronomic practices. This is why the African Cassava Agronomy Initiative (ACAI) has been set up. ACAI's extension services will first be active in Tanzania and Nigeria, and after that in Kenya, the Democratic Republic of the Congo, and Ghana.

To improve the efficiency and impact of extension services, ex-ante research is sometimes used as a tool to recognize the stated preferences of farmers on certain technology traits. With knowledge of these preferences, the extension services are adapted to the farmers' needs and thus adoption rates are supposed to be higher than the counterfactual. However, to our knowledge, no research has been done so far to find preferences for agronomic technology adoption for cassava cultivation in Tanzania. As this knowledge would help improve ACAI's extension services, this paper focuses on this very research objective. In particular, we focus on farmers' preferences for the following six attributes: cassava planting month, the number of months keeping the cassava in the field, fertilizer investments for cassava, the expected yield, the yield variability, and the market or contract type. These attributes are related to two of the agronomic practices on which ACAI focuses: staggered planting and fertilizer use.

For this research we conduct a discrete choice experiment of 333 households in three different zones in Tanzania, which are the Lake Zone (Mwanza Region), the Eastern Zone (Dar es

Salaam Region), and the Southern Zone (Mtwara Region). The results of the choice experiments are then linked to survey data and to insights from group discussions.

The research objectives are to discover: (i) what level of each attribute is generally preferred by the cassava farmers, (ii) how heterogenous are each of these preferences, (iii) can different classes with homogenous preferences be created, (iv) which socio-economic characteristics correlate with these different classes, and (v) how should extension services be adapted to each class in order to increase adoption rates of ACAI's recommendations.

With this introduction being section 1, the rest of the paper is organized as follows: section 2 shows what can be found in the literature on technology adoption, extension services, and ex-ante research; section 3 gives background information about cassava's current status in the world and in Tanzania, and gives more information about ACAI; section 4 explains why and how the discrete choice experiment was used, what the sampling strategy was, how the data was collected and how it was analyzed; section 5 reports the qualitative results from the group discussions, the descriptive results from our sample, and the econometric results using a mixed multinomial logit model and a latent class model; section 6 comprises the discussion about our results together with research and policy implications; section 7 concludes.

2 Literature review

2.1 Technology adoption in sub-Saharan Africa

Between the 1950s and the 1960s a Green Revolution occurred in most of the world thanks to a set of research technology transfer initiatives. The adoption of technologies such as fertilizers and high-yielding modern varieties started a rapid increase in crop productivity for the past 60 years in most developing countries (Evenson & Gollin, 2003). Yields grew in Africa too, but by far not as fast as in Asia or South-America. Moreover, while the production growth in Asian countries mostly came from the adoption of these improved technologies, the African growth is mostly explained by an increase in cultivated land (Otsuka & Larson, 2013). In Tanzanian rice cultivation for example, less than 30% of the farmers use fertilizers, and those who do apply less than 25% of the recommended amount (Nakano, Kajisa, & Otsuka, 2015). Next to the adoption of chemical fertilizers, also improved varieties and improved agronomic practices are not widespread in sub-Saharan Africa. This discrepancy between the impact of the Green Revolution on technology adoption and yields in Asia and in Africa is among other factors explained by the fact that agro-climatic conditions, diets and population densities are much more heterogenous in Africa (Otsuka & Larson, 2013). This implies that, while a one-size-fits-all approach might work in Asia, more research is necessary to find technologies that suit different locations in Africa. It also implies a greater task to transmit these accustomed technologies to the African farmers via so-called 'extension services'. Failing to do so, and thus failing to install a similar Green Revolution in Africa, will lead to significant challenges to meet the expected increase in food demand (Cai, Golub, & Hertel, 2017).

2.2 Extension services

2.2.1 Definition

There is not one generally accepted definition for agricultural extension service. However, the FAO describes the concept as "… an informal educational process directed toward the rural population. This process offers advice and information to help them solve their problems. Extension also aims to increase the efficiency of the family farm, increase production and generally increase the standard of living of the farm family" (Oakley & Garforth, 1985). Many different strategies for this educational process exist.

2.2.2 Historical perspective

The goal of agricultural extension, how it is done and what technology they disseminate, has changed over time in developing countries. We see an evolution from paternalistic or top-down extension to participative or bottom-up extension, and from persuasive to educative extension (NAFES, 2005).

During colonial times, agricultural research focused mainly on export products and adopted the industrial 'plantation' farming system (Eicher, 1990). This was paired with a high increase in productivity. The extension was top-down, because the technology transfer went in one direction from the researcher to the farmers. The opinion and needs of the farmers was hardly recognized. Extension services were also persuasive, in the sense that institutions and researchers decided what technology should be adopted by the farmers (NAFES, 2005).

As soon as African countries became independent, productivity fell due to a high level of dis-adoption of the improved technologies, even though extension services were still in practice. The extension now also covered local crops, but was still top-down and persuasive. As a consequence of the decrease in productivity, a new strategy was put in place by the World Bank. This 'Training and Visit' (T&V) system gave general recommendations to the farmers via regular visits of trained agents, or by using widespread communication methods such as the radio. However, the system was proven to have no significant impact on agricultural productivity by the end of the 1990's because of not giving a voice to the farmer and by consequence not taking into account the heterogeneity in diet, climatic conditions, and farmer's preferences and limitations (World Bank, 1999).

While the funding of the World Bank came to an end, the centralized T&V dissolved into many fragmented extension programs. This decentralization of extension automatically led to a more bottom-up approach, where the farmer's empowerment became the goal of all research, education, and extension. The needs and problems of the farmers were taken into account, as well as their feedback on prior extension services and the demand on the market. The extension also became educational, because the farmers could decide which technology they adopted. Other methods of technology dissemination appeared, such as farmer-to-farmer extension and experiential learning. Also Farmer Field Schools (FFS) and Agricultural Knowledge and Information Systems (AKIS) arose (NAFES, 2005). Since the general acceptance approximately twenty years ago that a bottom-up, educative approach is the best practice for extension, it has widely been put into practice. One example of an institution that has adapted towards this new holistic approach is the Consultative Group of International Agricultural Research (CGIAR), which is a network of "15 top-class research centers and more than 3000 partners from national governments, academic institutions, global policy bodies, private companies and NGO's within 70 countries" (CGIAR, 2019).

2.2.3 Impact of extension on technology adoption

The impact of extension services is measured in four distinctive ways in the literature: knowledge on technologies, adoption rate, farm efficiency, and production (Dinar, Karagiannis, & Tzouvelekas, 2007). Assuming that adopting a technology requires the knowledge of it, we first focus on adoption rate. The literature shows that the rate of technology adoption depends on many factors.

Firstly, the method of extension seems to matter. Intensive training of farmers has found to significantly increase technology adoption in Tanzania (Nakano, Tsusaka, Aida, & Pede, 2018). Radio-based extension services also proved to have a positive impact on farmers changing their farming practices (Sanga, Kalungwizi, & Msuya, 2013).

Secondly, the rate of technology adoption is negatively affected in areas where there are labor or capital constraints (Nakano et al., 2018). This negative effect of capital or credit constraints on fertilizer adoption specifically has been widely documented (Dercon & Christiaensen, 2011; Lambrecht, Vanlauwe, Merckx, & Maertens, 2014; Liverpool & Winter-Nelson, 2010), and Emmanuel et al. (2016) recommends to facilitate credit access to encourage chemical fertilizer adoption. For cassava specifically, credit access was found to have a significantly positive effect on general technology adoption, and as a consequence also on the cassava yield and income of the adopters (Obisesan, Amos, & Akinlade, 2016).

Thirdly, the technologies that have already been adopted by the farmer and the resources needed to adopt new technologies have a significant effect. Lambrecht et al. (2016b) distinguish sequential adoption of first less resource-intensive technologies followed by more resource-intensive technologies.

Fourthly, the person disseminating the information influences technology adoption. The adoption rate following visits from extension agents were found to be high at first but decreasing after a certain time, while the effect of peer learning became more important (Krishnan & Patnam, 2014). This idea can be explained by the findings showing that early adopters of the service given by extension agents could convince ordinary farmers through farmer-to-farmer extension, even if the ordinary farmers did not receive the service from the extension agent in the first stage (Maertens & Barrett, 2012; Nakano et al., 2018). This would mean that intensive training of carefully selected farmers can increase the performance of other farmers within the community after time. However, the ordinary farmers with a pre-established social connection to the progressive farmers have been found to have a higher adoption rate than others (Nakano et al., 2018).

Fifth, socio-economic characteristics of the farmer show to have a significant effect on technology adoption. For example, it has been found that women's participation in extension leads to more effective technology adoption in female-headed households than in male-headed households, unless both spouses participate (Lambrecht, Vanlauwe, & Maertens, 2016a). Based on similar findings, Emmanuel et al. (2016) recommends to sensitize female farmers in order to increase adoption of chemical fertilizers. Suvedi, Ghimire, & Kaplowitz (2017) have found that membership in a farmer's group and distance of the house to the extension officer increase the degree of technology adoption after extension services.

Sixth, Dalemans et al. (2019) show that also the market of the targeted crop matters, and they explain that value chain reorganization can be an important factor in adoption rates. Moreover, new extension programs that are integrated with market development models have shown to improve technology adoption and farm efficiency as a result (Ayenew, 2016). Meanwhile, Skreli et al. (2014) ascribed the limited effect of the public extension services in Albania to the fact that they do not meet the farmer's needs. These findings are in line with the latest paradigm for bottom-up extension services as described before.

Finally, the stage in which you measure technology adoption rates affects the numbers. Lambrecht et al. (2014) split technology adoption into try-out adoption and continued adoption. Try-out adoption appeared to be positively influenced by extension services. With the extension being about mineral fertilizer, it was found that 70% of the try-out farmers became continued adopters. However, capital and credit constraints were again significant indicators of non-fertilizer-adoption after try-out. Moreover, it has been found that the resulting yield after the fertilizer try-out also significantly affects the continued use (Dercon & Christiaensen, 2011). For cassava specifically, Hillocks (2014) found that the effect of inorganic fertilizer use on the cassava yield was significantly reduced in rainfed agriculture, thus disincentivizing the farmers without irrigation facilities to continue adoption.

2.2.4 Impact of extension on farm efficiency and production

Once a farmer knows the technology, we can still wonder whether this will truly result in the end-goal of the extension services, as was described in the definition: an increase in farm efficiency, production, and generally the living standard of the farming families. In the literature we distinguish both the efficiency-based approach and the production-based approach to measure the final effect of extension. Using the efficiency-based approach, means to add the presence of an extension service as an extra variable to explain differences in farming system efficiencies. Other variables that have shown to also influence technical efficiencies, and that thus should be included as well, are age, gender, education, crop diversity, etc. (Haji, 2007; Mathijs & Vranken, 2010). With this approach the extension service's indirect impact on production is measured. Other papers use the production-based approach. In this case, the extension service is seen as another input for a production function. The marginal product is then the direct impact of the extension service on the production (Dinar et al., 2007). Finally, some papers have analyzed the impact of extension services on poverty.

By using the efficiency-based approach, Kidanemariam (2017) found that the new nationally-installed extension system in Ethiopia significantly increased a farm's technical efficiency. This positive effect of extension services in general was echoed by multiple other papers (Ayenew, 2016; Dinar et al., 2007; Emmanuel et al., 2016). However, others found that extension services did not affect, or even significantly negatively affected, efficiencies (Haji, 2007; Skreli et al., 2014; Young & Deng, 1999). When using the production-based approach, the results of extension services on production are again mixed. For example, Khan & Akbari (1986) and Owens & Hoddinott (2001) separately found that extension services visits increased the crop production by 35% and 15% respectively, while Gangwar, Saran, & Kumar (2013) did not see a positive effect on the production. Interestingly, Dinar et al. (2007) evaluated the effect of public and private extension services by combining both approaches. They found that both extension services individually increased both the farm efficiency and the production. For cassava specifically, different results suggest that extension for the adoption of improved varieties by smallholder farmers reduces their poverty (Awotide, Alene, Abdoulaye, & Manyong, 2015; Wossen et al., 2018). The results of Obisesan (2014) show that, generally, improved technology adoption for cassava production is poverty reducing.

The above differences in result can be explained by differences in adoption rates, due to reasons stated in the previous chapter. The differences in result can also be ascribed to the differences in information shared in the extension services. For example, the respondents from one survey where a negative effect was observed, said they did not learn anything new from the services (Haji, 2007; Kalirajan & Shand, 1988). Furthermore, for technologies like fertilizers and improved seeds the different final effects of extension services can be explained by the quality of the extension. This means that it's not only about whether a farmer adopts a technology, but also about how well he/she adopts it. For example, in Tanzania, extension services for fertilizers and improved seeds to one lead farmer followed by farmer-to-farmer dissemination have found to increase crop productivity among the community, and the significant indicator was then the quality of the training of the lead farmer (Nakano et al., 2018). Moreover, Ngailo et al. (2016) found that one of the main production constraints of sweet potato was inadequate extension services in the Morogoro and Coast Region of Tanzania. Finally, the differences in impact on production or efficiency can also be explained by how well the disseminated technologies fit the different agro-climatic conditions (Kidanemariam, 2017). This is in line with the more heterogenous needs that are typical for sub-Saharan Africa, as stated before (Otsuka & Larson, 2013).

2.3 Ex-ante research

2.3.1 Definition

In the articles cited above, the evaluation of the technology adoption rate and the consequential production or farm efficiency was done after, or 'ex-post', the extension service. However, it is also possible to predict these outcomes beforehand, or 'ex-ante', by estimating the preferences of the target population about hypothetically adopting certain technologies. With similar and other objectives, choice experiments are used increasingly in agricultural economics (Bennett & Birol, 2010). In a choice experiment, the respondent is offered several cards with each showing different scenarios to choose from. By analyzing the choices made, the stated preference of the respondent about elements in the scenarios is revealed. This is why choice experiments are called ‘stated preference methods’. Even though such ex-ante, stated preference methods are not completely waterproof because of a possible hypothetical bias, it can still give us valuable insights in which technology traits which farmers prefer, how extension services can be adapted to each farmer, and ultimately how technology adoption can be accelerated.

2.3.2 Choice experiments on technology adoption

After extension service, a farmer adopts or does not adopt the technology depending on its traits. Thus, in the literature, most choice experiments for technology adoption are investigating which requirements and consequences of a technology the target audience likes or dislikes. For example, Kassahun & Jacobsen (2014) researched via a choice experiment what incentives would be preferred to make farmers manage their land to avoid soil erosion, and which kind of management (labor or watershed management) was preferred. They found that there were two classes with homogenous preferences. One class required less subsidies and was ready to invest more labor than the other class. This first class probably comprised more literate farmers with easier access to credit. Another result was that for both classes an increased or more seasonally concentrated labor cost seems to be in disfavor. Lambrecht et al. (2015) investigated in Burundi which traits of a new climbing bean variety were preferred among 200 farmers, and they found that higher yields and improved soil fertility are appreciated, while the required amount of time in the field for maturation of the crop and the crop’s responsiveness to fertilizers was less important. They also found that the financial cost, such as the price of improved seeds, seems to be disliked only by the most food-insecure farmers. Asrat et al. (2010) had quite the similar research objective, as they quantified via a choice experiment the preferences for the traits of different crop varieties, and the willingness to pay for each crop variety attribute. It was found that output stability was the most appreciated variety trait. Finally, Duquette et al. (2013) wanted to know the underlying reason for early and/or late adopting of technology. Via a choice experiment on U.S. farmers, they found that the waiting time necessary to enjoy the results from the technology adoption seem to matter. Farmers appear to prefer technologies that show results sooner. They thus believed that rather a farmer’s time preference instead of his/her risk aversion would determine whether he/she would adopt a new technology.

Sometimes, there is preference heterogeneity among the respondents in the sample. In the literature we find that in this case often the sample is split into different classes with homogenous preferences, and then the different socio-economic characteristics between these classes are analyzed. The goal is to be able to explain the differences in preference by differences in characteristics, so that extension services can be adapted to each class in order to maximize technology adoption. From the literature, we find several significant characteristics. The education level, described by literacy, level of completed school degree, or age as a proxy for farming experience, shows a positive correlation with technology adoption preferences (Asrat et al., 2010; Kassahun & Jacobsen, 2015). A better financial situation or the perception of it, described by assets or access to credit, contribute to higher preferences for cost-intensive technology adoption (Gómez, Salgado, Vásquez, & Chávez, 2014; Kassahun & Jacobsen, 2015). This is confirmed by Asrat et al. (2010), assuming that the size of the farm and the presence of livestock influence a farmer's perception of wealth. Finally, gender also seems to matter, as Kassahun & Jacobsen (2015) found that more women prefer to stick to the status quo.

We build further on these findings, looking if the same preferences are found for technology adoption for cassava cultivation in Tanzania. To our knowledge, no previous research with the same objective has been done so far.

3 Background

3.1 Cassava roots in the world

Cassava (*Manihot esculenta* Crantz) is, even though natively from South-America, now cultivated in tropical and subtropical regions around the world for its high-starch tuberous roots. Figure 1 shows the cassava production in the three largest cassava producing regions: Africa, the Americas, and Asia. We deduce that more than 50% of the global cassava production is based in Africa. There is also cassava cultivated in Oceania, but the amounts are marginal compared to the other continents (FAOSTAT, 2017).

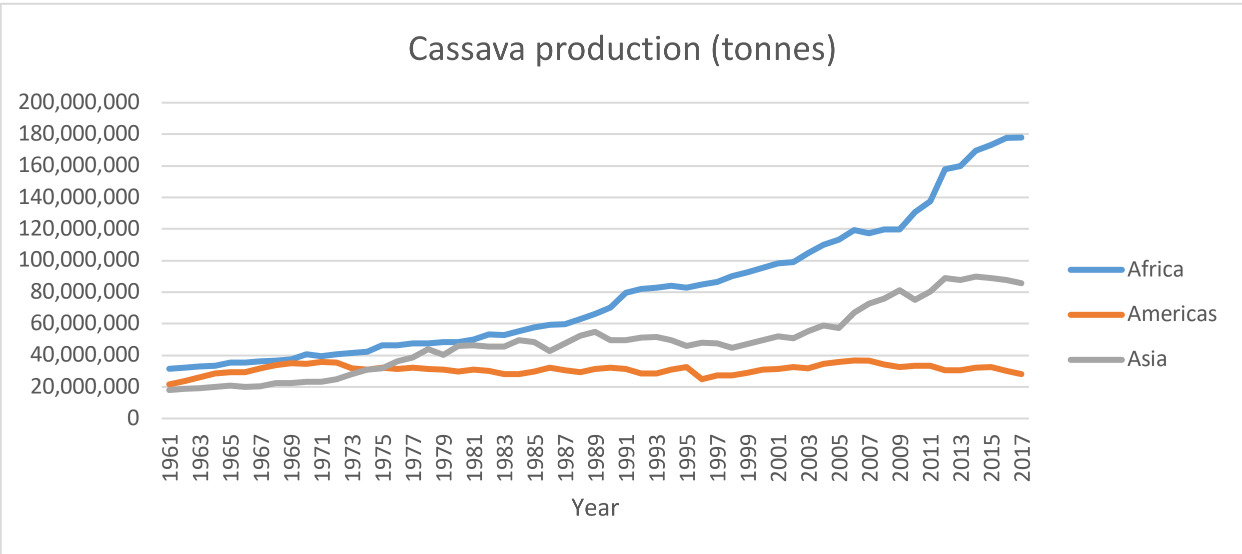

Figure 1: Cassava production in Africa, Americas, and Asia

Even though starting at approximately the same amount of production in 1961, we see a more or less steady production growth for cassava in Asia, but almost an exponential growth in Africa for the past 60 years (Figure 1). However, looking at how the cultivated area for cassava and the cassava yield have evolved in Africa (Figure 2, Figure 3), it is clear that the cassava production growth is more due to the exponential increase in harvested area than the small increases in productivity. Considering the impact of the Green Revolution in Asia as described before, the opposite should be true for Asia. Indeed, we see that cassava productivity has increased significantly in Asia in the past 60 years while the cultivated land has more or less remained constant. The cassava productivity and the harvested area for cassava has remained rather constant in the Americas, resulting in a comparatively stable production since 1961.

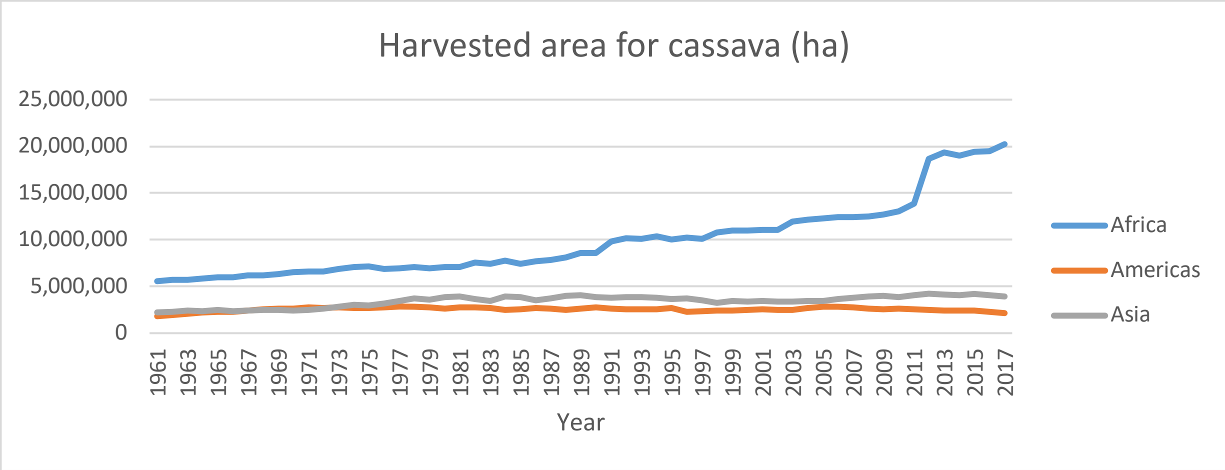

Figure 2: Harvested area for cassava in Africa, Americas, and Asia (FAOSTAT, 2017)

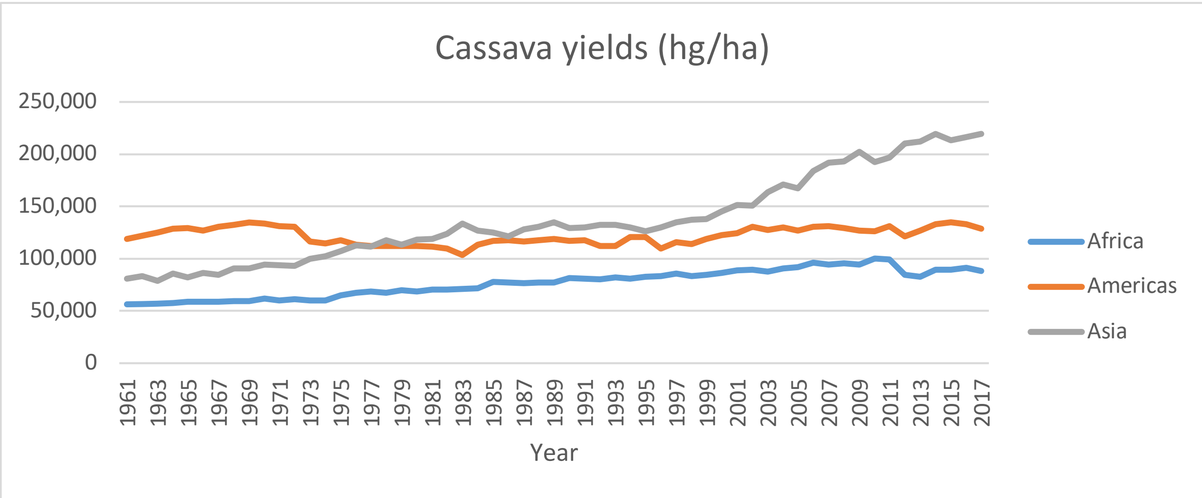

Figure 3: Cassava yields in Africa, Americas, and Asia (FAOSTAT, 2017)

From Figure 3 it is clear that most countries in the Americas and in Africa deal with a large yield gap. Looking at the current trends in the world, there is enough reason to deem this problematic. Firstly, cassava today is the staple food for almost 800 million people in developing countries. For many people it is regarded as an easily cultivated crop, especially during difficult conditions, due to its ability to grow on marginal soils and in dry conditions, its resistance to pest and diseases, and its flexible harvesting periods (Khandker & Mahmud, 2012). Considering the projected continued rise of the global population, especially in the tropical and subtropical regions, the amount of people's diet dependent on cassava is expected to increase (FAOSTAT, 2017). Secondly, the demand of the cassava root as a cash crop is believed to rise on an industrial scale in the future because of the growing interest of food processing factories in the high-starch content of cassava (FAO & IFAD, 2005; Parmar, Sturm, & Hensel, 2017; Uchechukwu-Agua, Caleb, & Linus Opara, 2015). The 'Cassava

Transformation' is the transition toward fully exploiting cassava's potential by, for example, using it in livestock feed or industrial raw material. Potential processed products from cassava roots are starch and starch-based products, bio-ethanol, beverages, and livestock feed. Asia and South-America have almost completed the Cassava Transformation towards an industrialized cassava market, while in most countries in sub-Saharan Africa the Transformation is still in the early stages. In Ghana and Nigeria cassava has become a cash crop and is consumed in urban areas, in Uganda and the DRC cassava has become a rural food staple, and in Tanzania cassava is still seen as a secondary staple, preferably consumed in times of hunger (Parmar et al., 2017). However, looking at the global trend, this Cassava Transformation sooner or later seems inevitable in all African countries. Thirdly, with the continued climate change the importance of resilient crops is expected to rise. Cassava in sub-Saharan Africa has been shown to be the most resilient to climate change conditions predicted for 2030 compared to other leading crops like maize, sorghum, millet, beans, potato and bananas, and this comparatively higher resilience is true in other parts of the world too (Howeler, Lutaladio, & Thomas, 2013; Jarvis, Ramirez-Villegas, Herrera Campo, & Navarro-Racines, 2012). To conclude, the current and future importance of cassava is clear by the (projected) amount of people's diets that are dependent of it, the expected demand from food processing factories, and the crop's resistance to climate change. To face these new challenges and to meet the expected rising demand, we must strive to close the cassava yield gaps where present.

3.2 Cassava in Tanzania

Tanzania is a country in Eastern Africa, located between 1 to 11 degrees south of the equator, which results in a tropical climate with regional topographical variations. It has a bi- or unimodal seasonal rainfall, dependent on the region: the north and east of Tanzania experience rain from October to December and from March to May, while the south, center and west of the country only experience rain during one period from October to April or May (McSweeney, New, & Lizcano, 2010). About 80% of the Tanzanian population works primarily in agriculture, and the majority of them is mainly farming for subsistence use. Consequentially, because of the low production and productivity of cash crops, only 45% of the country's GDP comes for agriculture (Adam, Bevan, & Gollin, 2018).

In Figure 4 we compare the average cassava productivity of Tanzania, expressed in hectogrammes per ha, with the average yields in the four largest cassava producers in the world

(Brazil, Indonesia, Thailand and Nigeria) (FAOSTAT, 2017). If we take the average yields from Indonesia and Thailand as the optimum, it shows that Brazil, Nigeria, and especially Tanzania have large yield gaps. Even more, these gaps seem to keep on growing, because the yields of Indonesia and Thailand have steadily been increasing since 1995, while the other yields seem to be stagnating or even decreasing. But, this trend can be reversed. For example, with the use of improved varieties and NPK fertilizers alone, Fermont et al. (2009) have found that the Tanzanian cassava productivity could double.

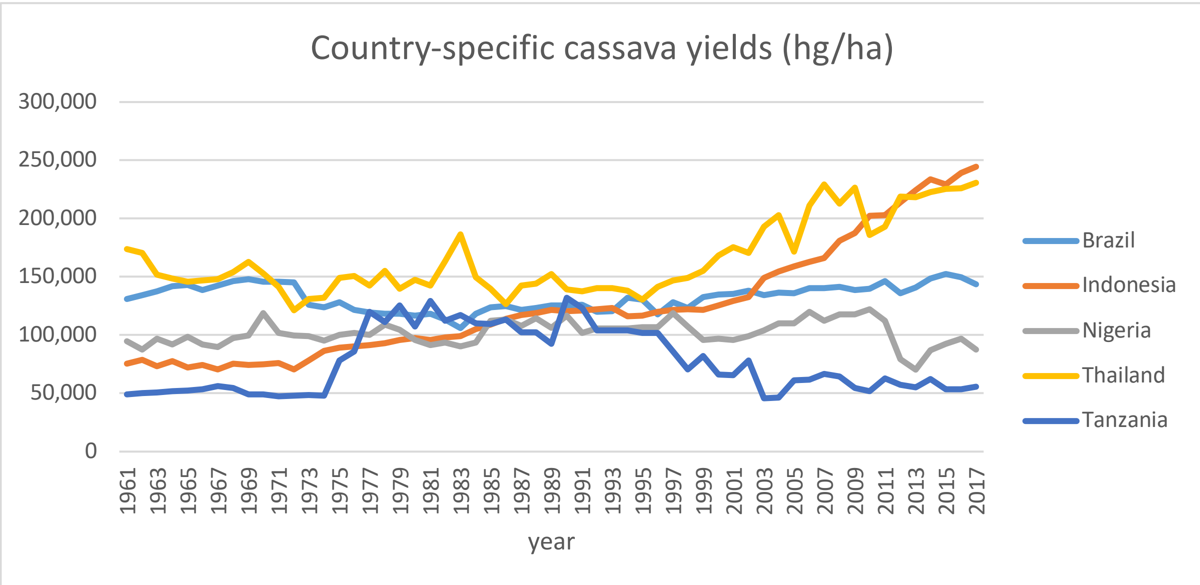

Figure 4: Cassava yields for Brazil, Indonesia, Nigeria, Thailand, and Tanzania (FAOSTAT, 2017)

One possible explanation for the seemingly comparatively low motivation to invest in and improve cassava cultivation among Tanzanian farmers, is that Tanzania is still in the first stages of the Cassava Transformation. This means that cassava is not even a staple crop in rural areas, but only a "famine reserve crop" (Khandker & Mahmud, 2012). So when times are good, most farmers consider it unnecessary to consume the crop. This again leads to a low level of commercialization. If the majority of the population only wants to consume cassava during the bad times, no investments in the value chain, for example in cassava processing factories, will happen. Indeed, Sewando (2014) has found that Tanzania has an underdeveloped cassava value chain, due to limited cassava processing and deficient market coordination.

We can say that Tanzania could benefit a great deal from an increase in its cassava productivity for several reasons. Firstly, Tanzania's large yield gap for cassava is in sharp contrast with its current position on the global cassava market: Tanzania is the eleventh country for total cassava production and the fifth country with the largest area for cassava cultivation (FAOSTAT, 2017)). Secondly, thanks to the global 'Cassava Transformation' and all the innovations it brings along, new opportunities arise in the cassava value chain. Thirdly, also Tanzania will need climate change resilient crops: with most Tanzanian farmers being reliant on rain-fed agriculture, Arndt et al. (2012) show that the country's food security risks to be heavily affected by climate change. Lastly, the projected demographic numbers of Tanzania (Figure 5) show that the country's overall food demand will increase.

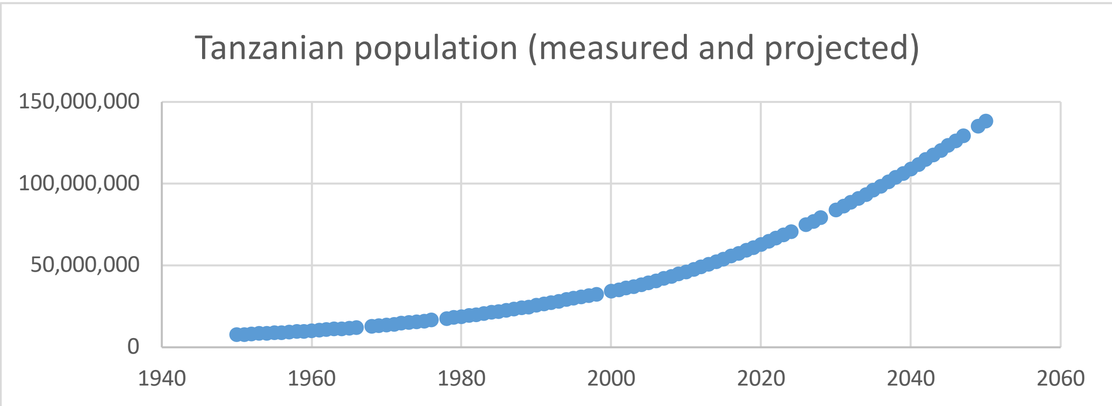

Figure 5: Measured Tanzanian population until 2017, projected Tanzanian population from 2018 to 2050 (FAOSTAT, 2017)

3.3 The African Cassava Agronomy Initiative

To close the cassava yield gap in sub-Saharan Africa, many investments have been made in technologies such as pest- and disease-resistant varieties, storage facilities, and cassava processing. Considering the continued stagnation in yield productivity, these have not reached the desired effect. One area for which investments have continuously lagged behind, are the research about and the extension of improved agronomic practices. However, a preliminary research conducted by the African Cassava Agronomy Initiative (ACAI) has shown that, to close cassava yield gaps in sub-Saharan Africa, there is still much room for improvement in cassava management. This has also been confirmed by previous research done by Fermont et al. (2009).

ACAI was set up in 2015 as a 5-year project, managed by the International Institute of Tropical Agriculture (IITA) and funded by the Bill & Melinda Gates Foundation. ACAI's goal is to sustainably improve the short- and long-term productivity of cassava by recommending improved agronomic practices to the farmers. The focus of the agronomic practices lays on six 'use cases' which comprise intercropping, fertilizer application, scheduled planting, and general best practices for high-starch content. The essence of ACAI's activities is the bottom-up approach, whereby the recommendations are in line with the local climatic and soil conditions, the farmers' needs and their local cassava value chain. To facilitate the personalization of the recommendations, the local extension agents will have a decision support tool for each of the six use cases. The data collected by ACAI will potentially also result in recommendations for governments.

ACAI's extension services will be set up in Nigeria and Tanzania at first, and later in the DRC, Ghana and Kenya. By increasing cassava root quality and yields within the 5 years of the initiative, ACAI also expects the cassava processing industry and the fertilizer sales in the target countries to grow. In the end, over 150,000 households, of which 30% women farmers, are expected to be positively affected by the initiative, resulting in over 42 million USD of value creation. (ACAI, 2015; IITA, 2014)

4 Methodology

For our research we use a discrete choice experiment (DCE) combined with survey data and focus group discussions.

4.1 Discrete Choice Experiment

4.1.1 Definition

A discrete choice experiment is a method to find the stated preference of the respondent on certain attributes. A stated preference method is not the same as a revealed preference method, where the preferences of the target group are deduced from their actions or behavior. Hence there is one major disadvantage to the stated preference method: if the respondent would behave in a different way than he/she says, a hypothetical bias is present in the results (Brownstone & Small, 2005). However, the advantage is that the stated preference method can be used "ex ante" or before the actual scenarios are put into place in real life.

In a choice experiment we show several choice cards with different scenarios, where the respondent needs to state which scenario he/she prefers. These scenarios all have the same attributes, but the level of the attributes change each time. The goal of the choice experiment is to know which levels are preferred within each attribute, and by looking at interaction effects we can also find out how these preferred levels change when combined with another attribute. This method relies on the assumption that all respondents are utility maximizing decision makers (Audibert, He, & Mathonnat, 2013). This means that the farmers will always choose one hypothetical scenario over the other if it would give them a higher utility. That utility, represented in Equation 1 by U_{in}, is defined by a deterministic component V_{in}, which are the attributes and attribute levels, and a random component ε_{in}. We can see that V_{in} is dependent on scenario i with attribute (levels) X_i and on respondent n with the characteristics of that respondent S_n. Then, the random component is shown by the error term ε_{in}. This error term contains all variability in utility U_{in} that cannot be explained by the deterministic component. Because in choice experiment theory we assume all error terms to be identically and independently distributed (i.i.d.) or random, we also call it the Random Utility Theory (RUT) (Cascetta, 2009; Kassahun & Jacobsen, 2015).

$$U_{in} = V_{in}(X_i, S_n) + \varepsilon_{in} \qquad \textit{(Equation 1)}$$

The amount of randomness inherent to the utility means that we will never be able to perfectly predict the utility of one scenario. However, to a certain degree of probability we will be able to predict the preferences by working with the deterministic component. How this component is calculated depends on the model chosen. More information about the possible models is given in section 4.4.

4.1.2 Attributes and levels

Choice experiments were originally used in marketing and transport sectors to find the optimal settings of different characteristics of a product or service, in order to maximize its appeal to the clients. The ACAI decision support tool can be seen as a product that needs to appeal to its customers, the cassava farmers. Thus, to maximize the adoption of the recommendations given by the tool, we want to gain insights in the farmers' preferences on these different recommendations.

The decision support tool of ACAI gives advice on six agronomy-related so-called "use cases": one tool for fertilizer blending, one for site-specific fertilizer recommendations, one for planting practices, one for intercropping, one for staggered planting, and one for agronomic practices for high root starch content. To optimize each of these use cases for maximal adoption, many attributes should be included in the DCE. However, too many attributes can cause fatigue to the respondent and has as risk that the respondent will ignore certain attributes or will be inconsistent in its choices (Caussade, Ortúzar, Rizzi, & Hensher, 2005). This is why the number has been toned down to six. The attribute selection, its levels, and the level translation to each zone, have been chosen after extensive discussion with five experts in cassava cultivation in Tanzania (two researchers from ACAI IITA, two researchers from TARI, and one extension officer). Finally, we decided that the characteristics of which we want to know the preferences of the farmers the most are: the planting date, the amount of months in the field, the fertilizer investment per acre, the cassava yield per acre, the variability in yield per acre, and the type of market present. An overview of these attributes and their levels is shown in Table 1.

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

Attribute	# Levels	Attribute Levels	Levels shown on DCE card
Planting month	5	Very early, Early, Normal, Late, Very Late	**LZ**: March, September, October, November, December **EZ**: March, September, October, November, December **SZ**: January, September, October, November, December
Months in the field	4	9, 10, 11, 12	9, 10, 11, 12
Fertilizer investment[1] (TSH/acre)	4	0 TSH, 70k TSH, 140k TSH, 280k TSH	0 TSH, 70k TSH, 140k TSH, 280k TSH
Yield (ton/acre)	4	3, 6, 9, 12 ton of fresh cassava	**LZ**: 10, 20, 30, 40 bags of dried cassava **EZ**: 5, 10, 15, 20 kirikuus of fresh cassava **SZ**: 60, 120, 180, 240 bags of fresh cassava
Yield variability	2	Low, High	+/- 33%, +/- 66%
Contract type	4	No guaranteed market & - 0%; Guaranteed market & - 20%; Guaranteed market & - 40%; Guaranteed market & - 60%	No guaranteed market & - 0%; Guaranteed market & - 20%; Guaranteed market & - 40%; Guaranteed market & - 60%

[1] 0, 1, 2, 4 bags of 50 kg, and each bag costs 70k TSH

Planting month is the month in which the cassava is planted. In all three zones (LZ, EZ, SZ) the main planting season for cassava is during September, October, November and December, with October and November being the peak planting time. In the EZ and LZ there is also a second raining season before, in which sometimes cassava is planted as well. This short rain season mainly occurs in March. In the SZ, which has one long raining season, we see that occasionally farmers plant cassava in January too. September is in all zones a drier month with only very sporadic rains, so to avoid confusion to the farmers it was stated that they should imagine the soil being moist for two days before they planted their cassava.

To correctly analyze the preference for each attribute, they all need to be independent from each other. So even though we wanted to know the preferences of the farmers on 'months in the field' and on 'harvesting month', we could not include both because 'harvesting month' is a result of the 'planting month' and 'months in the field' combined. Eventually 'months in the field' was chosen as the attribute, because the experts believed this was a more important factor to the farmers. The reason for this is that there is an associated opportunity cost: the longer your cassava stays in the field, the shorter the time is for other crops to grow there. However, the harvest month can have an influence on the preference as well due to the seasonal market price for cassava, especially for farmers that cannot store cassava. Hence the harvesting month, as a result of 'planting month' and 'months in the field', was shown in the choice card (see Figure 9 and Figure 10). However, because we clearly connect the attributes 'planting month' and 'months in the field' on the choice cards, we should take this into account during the analysis (further explained in Results). For the levels of the attribute 'months in the field', it was commonly agreed upon during the pre-field discussion that in all of Tanzania cassava was mainly left in the field for a period of 9 to 12 months.

The attribute 'fertilizer investment' shows the amount of fertilizer bags of 50 kg that need to be bought per acre, together with the total cost. In Tanzania, we took as reference a bag of urea of 50 kg, for which the price is around 70,000 TSH according to the experts. For one acre, dependent on the fertility of the soil, the necessary amount of fertilizer ranges between 0 to 200 kg, or 0 to 4 bags of 50 kg.

Even though it has been proven that fertilizers have a positive effect on yields if used correctly (Bationo, Ngaradoum, Youl, Lompo, & Fening, 2018), there can still be said that yield and fertilizer investment can vary independently due to effects of other, mostly climate-related, factors. This is why we will show both attributes as independent ones on the choice cards. Buying and selling of cassava in Tanzania is mostly done without weighing the product, but by instantaneous estimation of the quantity by the eye. Each region has specific units in which they commonly trade. To translate the harvests into these units, very rough estimations need to be made for the weight of the units. In the LZ they often sell by bags of chips of dried cassava (see Figure 6). The weight ratio fresh cassava/dried cassava is approximately 3.5, so 1 bag of dried chips of around 85 kg is roughly equal to 300 kg of fresh cassava. In the EZ they often sell by 'kirikuus' (see Figure 7) , which contains roughly 600 kg of fresh cassava. Finally, in the SZ they often sell by well-filled bags of fresh cassava (see Figure 8), which contains roughly 50 kg. The average cassava yield per acre varies between 3 to 12 tons. This results in roughly 10 to 40 bags in the LZ; 5 to 20 kirikuus in the EZ; and 60 to 240 bags in the SZ.

The attribute ‘yield variability’ is a way to distinguish the risk-averting farmers, and to look if certain factors, especially the fertilizer cost, can make farmers more or less risk-averting. It is the same for all zones, and has two levels: a variability of 33% and of 66% on the yield.

To understand the preferences for a guaranteed market with a reduced price, we include the attribute contract type. This attribute contains two elements: a guaranteed or non-guaranteed market, and a price reduction. A guaranteed market happens when the farmer knows before planting that he/she will definitely be able to sell its cassava after harvest. The price then goes from market price -20% to market price -60%. A guaranteed cassava market is rare in Tanzania, but if agreements happen between a cassava seller and a buyer, this contract with a reduced market price is the most common according to the experts. A non-guaranteed market logically happens with a 0% reduction, and we assume that no large cassava buyer would guarantee a market to a farmer without asking for a price reduction. Thus, the attribute ‘contract type’ has four levels: no guaranteed market but full market price, a guaranteed market with -20% market price reduction, a guaranteed market with -40% market price reduction, and a guaranteed market with -60% market price reduction.

Figure 6: The unit of the LZ

Figure 7: The unit of the EZ, a so-called 'kirikuu'

Figure 8: The unit of the SZ

4.1.3 Design of choice cards

With the final six attributes and their levels, we could design one DCE where all levels are changing randomly across the scenarios on the choice cards. However, considering the fact that a guaranteed market for cassava is not a common feature in the Tanzanian agricultural landscape, we would only present a realistic scenario to the farmers 1 out of 10 times (= the chance to have 'no guaranteed market' in both option A and B). Moreover, the experts already had strong reasons to believe that the attribute levels with a guaranteed market will be decisive for the choice of most farmers, which means that we would not have enough information about preferences for the other attributes. Thus, we opted to work with two choice experiments: one DCE with only the first five attributes and keeping the sixth attribute on its first level of non-guaranteed market, and one DCE with the sixth attribute and all its levels included. Because we were still not sure enough about to which extent the sixth attribute would be decisive, we decided to have a 50/50 distribution of choice cards from the first DCE and the second DCE for each respondent.

Secondly, for the design of both DCE's we need to decide how many choice tasks we will give to each respondent. The more choice cards you have per interview, the more information you collect about the respondent. But, if you have too many choice cards, after a while the increase in error due to respondent fatigue becomes larger than the decrease in error due to the learning effect (Bradley & Daly, 1994; Hu & Wuyang, 2006). Hence a good middle ground had to be found. We opted for 16 choice cards, taking into account that the first 8 cards of the first DCE are quite easy to decide upon due to the constant sixth attribute.

Thirdly, we can opt to install blocks. This is interesting because the more combinations of attribute levels there are, the more main and interaction effects can be estimated. By installing 6 blocks of each 16 choice cards, we increase the amount of attribute level combinations six-fold. With two scenarios and one opt-out per choice card, we can thus have 192 different combinations in total (= 6 blocks * 8 choice cards * 2 DCE's * 2 scenarios shown per choice card). This means that 96 different choice cards (= 192 combinations / 2 scenarios per card) are designed for each zone.

Now the optimal design of the choice cards can be found. In total we have six attributes, with four times four levels, once two levels, and once five levels. It is clear that a full factorial design is not possible, since we would have to make 2560 (= $4^4 * 2 * 5$) possible combinations, or, with two choice options per card, we would have to make 1280 (= 2560/2) different choice cards. With a full factorial design we would also need a much larger sample. Instead, we decide to use the Bayesian Efficient design in Ngene to optimally design the combinations of attribute levels for both DCE's. The scripts can be found in Appendix A. With the Bayesian approach we assume the prior estimates of the attribute parameters to be random with a given probability distribution (ChoiceMetrics, 2018). For each DCE's script we define that we want to have two scenarios per choice card, and one opt-out. The respondent should choose the opt-out when none of the two scenarios are of interest to him/her. The amount of rows are put at 48, because we want 6 blocks with each 8 choice cards. Each row contains information on what should be in choice A and in choice B. Then we state that Ngene needs to optimize on efficiency measures for a multinomial logit model (MNL). We also specify that it needs to draw Bayesian parameter distributions with 100 Halton draws, which is a type of quasi-random Monte Carlo draws. This means that the draws are intelligent and structured (ChoiceMetrics, 2018). Next in the script, we specify that it needs to find the most efficient design using the modified Federov algorithm. This algorithm starts with a fractional factorial design, and then replaces each design each time it finds a choice situation with a lower efficiency error, until the choice situation with the lowest efficiency error is found or until the 100 draws have been checked. Next, the constraints in the choice situations are defined. Firstly, for each scenario we don't want to have the highest fertilizer cost (i.e. 4 bags or 280k TSH) combined with the low yield variability. Vice versa, we want to avoid a scenario where the lowest fertilizer cost (i.e. 0 bags or 0 TSH) is combined with the high yield variability. Secondly, we reject the situations where the fertilizer cost is the highest and the yield is the lowest at the same time, and vice-versa. The third constraint is only for the second DCE with all the levels of the 'contract type'-attribute: we want to avoid choice cards that are similar to the first DCE, namely where the market is non-guaranteed in both option A and B. After the constraints, the dummy-coded model for each scenario or choice is finally defined with all its attributes, attribute levels, expected sign, and expected relative preferences between the levels. The model of the first DCE is Equation 2, and the model of the second DCE is Equation 3:

U(alt1) =
*b_1.dummy[(n,0.001,0.0005)|(n,0.002,0.001)|(n,0.003,0.0015)|(n,0.004,0.002)] * planting[early, normal, late, very late,very early]*
*+ b_2[(n,-0.1,0.05)] * months[10,11,12,9]*
*+ b_3[(n,-0.01,0.005)] * yieldvar[+/- 66%, +/- 33%]*
*+ b_4.dummy[(n,0.01,0.005)|(n,0.02,0.01)|(n,0.03,0.015)] * yield[6, 9, 12, 3]*
*+ b_5[(n,-0.01,0.005)] * fertcost[1,2,4,0]*
*+ i_5[-0.1]*yieldvar*fertcost* (*Equation 2)*

U(alt1) =
*b_1.dummy[(n,0.001,0.0005)|(n,0.002,0.001)|(n,0.003,0.0015)|(n,0.004,0.002)] * planting[early, normal, late, very late,very early]*
*+ b_2[(n,-0.1,0.05)] * months[10,11,12,9]*
*+ b_3[(n,-0.01,0.005)] * yieldvar[+/- 66%, +/- 33%]*
*+ b_4.dummy[(n,0.01,0.005)|(n,0.02,0.01)|(n,0.03,0.015)] * yield[6, 9, 12, 3]*
*+ b_5[(n,-0.01,0.005)] * fertcost[1,2,4,0]*
*+ b_6.dummy[(n,1,0.5)|(n,1.2,0.6)|(n,1.4,0.7)] * gm[guaranteed & -20%, guaranteed & -40%, guaranteed & -60%, no guaranteed market]* *(Equation 3)*

All categorical variables are dummy-coded. Since we are not entirely sure of the signs of all main effects, we do not specify them. However, we have to state how we expect the preferences for each level to be compared to a reference level. For example, for the planting attribute the 'very early' level is the reference. As we believe that farmers prefer to plant as late as possible, we show to expect an increase in preference of +0.001 when going from the very early month to the early month. The increase in preference for the 'normal' level will then be twice as large, so +0.002, and so on. In the first DCE (Equation 2) we want Ngene to make a design that will allow us to also estimate the interaction effect between the yield variability and the fertilizer cost. As we expect the farmers to be more reluctant to invest in fertilizers when the yield variability is higher, we already predict this effect to be negative in Ngene.

4.1.4 Presentation of the choice cards

The complexity of a choice experiment can be split into five dimensions: the number of choice cards shown to the respondent, the number of different scenarios on each choice card, the number of attributes per scenario, the amount of levels per attribute, and the range of the attribute levels. An increase in such complexity affects the choice consistency of the respondent, because it increases the cognitive burden on the respondent (Caussade et al., 2005). We already dealt with the five dimensions, but we further try to decrease the cognitive burden by (i) illustrating the cards in an easily understandable way, (ii) thoroughly explaining the choice cards while personalizing the numbers.

Firstly, the choice cards are illustrated as shown in Figure 9 and Figure 10. Such illustrations are especially necessary in countries such as Tanzania, where more than 20% of people older than 15 are illiterate (UNESCO UIS, 2015). Figure 9 is one of the choice cards from the first

DCE, where the sixth attribute has the constant level of ‘no guaranteed market’. All the cards from this first DCE are green, and are shown first in the interview. Figure 10 is a choice card from the second DCE, where the sixth attribute can vary. These cards are all blue, and in the interview they are shown after all green choice cards have been shown. The first and second attributes are linked to a timeline. The timeline comprises two years, and the months are shown as numbers. This is because in Swahili, the months are often referred to as their number instead of their name. For example, January is said to be ‘the first month’. By combining the planting month with the amount of months in the field, the harvest month is also illustrated. The amount of fertilizer (urea) bags and the corresponding cost are shown underneath the timeline. The yield level is illustrated as a number which should be multiplied by the zone’s unit. The yield variability is shown as what the amount of units is in a very dry year and what it is in a very wet year. This is illustrated with a picture of a dry cassava field on the left, and a picture of a very healthy cassava field on the right. On the blue choice card, the sixth attribute is also illustrated: the market is either guaranteed or not, and the consequence of this on the market price is shown after the arrow.

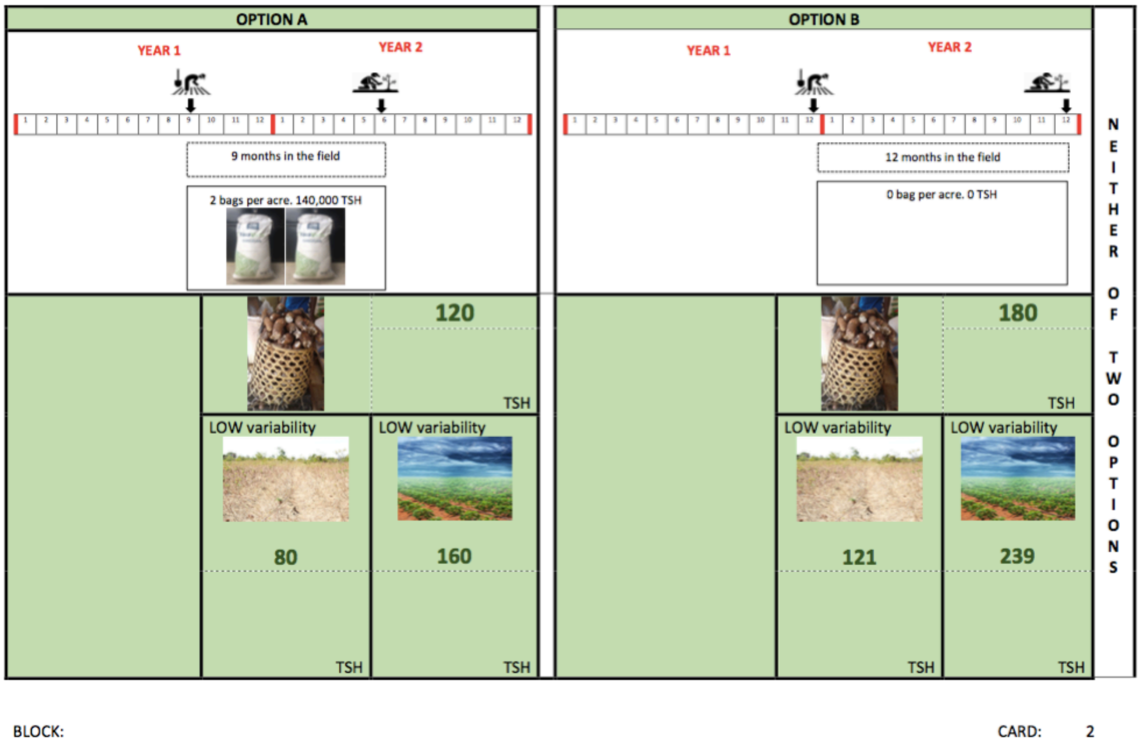

Figure 9: Green choice card for the SZ

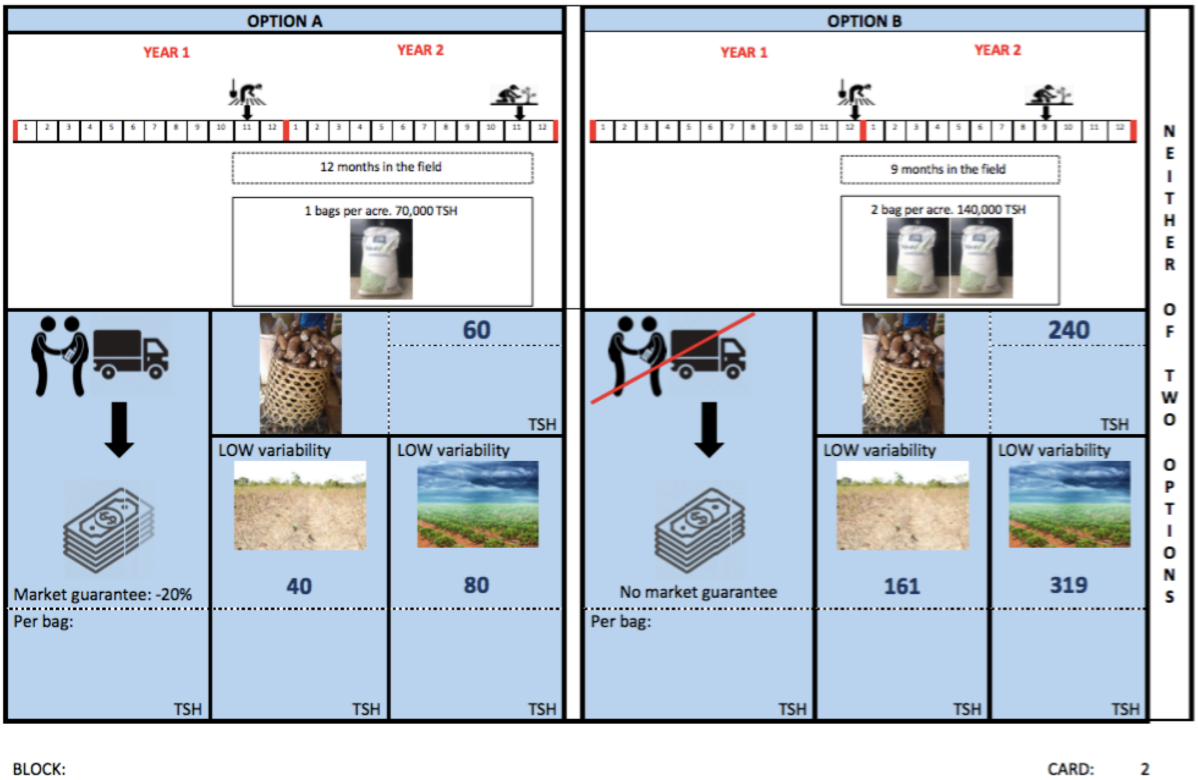

Figure 10: Blue choice card for the SZ

Secondly, the enumerators explained each option in a strict predefined order. They first went through the planting month, amount of months in the field, the resulting harvesting month, and the amount of fertilizer invested. Then, for the blue choice cards, they explained the contract type, and wrote down with an erasable marker the expected price for one unit taking into account the possible reduction. This price was automatically calculated by the ODK-tool by combining the expected price per month for one unit with the harvesting month of that option. Then, they indicated the average number of units of cassava the respondent could expect per acre, and wrote down the total revenue per acre (= expected price for one unit * amount of units per acre) which was again calculated by the tool. The enumerator did the same for the yield in a bad and in a good year. This interactive and personalized way of working encouraged the farmer to follow a train of thought from beginning to end, taking into account and fully understanding all attribute levels.

Finally, the order of choice tasks within each DCE was randomized across the respondents. This meant that each choice card was shown in different stages of the interviewing process, and thus at different stages of the respondent's learning effect and fatigue or boredom. By doing so, the correlation between the choice cards and the error variance was minimized.

However, we must take into account that the green cards (first DCE with five attributes) always came first. So, the green cards could contain slightly more inconsistent responses due to a learning effect. Consequentially, since the blue cards (second DCE with six attributes) always came second, they could contain slightly more inconsistent responses due to fatigue or boredom.

4.2 Sampling strategy

All DCE interviews and group discussions were conducted from September 26th to October 19th 2018, except for the last 26 interviews in the SZ which were conducted in January 2019. The target group includes all cassava farmers living in the Tanzanian districts/wards where ACAI technologies will be disseminated by development partners. ACAI already worked with a sampling frame to divide the target area in a treated and a control group, to record the impact of their project. This was done by putting all cassava farmers located within 30 km reach of ACAI's or a development partner's extension agent (EA) in the treatment group, and all farmers further away in the control group. An example of ACAI's strategy can be seen in Figure 11. For ACAI, farmers linked to a total of 96 EA's are included in the treated group.

The sampling strategy for this particular research was built further on ACAI's strategy, because we wanted to avoid contact with the control group and enjoy the connections already made with the extension agents in the treated group. However, due to a limited amount of resources and time, three regions in Tanzania have been selected for the sample: the Lake Zone, the Eastern Zone, and the Southern Zone. In these zones, ACAI works with respectively 30, 7, and 20 extension agents. We asked the head enumerators of each zone to randomly select from this group respectively 18, 7 and 12 extension agents.

This resulted in a total of 367 households being reached: 165 from villages in the Mwanza Region (Lake Zone, LZ), 108 from the Mtwara Region (Southern Zone, SZ), and 94 from the Dar es Salaam Region (Eastern Zone, EZ). We should thus have 367 respondents in total. However, the responses of the 26 last interviews in the SZ were dropped because we were hesitant about the correctness of them[1]. Another 8 interviews were removed because they were

[1] These interviews were conducted several months later than the rest, and after some disagreements with the enumerators. The preferences of only those 26 farmers were compared with the preferences of the other respondents of the SZ, and they showed clear differences. Looking at the socio-economic differences between the same two groups, we could not say that the differences in preferences could be explained enough by significant

trials for the enumerators, and they didn't went through the process of the choice experiment well enough yet[2]. So in total we reach 333 responses for the analysis of the choice experiment. The household ID of 8 respondents of the choice experiment could not be linked to one of the ID's in the baseline survey. Hence, the descriptive results and the two-sided t-tests are based on 325 respondents instead of the full 333 respondents of the choice experiment.

When I was present at the interviews, occasionally there were some selected respondents that did not show up[3]. The enumerators then conducted more interviews to reach the expected number of respondents per zone. Thus, a nonresponse bias could be present. However, since the amount of absent people was low, the reasons for being absent varied, and because the absentees were quite geographically distributed, we expect the nonresponse bias to be limited.

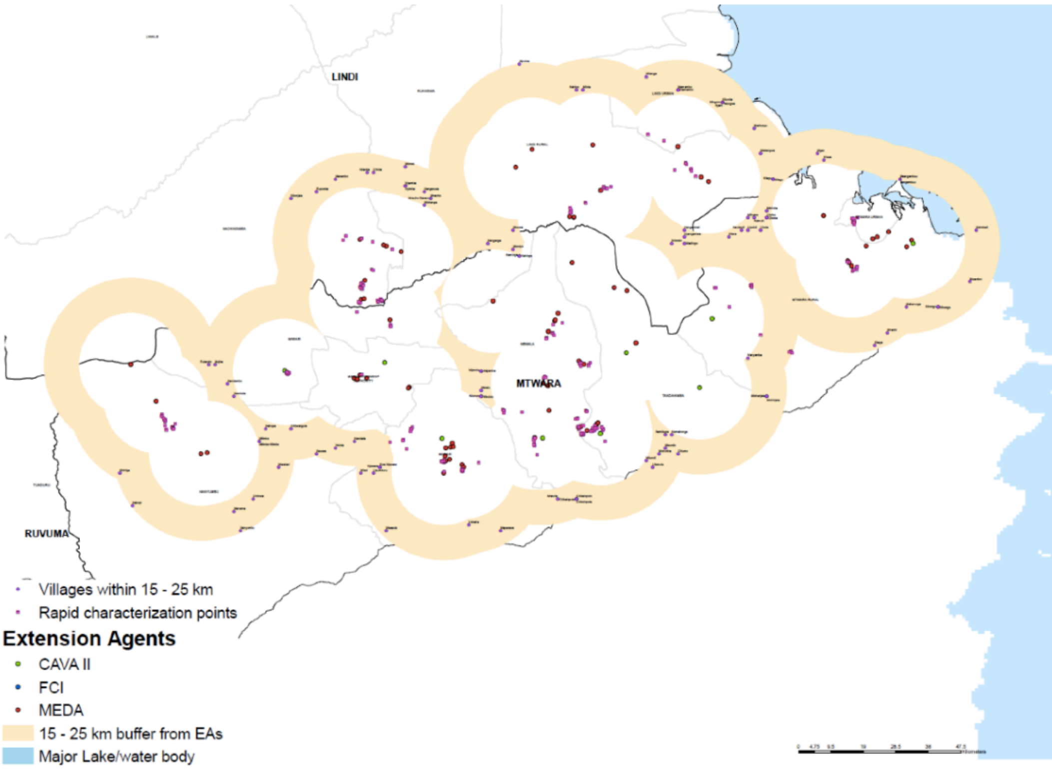

Figure 11: Example of the sampling strategy applied by ACAI in the Mtwara Region (Southern Zone)

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differences in socio-economic characteristics. Hence, we suspect something went wrong during the choice experiments of those 26 farmers, so we decide to drop them.

[2] For example, we saw many cards being answered twice by the same person, but then a different preferred scenario was chosen.

[3] For the interviews in the LZ I was present at the interviews of 6 groups, which consisted of a total of 59 people. During the time I was there, five of the selected people did not show up. I was present at the interviews of nine groups from the EZ, which comprised 72 interviews. Only four of the selected respondents were absent. In the SZ I was present at the interviews of 5 groups, a total of 39 people. Six selected respondents from two different villages did not show up.

4.3 Data collection

4.3.1 Choice experiment implementation

The data collection in each zone (LZ, EZ, SZ) was made by four to five Tanzanian enumerators that speak Swahili and English fluently. The strict procedure was communicated beforehand to the enumerators with a guideline. In this guideline was also stressed that they could not influence the farmer in their choices during the interview, but only explain the question. Before starting the interview process in each zone, we made sure that all enumerators understood the context of the choice experiment, the questions they had to ask, and generally what was expected of them. The enumerators also learned how to use the Open Data Kit (ODK) collect tool on their smartphone, in which they had to record the answers of the farmers.

The head enumerators made arrangements with the EA's to bring their nine to twelve selected household representatives together at a convenient place and time. The farmers were given a financial contribution and occasionally we provided breakfast or lunch for the farmers. After arrival of all farmers and the introduction of the people present, the ACAI project and the context of the interview was explained. Then, the cassava unit of their zone was shown, and the group of farmers was invited to discuss what price they expected for that unit for each month of the following year. This discussion is necessary because cassava prices have known to vary a lot annually and seasonally, and thus the personal expectation of prices varies a lot as well. During the first trial of the choice experiment, where farmers were asked about their individual views on prices, it was clear that sometimes they stated unrealistic low or high expectations. These were probably farmers who do not know the cassava market very well. Hence, to eliminate outlier price expectations, it was decided to make each group of farmers collectively agree on the twelve expected prices per month of the next year. With this information on the farmers' expected prices, we could personalize the expected revenue on the choice cards to the farmer's price expectations. This is one of the great advantages of the ODK collect tool: it can automatically calculate and adapt numbers to the interviewee. With the information on the expected prices of the farmers, we also had a better idea of the stability of the local cassava market. Next, to analyze the effect that showing an informative video has on the stated preference of using fertilizers, we showed a self-made video to some farmers before the interviews. In the video, a researcher from ACAI explains the different kinds of fertilizers and their effect, and a farmer shares his experience with chemical fertilizers on cassava. The goal was to have a 50/50 split between the groups who saw the video and those who did not.

This was difficult to manage, because the groups of farmers weren't always of the same size, and occasionally the enumerators forgot to show the video. In the end, 152 farmers saw the video before their interview, and 215 did not. Finally, to have an idea of how farmers assign relative importance to the attributes, we asked the respondent after each choice card which attribute was decisive for their choice.

4.3.2 Baseline data ACAI

Because all targeted households for this particular research are part of the treated group in the ACAI project, their responses can be linked to their baseline data taken beforehand by the ACAI team. This data contains both qualitative and quantitative data on the household. The retrieval of this information was facilitated thanks to the household ID cards (see Figure 12) which each household received after answering ACAI's baseline data questions.

Figure 12: Household ID cards

The baseline data has been collected in three phases, with the first survey focusing on the household data, the second focusing on the cassava cultivation practices, and the third on the current cassava yield. For the household survey a total of 1260 Tanzanian households answered questions about their gender, education, family situation, age, assets, acreage, cultivation practices, and crops or livestock they cultivate and own. For the cultivation survey a total of 1214 households answered detailed questions about the way they cultivate and have cultivated their (cassava) fields in the past. This comprised questions about weeding, tilling, using chemical inputs, etc. For the yield survey 766 households were visited during harvest, and the enumerators counted the total cassava harvest together with other details about the cultivation and the way of selling.

4.3.3 Focus group discussions

Each enumerator started interviewing one farmer at the time, sitting far enough from the others so to not be disturbed. Finally, when all farmers present had been interviewed, they were asked if they had any questions or remarks about the interviews. Often this led to very useful information being shared. When this was not the case, direct questions were asked about the local cassava market, their knowledge about possible cassava cultivation techniques, their access to inputs, and their attitude towards cassava in general. We say that the data collected from the choice experiment is quantitative data, while the information from the group discussions is qualitative data.

4.4 Econometric Approach

4.4.1 Mixed Multinomial Logit model

With the data collected from our choice experiment, we first want to estimate the general preferences of the respondents on the attribute and attribute levels. To do this, there are two common models to choose from: the Multinomial Logit (MNL) model or the Mixed Multinomial Logit (MMNL) model. The MNL model is based on two important assumptions, namely that the preferences are fixed among all respondents, and that the unobserved factors in the utility function are identically and independently distributed (i.i.d.). However, there is multiple evidence that farmers can have different preferences for technology adoption due to different inherent characteristics (e.g. risk preferences) or different characteristics in their environment (e.g. access to markets, access to information, time of the interview) (Carter, 2016; Mooney, Assistant, Student, & Barham, 2013). Next to this, the MNL model assumes the rather strict IIA property[4]. Hence, using the MNL model would very possibly bias our results due to wrong assumptions. Because the MMNL model considers the effects to be random instead of fixed, does not assume that the unobserved factors are i.i.d., and does not assume the IIA property, it performs better at predicting heterogenous preferences (Audibert et al., 2013). We thus choose to work with this model. Another advantage of the MMNL model is that it can measure the extent of preference heterogeneity for each attribute (level).

[4] The IIA or 'Independent of Irrelevant Attributes' property assumes that the relative preferences between two attribute levels does not change when one new attribute level is added.

To include that each individual's preference can change from the general preference due to an unobserved effect, the MMNL model considers the utility function with main-effects as follows:

$$U_{in} = (\beta_i + \gamma_{in})x_i + \varepsilon_{in} \qquad \text{(Equation 4)}$$

Equation 4 shows the utility that respondent n receives from scenario i, where x_i is the vector with all the attribute (levels) within scenario i. β_i then contains all the mean effects of these attribute (levels), and γ_{in} is the personalized standard deviation from the mean. In the results it will show the mean standard deviation γ_i for each attribute (level). If it is high, it means that there is a large preference heterogeneity for that attribute (level) among the respondents. The MMNL model is then described as the probability of respondent n choosing scenario i, which is the expected utility he/she will receive from scenario i over the sum of the utilities it will receive from all available scenarios

When specifying the MMNL model in Stata 15, we state that the effects of all attributes or attribute levels are random.

4.4.2 Latent Class Model

Even though the MMNL model allows for preference heterogeneity, it does not show the source of it. This is why the Latent Class model is used. The model is based on the idea that we can split the sample with heterogenous preferences into smaller classes with homogenous preferences. In a way, it simplifies the MMNL model by categorizing the personalized standard deviations γ_{in} into fixed effects per class. This is done by specifying a different mixing distribution. While in a MMNL model the mean effects β are allowed to vary across the respondents following a normal mixing distribution, in a Latent Class model they vary following a discrete mixing distribution. The number of discrete values is equal to the specified number of classes. Then, an unobserved latent class membership likelihood function assigns to each respondent a probability for each class based on the respondent's choices. The respondent then belongs to the class for which he/she has the highest membership probability (Boxall & Adamowicz, 2002). Next, for each class j and for each attribute (level) i the homogenous preferences β_{ji} are found the same way as the multinomial logit model would do it: by ignoring heterogenous preferences within each class. In other words, the γ_{in} in Equation 4 is considered to be 0 for each respondent. We thus assume that within the classes the assumptions of the MNL model hold if the number of classes have been chosen well.

The number of classes needs to be chosen beforehand. One method to help the decision is to compare the consistent Akaike Information Criterion (CAIC)- or Bayesian Information Criterion (BIC)-values between models with different number of classes. The model with the lowest CAIC- and BIC-values is the one with the best fit. The distribution of the total group within the different classes is also important for practical reasons. For example, if one model has lower CAIC- and BIC-values but has a class which contains only 1% of the population, then another model with slightly higher values but a better distribution is more interesting. We compare the models with two, three, and four classes.

The final latent classes are then linked to the socio-economic information we have on the respondents. Finding significant correlations between respondents' survey information and their classes, could help predict the preferences of a farmer outside the sample based on its characteristics. To find this correlation for each variable, we apply a simple two-sided t-test that shows whether the difference between the characteristic's levels of each of the classes is significant.

5 Results

5.1 Qualitative Results

In 45% of the choice cards the respondents stated that yield was the decisive attribute. In 21% of the cards it was the fertilizer investment, and in 18% of the cards it was the contract type. The other attributes were said to be decisive in 5% of the choice cards or less. The harvest month, which is the result of the planting month and months in the field combined, was chosen as decisive attribute in only 3% of the times. The most important conclusions from the group talks in the three different zones are now discussed.

5.1.1 Lake Zone (LZ)

Talking about fertilizers, some groups of respondents told us that it was difficult to find. And even if they found fertilizer, it was often too expensive. Other respondents said that they use fertilizer for other crops, but they had never considered the idea of using it for cassava. They, too, said it would be too expensive. Even more, several farmers seemed to misunderstand the effect of fertilizers on cassava: they believed it increased yield, but that it decreased the quality of the root, making it less tasty. Others thought that there was no point in using fertilizers on cassava from local seeds, while buying improved seeds was too expensive or simply not possible because it wasn't available. Only a small handful of farmers understood the long-term beneficial effects of using fertilizers on their field.

Interestingly, in the LZ the farmers appeared to be the most enthusiastic about the idea of a guaranteed market, because the demand for cassava is much lower than in the other zones, and because the current market is highly uncertain. The former is clear when we compare the expected prices of the LZ (Figure 13) with the much higher expected prices of the EZ and SZ (Figure 14, Figure 15). The latter is also demonstrated in Figure 13: within one month some groups could say they expected the price to be 5 times higher than what another group stated. This low demand and unstable market appeared to have an impact on the fertilizer use, as one reoccurring question among the respondents was: "Why would we invest in fertilizers to increase our yield, if we aren't even sure we will be able to sell our cassava after harvest?". Consequentially, farmers claimed that if they were guaranteed to have a buyer for their cassava after harvest, they would be more eager to invest in fertilizers, especially if they were able to pay for the fertilizers after harvest.

The attribute ‘planting month’ is, according to them, a less important one in their zone, because they already plant their cassava across a very large time frame. This is because the LZ is an area where it rains more often than in the rest of the country. However, the moment of harvesting the cassava is not as flexible, because most farmers dry their cassava in the sun, and this is not possible during the rainy season. Storing the fresh cassava is not possible because it rots very rapidly. Hence, the data of the choice experiment will potentially show a significant correlation between the attributes ‘planting month’ and ‘months in the field’, showing a negative preference for harvesting in the rainy season.

The farmers also gave some recommendations for ACAI’s decision support tool and extension services in general. For example, if they were to receive advice on which type of fertilizer to use at a certain moment, they needed to know this enough in advance to purchase the bags. Also, for certain cultivation practices like intercropping, they said that receiving a training is the best way to help them understand how to do it right. Furthermore, many farmers talked about the much needed improved seeds that are resistant to diseases. Finally, there was a strong message that several groups of respondents wanted to put across: any tool or extension service that is set up to increase cassava productivity will only be truly successful when the market becomes more reliable or if a new, guaranteed market comes up.

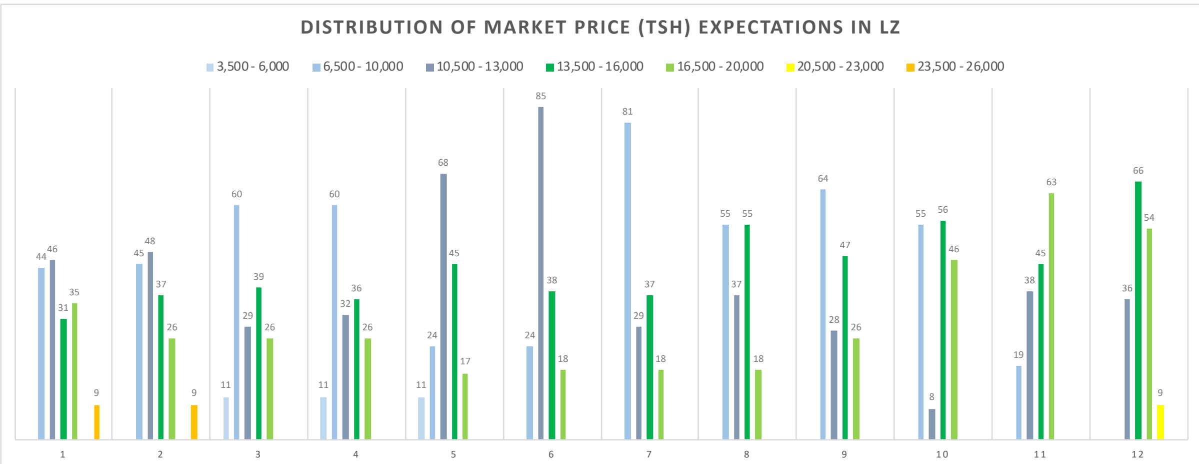

Figure 13: Distribution of the expected market price for 100 kg of fresh cassava (1/3 bag of dried cassava), given by 165 farmers from the LZ

5.1.2 Eastern Zone (EZ)

Most things said were similar to the LZ, like the too expensive cost of fertilizer, the surprise that fertilizers can also be used on cassava, the demand for training on how to correctly use fertilizers, and the need for improved varieties that are resistant to brown streak virus or the mosaic virus disease. Here too, some farmers misunderstood the effect and usefulness of fertilizers.

The greatest difference with the LZ, is that in the EZ the expected prices are much higher, as can be seen from Figure 14. This is most probably due to the large nearby market, which is Dar es Salaam. Indeed, we saw that farmers who lived further away from the city had price expectations reduced by half compared to the ones living closer. Next to the location, the prices could be higher in the EZ because they mostly sell fresh cassava. Fresh cassava is often sweet cassava, which has a higher value than bitter cassava. However, the farmers tell us that the demand and thus the price of cassava has greatly reduced in the past years. Most farmers have even stopped commercializing their cassava and kept it for subsistence farming. So even though the higher prices would suggest that the demand for cassava is much higher than the LZ, it appears that the demand for cassava compared to other crops is relatively lower. This is in line with their persistent view on cassava as a 'hunger crop' in the EZ. Consequentially, also in this zone they ask what the point is of investing in new technologies to increase their cassava yield, if the market is becoming more uncertain.

Finally, in three of the nine groups the farmers told us about a cassava-processing factory nearby of which the activities never took off.

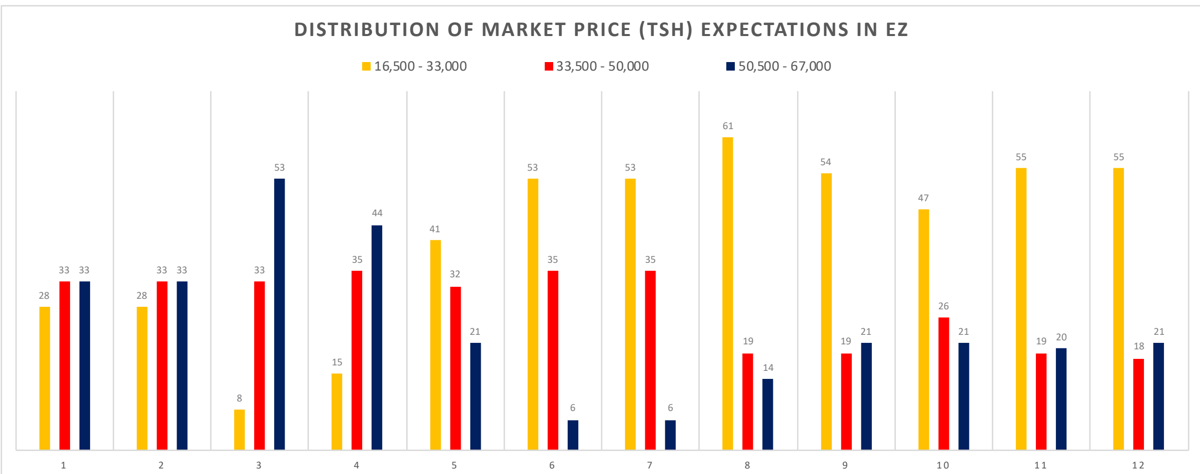

Figure 14: Distribution of the expected market price for 100 kg of fresh cassava (1/6 kirikuu), given by 94 farmers from the EZ

5.1.3 Southern Zone (SZ)

Here too, cassava is seen as a 'hunger crop'. Even though NGO's and the government have donated processing machines in several villages we have visited, they are not used according to one extension agent. However, a new factory for cassava flour is being built in the area, and farmers expressed their hope that it would become a new important buyer of their harvest.

One crop that typifies the cultivation practices in the SZ is the cashew-nut. One group of farmers told us they preferred to focus on their cashew-nut activities, for which there is a higher return on investment according to them. They say they would only start investing in fertilizers for cassava once they are certain of the demand for it. Then, the money to buy fertilizers would be available during the cashew-nut harvesting, so in October, November and December.

Many farmers from the SZ tell us they only sell their cassava in dried form, because, due to the decreased soil-fertility, they can only cultivate bitter cassava. This type, contrary to sweet cassava, can only be consumed in dried form because of its bitterness and high cyanide content.

When looking at Figure 15, we can see that the price distribution of the SZ is relatively narrow compared to the EZ and LZ: prices range from 20,000 to 40,000 TSH for 100 kg of fresh cassava. The price is lower than the EZ, but still much higher than the LZ. It does seem that certain months, like January and February, are more interesting periods to sell. When asking the farmers why they would not wait until then to sell their dried cassava, they answered that even if storing facilities are available, it is still difficult to store the cassava for a long time due to insect infestations.

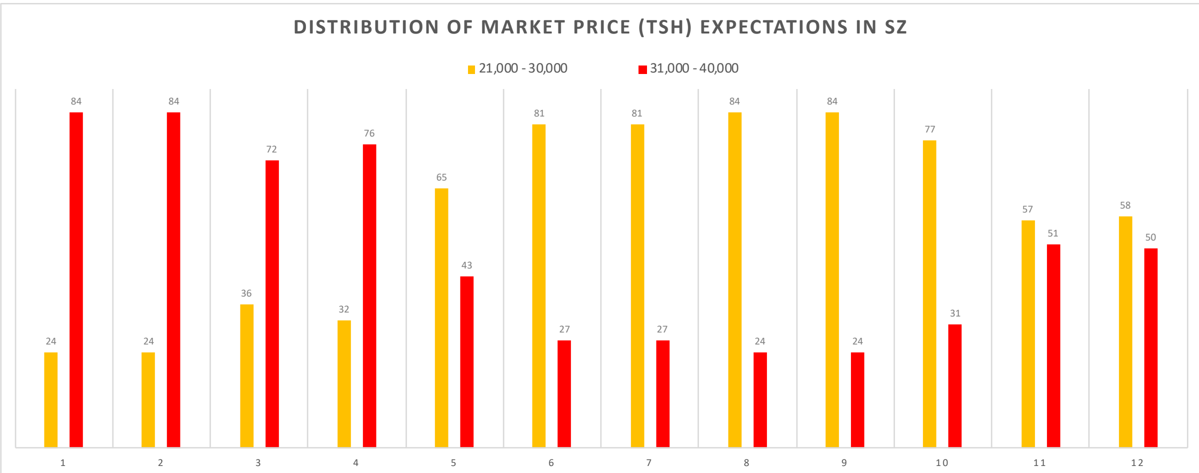

Figure 15: Distribution of the expected market price for 100 kg of fresh cassava (2 bags), given by 108 farmers from the SZ

5.2 Descriptive Results

Through the questionnaire that preceded the choice experiment, but mostly via ACAI's baseline survey, information has been collected about the respondent's household, cultivation practices for cassava, and cassava market.

Table 2 shows the household characteristics of the respondents. The average age of the respondents is 47, and 62% are men. The large majority of the respondents is married (86%), a smaller proportion is widowed (5%), and a fraction of the respondents is either divorced, separated, or single. 80% of the respondents' highest education level is primary school, 10% of the farmers have not been to school at all, and 10% have accomplished either secondary or tertiary education. 49% of the respondents live in the LZ, 28% live in the EZ and 23% are from the SZ. As our target population was farmers who cultivate cassava, the result is that the primary occupation is crop cultivation for 99% of the respondents. 85% of the respondents own their land, while 8% rents it and another 3% cultivates their cassava on communal land. The informative video about fertilizers for cassava was shown to 42% of the respondents.

Table 2: Household characteristics of the respondents

		Mean	St. Dev.	Min.	Max.
Age		46.8	11.8	21	79
Gender respondent (%)	Female	38.0			
	Male	62.0			
Marital status (%)	Divorced	0.3			
	Married	86.3			
	Separated	3.7			
	Single	5.2			
	Widowed	4.6			
Education (%)	None	10.0			
	Primary	80.2			
	Secondary	7.1			
	Tertiary	2.7			
Zone (%)	EZ	27.9			
	LZ	49.3			
	SZ	22.8			
Occupation	Crop cultivation	99.1			
	Livestock	0.6			
	Salary job	0.3			
Ownership of land? (%)	Communal	2.5			
	Own	85.2			
	Rented	7.7			
Informative video seen? (%)	Yes	41.8			
	No	58.2			

Based on 325 respondents

In Table 3 we see the characteristics of the respondents related to the way they cultivate their cassava and sell it afterwards. Around 6% of the farmers have previously used fertilizer on their cassava field. The average farm is around 9 acres large, but the variability on the size of the farm is rather high with a standard deviation of 12 acres. The size of the cassava field is on average only a fraction of the farm: the mean size is only 2 acres. Around 12% of the respondents sell their cassava on the local market, 45% sell it to a middle man, and only 1% sells it to a processor. The amount of respondents selling their cassava in a city is not even 1%. 41% of the farmers don't sell their cassava at all. 66% of all respondents have been in contact with extension services related to cassava before.

Table 3: Cassava cultivation and market characteristics of the respondents

		Mean	St. Dev.	Min.	Max.
Previous fertilizer use?[1] (%)	Yes	5.8			
	No	89.6			
	Not registered	4.6			
Farm size (acre)		8.65	12.2	0.04	120
Cassava field size (acre)		2.30	1.93	0	15
Market for cassava (%)	Processor	1.2			
	Middle man	44.7			
	Local village	11.8			
	Urban	0.6			
	None	40.7			
Previous extension service?[2] (%)	Yes	66.3			
	No	33.7			

Based on 325 respondents
[1] Has the farmer ever used fertilizers on his/her cassava?
[2] Has the farmer been in contact with extension services on cassava before?

5.3 Econometric Results

A total of 333 respondents each received 16 choice cards. This should result in 5328 recorded choice cards, but because sporadically enumerators forgot to show the last one(s), a total of 5319 choice cards have been recorded. The opt-out choice was picked in only 43 cases, which accounts for 1%.

5.3.1 Mixed Multinomial Logit (MMNL) Model

The results of the Mixed Logit Model are presented in Table 4. The first column of results shows the coefficient of each attribute and its corresponding significance. At first we see that the ASC[5] is strongly significant and negative. This means that choosing the opt-out gives the respondent a negative utility on average. In other words, the farmers have a strong preference for one of the scenarios presented instead of the opt-out option. Then, looking at the planting moments and the significant positive sign of planting very late at a significance level of 10%, it seems like farmers prefer to postpone planting cassava as late as possible. Looking at the significant negative sign of the attribute 'months', the farmers seem to want to reduce the amount of time of cassava in the field. Next, it is quite logical that the coefficient for cost of fertilizer is significantly negative, and that the attribute of cassava yield is significantly positive. The risk attribute is also significant and positive. This is rather surprising, but we believe that this is due to the farmers more paying attention to the upper side of the yield variability instead of the underside. Finally, the guaranteed market with a market price reduction of 20% and 40% are significant compared to the current situation (no market guarantee). At 60% the price reduction must be too large for most respondents, because then the sign is insignificant and negative.

The second column of Table 4 shows the preference heterogeneity of each attribute within the group of respondents. Whereas the first column showed the general preferences, the second column now shows whether there is significant preference heterogeneity among the respondents for each attribute (level). Looking at the results, the key take-away is that the standard deviations are significant for all attribute or attribute levels at a level of at least 10%. We were thus correct to define all effects of the attribute (levels) to be random and not fixed during the specification of the MMNL model. To find the source of these preference heterogeneities, we apply the latent class model.

[5] The ASC or 'Alternative Specific Constant' is an additional parameter of which we set the value at 1 if the opt-out is chosen, and a value 0 if one of the two available scenarios are chosen (dummy-coded)

Table 4: Results of the dummy-coded MMNL model

		Mixed Multinomial Logit Model			
		Coefficient (se)		*Standard Deviation (se)*	
ASC		- 4.337 (0.412)	***		
Planting month[1]	Very early	- 0.038 (0.093)		0.461 (0.166)	***
	Early	- 0.091 (0.092)		0.288 (0.187)	
	Late	- 0.076 (0.083)		0.180 (0.182)	
	Very late	0.156 (0.086)	*	0.224 (0.186)	
Months in the field		- 0.071 (0.020)	***	0.154 (0.029)	***
Fertilizer cost		- 0.002 (0.0003)	***	0.005 (0.0004)	***
Yield		0.136 (0.007)	***	0.092 (0.007)	***
Yield variability		0.004 (0.002)	***	0.006 (0.003)	**
Market[2]	Guaranteed market w. -20%	1.584 (0.146)	***	0.962 (0.163)	***
	Guaranteed market w. -40%	1.080 (0.149)	***	0.836 (0.175)	***
	Guaranteed market w. -60%	- 0.163 (0.155)		0.516 (0.292)	*
Statistical properties					
Log likelihood	- 2653.6 ***				

* p<0.1 ; ** p<0.05 ; *** p<0.01

[1] Reference level is the 'normal planting month', which is October for all three zones

[2] Reference level is the usual non-guaranteed market wherein the cassava is sold at the market price (0% reduction)

We also analyzed the different interaction effects as discussed in methodology: the interaction between yield and yield variability, the interaction between months in the field and planting month, the interaction between fertilizer cost and yield variability, and finally the interaction between fertilizer cost and guaranteed market. However, the results of these MMNL models do not contribute to our research objectives or the conclusion of this paper. For reason of completeness, the results of these interaction effects are nevertheless included in Appendix B.

5.3.2 Latent Class Model

Description of the classes

Based on its low CAIC- and BIC-values and its evenly distributed classes, we choose to work with a model with three latent classes. The results are shown in Table 5. We can see that the average farmer has 34% chance to belong to class 1, 35% chance to belong to class 2, and 31% for class 3.

The farmers from latent class 1 could be called 'independent farmers', because at a 5% significance level they already have a significant aversion for the guaranteed market at - 40%

market price reduction. Next to this, they also significantly prefer a higher yield, and a higher yield variability. All other attributes are not significant. Latent class 2 seems to comprise ‘contract farmers’, because they have a significantly strong preference for a guaranteed market, even if their price is reduced to up to 60%. They also appear to have a significantly positive preference to plant in a different month (very early, early, and very late) than usual, and they have a significant preference to keep their cassava in the field for the shortest amount of time possible. Moreover, just like the independent farmers, they have a significant preference for a higher yield and a higher yield variability. Finally, we can say farmers in class 3 are like ‘investment averse farmers’: they have a significant disfavor to invest in fertilizers for cassava, while the other classes do not. Next to this, they seem to significantly dislike planting in very early months and leaving their cassava longer in the field. They do not have a significant (dis)preference for a guaranteed market with - 20% or - 40% market price reduction, but at - 60% it becomes a significant aversion. Just like the two other classes, they have a strong significant preference for a higher yield.

Table 5: Results of the latent class model for dummy-coded data

		Latent Class 1 'Independent farmers' Class probability = 34.1%		Latent Class 2 'Contract farmers' Class probability = 34.5%		Latent Class 3 'Investment averse farmers' Class probability = 31.4%	
		Coefficient (se)		Coefficient (se)		Coefficient (se)	
ASC		- 4.43 (3.36)		- 4.56 (1.28)	***	- 3.13 (0.39)	***
Planting month[1]	Very early	- 0.05 (0.19)		0.50 (0.19)	***	- 0.42 (0.14)	**
	Early	- 0.17 (0.20)		0.41 (0.21)	*	- 0.09 (0.13)	
	Late	- 0.22 (0.16)		0.13 (0.14)		- 0.12 (0.12)	
	Very late	0.17 (0.17)		0.48 (0.16)	***	- 0.11 (0.13)	
Months in the field		0.03 (0.04)		- 0.09 (0.03)	***	- 0.05 (0.03)	*
Fertilizer cost		- 0.00 (0.00)		0.00 (0.00)		- 0.00 (0.00)	***
Yield		0.18 (0.02)	***	0.09 (0.01)	***	0.07 (0.01)	***
Yield variability		0.01 (0.00)	*	0.00 (0.00)	*	0.00 (0.00)	
Market[2]	Guaranteed market w. - 20%	- 0.20 (0.43)		4.14 (0.85)	***	0.11 (0.21)	
	Guaranteed market w. - 40%	- 1.00 (0.48)	**	3.77 (0.87)	***	- 0.07 (0.23)	
	Guaranteed market w. - 60%	- 1.71 (0.57)	***	2.52 (0.75)	***	- 0.89 (0.23)	***
Statistical properties							
Log likelihood	-2711.0						

* p-value < 0.1 ; ** p-value < 0.05 ; *** p-value < 0.01

[1] Reference level is the 'normal planting month', which is October for all three zones

[2] Reference level is the usual non-guaranteed market wherein the cassava is sold at the market price (0% reduction)

Socio-economic characteristics of the classes

In Table 6 we compare the socio-economic characteristics of all three classes. We consider the characteristics of the respondent and the farm. In the first two-sided t-test we look for each characteristic whether it is significantly different between class 2, the contract farmers, and class 3, the investment averse farmers. The second two-sided t-test analyses the differences between class 1, the independent farmers, and again class 3.

For the first t-test, farmers of class 2 seem to comprise significantly younger, more male, and more divorced and married respondents than class 3. Class 3 has significantly less people that pursued none or a primary education as highest level, and significantly more people that pursued a secondary or tertiary education. The informative video appears to have a positive effect for contracts and investments in fertilizers for cassava, because on a 10% significance level we can say that class 2 comprises more farmers who have seen the video before the interview. With the information on the assets of each household, we have computed a Wealth Index with a factor analysis in Stata, using the principal-component factors method.[6] Assuming that this index is a good indicator of a household's wealth, we can say that the 'investments averse farmers' (class 3) are significantly wealthier than the 'contract farmers' (class 2). Looking at the farm characteristics, still comparing class 3 with class 2, the 'contract farmers' contain significantly more farmers from the EZ and the SZ, and significantly less from the LZ. There are also more farmers who own their cultivated land among the 'contract farmers' class, but also significantly more farmers who use communal land. The size of the farm is also significantly different between the 'contract farmers' and the 'investment averse farmers', and the size of the cassava field is too, but in an opposite direction: 'investment averse farmers' appear to have a larger farm size, while 'contract farmers' appear to have a larger cassava field. Furthermore, previous fertilizer use for cassava is significantly more frequent among the farmers from the 'contract farmers' compared to the 'investment averse farmers'. The farmers who sell their cassava on a market different from the local market, have a significantly higher chance to belong to the 'contract farmers' than to the 'investment averse farmers'. Finally, also the farmers who have been in contact with extension services about cassava are significantly more present in the contract farmers' class.

The second t-test compares class 1, the so-called 'independent farmers', with the 'investment averse farmers'. We can see from Table 6 that significantly older, more males, more married farmers, more farmers without any education but also less farmers with secondary education and more farmers with tertiary education, and more farmers who have seen the informative video, are present among the 'independent farmers'. Here, too, there is a significant difference between the two classes' wealth index: the 'independent farmers' appear wealthier than the 'investment averse farmers'. Finally, looking into the characteristics of the farm, the proportion of farmers from the SZ or LZ, with a larger farm and a larger cassava field, previous fertilizer use, an local cassava market and previous contact with cassava extension services is also significantly higher for the 'independent farmers'. There are significantly less farmers from the

[6] Factor analysis is a statistical technique that compresses the values of several variables in one value, by finding a way to describe a linear relationship between these variables (Stata, 2019). The index in this paper is based on the following variables: household's transport methods (truck, car, SUV, motorbike, tuc-tuc, bicycle, tricycle, none), toilet facilities (water toilet, improved latrine, latrine, none), floor materials (tiles, concrete, wood, earth), roof materials (slate, metal sheets, thatch), source of drinking water (protected and private, protected but communal, communal pipe, unprotected), and the ownership of a radio, television, or fridge.

EZ and farmers selling to a market other than the local market, among the 'independent farmers'.

Table 6: Comparison of the three latent classes using two-sided t-tests

		Class 3 - ***'Investment averse farmers'***		**Class 2** - ***'Contract farmers'***		**First t-test** (3–2)	**Class 1** - ***'Independent farmers'***		**Second t-test** (3-1)
		Mean	se	Mean	se		Mean	se	
Respondent characteristics									
Age		46.7	12.5	44.9	11.2	***	48.8	11.0	***
Gender (%)	(males)	58.3		62.8		***	64.7		***
Marital status (%)	Divorced	0		0.8		***	0		.
	Married	82.4		87.9		***	88.1		***
	Single	4.9		5.6			5.0		
Education (%)	None	8.6		11.1		***	10.3		***
	Primary	79.0		83.3		***	78.5		
	Secondary	10.5		4.7		***	6.1		***
	Tertiary	2.0		0.9		***	5.1		***
Video (%)	(seen)	39.9		41.6		*	43.7		***
Wealth Index		- 0.00	1.03	- 0.14	0.82	***	0.14	1.10	***
Farm characteristics									
Zone (%)	EZ	23.9		52.5		***	8.6		***
	LZ	68.4		27.2		***	52.8		***
	SZ	7.7		20.2		***	38.6		***
Farm size	(acre)	9.10	14.31	6.73	9.49	***	10.05	12.10	***
Ownership (%)	Communal	2.0		3.7		***	1.7		
	Own	84.4		86.0		*	85.2		
Size cassava field	(acre)	2.00	1.75	2.49	1.97	***	2.40	2.03	***
Previous fertilizer use (%)	(yes)	2.0		5.4		***	9.6		***
Market (%)	Processor	1.0		2.8		***	0		***
	Middleman	41.3		57.7		***	35.5		***
	Local	16.5		5.4		***	13.7		***
	Urban	0		0.9		***	0.9		***
Extension (%)	(yes)	58.6		61.6		***	77.6		***

Two-sided t-test with: * p-value < 0.1 ; ** p-value < 0.05 ; *** p-value < 0.01

6 Discussion

6.1 Insights from results

As announced in the literature review, we have seen an evolution toward a more bottom-up approach in the history of extension services. The first key take-away from this paper is that we confirm the necessity of such an approach. Namely, except for the attribute planting month, all other attributes show to have significant preference heterogeneity. This indicates that, also for cassava extension services, a one-size-fits-all approach would not satisfy all farmers, and hence would not lead to the desired technology adoption rates.

Firstly, for the attribute planting month, we find our main results from the MMNL model. We see that there is a significant preference to plant in December ('very late month' in all three zones) and an insignificant preference to plant in September ('early month' in all three zones), with both preferences having no significant standard deviation in the group. In Tanzania, December is either the third month of the raining season (for the SZ) or the last month of the raining season (for the LZ and EZ), while September is the month just before a raining season starts again in all three zones. This significant preference for planting as late as in December and no significant dislike to plant in a dry month like September, confirms that most respondents still see cassava as a non-commercialized secondary staple crop. Namely, when the raining seasons starts, they prefer to give priority to planting more drought-sensitive crops such as maize. In dry months, they don't mind planting the more drought-tolerant cassava because it will still give a reasonable yield for own consumption. However, even though seeing cassava as a secondary staple crop is generally bad for technology adoption rates, the generally non-significant preferences to plant 'early' and 'late' is a good thing if the extension service wants to convince farmers to practice staggered planting. This is one of the recommendations that ACAI wants to put across.

Secondly, for the attribute months in the field, there is generally a strongly significant preference to keep the number of months in the field as low as possible. However, the significant standard deviation shows that there is some preference heterogeneity for this attribute. With the Latent Class model, the contract farmers appear to be those with the highest aversion to keep their cassava long in the field, followed by the investment averse farmers. The independent farmers do not have a particular preference for this attribute. The latter can be linked to their aversion for a contract. These are farmers that want freedom in when they sell their cassava, and thus also in when they are going to harvest. Overall, the results of this attribute are not compatible with the results of Lambrecht et al. (2015), who analyze farmers' preferences for technology adoption for climbing bean varieties. Lambrecht et al. (2015) namely predicted that the amount of time in the field was generally less important for the farmers. In our results we thus see that this is only true for the independent farmers. The difference in results can however be due to the possibility that farmers' preferences for climbing bean cultivation are very different from their preferences for cassava cultivation. To conclude: if we assume that having no particular preferences for both planting month and months in the field means being more willing to follow recommendations for staggered planting and harvesting, then it seems that personalization is not really necessary for such recommendations. However, the results predict that there will be a higher adoption rate of staggered planting and harvesting among the wealthier farmers (the class of the independent farmers).

Thirdly, the mean preference for fertilizer cost or investment is significantly negative. From the group discussions we can assume that this general negative preference is due to a lack of knowledge on the effect of fertilizers, due to capital constraints, and due to the lack of access to fertilizers in their region. Also, many farmers expressed not knowing enough about how they should use fertilizers for maximal output. However, again, we see preference heterogeneity for this attribute: both the independent farmers and the contract farmers do not seem to have a significant (dis)preference for fertilizers. For the independent farmers this could be due to their higher wealth, which means that investing in fertilizers does not bring along as great a risk as for the other classes. Or it could be due to the significantly higher number of farmers that have previously used fertilizers for cassava among the independent farmers, and/or due to their significantly higher number of people with past experience with extension services for cassava. The correlation between current preferences for fertilizer investment and previous experience with fertilizer use for cassava or extension services for cassava, has also been revealed in practice (Lambrecht et al., 2016b, 2014; Suvedi et al., 2017). As a contrast, the investment averse farmers are those who significantly want to keep their fertilizer costs as low as possible. This aversion could be linked to their cassava field size, their lower past experience with fertilizers on cassava, their gender, the exposure to the informative video, and/or past extension services about cassava. Namely, the investment averse farmers have the smallest cassava field of all classes, and only 2% of them have ever used fertilizers on cassava. This can be explained by reasoning that these farmers attribute comparatively less importance to cassava altogether, and thus have a lower incentive to invest in a higher yield. Furthermore, we can see that there are significantly more women in this class. This could indicate that generally, female respondents are less eager to invest in fertilizers. This is in line with the findings that showed that women generally prefer to stick to the status quo (Kassahun & Jacobsen, 2015; Lambrecht et al., 2015). Interestingly, we see that significantly less investment averse farmers have seen the video. Showing an informative video about fertilizers beforehand might thus positively influence the preferences to adopt the fertilizers on cassava. However, we must take a possible social desirability bias into account. This bias happens when farmers feel like they should answer in favor of fertilizers after having seen the video, and thus show a preference not true to their own. Finally, the same can be said about past contact with extension services about cassava: it appears to have a positive effect for fertilizer use, because significantly less farmers with past extension experience are now among the investment averse. This affirms one of the conclusions from the analysis of the independent farmers, and it again confirms what has been revealed in practice (Lambrecht et al., 2016b, 2014; Suvedi et al., 2017). Interestingly, it was clear in the literature for revealed preference that capital constraints were negatively correlated with fertilizer use (Dercon & Christiaensen, 2011; Emmanuel et al., 2016; Lambrecht et al., 2014; Liverpool & Winter-Nelson, 2010). We must say that this correlation between wealth and fertilizer use is not as obvious in our results, because the investment averse farmers have a wealth index in between the two other classes. It is the class of the contract farmers that has the lowest wealth index, and thus we would expect them to also have the greatest aversion for fertilizer costs. But the fact that this is not the case, could be due to the hypothetical bias peculiar to stated preference methods. Even though the contract farmers might show a preference to invest in fertilizers in our choice experiment, they simply would not be able to do this in real life. However, Obisesan et al. (2016) have showed that increasing credit availability could increase adoption among the farmers with a preference for fertilizer but without the means to buy them. For the contract farmers, this credit could be included in the contract.

Fourthly, the mean preference for yield is strongly significant and positive. This confirms the results of Lambrecht et al. (2015). Even though the standard deviation of the MMNL model shows preference heterogeneity for this attribute, we see that this is merely because the independent farmers have an even larger preference for higher yields than the two other classes. Also the mean yield variability is strongly significant and positive. As we considered this attribute to show us how farmers looked at risk, this outcome is rather surprising. It is also contradicting Asrat et al. (2010), who found that output stability was an appreciated technology trait. We believe that the surprising outcome is due to the farmers mostly looking at the upper side of the yield variability, and due to the sub-optimal way of having illustrated the attribute yield variability on our choice cards. However, a larger-than-expected preference for risk is normal due to the effect of 'ambiguity aversion'. This means that farmers are generally more prepared to accept risk when they know its probabilities (Ellsberg, 1961). But, knowing that an exact yield variability does not reflect the situation in real life, we take into account that the results from this attribute might also not reflect the true preference of the farmer. To conclude, we believe that the results for both yield and yield variability are not helping us in our research objectives, so we will not further consider them.

Fifth, from the MMNL model we see that the farmers generally significantly prefer contracts where their market is guaranteed and in return the market price gets reduced, up to the point of 40% price reduction. A reduction of 60% seems to be too high, as then the mean (dis)preference is not significant anymore. However, there is a large preference heterogeneity among the respondents for this attribute. The contract farmers are those that have a high preference for the contracts, even to the point of 60% market price reduction. The first remarkable indicator about this class is that they seem to be lower-schooled than the other classes: there are significantly more farmers with no or primary education, and there are comparatively less farmers among this class with a higher education than primary. They also have a significantly lower wealth index than the two other classes, and a smaller farm size. It thus appears as if less-educated and less-wealthy farmers are most in favor of decreasing their cassava prices in return to a more guaranteed income. The second indicator for contract farmers is that more than half of the farmers in this class are from the EZ and that significantly more contract farmers are selling their cassava to a middle man. From this, we can theorize that contract farmers are farmers who acknowledge the potential of a large cassava market nearby (like Dar es Salaam in the EZ), but have to sell their cassava to a middle man at a reduced price as they cannot afford the cost for fast transportation to the city. Hence, for such farmers a contract seems more attractive than their current situation. On the other side of the spectrum there are the independent farmers who have a significant aversion for the contracts already at 40% market price reduction. One indicator of this class is its much higher wealth index compared to the two other classes. Based on these results, we can assume that wealthier farmers do not want to decrease their market prices in return for a guaranteed market. That these farmers are wealthier is also confirmed by the fact that the average farm size of the independent farmers is significantly larger than the other classes, and that the percentage of farmers that have used fertilizers for cassava before is significantly larger. Moreover, we see that, compared to the other classes, many more farmers from the SZ belong to the class of the independent farmers. There are two possible explanations for this. Firstly, from the interviews it was apparent that our assumptions that farmers sell their cassava in the fresh form in the SZ were wrong, and that actually most farmers sell it in dried form due to the low soil fertility. One related aspect to this is that they can store it for a longer time, giving them more freedom to choose when to sell it, to whom, and how. The incentive to agree on a contract up front is thus less present. Secondly, when looking at their expected prices it is clear that the cassava market in the SZ is much more stable compared to the EZ and LZ. Hence, with a more predictable and constant demand, the need for a contract is greatly reduced, especially if a price reduction is attached to the contract.

6.2 Implications

6.2.1 Research implications

As the results of our choice experiment are mostly consistent with the insights from the literature on both stated and revealed preferences, we see that choice experiments are useful to confirm farmers' preferences. As a consequence, this stated preference method can help to increase technology adoption rates and farm efficiency/production. We also confirm that choice experiments are a good first tool to recognize the source of heterogeneous preferences. By linking the preferences to certain socio-economic characteristics, choice experiments can help research institutes and extension agents to put a probability on the preferences of a new, unknown farmer.

The key take-away for further research is that we confirm that, also for cassava cultivation, there is a large preference heterogeneity for technology adoption among farmers. Thus, the usefulness of adapting the extension services according to the farmers' wishes, is clear. For example, from the group discussions we would think at first that offering a guaranteed market would be appreciated by all farmers, and that it would enhance technology adoption. However, from the econometric results we see that if extension services were carried out to uniformly recommend the uptake of contracts with processing factories, then approximately 34% of the farmers (the proportion of the 'independent farmers' in our sample) would not be interested and thus not adopt this recommendation. This also means that more research needs to be done in order to map all these different preferences and find the right technology for each (type of) farmer.

6.2.2 Implications for ACAI

For ACAI's extension services for agronomic best practices, the adoption rates of the recommendations can be increased by either adapting the recommendations to each farmer's preferences, or by targeting those farmers whose preferences are aligned with the recommendations. The farmers' preferences can be recognized by the correlation between the socio-economic characteristics and the classes. Independent farmers appear to be characterized by their higher wealth, their larger farm size, their past experience with fertilizers on cassava, and their higher past contact with extension services about cassava. Contract farmers can be recognized by their lower education, lower wealth index, smaller farm size, and middlemen as the main buyer of their cassava. Finally, investment averse farmers are the farmers with a small cassava field, little past experience with fertilizers on cassava, and little contact with extension services about cassava. This class is also significantly more female than the two other classes.

The importance of adaptation of extension to optimize the adoption rates is stressed by the fact that the proportions of the type of farmers are very evenly distributed. Firstly, the group of 'independent farmers', which are mostly found in the SZ, is the group most likely to follow up the recommendations on fertilizer adoption because they are not significantly averse to it and have the highest financial means to buy fertilizers. They will likely also be the most open to staggered planting. However, their adoption rates are not going to increase by offering contracts with buyers. Secondly, for the 'contract farmers', the preference for fertilizer adoption is present, but the adoption rates might be greatly reduced due to the financial constraints among them. However, as they have a high preference for contracts, these farmers might overcome the financial constraint by taking up contracts with credit access. The positive effect of credit access on chemical fertilizer adoption is confirmed in several papers (Emmanuel et al., 2016; Obisesan et al., 2016). Considering that such farmers are also open to staggered planting, ACAI should look into the possibility of integrating the needed supply of local processing factories into the decision support tools. This could guarantee a constant stream of supply for the factories, and thus be an incentive for new factories to settle in rural areas. By doing this, also the overall demand for cassava will increase, and farmers would again receive the incentive to continue investing in their cassava production. Thirdly, considering that they have the smallest average cassava field and have spent the least fertilizers on this field, the 'investment averse farmers' seem to not spend much attention to cassava production. For these farmers the first step towards technology adoption for cassava will be to make them aware of the commercial opportunities it brings along, and what possible yields they could reach if the right agronomic practices are used. This class has a significant aversion for planting their cassava very early, but for all three other months, staggered planting is possible. Fourthly, regardless of which type of farmer is targeted, we suspect that showing an informative video about fertilizers on cassava has a general positive effect on fertilizer adoption preferences. Finally, from the group discussions we recognize that adoption of improved cassava varieties is still very low, and that farmers strongly believe that fertilizers are useless on local varieties. Hence, we recommend ACAI to introduce information on improved varieties in their decision support tool, or, even better, include recommendations on which varieties should be used and where to buy them.

6.3 Reflection

Important to note is that the above socio-economic characteristics should not be confused with causal effects. We rather only show where a correlation exists. For example, when we see that comparatively more lower-schooled farmers are interested in contracts, it could be not because of their education, but because lower-schooled farmers are generally also poorer. Or, next to wealth as an independent variable, a totally different factor could be playing a role in the correlation. Another important aspect to keep in mind is the possibility of a selection bias. Our sampling approach meant that our respondents are closer to extension agents than the average Tanzanian farmer. This could thus result in a better-than-average knowledge on different technologies, and thus some inflation in fertilizer adoption preferences might be present. However, we believe that this bias does not affect our conclusions, because we can still see a significant difference in preferences for fertilizer use between the three classes. Moreover, the ASC-values are relatively low compared to ASC-values in other papers around choice experiments. Even more, only in 1% of all choices made by the respondents, the opt-out was chosen. This suggests that the option to opt-out was not obvious enough on the choice cards, and thus the ASC-values might be inflated. Finally, when designing our choice cards in Ngene, we indicated that a MNL model would be estimated with the experiment. In the end, we decided to use an MMNL model. Our design was thus sub-optimal, which might have caused larger standard errors and thus some effects to be less significant.

7 Conclusion

The goal of this paper is to improve the extension services of ACAI before they are put in place. We do this by using an ex-ante research method, namely a discrete choice experiment (DCE). With this DCE, we analyze the farmer's preferences on attributes related to adoption of fertilizer and staggered planting. These different attributes are the planting month, the amount of months in the field, the fertilizer input and cost, the expected average yield, the yield variability, and the market type. The choices of a total of 333 Tanzanian farmers from three different zones (Lake Zone, Eastern Zone, Southern Zone) are collected, and combined with survey data and group discussions.

For the planting month, it appears that there is no significant preference for planting one month earlier or one month later than the normal planting time for cassava, and this is the case among all respondents. This implies that there should not be any aversion to staggered planting. For the attribute 'months in the field', there is the general significant preference to keep the cassava as shortly as possible in the field. However, when looking at the three different classes with homogenous preferences, it seems that the class of the wealthiest farmers (in this paper referred to as the 'independent farmers' because of their aversion to contracts) do not have a significant preference for this attribute. This implies that wealthier farmers might be more open to staggered harvesting than the others. The results for the attribute 'fertilizer cost', show that the preferences are very different among the classes. We can conclude that the farmers with the least experience with cassava cultivation are also the ones who have a significant aversion toward investing in fertilizers. With least experience we mean that these farmers have the smallest cassava field, and have the tiniest experience with using fertilizers on cassava. Among the two other classes with a higher preference for fertilizer use, is the class of the farmers with the most restricted financial means. This implies that increasing credit access might also increase fertilizer adoption, which has been confirmed in previous research. Finally, for the attribute market type we can deduce from both the group discussions and the results of the choice experiment that a guaranteed market with market price reduction to up to 40% is generally appreciated by the farmers. This implies an interesting opportunity for potential investors in the cassava processing industry. By guaranteeing farmers that they will buy their cassava after harvest, farmers accept that they can pay them as little as 60% of the market price. When looking at the different classes, we see that one third of the respondents is indifferent toward such contracts, one third has a significant aversion toward these contracts, and one third has a significant preference for them. It appears that the latter are the least wealthy and the least educated farmers. As this is the same group who is willing to invest in fertilizers but is financially constrained, the contracts could be even more effective if they are linked to credit access. We thus commend policy makers who want to reduce poverty to also look into the opportunity of such contracts.

Considering the large preference heterogeneity for most attributes, it is clear that a one-size-fits-all approach for the ACAI extension services would not optimize the adoption rates of their recommendations. We thus recommend them to adapt their advice to the preferences of the farmers when needed, even if the advice becomes sub-optimal then. We also recommend ACAI to implement a similar choice experiment in all their target countries, as it is clear that these results are very region-specific and cannot be generalized to all of sub-Saharan Africa. Finally, we recognize the usefulness of choice experiments for improving extension services as a whole, and thus recommend to implement similar research for all future extension programs.

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Appendix A: Scripts for Ngene

Script for first DCE:

Design ? Design 1: zonder guaranteed market - attribute
;alts = alt1*, alt2*, alt3
;rows = 48 ? 8 choice cards per block
;block = 6
;eff = (mnl, d, mean)
;bdraws = halton(100)
;alg = mfederov ? nodig als constraints worden toegevoegd

;reject:
alt1.yieldvar = 1 and alt1.fertcost = 4, ? not possible to invest a lot (fertilizer cost is 4), and have a low yield variability (of 33% = level 1)
alt2.yieldvar = 1 and alt2.fertcost = 4, ? idem
alt1.yieldvar = 2 and alt1.fertcost = 0, ? vice versa
alt2.yieldvar = 2 and alt2.fertcost = 0,
alt1.yield = 4 and alt1.fertcost = 0,
alt2.yield = 4 and alt2.fertcost = 0,
alt1.yield = 1 and alt1.fertcost = 4,
alt2.yield = 1 and alt2.fertcost = 4

;model:
U(alt1) = b1.dummy[(n,0.001,0.0005)|(n,0.002,0.001)|(n,0.003,0.0015)|(n,0.004,0.002)] * planting[2,3,4,5,1] ? 1 is january/march, 2 is september, 3 is october, 4 is november, 5 is december
+ b2[(n,-0.1,0.05)] * months[10,11,12,9] ? 9, 10, 11, 12 months in the field
+ b3[(n,-0.01,0.005)] * yieldvar[2,1] ? 1 is yield +/- 33% , 2 is yield +/- 66%
+ b4.dummy[(n,0.01,0.005)|(n,0.02,0.01)|(n,0.03,0.015)] * yield[2,3,4,1] ? 1 is lowest yield, 4 is highest yield (needs to be adjusted per zone)
+ b5[(n,-0.01,0.005)] * fertcost[1,2,4,0] ? amount of bags per acre, price per bag is app. 70,000 TSH
+ i5[-0.1]*yieldvar*fertcost ? zeer belangrijk
/

U(alt2) = b1* planting
+ b2 * months
+ b3 * yieldvar
+ b4 * yield
+ b5 * fertcost
+ i5 * yieldvar * fertcost /

U(alt3) = b0[(n,0.001,0.0005)]

$

Script for second DCE:

```
Design ? Design 2: with guaranteed market
;alts = alt1*, alt2*, alt3
;rows =  48
;block =  6
;eff = (mnl, d, mean)
;bdraws = halton(100)
;alg = mfederov  ? nodig als constraints worden toegevoegd

;reject:
alt1.yieldvar = 1 and alt1.fertcost = 4,      ? not possible to invest a lot (fertilizer cost is 4), and have a low yield variability (of 33% = level 1)
alt2.yieldvar = 1 and alt2.fertcost = 4,      ? idem
alt1.yieldvar = 3 and alt1.fertcost = 0,      ? vice versa
alt2.yieldvar = 3 and alt2.fertcost = 0,
alt1.yield = 4 and alt1.fertcost = 0,
alt2.yield = 4 and alt2.fertcost = 0,
alt1.yield = 1 and alt1.fertcost = 4,
alt2.yield = 1 and alt2.fertcost = 4,
alt1.gm = 0 and alt2.gm = 0

;model:

U(alt1) = b1.dummy[(n,0.001,0.0005)|(n,0.002,0.001)|(n,0.003,0.0015)|(n,0.004,0.002)] * planting[2,3,4,5,1]      ? 1 is january/march, 2 is september, 3 is october, 4 is november, 5 is december
+ b2[(n,-0.1,0.05)] * months[10,11,12,9]      ? 9, 10, 11, 12 months in the field
+ b3[(n,-0.01,0.005)] * yieldvar[2,1]      ? 1 is yield +/- 33% , 2 is yield +/- 66%
+ b4.dummy[(n,0.01,0.005)|(n,0.02,0.01)|(n,0.03,0.015)] * yield[2,3,4,1]      ? 1 is lowest yield, 4 is highest yield (needs to be adjusted per zone)
+ b5[(n,-0.01,0.005)] * fertcost[1,2,4,0]      ? amount of bags per acre, price per bag is app. 70,000 TSH
+ b6.dummy[(n,1,0.5)|(n,1.2,0.6)|(n,1.4,0.7)] * gm[20,40,60,0]   ? guaranteed market attribute: 1 is 0% decrease of the market price but market is not guaranteed, 2 is 20% off the market price but market is guaranteed, 3 is 40% off the market price but market is guaranteed, 4 is 60% off the market but market is guaranteed
/

U(alt2) = b1* planting
+ b2 * months
+ b3 * yieldvar
+ b4 * yield
+ b5 * fertcost
+ b6 * gm  /

U(alt3) = b0[(n,0.001,0.0005)]

$
```

Appendix B: Mixed Multinomial Logit Models with Interaction Effects

Interaction between yield and yield variability

We control for the interaction effect between yield and yield variability because they were shown in a combined way on the choice cards. In Table 7 we can see that the interaction effect is significantly negative at 10%. This implies that if the yield is low, the farmer would choose for a larger yield variability. This seems rather illogical at first, but can be understood if we assume that the farmers generally look more at the upper side of the yield variability instead of the underside. As the standard deviation is not significant, it appears like this preference is homogenous across the group of respondents.

Table 7: Results of the dummy-coded MMNL model with interaction effect between yield and yield variability

		Mixed Multinomial Logit Model			
		Coefficient (se)		*Standard Deviation (se)*	
ASC		- 4.202 (0.447)	***		
Planting month[1]	Very early	- 0.020 (0.093)		0.368 (0.171)	**
	Early	- 0.062 (0.090)		0.154 (0.184)	
	Late	- 0.050 (0.084)		0.026 (0.209)	
	Very late	0.159 (0.091)	*	0.535 (0.148)	***
Months in the field		- 0.085 (0.021)	***	0.204 (0.021)	***
Fertilizer cost		- 0.002 (0.0003)	***	0.005 (0.0003)	***
Yield		0.160 (0.014)	***	0.090 (0.007)	***
Yield variability		0.014 (0.005)	***	0.009 (0.003)	***
Market[2]	Guaranteed market w. -20%	1.602 (0.156)	***	1.158 (0.169)	***
	Guaranteed market w. -40%	1.068 (0.152)	***	0.791 (0.182)	***
	Guaranteed market w. -60%	- 0.200 (0.161)		0.667 (0.196)	***
Yield * Yield variability		- 0.0005 (0.0003)	*	0.0001 (0.0001)	

* p<0.1 ; ** p<0.05 ; *** p<0.01

[1] Reference level is the 'normal planting month', which is October for all three zones

[2] Reference level is the usual non-guaranteed market wherein the cassava is sold at the market price (0% reduction)

Interaction between months and planting month

The interaction between the attributes 'months in the field' and 'planting month' should also be checked, because combining them resulted in a specific harvesting month which was also shown on the card. The results are shown in Table 8. All interactions have a negative sign, and only the interactions between months and the levels 'early' and 'very late' are significant. It is not possible to find a meaningful interpretation for this result.

Table 8: Results of the dummy-coded MMNL model with interaction effect between months and planting months

		Mixed Multinomial Logit Model			
		Coefficient (se)		*Standard Deviation (se)*	
ASC		- 3.555 (0.625)	***		
Planting month[1]	Very early	0.669 (0.841)		0.479 (0.159)	***
	Early	2.723 (0.806)	***	0.276 (0.141)	**
	Late	0.439 (0.804)		0.258 (0.146)	*
	Very late	1.628 (0.830)	**	0.419 (0.157)	***
Months in the field		0.035 (0.054)		0.187 (0.025)	***
Fertilizer cost		- 0.002 (0.0003)	***	0.005 (0.0003)	***
Yield		0.142 (0.007)	***	0.086 (0.005)	***
Yield variability		0.004 (0.002)	**	0.009 (0.003)	***
Market[2]	Guaranteed market w. -20%	1.742 (0.158)	***	1.138 (0.164)	***
	Guaranteed market w. -40%	1.126 (0.154)	***	0.780 (0.169)	***
	Guaranteed market w. -60%	- 0.173 (0.158)		0.570 (0.197)	***
Months * Planting month[1]	Very early	- 0.065 (0.082)		0.006 (0.020)	
	Early	- 0.272 (0.078)	***	0.004 (0.014)	
	Late	- 0.048 (0.079)		0.027 (0.014)	**
	Very late	- 0.142 (0.082)	*	0.019 (0.015)	

* p<0.1 ; ** p<0.05 ; *** p<0.01
[1] Reference level is the 'normal planting month', which is October for all three zones
[2] Reference level is the usual non-guaranteed market wherein the cassava is sold at the market price (0% reduction)

Interaction between fertilizer cost and yield variability

As specified in Ngene when designing the choice experiment, we want to analyze how the preferences for fertilizer cost change with the yield variability levels. When running a MMNL model with such interaction effect, we receive the results shown in Table 9. The preference for yield variability remains strongly positive, but the preference for fertilizer cost becomes positive at a significance level of less than 1%, and the interaction effect is strongly significantly negative. This would mean that when the yield variability or the risk increases, the preference to invest in fertilizers decreases.

Table 9: Results of the dummy-coded MMNL model with interaction effect between yield variability and fertilizer cost

		Mixed Multinomial Logit Model			
		Coefficient (se)		*Standard Deviation (se)*	
ASC		- 4.259 (0.444)	***		
Planting month[1]	Very early	0.001 (0.090)		0.119 (0.248)	
	Early	- 0.095 (0.092)		0.217 (0.150)	
	Late	- 0.079 (0.084)		0.132 (0.254)	
	Very late	0.196 (0.093)	**	0.523 (0.136)	***
Months in the field		- 0.065 (0.022)	***	0.243 (0.025)	***
Fertilizer cost		0.004 (0.001)	***	0.004 (0.0003)	***
Yield		0.144 (0.007)	***	0.087 (0.006)	***
Yield variability		0.020 (0.003)	***	0.008 (0.003)	***
Market[2]	Guaranteed market w. -20%	1.530 (0.146)	***	0.977 (0.168)	***
	Guaranteed market w. -40%	1.222 (0.147)	***	0.624 (0.275)	**
	Guaranteed market w. -60%	- 0.217 (0.159)		0.692 (0.204)	***
Yield variability * fertilizer cost		- 0.0001 (0.00001)	***	0.00002 (0)	***

* p<0.1 ; ** p<0.05 ; *** p<0.01
[1] Reference level is the 'normal planting month', which is October for all three zones
[2] Reference level is the usual non-guaranteed market wherein the cassava is sold at the market price (0% reduction)

Interaction between fertilizer cost and guaranteed market

As said in methodology, we also want to know how the preferences to invest in fertilizers change when the market is guaranteed. The results from the interaction effects between fertilizer cost and the market levels are shown in Table 10. The first interaction, namely the interaction between fertilizer cost and a guaranteed market with 20% market price reduction, is strongly significant and positive. This would mean that if such a market is guaranteed, the preferences for fertilizer investment decrease even more. Considering this, the significant and negative sign for the interaction with the guaranteed market with 40% market price reduction is very surprising and illogical. Again, we cannot find a meaningful interpretation for these results.

Table 10: Results of the dummy-coded MMNL model with interaction effect between fertilizer cost and market

		Mixed Multinomial Logit Model			
		Coefficient (se)		*Standard Deviation (se)*	
ASC		- 4.431 (0.392)	***		
Planting month[1]	Very early	- 0.081 (0.097)		0.546 (0.138)	***
	Early	- 0.049 (0.093)		0.359 (0.131)	***
	Late	- 0.037 (0.084)		0.117 (0.147)	
	Very late	0.166 (0.089)	*	0.383 (0.161)	**
Months in the field		- 0.045 (0.022)	**	0.186 (0.024)	***
Fertilizer cost		- 0.002 (0.0004)	***	0.005 (0.0003)	***
Yield		0.143 (0.007)	***	0.086 (0.005)	***
Yield variability		0.004 (0.002)	**	0.009 (0.002)	***
Market[2]	Guaranteed market w. -20%	1.259 (0.196)	***	1.175 (0.168)	***
	Guaranteed market w. -40%	1.365 (0.180)	***	0.756 (0.169)	***
	Guaranteed market w. -60%	- 0.097 (0.175)		0.498 (0.237)	**
Fertilizer cost * Market[2]	Guaranteed market w. -20%	0.002 (0.0006)	***	0.001 (0.0008)	
	Guaranteed market w. -40%	- 0.001 (0.0005)	**	0.002 (0.0007)	***
	Guaranteed market w. -60%	- 0.0006 (0.0004)		0.0004 (0.0006)	

* p<0.1 ; ** p<0.05 ; *** p<0.01

[1] Reference level is the 'normal planting month', which is October for all three zones

[2] Reference level is the usual non-guaranteed market wherein the cassava is sold at the market price (0% reduction)

Popularized summary

In the past 60 years, the productivity of crops has seen an immense surge around the world, leading to a higher global food security. In the same time period an increase in production is observed in sub-Saharan Africa (SSA), but this appears to be due to an increase in cultivated land rather than an increase in productivity. Unfortunately, this unstable way of working leads to a constant or even decreasing food security in the region. To maneuver this trend in a more sustainable direction, extension services are installed to spread innovative agricultural techniques and ultimately increase crop productivity. In the past, the consensus was that simply explaining and making available the same agricultural techniques from other parts of the world would give the same rise in productivity. However, the low adoption rates of these techniques showed that this was not the right approach. Then, adapting the techniques to the farmers' needs and wished proved to be successful. The African Cassava Agronomy Initiative (ACAI), a five-year project, aims to improve agronomic practices in cassava cultivation in SSA to increase its average yields. The objective of this paper is to optimize the adoption rates of their recommendations, by considering the specific preferences of subgroups, instead of only looking to the wishes of the majority. With this information the personalization of the taught techniques are taken to another level, and we expect even higher adoption rates. The first results are about staggered planting, which is a term for planting at successive periods instead of everything at once. The outcome shows that almost all farmers are willing to practice staggered planting, and thus that personalization is not required for this recommendation. In contrast to this, personalization for fertilizer investment advice is most probably needed to increase adoption rates. More specifically, we propose ACAI to limit recommending fertilizers to farmers with smaller cassava fields and little experience with using fertilizers on cassava, because these farmers have shown to significantly dislike it. As we see that one third of the respondents are willing to invest in fertilizers, but are most likely financially constrained to do so, we further commend ACAI to look into possible collaborations with large cassava buyers, such as processing factories. They could offer contracts that guarantee a buyer for their cassava, and give access to credit for fertilizers investments. Our results show that this same group of farmers has a high preference for such contracts.