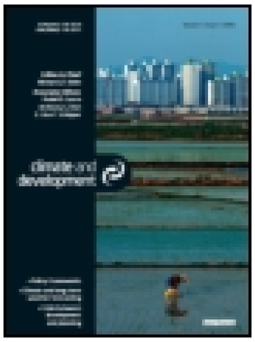


Climate and Development

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tcld20

Farmers’ preferences for climate-smart cowpea varieties: implications for crop breeding programmes

Edward Martey, Prince M. Etwire, Desmond Sunday Adogoba & Theophilus Kwabla Tengey

To cite this article: Edward Martey, Prince M. Etwire, Desmond Sunday Adogoba & Theophilus Kwabla Tengey (2021): Farmers’ preferences for climate-smart cowpea varieties: implications for crop breeding programmes, Climate and Development, DOI: 10.1080/17565529.2021.1889949

To link to this article: https://doi.org/10.1080/17565529.2021.1889949

Published online: 23 Mar 2021.

CLIMATE AND DEVELOPMENT
https://doi.org/10.1080/17565529.2021.1889949

Taylor & Francis
Taylor & Francis Group

RESEARCH ARTICLE

OPEN ACCESS Check for updates

Farmers' preferences for climate-smart cowpea varieties: implications for crop breeding programmes

Edward Martey [a], Prince M. Etwire [a], Desmond Sunday Adogoba[a] and Theophilus Kwabla Tengey [b]

[a]Socioeconomics Section, CSIR-Savanna Agricultural Research Institute, Tamale, Ghana; [b]Cowpea Improvement Program, CSIR-Savanna Agricultural Research Institute, Tamale, Ghana

ABSTRACT
Despite sustained efforts to promote climate-smart technologies in Sub-Saharan Africa (SSA), adoption remains low. At the same time, the downside risks associated with climate change and food insecurity are becoming acute. Improved cowpea varieties are climate-smart and contribute to food and nutrition security. Limited evidence exists, however, regarding how cowpea attributes influence adoption. We use a discrete choice experiment to investigate farmers' preferences and mean willingness to pay (WTP) for cowpea variety attributes. Our results show that farmers' decision to adopt improved cowpea varieties increases in response to the following attributes: higher yields, early maturity, and white seed coat colour. The results indicate that 86% of the sampled farmers prefer climate-smart cowpea. Secondly, while we observe a wide dispersion of WTP among female cowpea farmers relative to male cowpea farmers, participation in cowpea training reduces the dispersion of WTP for both men and women. Moreover, controlling for farmer risk aversion further decreases the dispersion of WTP for all respondents. Our experiment reemphasizes the need for crop breeding programmes to be participatory. Moreover, such programmes would do well to satisfy the demands of different segments of the population based on risk, gender, and geographical characteristics.

ARTICLE HISTORY
Received 5 November 2020
Accepted 7 February 2021

KEYWORDS
Climate-smart cowpea variety; choice experiment; random parameter logit; willingness to pay

1. Introduction

Agriculture production is a risky activity especially for developing economies where farmers rely heavily on the weather, cultivate on degraded soils, have inadequate access to good quality inputs and markets (Kuhl, 2020; Sova et al., 2018). In Africa, the importance of agriculture cannot be overemphasized as the sector is critical for meeting the food demands of its fast growing population which is exacerbated by climate change.[1] Climate change is expected to have dire consequences for the continent. Temperature is projected to rise more than the global average and accompanied by unfavourable changes in precipitation leading to stressed agricultural and natural systems characterized by increased drought, shorter growing season, increased incidence of pests and diseases, increased floods and decreased agricultural productivity (Ahenkan et al., 2020; Asfaw & Branca, 2018; Branca et al., 2012; FAO, 2013; Mensah et al., 2020; Muchuru & Nhamo, 2019; Senyolo et al., 2018).

Even though climate change poses a serious risk to the economic growth of Africa, the agricultural sector provides an opportunity to contribute towards climate change mitigation. Climate-smart agriculture (CSA), which entails the application of sustainable agricultural adaptation practices, could lead to improved productivity and food security while leading to an enhancement of the resilience of farming systems, a reduction in greenhouse gas emissions and better climate change mitigation through a creation of carbon sinks and carbon sequestration (Branca & Perelli, 2020; FAO, 2013). The definition or characterization of CSA varies across regions and often reflects context-specific technologies and practices such as crop tolerance to stress, conservation agriculture, intercropping, agroforestry and soil and water conservation practices (Senyolo et al., 2018; Sova et al., 2018).[2]

Food insecurity remains a in Sub-Saharan Africa (SSA), where majority of the population are smallholders and poor (Thome et al., 2019). Several studies have identified low use of modern inputs, lack of efficient credit and insurance schemes, inefficient market and pricing systems, and lack of information as part of factors influencing decline in crop yield and increasing food insecurity (Hansen et al., 2019; Martey, Etwire, & Kuwornu, 2020). The United Nations acknowledges the food insecurity challenge and therefore puts forward a transformational roadmap enshrined in the sustainable development goal (SDG) two which seeks to 'end hunger, achieve food security and improve nutrition and promote sustainable agriculture by the year 2030' (United Nations, 2015). The results achieved so far show that SSA lag other regions though Africa has observed marginal reduction in food insecurity (FAO et al., 2019; Tandon et al., 2017).

The agricultural sector is expected to lead the transformation process in achieving the SDG2. In most developing regions such as SSA, the sector contributes towards food and nutrition security, employs about 65% of the labour force, and contributes almost 32% of gross domestic product

CONTACT Edward Martey eddiemartey@gmail.com Socioeconomics Section, CSIR-Savanna Agricultural Research Institute, P.O. Box TL 52, Tamale, Ghana

(GDP) (Fuglie, 2018). In Ghana, the sector employs about 75% of the rural population of which majority are women (Ghana's Ministry of Food and Agriculture, 2017; MoFA). Despite the importance of the sector, agriculture in Ghana remains underinvested and coupled with several challenges such as poor soil health, climate variability and shocks, inadequate infrastructure and institutional bottlenecks, and land degradation (Issahaku & Abdulai, 2020; Martey, Etwire, & Abdoulaye, 2020). Climate simulation and empirical studies have shown that agricultural production will decline if climate-smart strategies are not employed (see Asfaw et al., 2016; Brown et al., 2017).

Development partners have been promoting climate-smart agriculture (CSA) as a strategy to achieve sustainable agricultural production to address food insecurity (Global Nutrition Report, 2015). Ghana has witnessed several development intervention programmes aimed at promoting climate-smart technologies (Martey et al., 2019). Despite sustained efforts to promote climate-smart technologies, adoption remains low (Martey, Etwire, & Abdoulaye, 2020). At the same time, the downside risks associated with climate change and food insecurity are becoming severe. In response to addressing the low use of climate-smart technologies, the Accelerated Varietal Improvement and Seed Delivery of Legumes and Cereal in Africa (AVISA) project has been promoting improved cowpea varieties in northern Ghana. The cowpeas promoted are climate-smart and expected to contribute to food and nutrition security. The crop is drought tolerant with high levels of protein, minerals, and amino acids. Cowpea is a commercial crop that saves cost by improving soil fertility through nitrogen fixation. Limited evidence exists, however, regarding how cowpea attributes influence adoption. In this research, we use a discrete choice experiment to investigate farmer preferences and mean willingness to pay (WTP) for cowpea variety attributes. The study also explores preference heterogeneity of cowpea attributes based on gender and participation in cowpea training.

The superior performance of advanced lines of improved varieties identified by researcher on-station needs to be validated under farmer conditions given that farmers are the ultimate beneficiaries of improved varieties released by researchers. Participatory breeding and more specifically participatory varietal selection are one technique that can be used to validate on-station results under farmer conditions thereby guaranteeing widespread adoption of improved new varieties. Farmers derive utility, not just from new varieties, but from specific attributes of a new variety thus participatory evaluation is required to identify traits that are important to farmers (Worku et al., 2020).

There is evidence that farmers have the capacity to select from a pool of crop varieties that meet their preferences and growing conditions (Asfaw et al., 2011). Participatory evaluation increases the likelihood of adoption of improved varieties and by extension productivity in marginal environments (Worku et al., 2020). Unlike breeders, farmers (especially those located in areas characterized by erratic rainfall) often prefer varieties with multiple traits. Even when the focus of a farmer is a single trait, the farmer's assessment may differ from that of a breeder. For example, whereas a breeder's assessment of yield may be the output obtained per unit areas, a farmer's assessment may also include flour yield. Therefore, it is important to undertake studies to explicitly reveal farmers' trait preferences (Vom Brocke et al., 2010). Men and women use different criteria to assess or place value judgement on the importance of some crop traits (Vom Brocke et al., 2010). In that regard, there is also a need to further disaggregate farmers' preferences for different traits by sex.

There are studies that have analysed the factors influencing the adoption of climate-smart technologies and their impacts on household welfare. Manda et al. (2020) used a control function and propensity score matching methods to estimate the causal effects of adoption of improved cowpea varieties in Nigeria**.** The first stage result shows that improved cowpea varieties are significantly influenced by age, education, number of traders, wage rate, herbicide prices, male labour availability, distance to the plot from the homestead, access to research organization, government extension, and geographical location. An earlier study by Manda et al. (2019) on the poverty impacts of improved cowpea varieties in Nigeria revealed that age, age square, education, information index, years of awareness, and geographical location significantly influence the adoption of improved cowpea varieties. A study by Asfaw et al. (2011) in Ethiopia find that knowledge of existing varieties, perception about the attributes of improved varieties, household wealth (livestock and land) and availability of active labour force are major determinants for adoption of improved chickpea. Kristjanson et al. (2005) studied farmers' perceptions of benefits and factors affecting the adoption of improved dual-purpose cowpea in the dry savannas of Nigeria. They find that fodder, and soil fertility-enhancing characteristics of cowpea influence adoption while adoption intensity is determined by village and household level factors. In assessing the socio-economic diversity in cowpea preferences in Ghana, Quaye et al. (2011) find that attributes of cowpea preferred by traders are stone-free, white seed colour, easy cooking, tasty, medium to large size, less weevil damage, dryness and place of origin. On the consumer side, cleanliness is ranked as the highest followed by the extent of weevil damage, white seed colour, short cooking time, medium to large size, and taste.

Despite these findings, there is a lack of evidence on how cowpea attributes specifically drives adoption among smallholder farmers in SSA (especially in Ghana). This study provides valuable information on farmers' preferences in order to enable cowpea breeding programmes to design quick and efficient participatory breeding projects to facilitate the development and use of cowpea varieties in northern Ghana. Northern Ghana is an obvious area in Ghana that can be targeted for the dissemination of climate-smart technologies, such as improved cowpea varieties, due to the harsh weather conditions (Ministry of Environment, Science, Technology and Innovation, 2013; MESTI). According to Quaye et al. (2011), the crop thrives well in the Guinea Savannah and forest transition zones.

The rest of the paper is structured as follows: Section 2 describes the experimental design and the study sites while Section 3 presents the empirical model. Section 4 presents and discusses the empirical results and Section 5 provides the concluding remarks.

2. Experimental design and study sites

2.1. Selection of attributes

This study employs a discrete choice-based experiment approach to investigate farmers' preferences and mean willingness to pay (WTP) for cowpea variety attributes based on farmers' stated preferences. Choice experiment has been applied widely in agriculture, environmental economics, health, and marketing literature (refer to Hensher, 2010; Holmes et al., 2017 for detail exposition). Several authors have employed choice experiment in empirical works. For example, Krah et al. (2019) used choice experiment to examine the constraints and drivers of soil fertility management (SFM) practice adoption. Waldman et al. (2017) evaluate farmers' preference for perennial attributes of pigeon pea intercropped with maize in Malawi. Ellison et al. (2016) determine the effect of retail outlet on consumer perceptions of and willingness to pay (WTP) for organic grape tomatoes. Kadjo et al. (2016) estimate the extent that markets in SSA discount damaged maize. Asrat et al. (2010) investigate Ethiopian farmers' crop variety preferences and estimate the mean willingness to pay for each crop variety attribute.

In a choice experiment, researchers stimulate market and production settings by presenting individuals with a hypothetical scenario and then ask respondents to make multiple decisions from several alternatives in a choice set. Usually, each scenario includes two or three alternatives defined by several attributes that takes on different levels. Respondents choose their preferred alternative from the alternatives provided. In our case, we provided cowpea farmers with a set of attributes for the experimental design through survey reports, focus group discussions (FGDs) and consultations with crop breeders both at the national agricultural research systems (NARS) and the consultative group for international agricultural research (CGIAR[3]) systems. The outcome of the literature search, FGD, and expert consultations reveal that yield, colour, size, maturity period, and price are the most important attributes of improved cowpea variety among farmers. Table 1 presents a summary of the attributes and the levels. These attributes reflect a general preference among farmers. Fewer attributes in a choice set allow farmers to make an actual choice by eliminating the tendency to ignore one or more of the attributes in the experiment, referred to as attribute non-attendance (ANA) (Hensher & Greene, 2010).

Yield: several cowpea breeding programmes have focused on addressing low cowpea yield in the Guinea and Sudan Savannah agro-ecological zones of Ghana. High yielding varieties have been promoted in recent years, but the adoption rate is low due to low incentives and constrains associated with adoption. Low cowpea yield is attributed to lack of access to improved seeds, high pests and diseases, poor farm practices and inability to access market. For example, farm level yields of cowpea on area basis have remained low (600–800 kg ha^{-1}) compared to research fields (1600–2500 kg ha^{-1}) (Savanna Agricultural Research Institute [SARI], 2014; Yirzagla et al., 2016). The high yield effect is realized when high-yielding improved cowpea varieties and complementary inputs such as mineral fertilizer are jointly adopted. According to Duflo et al. (2011), such effect may not be realized due to liquidity constraints.

Maturity: as a response to the long dry spells in northern Ghana, short duration improved cowpea varieties have been developed and promoted among smallholder farmers who are largely the most affected. Smallholder farmers in northern Ghana use traditional seeds which are long duration and associated with high risks of crop failure due to pests and diseases. Consistently, farmers have been urged to adopt early maturing cowpea varieties, but the constraint of limited access remains (Owusu et al., 2018).

Size: the study presents two different sizes (big and small) of cowpea following from the focus group discussion and expert consultation. Buyers and consumers generally prefer large grain size. Trade occurs by weight; thus, smaller grain size produces less volume within the standard 100 kg bag (Lopes et al., 2003).

Colour: the adoption of improved cowpea variety is associated with colour. Colour signals healthy grains. Buyers and consumers associate unhealthiness to grains that are stained (Guinn, 2002; Quaye et al., 2011). Generally, farmers associate cooking time with the colour of the grains. Cowpeas that are large seeded and have rough seed white coat colour cooks faster relative to the brown and mottle cowpea varieties (SARI, 2018). This attribute gives an indication of climate-smartness. Some white seed coat cowpea varieties have a rough seed coat which easily absorb moisture thus reducing the cooking time. The main cooking fuel among the sampled farmers are firewood and charcoal which require harvesting of firewood from the forest. Harvesting of firewood for cooking has a negative effect on the environment and the quality of human and animal life. In addition, most consumers of cowpea-based diets prefer the white colour.

Price: three levels of prices were specified: GH₵ [4]450 (US $83.80), GH₵480 (89.39), and GH₵510 (94.97) per bag (100 kg). Buyers of cowpea informed the choice of the price levels. The prices were selected to reflect the different levels of cowpea attributes and market prices across the three regions. According to Asrat et al. (2010) 'the price attribute is important for households that have access to markets and sell most of their products.'

2.2. Design of choice sets

The OPTEX procedure in SAS was used to establish the optimal experimental design using the attributes and levels described in Table 1. With three attributes varying across two levels each and two attributes varying across 3 levels, there were 108 ($3^3 * 2^2$) possible combinations of attributes and their levels. We use a D-optimal design with modified Federov search algorithm with a full-factorial design constituting the candidate set. A total of 9 choice sets (row) were generated and put into three blocks, with each block consisting of three choice sets. Each participant of the choice experiment was randomly assigned to a block and provided with three independent choice sets. Figure 1 shows an example of a choice set

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

Attribute	Levels 1	2	3	Preference/Description
Yield	Low	High		Average production (in 100 kg) harvested per hectare from planting a particular cowpea variety. High yield is mostly preferred.
Maturity	Early	Medium	Late	The period between planting and harvesting. Early-maturing variety is mostly preferred.
Size	Small	Big		The size of harvested grain. Smaller quantity of large grain sizes is required to fill a bag (100kg). A large grain size is mostly preferred to smaller grain size.
Colour	White	Brown	Mottle	White colour is associated with short cooking time and mostly preferred by consumers. A white colour is mostly preferred.
Price	GH¢ 450	GH¢480	GH¢ 510	The amount of money the farmer earns by selling 100 kg of harvested cowpea. GH¢480/100kg is the expected market price.

Note: 1 US$=GHS5.37 (Bank of Ghana, 2019).

scenarios with illustrations to accommodate different levels of literacy among the participants.

2.3. Study area and data

The study was conducted in the Guinea and Sudan Savannah agro-ecological zone[5] of Ghana consisting of Northern, Upper East and Upper West regions. Agriculture is predominantly the main source of income for most of the inhabitants (Gage et al., 2012; Statistics, Research and Information Directorate, 2012). The major crops grown are maize, sorghum, millet, rice, soybean and cowpea. Cowpea is usually the last crop to be cultivated by smallholder farmers. Figure 2 shows the map of the study area showing the location (districts) of the farmers interviewed.

This study combines both farm household and choice experiment survey data collected in 2019 for the 2018/2019 cropping season from 320 cowpea farmers in seven major cowpea growing districts (Tolon, Savelugu, Yendi, Bawku Municipal, Binduri, Wa West, and Nadowli) in northern Ghana. Our sampling[6] (320 farm households) procedure followed a multistage sampling technique. In the first stage, 7 districts were purposively selected from the three regions based on the quantity of cowpea produced, accessibility, and presence of active farmer-based organizations (FBOs). Second, 20 communities were purposively selected from Northern Region (North-East and Savannah) and 10 communities each from the Upper East and Upper West regions, respectively. The list was based on cowpea-producing communities in each of the selected districts based on the volume of cowpea production. Within the selected communities, 8 cowpea producers were randomly selected from a list of cowpea producers. In all, 320 cowpea producers were purposively and randomly selected from 40 communities within 7 districts (Table 2).

Table 3 reports the summary statistics of selected household characteristics. The majority (approximately 59%) of the household heads in our sample are males. Capital accumulation is measured by participation in cowpea training. Farmers are trained on good agronomic practices and business models by agricultural extension agents (AEAs) and non-governmental organizations to boost their production and market participation. The results show that 34% of the sampled farmers have participated in a cowpea training programme. Disaggregating[7] the results by sex indicate that on the average, equal number of male and female-headed households have been trained. There is a conscious effort by development practitioners to close the gender productivity gap by creating equal opportunities for both male and female-headed households. To achieve this objective, the efforts of both private and public institutions in providing capacity building must be sustained. Model farmers are selected household heads who have demonstrated competence in agricultural production. These farmers are trained and used as agents of change in the community. In communities where AEAs are non-existent, these farmers act as private extension agents. Our results show that 28% of the sampled household heads are model farmers. We observed an average certainty equivalent risk[8] preference of 5 indicating that on the average household heads in our sample are risk-loving farmers. The results imply that majority of the farmers may be the early adopters of agricultural technologies.

3. Econometric model

The underlying theoretical framework for modelling preference elicitation studies hinges on random utility theory (McFadden, 1973). Random utility framework postulate that an individual chooses among alternatives based on the utility associated with that choice. We assume that a farmer makes decision on the choice of improved cowpea varieties to maximize her subjective expectation of utility subject to budget constraints. Based on the random utility theory, we assume that the subjective expected utility of farmer i choosing a cowpea variety traits j is specified as:

$$EU_{ij} = V(X_j,\ Z_{ij}) + \varepsilon_{ij} \tag{1}$$

where X_j is a vector of cowpea attributes associated with alternative j (yield, maturity, colour, size, and price); Z_{ij} is a vector interaction between farmer-specific characteristics (participation in training and being a model farmer) and choice variables; ε_{ij} is the random error term that is unobserved by the researcher. Refer to Krah et al. (2019) and Campbell et al. (2018) for more detailed exposition on the conceptual framework.

In this paper, we model farmers' preferences for cowpea variety traits using the random parameter logit (RPL) model and the conditional logit (CL) model. However, we prefer the RPL over the CL model given that the CL model relies on the Independence of Irrelevant Alternatives (IIA) assumption (Benson et al., 2016). The study assumes that cowpea farmers are heterogeneous and their preferences for production and market attributes may also be heterogeneous. A

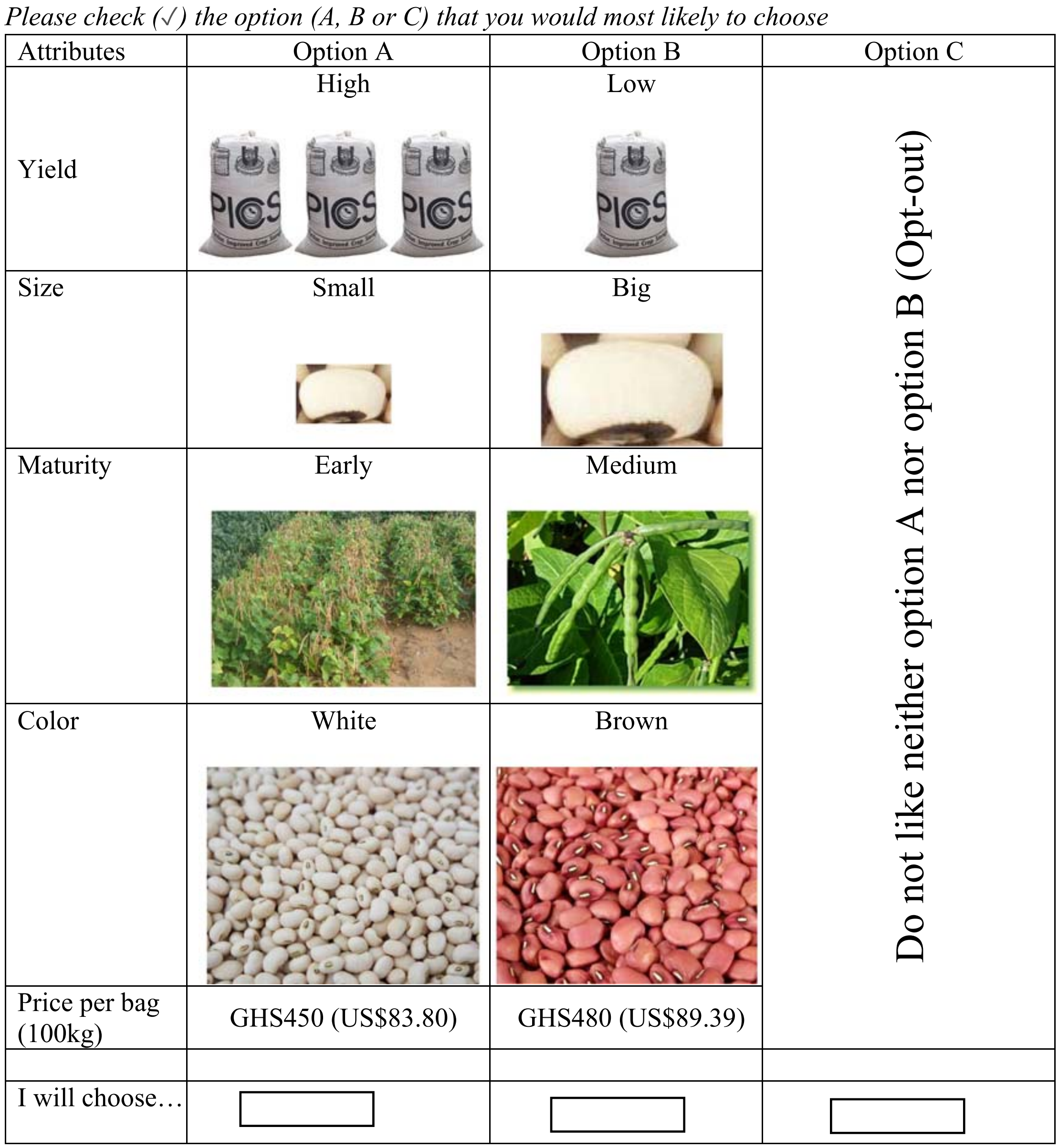


Figure 1. Example of choice set presented to survey respondents.

more frequent way of evaluating preference heterogeneity is the estimation of the RPL model that allows random taste variation within a sample based on a specified distribution (McFadden & Train, 2000).

We specify the subjective expected utility following Krah et al. (2019) and Asrat et al. (2010) where key socio-economic characteristics enter the utility framework through interaction with the attributes. The subjective expected utility of farmer i choosing cowpea traits j is specified as:

$$EU_{ij} = \beta' X_{ij} + \delta' P_{ij} + \varphi_i' X_{ij} + \lambda' Z_{ij} + \varepsilon_{ij} \quad (2)$$

where X_{ij} is the attribute vector (previously defines) excluding the price attribute, β are the associated coefficients to be estimated for each of the cowpea traits including an alternative specific constant (ASC); δ is the marginal utility of money; φ are smallholder-specific random terms that capture preference heterogeneity in the attribute; λ are the associated coefficients on the interaction terms (Z) to be estimated; ε_{ij} is the random error term that is identically and independently distributed (iid) extreme value (Train, 2009).

Following Hanemann (1984), we estimate the mean marginal willingness to pay (WTP) for a certain attribute as the ratio of the attribute coefficient to the marginal utility of income. A normal distribution of the random parameters is the most common assumption, although in principle any of the distributions expected to fit the estimated parameters can be chosen (Nahuelhual et al., 2004). Given that the attributes considered in this paper are not clearly predictable, we assume a normal distribution, which permits both negative and positive coefficients. For example, despite farmers associating positive preference weights with the yield attribute, we use a normal distribution given that the lognormal distribution produces a thick right tail. With respect to maturity, the drought situation in the study area makes the early maturing variety

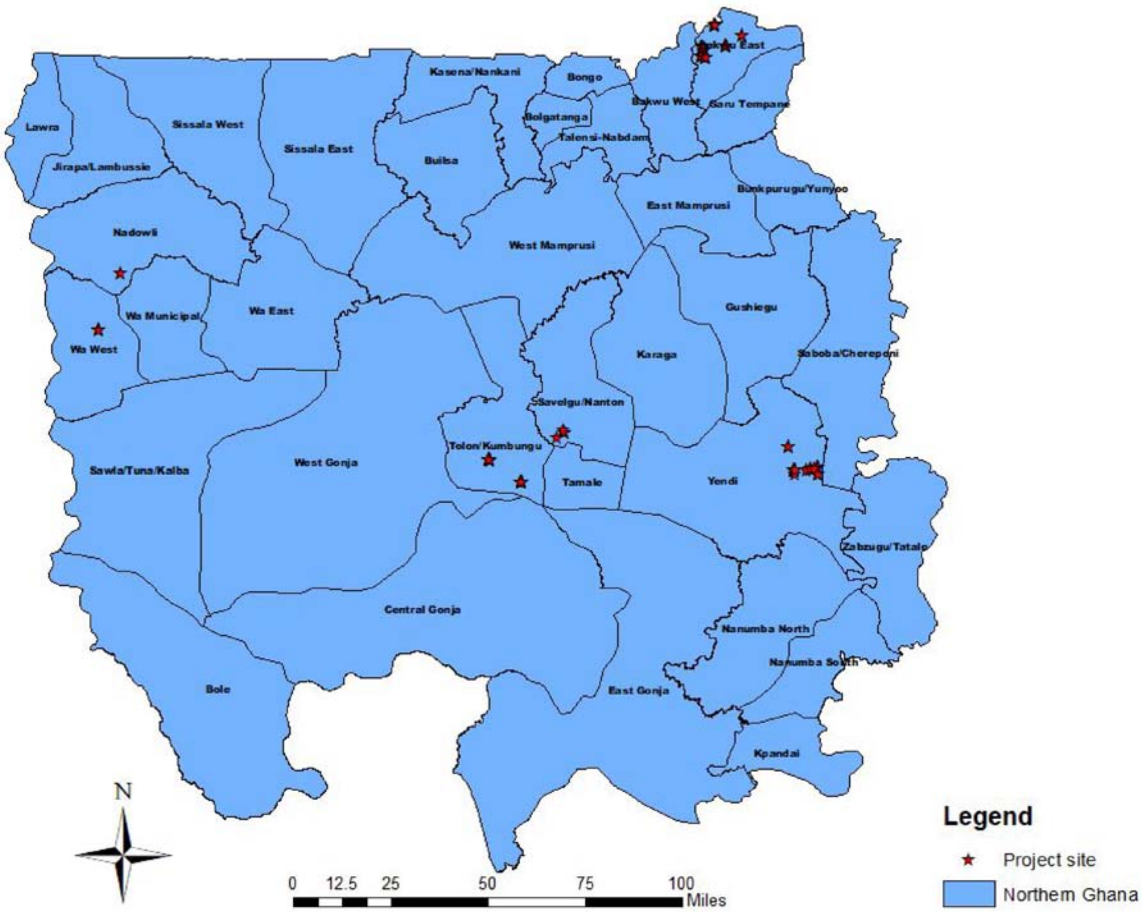


Figure 2. Study area showing the project sites.

more acceptable to the farmers while some farmers prefer the late maturing variety. The late maturing variety is more acceptable for intercrop as the crop provides plant cover for other crops thus reducing the rate of evapotranspiration. While majority of the farmers prefer large size cowpea in response to the preferences of the buyers, some of the farmers prefer the small size cowpea due to the high number of seed per kilogram when planting (i.e. increasing plant population) and household utilization. White seed coat cowpea is mostly preferred by majority of the farmers due to its ability to absorb moisture quickly and reduce cooking time. However, the brown and mottle seed coat cowpea is preferred by some of the farmers and traders for the preparation of special diets (such as 'waakye') for consumption purposes. For the price attribute, we use the lognormal distribution. Fitting a loguniform distribution will lead to a break down in the estimator given that a negative price coefficient is forced to be positive. This is resolved by computing a new variable (*PRS*) which is negative of the price variable (i.e. $PRS = -price$). The standard deviation of price is random. The RPL is estimated using simulated maximum likelihood with 1000[9] Halton draws.

4. Results and discussion

4.1. Farmers' willingness to pay – CL and RPL results

Results of the conditional logit (CL) and random parameter logit (RPL) results are presented in Table 4. Model (1) specifies the conditional logit results while models (2) and (3) are RPL estimates without and with correlations between attributes, respectively. Models (4) is RPL estimates that include non-random parameters without accounting for correlations between attributes while model (5) accounts for non-random parameters and correlation between attributes. The results show consistent signs in the CL and RPL results but differ in terms of the mean values. Consistent with theoretical predictions (Revelt & Train, 1998), the mean estimates of the RPL

Table 2. Distribution of sampled households by region.

Region	District	Communities	Households
Northern	3	20	160
Upper West	2	10	80
Upper East	2	10	80
Total	7	40	320

Table 3. Descriptive statistics of selected household characteristics.

Variable	Definition	Mean	SD
Sex	Sex of household head (1=male)	0.59	0.49
Training	Participated in cowpea training (1=yes)	0.34	0.47
Model farmer	Household head is a model farmer in the community (1=yes)	0.28	0.45
Risk aversion	Certainty equivalent (CE) risk preference	4.89	10.53

Table 4. RPL estimates for choice of cowpea traits.

Variables	Conditional Logit (CL) Model (1) Coefficient (Std. error)	Random Parameter Logit (RPL) Model (2) Coefficient (Std. error)	Model (3) Coefficient (Std. error)	Model (4) Coefficient (Std. error)	Model (5) Coefficient (Std. error)
ASC	−1.201	−3.708	−5.510	−5.218	−7.165
	(1.324)	(3.022)	(5.494)	(3.593)	(6.730)
Price	0.012***	−3.832***	−3.541***	−3.823***	−3.597***
	(0.003)	(0.293)	(0.361)	(0.299)	(0.422)
Yield (1=low)	−0.848***	−1.499***	−2.141***	−1.507***	−2.103***
	(0.097)	(0.286)	(0.600)	(0.299)	(0.660)
Maturity1 (1=medium)	−0.074	−0.103	−0.141	−0.118	−0.162
	(0.124)	(0.225)	(0.453)	(0.233)	(0.486)
Maturity2 (1=late)	−0.250**	−0.540**	−0.665	−0.565**	−0.648
	(0.123)	(0.230)	(0.406)	(0.239)	(0.442)
Size (1=small)	−0.188	−0.236	−0.207	−0.246	−0.211
	(0.131)	(0.227)	(0.491)	(0.231)	(0.445)
Color1 (1=brown)	−0.426***	−0.760***	−1.092**	−0.774***	−1.073**
	(0.124)	(0.246)	(0.439)	(0.258)	(0.431)
Color2 (1=mottle)	−0.120	−0.243	−0.196	−0.245	−0.207
	(0.126)	(0.248)	(0.393)	(0.265)	(0.466)
Non-random parameters					
Gender (1=male)				0.632 (1.327)	0.725 (1.581)
Household size				−0.006 (0.187)	0.001 (0.250)
Education (years)				0.037 (0.132)	0.029 (0.250)
Farming experience				−0.007 (0.017)	−0.012 (0.022)
Risk aversion				0.369 (1.327)	0.554 (2.020)
Region (1=Northern)				0.748 (1.737)	1.317 (2.734)
Standard deviations					
ASC		0.581	1.117	0.111	3.302
		(6.913)	(9.117)	(14.437)	(10.360)
Price		0.031	0.065	0.013	0.216
		(1.035)	(0.661)	(1.621)	(0.973)
Yield (1=low)		1.790***	2.900***	1.777***	2.818***
		(0.420)	(0.930)	(0.464)	(0.947)
Maturity1 (1=medium)		1.264**	2.881	1.236**	2.661
		(0.570)	(3.334)	(0.623)	(3.375)
Maturity2 (1=late)		1.149**	2.438	1.152**	2.377
		(0.509)	(2.756)	(0.547)	(5.855)
Size (1=small)		0.577	2.089	0.699	1.972
		(0.864)	(3.941)	(0.711)	(6.913)
Colour (1=brown)		1.283***	1.873	1.277***	1.870
		(0.422)	(4.717)	(0.450)	(6.701)
Colour (1=mottle)		1.554***	1.547	1.671***	1.346
		(0.478)	(7.431)	(0.502)	(6.125)
Observations	2884	2884	2884	2884	2884
AIC	1321.2	1298.4	1318.7	1304.2	1324.1
Log likelihood	−652.61	−633.21	−615.36	−630.10	−612.10

Note: ASC indicates alternative specific constant; ***, ** indicates significance at 1%, 5% respectively. Model (2) did not account for correlation between attributes while Model (3) does. Model (4) include non-random parameters without accounting for correlation but Model (5) accounted for correlation among attributes. Values in parentheses are standard errors.

model are higher than the CL model indicating that the CL model may be underestimating the effects. The significance of the standard deviations in the RPL results supports the hypothesis of preference heterogeneity indicating the presence of variation in the preferences of cowpea farmers in the population. Failure to account for the heterogeneity in farmers' preferences may lead to invalid inferences about farmer preferences for improved cowpea attributes.

Comparing across the RPL models, the Akaike Information Criterion (AIC) values indicate that model (2) is best fit for the data but the log-likelihood values suggest that model (5) is best fit for the data. However, none of the standard deviations in model (5) is significant indicating violation of preference heterogeneity. Comparing the magnitudes of the standard errors across the RPL models, model (2) recorded a relatively lower standard error relative to the mean values. Based on the AIC and magnitude of the standard errors, we focus the analysis on model (2) that does not account for correlation between attributes. Following from model (2), farmers consider yield (i.e. high vs. low), maturity (i.e. early vs. medium and late) and colour (i.e. white vs. brown and mottle) as important attributes in the selection of improved cowpea varieties. Note that the size (i.e. small vs. big) of cowpea is not statistically significant. Comparatively, the magnitude of the coefficient on price attribute is higher relative to all the other attributes.

Based on the preferred estimation (model 2), we examine the role of being a model farmer and participation in cowpea training on farmer preferences for improved cowpea varieties as well as the heterogeneity in the preferences. Table 5 reports the results of the RPL accounting for model farmer and training. Model (6) accounts for the cowpea attributes and the interactions between model farmer and the cowpea attributes; model (7) includes the interactions between participation in cowpea training and the cowpea attributes; and model (8) accounts for the interactions of both model farmer and training with the cowpea attributes. The interpretations and

Table 5. RPL estimates for choice of cowpea traits (accounting for model farmer and training).

	Random Parameter Logit (RPL)		
Variables	Model (6) Coefficient (Std. error)	Model (7) Coefficient (Std. error)	Model (8) Coefficient (Std. error)
ASC	−3.833	−3.817	−4.000
	(3.325)	(3.090)	(3.437)
Price	−3.819***	−3.832***	−3.813***
	(0.311)	(0.297)	(0.312)
Yield (1=low)	−1.913***	−1.451***	−1.863***
	(0.346)	(0.310)	(0.362)
Maturity1 (1=medium)	0.156	−0.196	0.065
	(0.277)	(0.282)	(0.323)
Maturity2 (1=late)	−0.574**	−0.504*	−0.549*
	(0.279)	(0.279)	(0.318)
Size (1=small)	−0.509*	−0.038	−0.310
	(0.277)	(0.284)	(0.320)
Color1 (1=brown)	−0.891***	−0.680**	−0.806**
	(0.293)	(0.296)	(0.342)
Color2 (1=mottle)	−0.300	−0.148	−0.202
	(0.293)	(0.309)	(0.348)
Non-random parameters			
Price*Model farmer	−0.000 (0.004)		0.000 (0.004)
Yield* Model farmer	1.348***(0.455)		1.396***(0.470)
Maturity1* Model farmer	−0.787 (0.537)		−0.753(0.554)
Maturity2* Model farmer	0.105 (0.498)		0.088(0.513)
Size*Model farmer	0.909**(0.442)		0.971**(0.469)
Colour1*Model farmer	0.335 (0.465)		0.355(0.475)
Colour2*Model farmer	0.194 (0.537)		0.191(0.555)
Price*Training		−0.001(0.001)	−0.001(0.001)
Yield* Training		−0.217(0.416)	−0.249(0.426)
Maturity1* Training		0.244(0.492)	0.212(0.487)
Maturity2* Training		−0.160(0.411)	−0.118(0.423)
Size* Training		−0.584(0.421)	−0.629(0.441)
Colour1* Training		−0.271(0.409)	−0.313(0.431)
Colour2* Training		−0.367(0.514)	−0.373(0.525)
Standard deviations			
ASC	0.032	0.033	0.035
	(1.670)	(0.943)	(1.521)
Price	0.307	0.604	0.318
	(15.099)	(6.174)	(13.926)
Yield (1=low)	1.720***	1.813***	1.752***
	(0.426)	(0.434)	(0.438)
Maturity (1=medium)	1.360**	1.320**	1.418**
	(0.561)	(0.585)	(0.582)
Maturity (1=late)	1.191**	1.151**	1.221**
	(0.519)	(0.530)	(0.534)
Size (1=small)	0.349	0.661	0.438
	(1.329)	(0.800)	(1.146)
Colour (1=brown)	1.308***	1.273***	1.298***
	(0.443)	(0.436)	(0.463)
Colour (1=mottle)	1.630***	1.591***	1.672***
	(0.481)	(0.486)	(0.493)
Observations	2884	2884	2884
AIC	1293.4	1308.3	1303.3
Log likelihood	−623.69	−631.17	−621.66

Note: ASC indicates alternative specific constant; ***, ** indicates significance at 1%, 5% respectively.

discussion of the results is based on model (8) due to the relatively low log-likelihood and the magnitude of the estimated standard errors relative to the mean estimates. The significance and magnitude of the attributes did not change after accounting for model farmer and training. However, we observe an improvement in the model as indicated by the log-likelihood value of −621.66 in model (8) compared to −633.21 in model (2).

Results of model (8) indicate that relative to high yielding cowpea varieties, farmers are less likely to adopt cowpea with low yield. Farmers generally associate higher disutility to low yielding cowpea varieties. Lack of consistent information about improved technologies negatively influence adoption due to high risk of adoption. Improved crop varieties that guarantee higher yield than the traditional varieties are more likely to be adopted. The finding is consistent with Asrat et al. (2010) who find that yield stability is an important attribute for farmers' choice of crop varieties. Common bean farmers in Ethiopia who were engaged in participatory breeding selected grain yield (represented by pod load, pod length and seeds per pod) and germination are their two most important traits (Asfaw et al., 2011). Similarly, Ward et al. (2014) demonstrate that farmers in Bihar, India value reductions in yield variability offered by drought-tolerant paddy but are willing to pay even more for seeds that offer yield advantages under normal conditions. However, farmers have higher preference for grain yield when adopting drought-tolerant maize varieties.

The coefficient and sign on the 'maturity2' attribute indicate that farmers prefer early maturing cowpea varieties compared to late maturing varieties. Farmers associate higher disutility to late maturing cowpea varieties relative to early maturing varieties. Northern Ghana is characterized by one major rainy season with long dry spells thus a variety that is early maturing will be highly preferred. Second, the risk of losses is minimized if the rains stop early than expected. Farmers who use irrigation for cowpea cultivation incur lower cost due to the short duration of the variety. These reasons may be accounting for the high preference for early maturing varieties. Early maturing cowpea varieties allow farmers to escape drought and diseases and pests infestation from the field. Worku et al. (2020) observed that maize farmers in East Africa (i.e. Kenya, Uganda, Tanzania and Rwanda) that were involved in participatory selection of varieties rated early maturity, germination and yield as the three most important traits that they desire in hybrids when they were asked to score different traits of hybrid maize using a Likert scale. The rankings of men were not significantly different from those of women. Farmers in Burkina Faso chose earliness as one of their most important sorghum traits. Productivity, defined by farmers in terms of panicle characteristics and flour yield, was found to be another important trait farmers desired in that country (Vom Brocke et al., 2010). In Ethiopia, farmers between earliness and drought tolerance with the former being a more important trait. Whereas tolerance refers to the capacity of plants to withstand drought at any stage of the season, earliness allows plants to mature before the onset of drought (Asfaw et al., 2011).

Though the mean of grain size (small) attribute is not significant, the interaction between size and model farmer show a significant positive effect. The results suggest that farmers' preferences for the grain size attribute is influenced by their status of being a model farmer. Model farmers are less likely to adopt improved cowpea varieties with large grain size (compared to small grain size) ceteris paribus. The result is contrary to our expectations given that more quantities of small cowpea grains are required to fill a sack in order to meet the weight requirement. The results indicate that being a model farmer may not necessarily guarantee high preference for cowpea with large grain size. Model farmers are trained and supported by local NGOs to technically backstop their fellow farmers and serve as agents for technology dissemination. The gains from yield outweighs the importance of big grain size traits thus the quantity required to achieve a bag full of cowpea may not necessarily be a challenge.

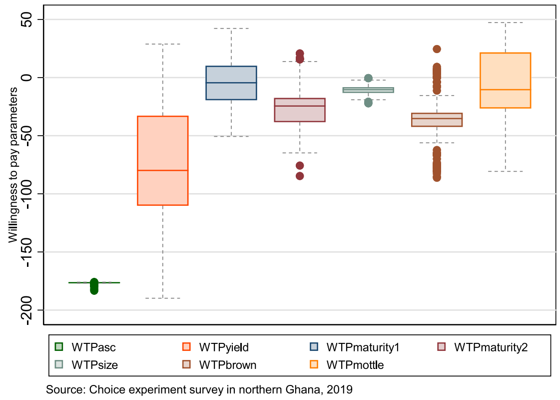
The results show that farmers associate lower utility to the adoption of improved cowpea varieties with brown colour relative to the white colour attribute. Colour of cowpea grains (white without spots) signal healthy grains to the traders that farmers engage with. Farmers associate length of cooking time with colour. The brown colour cowpea is perceived to take longer time in cooking relative to the white colour which have negative implication on household expenditure as well as the environment. Our results suggest that farmers have higher preference for environmental quality. Unlike our study, Asfaw et al. (2011) found that seed colour was a less important trait for common bean farmers in Ethiopia who had high preference for other traits. Farmers who participated in participatory breeding in India revealed that they prefer white to yellow maize and early maturing varieties that are well adapted to low rainfall and low soil fertility (Witcombe et al., 2003).

The inclusion of model farmer and training enhances overall model performance while the estimated standard deviations associated with yield, 'maturity1', 'maturity2', 'color1', and 'color2' are all statistically significant at 3%, 5%, 5%, 3% and 3% significance levels, respectively. This suggests that while being a model farmer influences farmer preferences for yield and size, the model farmer variable alone does not explain the overall heterogeneity in farmers' preferences for maturity and colour.

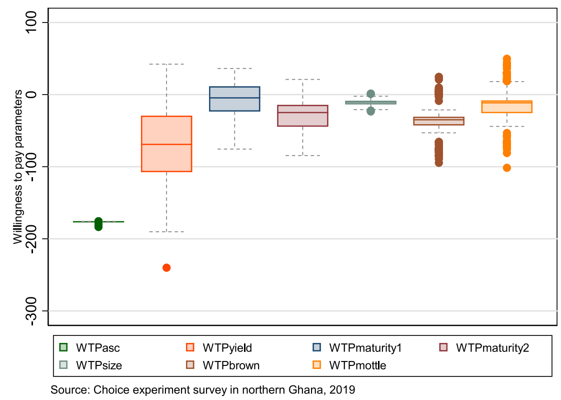
4.2. Distribution of farmers' WTP

Figure 3 illustrates the sex disaggregated (panels A and B), overall (panel C), and trained farmers (panel D) distributions of farmers' WTP for each attribute using a box plot. The box plots show that farmers associate negative WTP for all the attributes. The results show a wide distribution of WTP across farmers for the yield attribute followed by mottle colour, medium maturity (maturity1), late maturity (maturity2), brown colour and size in that order. With respect to the medium maturing and mottle colour cowpea, a proportion of the farmers associate positive willingness to pay for such attributes. A higher proportion of the farmers associate negative willingness to pay for late maturing and brown colour cowpea varieties below the mean WTP. Comparatively, farmers have high discount for low yielding cowpea varieties. A high number of farmers are willing to discount the price above the mean WTP for yield and mottle colour. However, the distribution of farmers' willingness to discount the price for medium maturing cowpea above and below the mean WTP is almost the same. This indicates that farmers are indifferent with respect to their preferences for medium maturing cowpea varieties. Trained farmers (panel D) have lower WTP for all the attributes relative to the pooled sample (panel C). The distribution of WTP for yield, mottle colour and medium maturity is wide with majority of the trained farmers recording a WTP value above the mean.

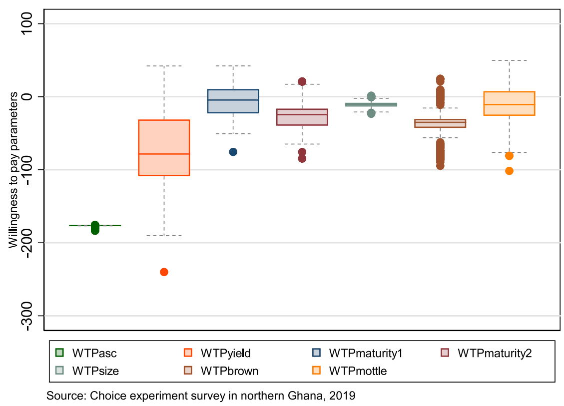
Based on sex disaggregation, female farmers record a wider distribution of price discounting around the mean WTP relative to the male farmers. This suggests that male farmerss may have more information about the attributes relative to the female counterparts thus the lower variation about the mean WTP. While all female farmers associate negative willingness to pay for the mottle cowpea, male farmers record a high proportion with positive WTP for the same attrubute. The result is not surprising given that fetching of fire wood and cooking is the sole responsibility of women. Women will nornally prefer a variety with relatively short cooking time to reduce the drudgery of fetching firewood and time allocation for home production. We find evidence of discounting for low yield attribute for both males and females, however, the variation of discounting is wide for males. The figure suggests that both males and females associate positive and negative WTP



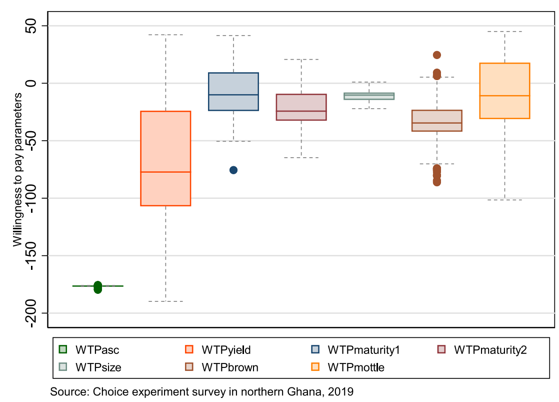
Panel A: Males' WTP



Panel B: Females' WTP



Panel C: Pooled sample WTP



Panel D: Trained farmers' WTP

Figure 3. Distribution of farmers' WTP for cowpea attributes.

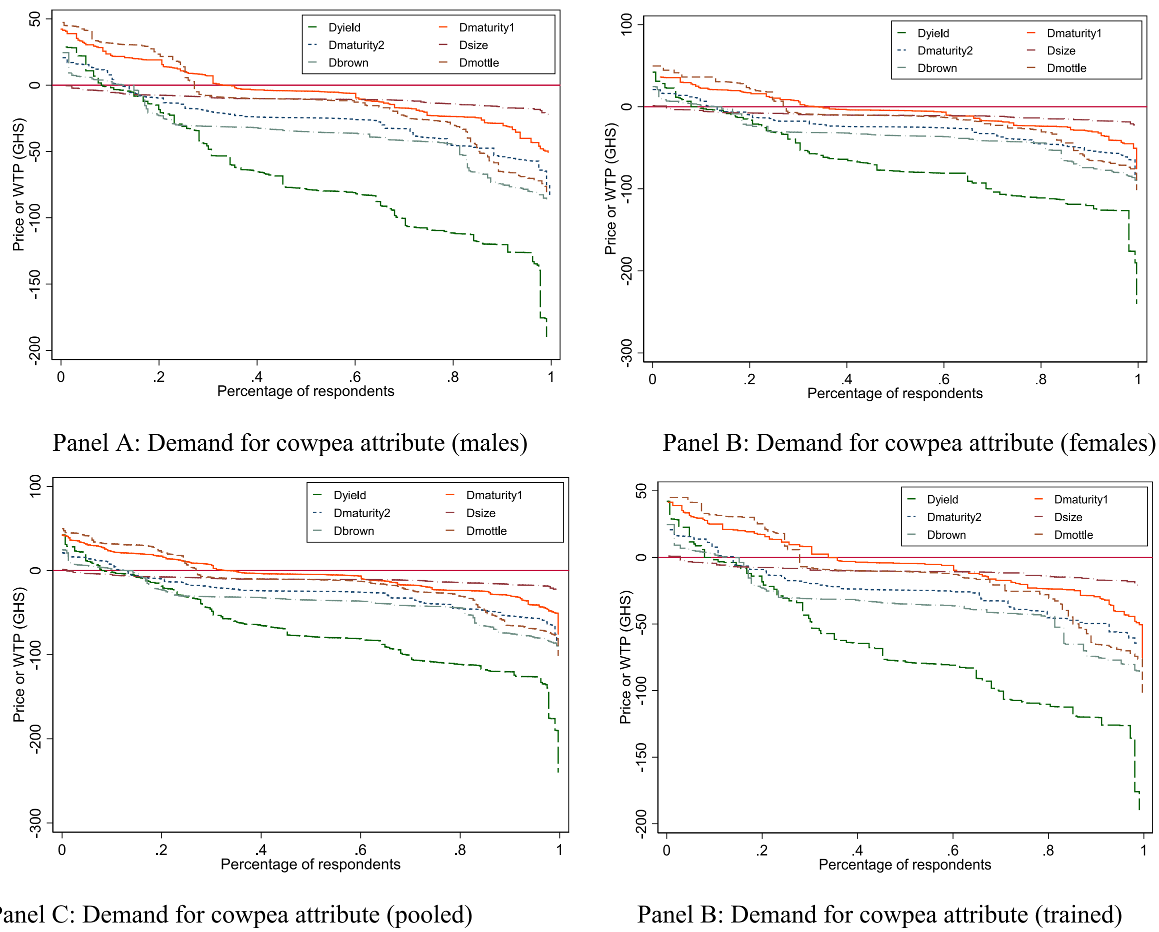
for medium maturing cowpea varieties. Asfaw et al. (2011) observed that female farmers place a higher priority on culinary traits.

4.3. Relative demand for cowpea attributes by sex and training

Figure 4 shows the relative demand for each of the cowpea attributes (in terms of price) based on sex disaggregation (panels A and B), overall sample (panel C) and participation in cowpea training (panel D). The figure indicates that all (100%) the respondents have negative demand for the size attribute which is consistent for both the entire sample and the disaggregated sample based on sex and training status. Similarly, low yield attribute is the least demand attribute among the cowpea attributes. Based on sex disaggregation (panel A and B), the demand for all the attributes of the cowpea varieties is negative for about 70% and 68% of male and female farmers, respectively. Nevertheless, 30% and 32% of the males and females, respectively showed positive demand for medium maturing variety while 8% of the male and female farmers respectively observed a positive demand for low yield. About 10% and 8% of the male and female farmers, respectively, record positive demand for late maturing cowpea. This indicates that high yielding cowpea is a highly valued attribute irrespective of sex. Demand for all attributes of improved cowpea is generally negative for about 73% of the overall sample (panel C). Less than 25% of the sample have positive demand for low yield, medium and late maturing, brown, and mottle colour cowpea. Based on training status (panel D), we observe that 67% of the trained farmers observed a negative demand for all the cowpea attributes. Above the zero price, 35%, 15%, and 10% of the farmers were willing to buy medium, late maturing, and low yield cowpea varieties respectively while 30% and 16% of the farmers are willing to buy mottle and brown colour cowpea varieties, respectively.

4.4. Regional differences in preferences for cowpea attributes

To account for the heterogeneity in the study area, we estimated RPL models for each of the regions individually using model (2). The results are reported in Table 6. Price and yield significantly influence the choice of improved cowpea variety in all the regions (Northern, Upper East and Upper West regions). Price is the most important attribute to farmers at the regional level, with the largest marginal utility in Northern Region. Comparatively, high yield is more valued among farmers in the Upper West Region relative to farmers in the Upper East and Northern regions. The significance of the standard deviation coefficient on yield suggests that there is a subset of the population in Northern and Upper West regions that



Panel A: Demand for cowpea attribute (males)

Panel B: Demand for cowpea attribute (females)

Panel C: Demand for cowpea attribute (pooled)

Panel B: Demand for cowpea attribute (trained)

Figure 4. Demand for attributes of improved cowpea.

have a higher value for the lower yield attribute. The coefficient on colour is significant in Northern Region indicating that farmers in this region have higher marginal disutility for brown cowpea. The significance of the standard deviation coefficients on size and colour in Upper West and Upper East regions, respectively indicate the presence of variation in the preferences of farmers. This means that there is subset of farmers in Upper East Region who prefer brown colour cowpea to white cowpea while a subset of farmers in the Upper West Region prefer big grain size to small grain size. Similarly, some farmers in the Northern Region prefer mottle colour cowpea relative to the white cowpea. The results suggest that development interventions across northern Ghana must be specifically targeted to ensure the highest impact.

4.5. Role of risk preferences in adoption of improved cowpea varieties

Figure 5 shows the effect of risk preferences on farmers' WTP for improved cowpea traits. Risk aversion as measured by certainty equivalent decreases farmers' willingness to pay for cowpea traits. Panel A describes the distribution of WTP for cowpea attributes among risk averse farmers while panel B describes the distribution of risk-lovers' WTP for cowpea traits. Generally, the distribution of WTP among risk averse (−200 to 50) farmers is lower than that of the risk-lovers (−300 to 100). The results indicate that risk averse farmers are willing to pay less for each of the cowpea attributes relative to the risk-loving farmers. This is consistent with theoretical predictions where risk preferences and perceptions influence individual choice when faced with uncertainty (Krah et al., 2018; Petrolia et al., 2015). Risk-loving farmers have tendency of engaging in risky ventures because of the higher probability of anticipated benefits. In promoting improved agricultural technologies among smallholder farmers, development practitioners must deliberately target and employ risk-loving farmers as model farmers to promote adoption through peer dissemination. Alternatively, the risk-averse farmers (late adopters) may be targeted and provided with critical information to reduce their uncertainties thereby increasing their adoption of improved cowpea varieties.

4.6. Who cares about climate-smart cowpea?

We further analysed farmers' preferences for climate-smart cowpea by disaggregating the sample into farmers (86%) who prefer white cowpea and those (14%) who do not prefer the white cowpea. The results are reported in Table 7. The cowpea varieties namely 'Wangkae', 'Kirkhouse Benga', and 'Diffeele' are white in colour with rough seed coat texture which easily absorb moisture, thus can cook very fast relative to the brown colour cowpea. In addition, majority of the

Table 6. RPL estimates based on regional analysis.

	Random Parameter Logit (RPL)		
Variables	Northern Model (9) Coefficient (Std. error)	Upper East Model (10) Coefficient (Std. error)	Upper West Model (10) Coefficient (Std. error)
Price	−4.273***	−3.605***	−3.761***
	(0.738)	(0.897)	(0.761)
Yield (1=low)	−1.227***	−1.643**	−2.222**
	(0.346)	(0.727)	(1.082)
Maturity (1=medium)	−0.305	0.643	−0.206
	(0.326)	(0.652)	(0.604)
Maturity (1=late)	−0.431	0.127	−1.111
	(0.312)	(0.521)	(0.723)
Size (1=small)	−0.343	−0.895	0.002
	(0.359)	(0.625)	(0.624)
Color1 (1=brown)	−0.764**	−1.302	−0.328
	(0.331)	(0.919)	(0.501)
Color2 (1=mottle)	−0.401	−0.182	0.200
	(0.407)	(0.651)	(0.535)
Standard deviations			
Price	0.331	0.000	0.133
	(94.186)	–	(18.542)
Yield (1=low)	1.260**	1.154	3.119**
	(0.613)	(1.227)	(1.558)
Maturity (1=medium)	1.150	0.050	1.793
	(0.797)	(21.763)	(1.943)
Maturity (1=late)	1.010	0.948	1.275
	(0.760)	(1.551)	(1.526)
Size (1=small)	0.001	0.036	2.266*
	(18.802)	(23.852)	(1.341)
Color1 (1=brown)	0.441	3.243**	0.855
	(1.086)	(1.619)	(1.077)
Color2 (1=mottle)	2.353***	1.811	0.089
	(0.668)	(1.397)	(13.330)
Number of observations	1440	684	720
AIC	660.5	299.3	356.7
Log likelihood	−314.25	−133.63	−162.37

Note: Values in parentheses are standard errors; ***, **, * indicates significance at 1%, 5% and 10% respectively. The distribution of price is log-normal while all other attributes are normally distributed. The standard deviation of the price is fixed.

Table 7. RPL estimates based on preference for white colour.

	Random Parameter Logit (RPL)	
Variables	Farmers who prefer white cowpea Model (9) Coefficient (Std. error)	Farmers who do not prefer white cowpea Model (10) Coefficient (Std. error)
ASC	−2.975***	−7.310
	(0.455)	(6.901)
Price	−4.690***	−4.075***
	(0.109)	(0.836)
Yield (1=low)	−0.670***	0.283
	(0.169)	(0.607)
Maturity (1=medium)	−0.305	−0.399
	(0.211)	(0.870)
Maturity (1=late)	−0.531***	−0.101
	(0.189)	(0.685)
Size (1=small)	−0.127	−0.630
	(0.185)	(0.737)
Standard deviations		
ASC	0.014	0.097
	(0.052)	(0.204)
Price	0.192	0.174
	(0.170)	(0.794)
Yield (1=low)	0.382	1.028
	(0.300)	(0.917)
Maturity1 (1=medium)	0.244	0.571
	(0.419)	(0.584)
Maturity2 (1=late)	0.512*	0.100
	(0.284)	(1.241)
Size (1=small)	0.074	0.703
	(0.273)	(0.912)
Number of observations	2484	360
AIC	904.9	136.0
Log likelihood	−440.46	−56.01

Note: ASC indicates alternative specific constant; ***, * indicates significance at 1%, 10% respectively.

cowpea-based diets are prepared using the white variety which is more attractive to majority of consumers. Reduction in cooking time of cowpea discourages indiscriminate harvesting of trees and high demand for fuelwood for cooking. This reduces the negative impact on the environment. The findings suggest that farmers with positive preference for white cowpea show significant positive preference for high-yielding and early maturing cowpea. However, a subset of the population associates positive preference weight to medium maturing cowpea varieties. Among farmers who prefer brown cowpea, we observe positive preference for the desirable attributes (high yield, early maturing, and large grain size) and no statistical significance in standard deviations for all the other attributes. The findings suggest that promotion of improved agricultural

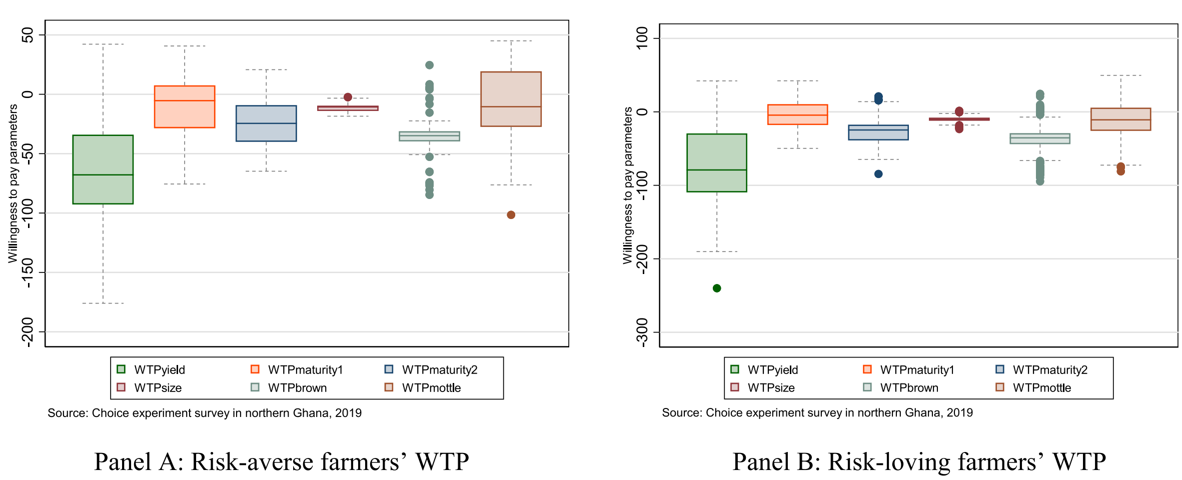


Figure 5. Distribution of farmers' WTP for cowpea attributes based on risk.

technology packages that allow for some degree of diversity will enhance uptake and utilization. Creating awareness, providing critical information about the white cowpea variety and making it accessible to farmers will increase adoption and improve environmental quality with subsequent positive effect on human and animal life.

5. Conclusion

Productivity enhancing and climate-smart technologies are integral in achieving food security and reducing the downside risk of adverse climate change. Given that a large share of the population in SSA are engaged in agriculture, promoting and utilizing climate-smart technologies will generate significant productivity growth in the agricultural sector with subsequent improvement in food security. Improved cowpea varieties are drought tolerant and contribute to food and nutrition security. However, promoting such technologies are associated with high risk due to limited access to critical information regarding the technologies. This has the tendency to reduce the rate of adoption despite the availability of the technologies and the economic impacts. Understanding the attributes, gender, and spatial dynamics as well as the role of risk preferences associated with technology adoption within an African context is non-negotiable. This study provides valuable information on farmers' preferences in order to enable cowpea breeding programmes to design quick and efficient participatory breeding projects to facilitate the development and use of cowpea varieties in northern Ghana.

Farmers in SSA are already burdened with multiple stresses with climate change and variability being an additional stressor, participatory breeding, which is driven primarily by farmer inputs and preferences, is necessary to quicken technology development and uptake especially as it related to the development and use of climate-smart varieties (Worku et al., 2020). This study employed a choice experiment to investigate farmers' preferences for improved cowpea variety attributes and identify the gender, spatial, capital accumulation, and risk preferences associated with farmers' WTP for improved cowpea varieties. Changes in climate and farmer circumstance will likely result in a change in farmer preferences hence there is a need to frequently study farmers preferences for different variety traits in order to inform breeding goals and programmes (Asfaw et al., 2011).

Our empirical results revealed that farmers consider attributes such as price, yield, early maturing, and white colour seed coat as important. However, we observe that cowpea grain size does not significantly influence the choice of improved cowpea variety adoption thus suggesting farmers' indifference between small and big grain size in our choice experiment. Asfaw et al. (2011) observed that some Ethiopian farmers who were involved in participatory breeding of common bean considered earliness as their most important trait.

Using the WTP values, we observed that farmers have the highest mean discounting for low yield followed by brown and late-maturing cowpea variety. These findings suggest that crop breeding programmes must address all desirable traits relative to the conventional methods of breeding for higher yields and early maturing varieties to enhance productivity. Based on sex disaggregation, the results show that females have a wider distribution of price discounting for undesirable traits of cowpea relative to male farmers. Female farmers are more likely to adopt climate-smart cowpea varieties relative to male farmers.

We further illustrated the relationship between farmers' capital accumulation and their preferences for yield, maturity, and colour. Our results revealed that being a model farmer may not necessarily guarantee high preference for cowpea with large grain size and high yield. Model farmers need to be engaged more frequently, trained and deployed in exchange programmes to enhance their decision-making regarding agricultural technologies. The spatial analysis reveals that price and yield significantly influence the choice of improved cowpea variety in all the regions but farmers in the Northern Region of Ghana have higher preference weight than those in other regions. The result is useful in planning and identifying the specific population to serve as entry point, operationalization, validation and out-scaling of improved crop varieties among smallholder farmers.

Consistent with the theoretical prediction, we observe that the distribution of WTP among risk-averse (−200 to 50) farmers is narrower than that of the risk-loving farmers (−300 to 100). This suggest that risk-averse farmers are willing to pay less for each of the cowpea attributes relative to risk-loving farmers. The implication of the result is that risk-loving farmers (early adopters) can be intentionally targeted to serve as community volunteers or model farmers in agricultural development programmes such as technology dissemination. Finally, we investigated farmers' preferences for climate-smart cowpea. The results indicate that 86% of the sample prefer climate-smart cowpea varieties (white colour) with positive preferences for high-yielding and early maturing cowpea varieties. There is no preference heterogeneity for farmers who prefer brown cowpea varieties. Promoting improved agricultural technology packages that allow for some degree of diversity will enhance uptake and utilization. The gains will be consolidated if farmers are informed about climate-smart varieties as well as improving access to these varieties. This will improve farmers' welfare and enhance environmental quality with subsequent positive effect on human and animal life.

The challenge of most breeding programmes is to develop varieties that combine multiple traits (yield, earliness, colour). Breeding programmes that focus on single traits restrict farmers' access to superior germplasm (Asfaw et al., 2011). From a policy perspective, developing improved crop varieties through a participatory breeding programmes that address farmers' desired attributes will increase adoption. Breeding programmes must satisfy the demands of different segments of the population based on risk, gender, spatial and preferences for climate-smart cowpea. Research institutions with the mandate of developing improved crop varieties must prioritize their research efforts in terms of specific attributes such as yield, maturity, and colour to satisfy the demands of Ghanaian farmers.

Notes

1. Agriculture is the mainstay of many African economies as it contributes the most to GDP, provide the bulk of the raw materials

needed by the manufacturing industry, serves as a source of employment for about two-thirds of the population and an essential pathway for pro-poor economic growth (Asfaw & Branca, 2018; Branca et al., 2012; Mensah et al., 2020; Muchuru & Nhamo, 2019; Senyolo et al., 2018).

2. Note that there are more than 1700 technologies and practices that improve yields, use water efficiently and impact on carbon stocks (Sova et al., 2018).
3. We engaged research scientists from the International Institute of Tropical Agriculture (IITA).
4. GH₵ represents Ghana cedi; Exchange rate is 1USD=GH₵5.37 (Source: Bank of Ghana, 2019).
5. The Guinea and Sudan Savannah agro-ecological zone (northern Ghana) comprise of Savanna, North East, Northern, Upper East and Upper West regions.
6. The sampling frame consists of all cowpea producing districts in (former) northern Ghana consisting of Northern, Upper East, and Upper West regions. The zone is made up of 52 districts with 26 in Northern, 15 in Upper East and 11 in Upper West regions.
7. The disaggregation results are not presented in the interest of brevity but available upon request.
8. The certainty equivalent (CE) risk preference $\delta_i^{CE} = (G/P_m)$, where G is the lowest price to lock in contract to eliminate all price risk for cowpea and P_m is the expected price during harvest. The interpretation are: $\delta_i^{CE} < 1$ are considered as risk-averse (RA), $\delta_i^{CE} = 1$ are considered risk-neutral (RN), and those with $\delta_i^{CE} > 1$ are considered risk-lovers (RL).
9. This is based on the recommendation by Bhat (2001).

Acknowledgements

We wish to acknowledge the farmers who took time off their busy schedule to voluntarily participate in the survey and all who assisted in diverse ways.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research was funded by the the Bill and Melinda Gates Foundation through IITA and ICRISAT for the flagship programme 'Accelerated Varietal Improvement and Seed Delivery of Legumes and Cereals in Africa (AVISA)'. The authors are grateful to Bayer Crop Science for their financial support. The Savanna Agricultural Research Institute (SARI) of the Council for Scientific and Industrial Research (CSIR) is acknowledged for the partnership to ensure successful implementation of the survey.

Notes on contributors

Edward Martey is an Agricultural and Applied economist at the CSIR-Savanna Agricultural Research Institute and a visiting scholar at the University of Illinois at Urbana-Champaign. He received his BSc (Agricultural Economics), MPhil (Agricultural Economics) and PhD (Agricultural and Applied Economics) degrees from the University of Ghana and University of Illinois at Urbana-Champaign, respectively. He is currently the Head of the Socio-economic section of CSIR-SARI. His key research interests are in the areas of management of innovation platforms, farming systems research, agricultural commercialization, gender, value-chain development, and impact evaluation.

Prince M. Etwire is Research Scientist (Agricultural Economist) at the CSIR-Savanna Agricultural Research Institute, Tamale, Ghana where he has been a faculty member of the socio-economic section since 2009. He received his BSc (Agricultural Technology), MPhil (Agricultural Economics) and PhD (Economics) degrees from the University for Development Studies, University of Ghana and University of Otago, respectively. His research interests are in the areas of modelling climate change adaptation, productivity studies, general microeconomic modelling, monitoring and evaluation of agricultural projects and building of organizational capacity.

Desmond Sunday Adogoba is a Biometrician with the CSIR-Savanna Agricultural Research Institute and a visiting Biometrician to the IFDC-FERARI Project, Ghana. He received his BSc (Statistics) and MSc (Biometry) from the University for Development Studies, Ghana. His current interest areas are database management, Gender integration into Agricultural Research and Management of Innovations Platforms.

Theophilus Tengey is a Research Scientist (plant breeder) at the CSIR-Savanna Agricultural Research Institute. His research focuses on applying molecular markers in developing stress tolerant legumes (cowpea) for use by farmers in the Guinea and Sudan Savanna of Ghana. He had his PhD studies at the Texas Tech University where his study focused on developing a SNP-based genetic linkage map for Tetraploid peanut and introgression of leaf spot resistant QTLs into West African Adapted and US high Oleic peanut cultivars. Currently he is applying the knowledge acquired on improving other crops such as cowpea. He is a member of the Crop Science Society of America, American Society of Agronomy, American Peanut Research and Education Society, and the African Plant breeders Association.

ORCID

Edward Martey http://orcid.org/0000-0002-6933-3685
Prince M. Etwire http://orcid.org/0000-0002-6533-2538
Theophilus Kwabla Tengey http://orcid.org/0000-0003-2822-878X

References

Ahenkan, A., Chutab, D. N., & Boon, E. K. (2020). Mainstreaming climate change adaptation into pro-poor development initiatives: Evidence from local economic development programmes in Ghana. *Climate and Development*, 1–13. doi:10.1080/17565529.2020.1844611

Asfaw, A., Almekinders, C. J. M., Blair, M. W., & Struik, P. C. (2012). Participatory approach in common bean *(Phaseolus vulgaris L.)* breeding for drought tolerance for southern Ethiopia. *Plant Breeding*, *131*(1), 125–134. https://doi.org/10.1111/j.1439-0523.2011.01921.x

Asfaw, S., & Branca, G. (2018). Introduction and overview. In L. Lipper, N. McCarthy, D. Zilberman, S. Asfaw, & G. Branca (Eds.), *Climate smart agriculture – building resilience to climate change* (pp. 3–12). Springer. doi:10.1007/978-3-319-61194-5

Asfaw, S., Di Battista, F., & Lipper, L. (2016). Agricultural technology adoption under climate change in the Sahel: Micro-evidence from Niger. *Journal of African Economies*, *25*(5), 637–669. doi:10.1093/jae/ejw005

Asfaw, S., Shiferaw, B., Simtowe, F., & Haile, M. (2011). Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. *Journal of Development and Agricultural Economics*, *3*(9), 436–477. http://www.academicjournals.org/JDAE

Asrat, S., Yesuf, M., Carlsson, F., & Wale, E. (2010). Farmers' preferences for crop variety traits: Lessons for on-farm conservation and technology adoption. *Ecological Economics*, *69*(12), 2394–2401. doi:10.1016/j.ecolecon.2010.07.006

Bank of Ghana. (2019). https://www.bog.gov.gh/treasury-and-the-markets/daily-interbank-fx-rates/

Benson, A. R., Kumar, R., & Tomkins, A. (2016). On the relevance of irrelevant alternatives. In *Proceedings of the 25th International Conference on World Wide Web, International World Wide Web Conferences Steering Committee* (pp. 963–973). https://doi.org/10.1145/2872427.2883025

Bhat, C. R. (2001). Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research Part B: Methodological*, *35*(7), 677–693. doi:10.1016/S0191-2615(00)00014-X

Branca, G., Arslan, A., Paolantonio, A., Cavatassi, R., Grewer, U., Cattaneo, A., Lipper, L., Hillier, J., & Vetter, S. (2012). Assessing the economic and mitigation benefits of climate-smart agriculture and its implications for political economy: A case study in Southern Africa. *Journal of Cleaner Production*, *285*, 125161. doi:10.1016/j.jclepro.2020.125161

Branca, G., & Perelli, C. (2020). 'Clearing the air': Common drivers of climate-smart smallholder food production in Eastern and Southern Africa. *Journal of Cleaner Production*, *270*, 121900. https://doi.org/10.1016/j.jclepro.2020.121900

Branca, G., Tennigkeit, T., Mann, W., & Lipper, L. (2012). *Identifying opportunities for climate-smart agriculture Investments in Africa*. FAO.

Brown, M. E., Carr, E. R., Grace, K. L., Wiebe, K., Funk, C. C., Attavanich, W., Backlund, P., & Buja, L. (2017). Do markets and trade help or hurt the global food system adapt to climate change? *Food Policy*, *68*, 154–159. doi:10.1016/j.foodpol.2017.02.004

Campbell, R. M., Venn, T. J., & Anderson, N. M. (2018). Heterogeneity in preferences for woody biomass energy in the US Mountain West. *Ecological Economics*, *145*, 27–37. doi:10.1016/j.ecolecon.2017.08.018

Duflo, E., Kremer, M., & Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review*, *101*(6), 2350–2390. doi:10.1257/aer.101.6.2350

Ellison, B., Bernard, J. C., Paukett, M., & Toensmeyer, U. C. (2016). The influence of retail outlet and FSMA information on consumer perceptions of and willingness to pay for organic grape tomatoes. *Journal of Economic Psychology*, *55*, 109–119. doi:10.1016/j.joep.2016.05.002

FAO. (2013). *Climate-smart agriculture sourcebook*. Food and Agriculture Organization. http://www.fao.org/climate-smart-agriculture-sourcebook/en/

FAO, I., WFP, W., & UNICEF. (2019). *The state of food security and nutrition in the world 2019: Safeguarding against economic slowdowns and downturns*. FAO. License: CC BY-NC-SA 3.0 IGO.

Fuglie, K. (2018). R&D capital, R&D spillovers, and productivity growth in world agriculture. *Applied Economic Perspectives and Policy*, *40*(3), 421–444. doi:10.1093/aepp/ppx045

Gage, D., Bangnikon, J., Abeka-Afari, H., Hanif, C., Addaquay, J., Antwi, V., & Hale, A. (2012). The market for maize, rice, soy, and warehousing in Northern Ghana. *This Report was Produced by USAID's Enabling Agricultural Trade (EAT) Project*.

Global Nutrition Report. (2015). Climate change and nutrition. *Global Nutrition Report*, 2015 (pp. 76–84).

Guinn, J. M. (2002). Domestic quality standards and trading rules and recommended export contract specifications for US soybeans and products. http://ussec.org/wpcontent/uploads/2015/10/Guinn_Quality_Standards_Trading_Rules2002.pdf

Hanemann, W. M. (1984). Discrete/continuous models of consumer demand. *Econometrica: Journal of the Econometric Society*, *52*(3), 541–561. doi:10.2307/1913464

Hansen, J., Hellin, J., Rosenstock, T., Fisher, E., Cairns, J., Stirling, C., Lamanna, C., van Etten, J., Rose, A., & Campbell, B. (2019). Climate risk management and rural poverty reduction. *Agricultural Systems*, *172*, 28–46. doi:10.1016/j.agsy.2018.01.019

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *Transportation Research Part B: Methodological*, *44*(6), 735–752. doi:10.1016/j.trb.2009.12.012

Hensher, D. A., & Greene, W. (2010). Non-attendance and dual processing of CommonMetric attributes in choice analysis: A latent class specification. *Empirical Economics*, *39*(2), 413–426. doi:10.1007/s00181-009-0310-x

Holmes, T. P., Adamowicz, W. L., & Carlsson, F. (2017). Choice experiments. In P. Champ, K. Boyle, & T. Brown (Eds.), *A primer on nonmarket valuation. The economics of non-market goods and resources* (pp. 133–185). Springer. https://doi.org/10.1007/978-94-007-7104-8_5

Issahaku, G., & Abdulai, A. (2020). Can farm households improve food and nutrition security through adoption of climate-smart practices? Empirical evidence from Northern Ghana. *Applied Economic Perspectives and Policy*, *42*(3), 559–579. doi:10.1093/aepp/ppz002

Kadjo, D., Ricker-Gilbert, J., & Alexander, C. (2016). Estimating price discounts for low-quality maize in sub-Saharan Africa: Evidence from Benin. *World Development*, *77*, 115–128. doi:10.1016/j.worlddev.2015.08.004

Krah, K., Michelson, H., Perge, E., & Jindal, R. (2019). Constraints to adopting soil fertility management practices in Malawi: A choice experiment approach. *World Development*, *124*, 104651. doi:10.1016/j.worlddev.2019.104651

Krah, K., Petrolia, D. R., Williams, A., Coble, K. H., Harri, A., & Rejesus, R. M. (2018). Producer preferences for contracts on a risky bioenergy crop. *Applied Economic Perspectives and Policy*, *40*(2), 240–258. https://doi.org/10.1093/aepp/ppx034

Kristjanson, P., Okike, I., Tarawali, S., Singh, B. B., & Manyong, V. M. (2005). Farmers' perceptions of benefits and factors affecting the adoption of improved dual-purpose cowpea in the dry savannas of Nigeria. *Agricultural Economics*, *32*(2), 195–210. https://doi.org/10.1111/j.0169-5150.2005.00338.x

Kuhl, L. (2020). Technology transfer and adoption for smallholder climate change adaptation: Opportunities and challenges. *Climate and Development*, *12*(4), 353–368. doi:10.1080/17565529.2019.1630349

Lopes, F. C. d. C., Gomes, R. L. F., & Freire Filho, F. R. (2003). Genetic control of cowpea seed sizes. *Scientia Agricola*, *60*(2), 315–318. https://doi.org/10.1590/S0103-90162003000200016

Manda, J., Alene, A. D., Tufa, A. H., Abdoulaye, T., Kamara, A. Y., Olufajo, O., Boukar, O., & Manyong, V. M. (2020). Adoption and ex-post impacts of improved cowpea varieties on productivity and net returns in Nigeria. *Journal of Agricultural Economics*, *71*(1), 165–183. doi:10.1111/1477-9552.12331

Manda, J., Alene, A. D., Tufa, A. H., Abdoulaye, T., Wossen, T., Chikoye, D., & Manyong, V. (2019). The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. *World Development*, *122*, 261–271. doi:10.1016/j.worlddev.2019.05.027

Martey, E., Etwire, P. M., & Abdoulaye, T. (2020). Welfare impacts of climate-smart agriculture in Ghana: Does row planting and drought-tolerant maize varieties matter? *Land Use Policy*, *95*, 104622. https://doi.org/10.1016/j.landusepol.2020.104622

Martey, E., Etwire, P. M., & Kuwornu, J. K. M. (2020). Economic impacts of smallholder farmers' adoption of drought-tolerant maize varieties. *Land Use Policy*, *94*, 104524. https://doi.org/10.1016/j.landusepol.2020.104524

Martey, E., Kuwornu, J. K., & Adjebeng-Danquah, J. (2019). Estimating the effect of mineral fertilizer use on land productivity and income: Evidence from Ghana. *Land use Policy*, *85*, 463–475. https://doi.org/10.1016/j.landusepol.2019.04.027

McFadden, D. (1973). *Conditional logit analysis of qualitative choice behavior*.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447–470. doi:10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1

Mensah, H., Ahadzie, D. K., Takyi, S. A., & Amponsah, O. (2020). Climate change resilience: Lessons from local climate-smart agricultural practices in Ghana. *Energy, Ecology and Environment*. https://doi.org/10.1007/s40974-020-00181-3

Ministry of Environment, Science, Technology and Innovation. (2013). *Ghana national climate change policy*. MESTI, Accra.

Ministry of Food and Agriculture (MoFA). (2017). *Planting for food and jobs strategic plan for implementation (2017–2020)*.

Muchuru, S., & Nhamo, G. (2019). A review of climate change adaptation measures in the African crop sector. *Climate and Development*, *11*(10), 873–885. doi:10.1080/17565529.2019.1585319

Nahuelhual, L., Loureiro, M. L., & Loomis, J. (2004). Using random parameters to account for heterogeneous preferences in contingent valuation of public open space. *Journal of Agricultural and Resource Economics*, 537–552. https://www.jstor.org/stable/40987248

Owusu, E. Y., Akromah, R., Denwar, N. N., Adjebeng-Danquah, J., Kusi, F., & Haruna, M. (2018). Inheritance of early maturity in some cowpea (*Vigna unguiculata* (L.) Walp.) Genotypes under rain fed conditions in Northern Ghana. *Advances in Agriculture*, *2018*, 1–10. doi:10.1155/2018/8930259

Petrolia, D. R., Hwang, J., Landry, C. E., & Coble, K. H. (2015). Wind insurance and mitigation in the coastal zone. *Land Economics*, *91*(2), 272–295. doi:10.3368/le.91.2.272

Quaye, W., Adofo, K., Buckman, E. S., Frempong, G., Jongerden, J., & Ruivenkamp, G. (2011). A socio-economic assessment of cowpea diversity on the Ghanaian market: Implications for breeding. *International Journal of Consumer Studies*, *35*(6), 679–687. doi:10.1111/j.1470-6431.2010.00980.x

Revelt, D., & Train, K. (1998). Mixed logit with repeated choices: Households' choices of appliance efficiency level. *Review of Economics and Statistics*, *80*(4), 647–657. doi:10.1162/003465398557735

Savanna Agricultural Research Institute (SARI). (2014). *Annual report* (pp. 91–08). SARI.

Savanna Agricultural Research Institute (SARI) (2018). Annual report. (pp 91–08). SARI.

Senyolo, M. P., Long, T. B., Blok, V., & Omta, O. (2018). How the characteristics of innovations impact their adoption: An exploration of climate-smart agricultural innovations in South Africa. *Journal of Cleaner Production*, *172*, 3825–3840. https://doi.org/10.1016/j.jclepro.2017.06.019

Sova, C. A., Grosjean, G., Baedeker, T., Nguyen, T. N., Wallner, M., Jarvis, A., Nowak, A., Corner-Dolloff, C., Girvetz, E., Laderach, P., & Lizarazo, M. (2018). *Ringing the concept of climate-smart agriculture to life: Insights from CSA country profiles across Africa, Asia, and Latin America*. World Bank, and the International Centre for Tropical Agriculture.

Statistics, Research and Information Directorate (SRID). (2012). *Production estimates*. Ministry of Food and Agriculture.

Tandon, S., Landes, M., Christensen, C., LeGrand, S., Broussard, N., Farrin, K., & Thome, K. (2017). *Progress and challenges in global food security* (No. 1476-2017-3897).

Thome, K., Michael, D. S., Kamron, D., Nicholas, R., Cheryl, C., & Birgit, M. (2019). International food security assessment, 2019–2029, GFA-30, U.S. Department of Agriculture, Economic Research Service, August 2019. https://www.ers.usda.gov/publications/pub-details/?pubid=93658

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge University Press.

United Nations. (2015). Transforming our world: The 2030 agenda for sustainable development. General Assembly 70 session.

Vom Brocke, K., Trouche, G., Weltzien, E., Barro-Kondombo, C. P., Gozé, E., & Chantereau, J. (2010). Participatory variety development for sorghum in Burkina Faso: Farmers' selection and farmers' criteria. *Field Crops Research*, *119*(1), 183–194. https://doi.org/10.1016/j.fcr.2010.07.005

Waldman, K. B., Ortega, D. L., Richardson, R. B., & Snapp, S. S. (2017). Estimating demand for perennial pigeon pea in Malawi using choice experiments. *Ecological Economics*, *131*, 222–230. doi:10.1016/j.ecolecon.2016.09.006

Ward, P. S., Ortega, D. L., Spielman, D. J., & Singh, V. (2014). Heterogeneous demand for drought-tolerant rice: Evidence from Bihar, India. *World Development*, *64*, 125–139. doi:10.1016/j.worlddev.2014.05.017

Witcombe, J. R., Joshi, A., & Goyal, S. N. (2003). *Euphytica*, *130*(3), 413–422. https://doi.org/10.1023/A:1023036730919

Worku, M., De Groote, H., Munyua, B., Makumbi, D., Owino, F., Crossa, J., Beyenea, Y., Mugoa, S., Jumboa, M., Aseac, G., Mutindad, C., Kwemoic, D. B., Woyengoe, V., Olsena, M., & Prasanna, B. M. (2020). On-farm performance and farmers' participatory assessment of new stress-tolerant maize hybrids in Eastern Africa. *Field Crops Research*, *246*, 107693. https://doi.org/10.1016/j.fcr.2019.107693

Yirzagla, J., Atokple, I. D. K., Haruna, M., Kusi, F., Suguri, I., & Muntari, A. (2016, February 28 to March 4). Scaling out cowpea production in Northern Ghana: Community seed production Scheme. In *Pan African grain Legume and World cowpea Conference*, Livingstone, Zambia.