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# A quantitative modelling of farm households' choices for improved sorghum variety profiles in sustainability and economic affordability-based attributes in Mali

Adama B. Coulibaly [a,*], Félix Badolo [a,b], Jummai O. Yila [a,c], Bourema Koné [d], Macdonald Bright Jumbo [a], Ayoni Ogunbayo [a], Kimseyinga Savadogo [e]

[a] International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Bamako, Mali
[b] African Development Bank (AfDB), Abidjan, Côte d'Ivoire
[c] International Rice Research Institute (IRRI), Kampala, Uganda
[d] Institute of Rural Economy (IER), Bamako, Mali
[e] Thomas Sankara University, Department of Economics and Management, Ouagadougou, Burkina Faso

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ABSTRACT

The adoption rate of improved sorghum varieties remains low in sub-Saharan Africa, including Mali. This raises concerns about whether these varieties adequately address farmers' needs. To better understand farmer preferences and align breeding programmes with participatory breeding objectives, this study employed a Discrete Choice Experiment (DCE) to investigate farmer preferences for improved sorghum varietal attributes in Mali. The study objectives were to identify preferred attributes and estimate farmers' Willingness To Pay (WTP) for these attributes. The analysis was based on a final sample of 5,616 observations. A $D_z$-efficient experimental design was used, and choice data were analysed using two models: the Conditional Logit (CL) and the Random Parameter Logit (RPL). Key findings indicated that sorghum farmers preferred varieties offering a grain yield of 3,500 kg/ha, drought tolerance extending 20 days into the maturity stage, grain storage capacity of 10 months, and benefits linked to membership in Farmer-Based Organizations (FBOs). Conversely, farmers showed a negative preference for higher seed cost of 750 FCFA/kg (1.18 USD/kg). Farmers also revealed a higher WTP for higher yield, extended drought tolerance, longer storage capacity, and FBOs membership. The study recommends that sorghum breeding programmes in Mali should exercise caution in seed pricing, as farmers are sensitive to higher costs. To promote sustainable adoption and intensification, future varietal development should prioritize higher grain yield, improved drought tolerance, longer grain storage capacity, and social networking benefits. The integration of these attributes would be essential for scaling improved and climate-resilient sorghum varieties in Mali.

## 1. Introduction

The adoption of agricultural technologies is still lagging with the rate under expectation in sub-Saharan Africa (SSA) including Mali [1,2]. This raises an important concern whether farmers' needs are met in varietal development processes [3]. Sorghum remains the third most important staple food for households' food consumption after rice and maize in Mali. Despite its third position, sorghum grains are the most consumed cereal in rural areas in Mali [4], where the majority of poor smallholder farmers (52 %) concentrate to thrive their livelihood [5].

Despite the relatively large number of 38 released improved sorghum varieties [6], farmers are not adopting them as expected although most of the released varieties have higher yield potential than the farmers' best local varieties. This is corroborated in the literature that only 5 % of sorghum cultivated lands are dedicated to improved sorghum varieties in Mali [7]. The controversial issue is that this adoption rate is lower than the household self-reported 30 % adoption rate [1,6]. As comparative insights, the improved sorghum varieties' adoption rate reached 98 % and 87 % in China and Iran respectively [8].

In this regard, research efforts have addressed some of the ex-post development issues like marketing conditions [9]. For instance, in Mali the Smart Food programme performed several culinary tests and

* Corresponding author.
*E-mail address:* adamany90@gmail.com (A.B. Coulibaly).

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food packaging training for both men and women. Those efforts are intended to increase the utilization by the end-user to foster adoption. However, crucial ex-ante development problems remained in improved sorghum breeding in Mali. Further investigation is needed to elicit farmers' general preferences for agricultural technologies in their internal features. This will also contribute to achieving the Participatory Plant Breeding (PPB) objectives as a key driver toward sustainable improved varieties adoption [10,11].

Several researchers have recently investigated farmers' varietal trait preferences for improved sorghum using the Participatory Rural Appraisal (PRA) qualitative approach [1,8,12,13] against the quantitative Discrete Choice Experiment (DCE) approach. The authors frequently reported higher yield, drought tolerance, and grain quality without specific expected quantities. In Mali, several authors [14–17] recently used the qualitative PRA approach to analyse farmer varietal preferences for improved sorghum profiles. The usual higher yield, drought tolerance, early maturity, and grain quality were highlighted from their studies with no specific expected quantities. As a result, the qualitative PRA method has limitations due to the nature of the data collection and the scope of statistical inferences.

Therefore, the use of quantitative DCE method for modelling sorghum farmers' choices to uncover their quantitative preferred attributes would be a tremendous contribution to breeding programmes in SSA including Mali. This will not only enhance the continuity of the improvement of existing varieties for wider adoption, but also the new varietal development scheme. The most recent literature on the use of DCE method in farmers' varietal attributes preferences is highlighted as follows [18–23]. In addition, Badolo et al. [24]; Miriti et al. [25]; Ouedraogo et al. [26] and Tijani et al. [27] used the DCE approach to elicit farmers' varietal attributes preferences for improved sorghum in SSA. Among them, Badolo et al. [24] applied the DCE to elicit sorghum farmer preferences in Mali. The authors did not consider attributes related to climate-resilience such as drought tolerance and early maturity, grain storage, and seed costs as financial aspects. These attributes are important as the rural farmers face increasing climate challenges in Mali.

Agricultural sector in Mali faces the increasing challenges of climate change i.e. the erratic rainfall patterns within a season and severe climate shocks such as recurrent drought spells. In contrast to that, drought tolerance (8 %) and environmental adaptability (5 %) were mentioned as the reasons for choosing a particular improved sorghum variety, where 73 % of the farmers reported not satisfied with the varieties they grew, expressing the need to find other varieties that may meet their needs [28]. This requires in-depth investigation of farmer preferences, raising the following research question. What are the farmer preferences for improved sorghum variety attributes in Mali? Answering this question through this study is thought to be insightful as it will uncover expected quantitative attributes that meet farmers' preferences.

The general objective of the study is to elicit farmer preferences for improved and climate-resilient sorghum varieties in Mali. Specifically, we determine quantitative preferred attributes that guide farmer choices among hypothetical profiles. The study hypothesised that high grain-yielding and climate-resilience attributes positively influence farmer choices. The study's contribution in the literature is twofold. On one hand, we used a novel "DCEtool" data collection technique using R Shiny package features. On the other hand, we fill the empirical void with quantitative preferred attributes in Mali.

The rest of the paper proceeded as follows: section 2 describes the experimental data collection processes and methodology, while Section 3 is dedicated to results and discussion. Section 4 concludes the study and formulates some policy implications.

## 2. Data and methodology

### 2.1. Exploratory survey data collection

Data were collected in four regions: Kayes, Koulikoro, Sikasso, and Segou as part of the "APSAN Mali" project's intervention zones in Mali. These regions represent the potentially improved sorghum cultivation zones where farmers grow sorghum as their major cereal crop for food consumption. Four-stage sampling design of the survey was established (Regions, Districts, Communities, and Village levels) with purposive selection at the region, district, and community levels while random selection was performed at village levels. In each region, 2 districts were selected and from each district, 2 communities were also selected purposively. Then, in each community, at least 2 villages were randomly selected based on the data collection stage objectives. For the whole DCE study, data were collected in two steps. In the first step, we conducted an exploratory Focus Group Discussions (FGDs) to define with farmers their five most relevant attributes of improved sorghum varieties according to the five sustainable intensification indicator domains i.e. 1-productivity, 2-environmental, 3-food utilization, 4-social, and 5-economic [29]. For this survey, a structured FGDs guide was administered on tablets and pretested before the use in the field. A total of 16 FGDs were organised in 16 villages covering the four regions of the study area in May 2022. At the village level, the discussion was done with 10–15 farmers considering gender aspects. This number (10–15) was set during the FGDs to avoid congestion and interact better with key informants. Data from this initial step allowed us to determine the following five most relevant attributes and their respective levels for grain yielding, drought tolerance grain storage capacity, FBOs membership, and seed purchasing cost according to the predefined five domains. These attributes and their respective levels were validated with the sorghum breeding research team at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) before undertaking the second step consisting of choice experiment design and choice data collection.

### 2.2. Choice experiment design

The second step of the data collection was dedicated to the DCE survey in June 2022. In each region, four villages were also randomly selected with a total of 16 villages. The villages were selected from four regions. In the Kayes region, they were drawn from the District of Kita, specifically the Communities of Bendougouba (villages: Bendougouba and Karaya) and Sebekoro (Sounti and Sangarebougou). In the Koulikoro region, villages were selected from the District of Dioila, from the Communities of Wacoro (Wacoro and Tonga) and Massigui (Serbila and Kenikela). In the Sikasso region, selection was from the District of Koutiala, covering the Communities of M'pessoba (M'pessoba and Kintieri) and N'golonianasso (N'golonianasso and M'pelogosso). Finally, in the Segou region, villages were drawn from the District of Bla, within the Communities of Dougouolo (Peguena and Petesso) and Somasso (Kadiala and M'petiona). For this survey, two types of data were simultaneously collected from the respondents. The first data were respondents' socio-demographic characteristics collected through a structured questionnaire. This questionnaire was also administered on tablets and pre-tested before deploying for the survey. The second data were the choice experiment data from the respondents. These data were collected through the computer with the "DCEtool" survey application in R software using mainly "idefix" and "shiny" packages [30]. In doing so, from each village 10 farmers (with gender balance) were assigned to the survey. Following this, before proceeding, the survey context and objectives were fully explained to respondents. A comprehensive pilot test was done to ensure a better understanding of the choice assignment. Then, respondents were moved away to another place to take the socio-demographic survey. Each respondent after successful completion of the socio-survey was invited to the choice classroom and he/she went through 12 choice sets each with three alternatives including the

Opt-out. The choice sets were arranged in two blocks of 6 to ease the fatigue for respondents. The choice set was made of two unlabelled alternatives (Option 1 and 2) compared to the farmers' best local varieties. The chosen alternative was repeated aloud so that the enumerator could select it from the computer. Finally, a total of 156 respondents were successfully assigned to the survey. This sample led to 5,616 observations with 1,872 choice cases.

The set of attributes and their respective levels were pre-defined by farmers through the exploratory survey. So, they were invited to select the most relevant to them in each domain. Thus, after choosing the most relevant attributes per domain, they proceeded to define the number of possible levels and their respective values. The statistical frequencies and rating scores were used to track the relevance of those selected attributes among the set of potential attributes presented to farmers. In the estimation procedure, the first level of each attribute will be used as reference attribute level. For that, they are forced to be 0 using the dummy coding [30,31]. In this study, the dummy coding was used over the effect coding based on the nature of data drawn from the “DCEtool” survey application which is dummy coded with a long format [30,32]. In contrast to the model specification, the first level of each attribute is missing in the dataset and nested from the models' outcomes. Table 1 below shows the five attributes and their respective levels and descriptions.

Considering all the attributes and their respective levels, it leads to a full fractional factorial design of $L^A = 3^3 \times 4^1$ x $2^1 = 216$. Eventually, 216 numbers of possible choice situations are too many. At this point, three types of design can be used to address this issue i.e., the efficient design, orthogonal design and serial design [33]. This study used a D-efficient approach which maximises the determinant of the information matrix and minimises the generalized variance of the parameter estimates [30]. There are however three types of D-efficient design i.e., $D_z$-efficient (z stands for zero priors), $D_p$-efficient (p stands for priors), and $D_b$-efficient (b stands for Bayesian) to generate the design matrix [34,35].

Following this, the study used the $D_z$-efficient fractional factorial design to generate 12 choice sets. Each choice set comprised 3 alternatives including the Opt-out or farmers' best local varieties. In practise, each respondent produced 12 choice events or 36 observations. The study design was made with the “DCEtool” survey application (in R software) developed by Pérez-Troncoso [32] using mainly “idefix” and “shiny” packages. The application allows the printing of D-error to show the efficiency level of the design matrix. Equally important, the $D_z$-efficient design in which the priors are set to zero (0) with minimal D-error would lead to an orthogonal design [33]. Our study design matrices were generated with an average of 1.578 D-errors implying orthogonality, level balance, minimal overlap, and utility balance [36].

Based on the low literacy rate among rural farmers in Mali [37], all the choice profiles were represented with visual items. The choice cards were also translated into the local language “Bambara,” making it readable for literate respondents. The following Fig. 1A-B shows an example of choice cards in computer view and the illustrative visual items in pictures, respectively for the choice survey.

This study used a novel computer-based preference data collection using R software with R shiny package features as shown in the above Fig. 1A.

**Table 1**
The most relevant attributes, levels and descriptions of improved sorghum varieties.

| Attributes | Levels | Descriptions |
|---|---|---|
| 1. Grain yielding | • Low 1,500 kg/ha<br>• Medium: 2,500 kg/ha<br>• High: 3,500 kg/ha | Levels 1, 2 and 3 indicate respectively the low, medium and high grain yield potential expected on average by sorghum farmers in the study area. |
| 2. Drought tolerance | • Low: 7 days<br>• Medium: 15 days<br>• High: 20 days | Levels 1, 2 and 3 indicate respectively the low, medium and high number of days of drought tolerance expected on average by sorghum farmers in the study area. |
| 3. Grain storage capacity | • Low: 4 months<br>• Medium: 8 months<br>• High: 10 months | Levels 1, 2 and 3 indicate respectively the low, medium and high number of months of grain storage capacity expected on average by sorghum farmers in the study area. |
| 4. Farmer-Based Organizations (FBOs) | • No<br>• Yes | Levels 1 and 2 indicate respectively no or yes whether the new hypothetic variety selected could increase sorghum farmer social capital through his/her integration in any FBOs. |
| 5. Seed purchasing cost | • 300f CFA/kg<br>• 450f CFA/kg<br>• 600f CFA/kg<br>• 750f CFA/kg | Levels 1, 2, 3 and 4 indicate the seed cost records that farmers are willing to pay for 1 kg of seed measured as a continuous variable with an increasing trend interval of 150f CFA. |

Source: Authors from the exploratory survey, May 2022.

## 2.3. Methodology

The general economic theory and model of choice experiment stand from Lancaster [38] microeconomics approach and the utility function developed by McFadden [39]. From the theoretical background, individuals derive utility from the characteristics/traits of the goods rather than directly from the goods/commodity itself. In other words, applied to the agricultural context, the farmers selecting a particular improved crop variety consider some attributes that define their choices. So far, the model has been widely used to elicit preferences in other fields before agriculture. Examples include transportation, market research, environmental economics, and health economics. Following that, this study used the DCE to elicit Malian households' preferences for improved sorghum variety profiles. The use of DCE is highly motivated by its features, allowing farmers to make trade-offs between attributes in choosing hypothetical improved sorghum variety profiles. DCE also permits the evaluation of attributes that have no direct market value due to their public good nature. For instance, environmental attributes are good examples of illustrating that concern. Compared to other fields such as health economics, transportation, and marketing, DCE methods are relatively less applied in agricultural economics for farmers' choice modelling.

Quantitative studies used either revealed or stated preference data. For revealed preferences, the techniques consist of using observation of the actual choices made by people to measure their preferences. But this approach requires much more time to collect such data. In contrast, the

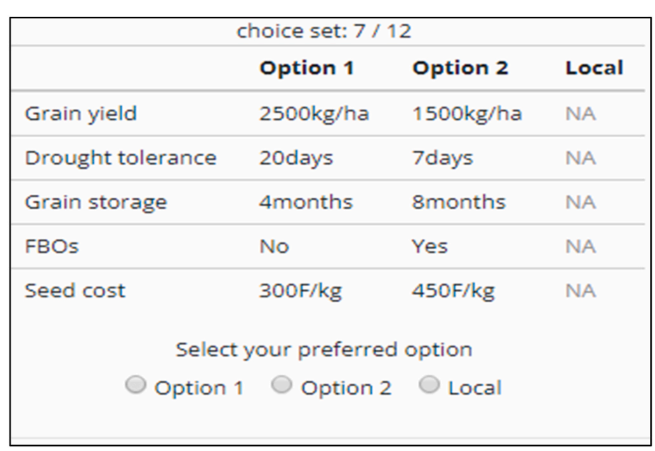


**Fig. 1.A.** Example of choice card in computer view. Source: authors' conception

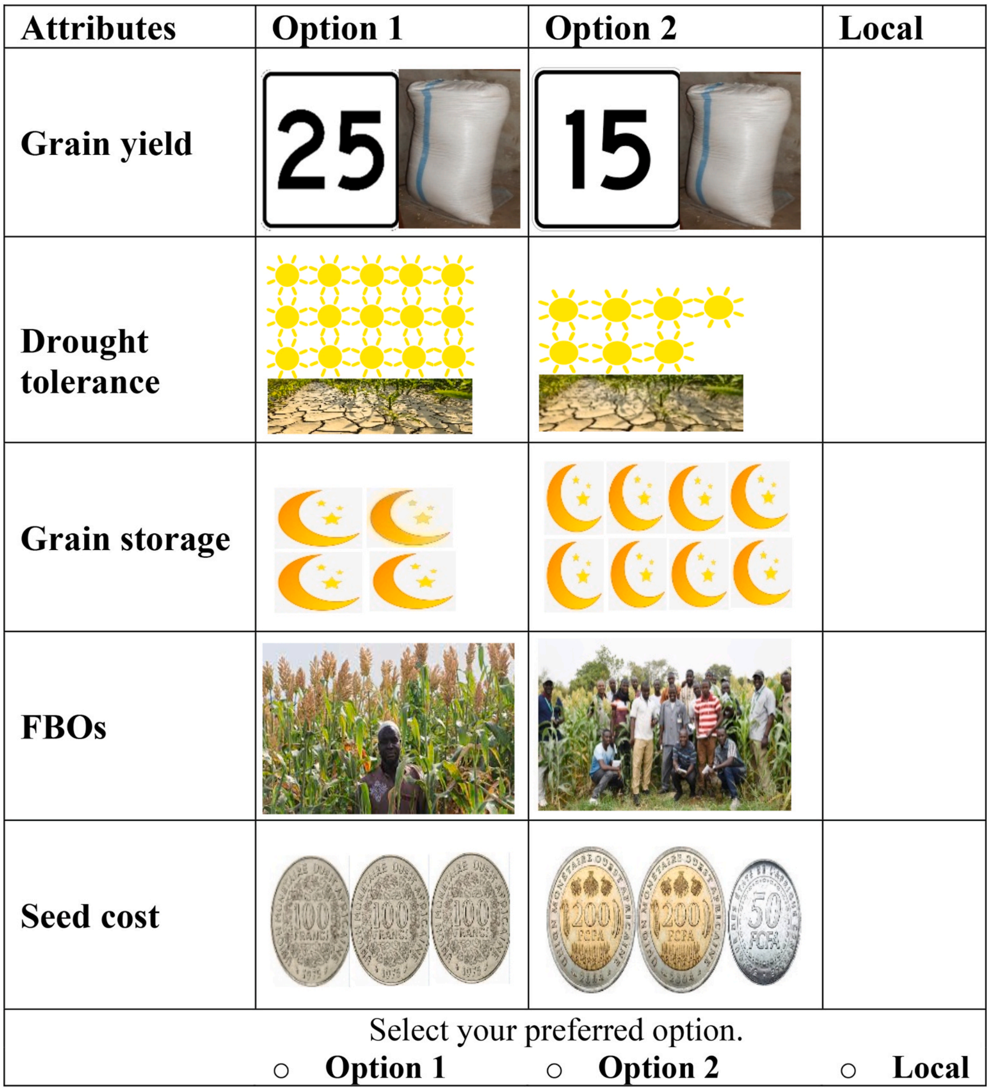


**Fig. 1.B.** Example of choice card with illustrative visual items. Source: authors' conception.

stated preference approach with the DCE method relies on the respondent making choices over hypothetical scenarios [40], and this method is used in this study to identify households' preferences for improved sorghum variety profiles. This method has some advantages i.e., allowing trade-offs between attributes in selecting among a set of hypothetical profiles or choice options over the alternatives. Furthermore, other analysis methods are also used such as conjoint analysis and contingent valuation methods [41]. The use of these alternative methods is out of the scope of this paper. The DCE may have its limit known as the moral hazard behaviour of individuals. Farm households may not use what they have stated as preferences in the future due to a lot of uncontrolled factors. Therefore, a follow-up study may be required to address this concern, but this is beyond the scope of this study given the time and resource constraints.

The general empirical econometric model originated from McFadden [39] Random Utility Theory (RUT) is presented as follows. Assuming the utility that a respondent $i$ derives from choosing alternative $j$ in choice scenario $s$ is given by:

$$U_{isj} = V_{isj} + \varepsilon_{isj}; i = 1, \ldots, \mathrm{N}; \mathrm{s} = 1, \ldots, \mathrm{S}; \mathrm{j} = 1, \ldots, \mathrm{J} \tag{1}$$

Where N decision makers are choosing amongst J alternatives across S scenarios. $V_{isj}$ represents the deterministic component of the overall utility of choosing alternative $j$. Then, $\varepsilon_{isj}$ is the error term capturing unobservable characteristics. Thus, $y_{is}$ is the probability of choosing alternative $j$ and it is written as follows:

$$P_{isj} = \mathrm{Prob}(y_{is} = j) = \mathrm{Prob}\left(U_{isj} - U_{isl} > 0; \forall l \neq j.\right) \tag{2}$$

The $y_{is} = j$ is the binary variable that will take the value of 1 if the alternative is chosen and 0 otherwise. Then, the standard Conditional Logit (CL), also known as the Multinomial Logit (MNL), under the assumption of independently and identically distributed type-I extreme values for the probability of choosing $j$ takes the following form:

$$P_{isj} = \frac{\exp(\lambda V_{isj})}{\sum_{l=1}^{J} \exp(\lambda V_{isl})} \tag{3}$$

Where $\lambda$ is the scale parameter (scale heterogeneity) normalized to unity given the binary choice nature of the logit models [42]. Finally, the specified CL model as an initial starting point of DCE under the strong assumption of Independence of Irrelevant Alternatives (IIA) and preference homogeneity across respondents is derived from the deterministic component of the utility function in the previous equation (1). Following Sanou et al. [43] a farmer $i$ faces $J$ choices including several alternatives to keeping his status quo. The utility function is written as:

$$U_{ij} = \beta_i' X_{ij} + \varepsilon_{ij} \tag{4}$$

Where $X_{ij}$ is a vector of attributes describing alternative $j$. For the conditional logit, $\beta$ is the parameter and assumed to be constant across choice scenarios. Then, $\varepsilon_{ij}$ represents the error terms.

Based on restrictive assumptions (i.e., IIA and the preference homogeneity) that may not be realistic sometimes in the context of DCE. Additionally, we present the Random Parameter Logit (RPL), also known as the Mixed Logit (MXL) model. This model relaxes the CL restrictions and assumes scale unity and random coefficients varying across alternatives and choice cases, suggesting preference heterogeneity among respondents. Alternately, other models such as the Generalized Multinomial Logit (G-MNL) developed by Fiebig et al. [44] capture both scale and preference heterogeneities and the Latent Class Model (LCM), which also considers population class preferences. These models are not used in this paper for two main reasons. First, the data generated by R software do not fit a multinomial and latent class estimations, which sometimes use the intersection with respondents' characteristics. In this study, respondents' characteristics data are collected and analysed as a side event (see appendix A1). Second, sorghum farming in Mali is subsistence dominated by self-consumption with no distinguished classes for farmers in seed selection. For the purpose of this study, the data covered 4 regions and we estimated cross-regional heterogeneities which are relevant in addressing regional policies in the sorghum seeds development scheme. The RPL specification has been for long the most popular model used in DCE studies [45–48]. Another reason is that given the experimental design, the present study seeks to ascertain any preference heterogeneities amongst sorghum farmers beyond the basic CL estimation. These reasons let us choose the RPL model among others. Consistent with the previous specification in equation (4), the utility function in the RPL model following Pérez-Troncoso [32] is written as:

$$U_{nj} = \beta X_{nj} + \varepsilon_{nj} \tag{5}$$

Where $U_{nj}$ represents the binary utility dependent variable and all the independent variables and parameters here are collapsed into single vectors X (the attributes and their respective levels) and $\beta$ (the estimated coefficients), respectively. The additional $\varepsilon_{nj}$ denotes the error terms. The study used five attributes represented by their respective levels. First, the yield attribute has three levels measured in kg/ha as low (1,500), medium (2,500), and high (3,500). Second, the drought tolerance attribute has three levels measured in a day as low (7), medium (15), and high (20). Third, the grain storage capacity attribute has three levels measured in months as low (4), medium (8), and high (10). Fourth, the social attribute is two-level dummy (yes or no). Fifth, the economic attribute has four levels measured in CFA as (300), (450), (600), and (750).

The empirical model's specification for both the basic CL and RPL is written as follows:

$$\begin{aligned} binresponses &= asc + \delta_1 1500kg/ha + \delta_2 2500kg/ha + \delta_3 3500kg/ha + \delta_4 7days \\ &+ \delta_5 15days + \delta_6 20days + \delta_7 4months + \delta_8 8months + \delta_9 10months + \delta_{10} no + \delta_{11} yes \\ &+ \delta_{12} 300f/kg + \delta_{13} 450f/kg + \delta_{14} 600f/kg + \delta_{15} 750f/kg + \varepsilon \end{aligned} \tag{6}$$

The same specification in equation (6) is used to estimate the RPL or model. In the RPL model, we allow all the coefficients to be random with normal distribution. In addition, the normal distribution is used over other distribution forms like correlated, log-normal, truncated normal, uniform, and triangular ones. The main reason for choosing normal distribution is based on the field reality preferences for improved sorghum attribute levels, which are assumed to be positive or negative. The models also contain Alternative Specific Constant (ASC) representing the status quo i.e., farmers' best local sorghum varieties. The attributes vector X contains the five most relevant attributes for grain yield, drought tolerance, grain storage capacity, FBOs membership, and seed cost.

The DCE models also allowed the calculation of farmers' Willingness To Pay (WTP) for a given attribute level. So, it is calculated by the ratio of the designated attribute level coefficient divided by the cost/price attribute [49,50]. Additionally, in the present study the farmer WTP for a particular improved sorghum attribute level is calculated by dividing the designated level coefficient by the seed purchasing cost level coefficient given the following formulas:

$$WTP(\text{i}^{th}\text{level}) = \frac{\partial u/\partial(\text{i}^{th}\text{level})}{\partial u/\partial(\text{cost})} = -\left(\frac{\beta_i}{\beta_{\cos t}}\right) \tag{7}$$

Where $\beta_i$ represents the desired attribute level coefficient and $\beta_{\cos t}$ is the average coefficient of the significant seed purchasing cost attribute levels in this study as the cost attribute is categorical. The use of categorical cost attribute seems to be an advantage over the fixed seed cost/price used in a recent study [21], who stated it as a limitation. On the other hand, the socio-demographic information related to respondents' characteristics comprised 31 (12 quantitatives and 19 qualitatives) variables that were analysed (see appendix A1). This is based on the fact that the basic model (CL) assumed preferences variance only across alternatives and the individual characteristics do not vary across alternatives [43,51–54]. Hence, once looking for the main effect, the model does not allow the interaction between attribute levels and individual characteristics as can be seen in the studies [19,55,56]. Lastly, choice experiment data were downloaded from the local survey application on the computer in Excel format and then aggregated and analysed using STATA 16.1 with the "cmset" command for McFadden choice model estimation.

## 3. Results and discussion

In this section, we present the CL and RPL models, respectively. Although both models are presented, the analysis and discussion that follow will focus primarily on the CL model. This choice is justified by model selection criteria: both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) indicate a better fit for the CL model compared to the RPL model. While the IIA assumption is rejected, the CL estimates still exhibit lower AIC and BIC values compared to the RPL estimates. For conciseness, BIC values are not reported in Tables 2 and 3 but are provided in appendix A2.

### 3.1. Conditional logit (CL) model

First, Table 2 (all regions, column 1) indicates that sorghum farmers in Mali preferred higher grain-yielding attributes for improved sorghum varieties. Relative to a reference of 1,500 kg/ha, farmers valued yields of about 3,500 kg/ha and 2,500 kg/ha, with respective coefficients of 1.26 and 0.86 (both statistically significant). These findings are consistent with that of Badolo et al. [24] and Singbo et al. [37], who noted that rural farmers in Mali are more likely to adopt improved sorghum seed yielding about two to three tons per hectare. The result also aligns with studies by Martey et al. [57] and Elaine et al. [12] in Ghana as well as Mwamahonje et al. [8] in Tanzania, which found high yield to be a preferred attribute for improved sorghum varieties. Similarly, Tijani et al. [27] in Nigeria and Miriti et al. [25] in Tanzania identified high

**Table 2**
Result from the conditional logit (CL) model.

| Variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | All_Regions | Kayes | Koulikoro | Sikasso | Segou |
| Choices | Coef. | Coef. | Coef. | Coef. | Coef. |
| Local | −3.410*** | −20.54 | −19.69 | −17.26 | −1.478*** |
| | (0.331) | (2.174e+06) | (2.681e+06) | (1.590e+06) | (0.376) |
| **Grain yield** | | | | | |
| level2 (2,500 kg/ha) | 0.862*** | 0.505*** | 1.128*** | 0.784*** | 1.058*** |
| | (0.0762) | (0.161) | (0.224) | (0.143) | (0.177) |
| level3 (3,500 kg/ha) | 1.261*** | 1.134*** | 1.565*** | 1.477*** | 1.216*** |
| | (0.0786) | (0.167) | (0.195) | (0.181) | (0.160) |
| **Drought tolerance** | | | | | |
| level2 (15 days) | 0.433*** | 0.721*** | 0.707*** | 0.148 | 0.427*** |
| | (0.0755) | (0.160) | (0.214) | (0.143) | (0.156) |
| level3 (20 days) | 0.517*** | 0.898*** | 0.325* | 0.803*** | 0.305* |
| | (0.0753) | (0.170) | (0.177) | (0.175) | (0.161) |
| **Grain storage capacity** | | | | | |
| level2 (8 months) | 0.406*** | 0.344** | −0.272 | 0.247 | 1.118*** |
| | (0.0759) | (0.167) | (0.209) | (0.155) | (0.163) |
| level3 (10 months) | 0.663*** | 0.719*** | 0.950*** | 0.213 | 1.139*** |
| | (0.0757) | (0.159) | (0.214) | (0.144) | (0.170) |
| **FBOs** | | | | | |
| level2 (yes) | 0.120* | 0.117 | 0.183 | −0.0517 | 0.245* |
| | (0.0633) | (0.139) | (0.203) | (0.125) | (0.137) |
| **Seed purchasing cost** | | | | | |
| level2 (450F/kg) | −0.0646 | 0.0100 | −0.188 | −0.0777 | −0.203 |
| | (0.0880) | (0.202) | (0.245) | (0.176) | (0.172) |
| level3 (600F/kg) | −0.482*** | −0.256 | −0.887*** | −0.723*** | −0.141 |
| | (0.0916) | (0.186) | (0.288) | (0.183) | (0.227) |
| level4 (750F/kg) | −0.549*** | −0.416** | −0.447** | −0.716*** | −0.133 |
| | (0.0895) | (0.180) | (0.215) | (0.193) | (0.236) |
| Log likelihood | −1095.2709 | −262.1494 | −192.5338 | −269.9707 | −293.3537 |
| AIC | 2212.542 | 548.2988 | 409.0677 | 563.9414 | 608.7073 |
| Number of cases | 1872 | 492 | 396 | 492 | 492 |
| Observations | 5616 | 1476 | 1188 | 1476 | 1476 |

Source: Authors from the Conditional Logit Model, Standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

yield as a preferred attribute in DCE-based studies. Finally, Andiku et al. [58] reported higher grain yield as the most preferred attribute using qualitative PRA in Uganda. As contrary result, Asrat et al. [59] found that farmers in Ethiopia prioritized yield stability over high yield attribute.

Second, within the environmental/climate-resilient domain, farmers showed a preference for drought-tolerant sorghum varieties that can withstand 20 and 15 days of drought at the maturity stage, with respective coefficients of 0.52 and 0.43 (both statistically significant) compared to a reference of 7 days. This suggests that drought is a major threat to sorghum farming in Mali and that farmers are likely interested in improved varieties with long-term drought tolerance. These findings can be explained by farmers' interest in both improved and climate-resilient varieties to cope with climate change such as erratic rainfall and shocks like recurrent droughts. The results align with recent DCE studies on improved sorghum preferences in Nigeria, Tanzania, and Uganda [25,27,58,60]. Additionally, Ouedraogo et al. [26] reported similar results in a multi-country study covering Mali, Senegal, and Burkina Faso, identifying drought assurance as a key component of farmers' preferred climate service packages. We argue that the drought tolerance attribute identified in this study could serve as a viable substitute for drought assurance. This is because a drought assurance premium would likely be higher, per hectare, than the price of drought-tolerant seed, when both options are available for farmers. In contrast, Martey et al. [57] identified early maturity as the preferred attribute among cowpea farmers in Ghana using a DCE.

Third, considering the food utilization domain, farmers showed a preference for higher grain storage capacity. Varieties that could be stored for 10 months and 8 months had respective coefficients of 0.66 and 0.41 (both statistically significant), relative to a reference of 4 months. This finding indicates that farmers are more interested in improved and climate-resilient sorghum varieties that can be stored for longer periods to support household food consumption. It also aligns with the subsistence nature of sorghum in Mali, where self-consumption is more dominant than market sales. These results are consistent with those of Elaine et al. [12] and Lindani et al. [61] in Ghana and Zimbabwe, where grain quality including longer storage capacity was identified as a preferred attribute among sorghum farmers. In contrast, studies in Nigeria and Tanzania emphasized grain white colour as a preferred trait for improved sorghum varieties [25,27].

Fourth, concerning the social dimension, farmers showed a preference for improved variety seeds that enable integration into FBOs, with a coefficient of 0.12 (statistically significant) compared to farming alone. This finding suggests that networking among farmers is important to fostering participatory improved sorghum varietal development in Mali. Such networks (for example: innovation platforms) can facilitate information exchange not only between breeders, agricultural service providers, and farmers, but also among peer farmers themselves, thereby easing technology adoption. This result is supported by Miriti and Lambarraa-Lehnhardt [62], who in a systematic review of DCE studies, highlighted the role of networking as a preferred attribute for sorghum farmers transitioning from traditional cropping systems toward sustainable intensification. Further evidence comes from My et al. [50] and Yangui et al. [63], who used DCE to identify farmer networking as a preferred attribute in an organic certification scheme in Vietnam and in integrated *Orobanche* management in Tunisia, respectively.

Fifth, regarding the economic affordability, farmers significantly preferred improved sorghum varieties with lower seed costs. Varieties priced at 750 CFA/kg and 600 CFA/kg (equivalent to 1.18 USD/kg and 0.94 USD/kg, respectively) had respective coefficients of −0.55 and −0.48 (both statistically significant), relative to a reference price of 300 CFA/kg (0.47 USD/kg). This result indicates that, despite the higher yield potential of hybrid improved varieties, their seed costs often exceed farmers' purchasing power due to rural poverty. In Mali, for

**Table 3**
Random Parameter Logit (RPL) or Mixed Logit (MXL) model.

| Variables Choices | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | All regions | | Kayes | | Koulikoro | | Sikasso | | Segou | |
| | Coef. | SD | Coef. | SD | Coef. | SD | Coef. | SD | Coef. | SD |
| Local | −3.259*** | 0.152 | −20.95 | 0.201 | −19.61 | 0.121 | −19.47 | 0.219 | −0.913* | 0 |
| | (0.491) | (2.264) | (4746) | (4674) | (2464) | (2446) | (1672) | (1634) | (0.497) | (0) |
| **Grain yield** | | | | | | | | | | |
| level2 (2,500 kg/ha) | 1.065*** | 0.0529 | 1.181 | 1.249 | 2.059*** | 2.985** | 0.954*** | 0.0395 | 1.551*** | 0.0181 |
| | (0.156) | (0.484) | (0.949) | (1.665) | (0.629) | (1.339) | (0.261) | (0.991) | (0.402) | (0.949) |
| Level3 (3500 kg/ha) | 1.609*** | 1.023* | 1.805 | 0.271 | 2.110*** | 0.0240 | 2.060*** | 1.886* | 1.794*** | 0.315 |
| | (0.251) | (0.566) | (1.555) | (6.155) | (0.420) | (0.520) | (0.593) | (1.001) | (0.423) | (1.273) |
| **Drought tolerance** | | | | | | | | | | |
| level2 (15 days) | 0.530*** | 1.236*** | 1.104 | 1.152 | 1.040** | 0.462 | 0.202 | 0.0798 | 0.600* | 2.599** |
| | (0.116) | (0.444) | (0.783) | (2.096) | (0.433) | (2.058) | (0.185) | (0.864) | (0.310) | (1.066) |
| Level3 (20 days) | 0.597*** | 0.0462 | 1.119 | 0 | 0.524* | 0.0268 | 0.918*** | 0.000821 | 0.225 | 0.118 |
| | (0.109) | (0.504) | (0.789) | (0) | (0.299) | (0.498) | (0.318) | (0) | (0.232) | (1.033) |
| **Grain storage** | | | | | | | | | | |
| level2 (8 months) | 0.483*** | 0.0341 | 0.461 | 0.220 | −0.228 | 0.0376 | 0.373 | 0.124 | 1.650*** | 0.0848 |
| | (0.107) | (0.353) | (0.377) | (1.462) | (0.296) | (0.630) | (0.242) | (0.952) | (0.403) | (0.699) |
| Level3 (10 months) | 0.801*** | 0.000550 | 1.081 | 0.320 | 1.872*** | 0 | 0.266 | 1.28e-07 | 1.766*** | 0.805 |
| | (0.127) | (0.896) | (0.822) | (3.588) | (0.619) | (0) | (0.192) | (0) | (0.481) | (1.178) |
| **FBOs** | | | | | | | | | | |
| level2 (yes) | 0.153* | 9.87e-06 | 0.193 | 1.091 | 0.376 | 0.00705 | −0.00255 | 0.170 | 0.515** | 0.0988 |
| | (0.0802) | (0) | (0.271) | (4.210) | (0.309) | (0.954) | (0.167) | (0.832) | (0.261) | (0.893) |
| **Seed cost** | | | | | | | | | | |
| level2 (450F/kg) | −0.0472 | 0.0381 | 0.0084 | 0.0427 | −0.434 | 0.0297 | −0.153 | 0.170 | −0.351 | 1.906* |
| | (0.111) | (0.648) | (0.307) | (1.360) | (0.360) | (0.658) | (0.242) | (2.095) | (0.341) | (1.068) |
| level3 (600F/kg) | −0.568*** | 0.478 | −0.844 | 2.589 | −1.708*** | 0.0479 | −0.977*** | 0.741 | −0.236 | 0.106 |
| | (0.129) | (1.062) | (0.758) | (2.798) | (0.600) | (0.571) | (0.356) | (1.509) | (0.348) | (1.486) |
| level4 (750F/kg) | −0.629*** | 0.0253 | −1.035 | 0.393 | −0.797* | 1.196 | −0.943*** | 0.0443 | −0.0393 | 0.0891 |
| | (0.128) | (0.423) | (0.776) | (2.249) | (0.432) | (1.113) | (0.342) | (0.684) | (0.369) | (1.120) |
| Log simulated-likelihood | −1090.2172 | | −276.1289 | | −186.3338 | | −268.024 | | −290.859 | |
| AIC | 2222.434 | | 594.2579 | | 414.6675 | | 576.0479 | | 623.7179 | |
| Number of cases | 1872 | | 492 | | 396 | | 492 | | 492 | |
| Observations | 5616 | | 1476 | | 1188 | | 1476 | | 1476 | |

Source: Authors from Random Parameter Model, SD: standard deviation, Standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

instance, most hybrid seeds must be purchased annually and are priced relatively high to reflect their yield potential. This finding aligns with previous DCE studies on improved sorghum attributes in Nigeria and Tanzania [27,60]. Furthermore, the ASC for the local variety (the opt-out option) was negative and statistically significant, indicating that farmers have less preference for their local varieties in favour of improved and climate-resilient alternatives. This was corroborated by the FGDs conducted during the preliminary survey, in which farmers reported that most released improved sorghum varieties yield more and mature earlier than their traditional ruling varieties. The negative and significant local coefficient in the CL model in Table 2 reflects this stated preference.

Additionally, the cross-regional estimation results (columns 2–5) show broadly consistent preferences across regions, with slight variations in attribute coefficients and significance levels. A key regional difference is evident in the ASC for the local variety. As example: in Segou region, farmers showed significantly less preference for their traditional sorghum varieties (significant at 1 %), whereas in the Kayes, Koulikoro, and Sikasso regions, the local variety coefficient was not statistically significant. Similarly, within the social dimension, farmers in Segou expressed a stronger preference for FBOs membership compared to those in other regions. However, no statistically significant effects were found for the seed purchasing cost attributes in Segou. In Kayes region, only the highest price level (750 CFA/kg, or 1.18 USD/kg) was significant. These regionally inconsistent estimates highlight the presence of preference heterogeneity among farmers, underscoring the relevance of the RPL model presented in Table 3.

### 3.2. Random Parameter Logit (RPL) model

Table 3 (all regions, column 1) indicates stated preferences consistent with those in the CL model. This suggests that, although the IIA assumption was rejected (see appendix A3), the assumption of preference homogeneity across respondents generally holds in the basic CL specification. It is worth noting that the violation of the IIA assumption in CL models is a known limitation and has been widely discussed in the DCE literature [64–66]. However, the RPL model relaxes these assumptions and accounts for preference heterogeneity, revealing significant heterogeneity for some attribute levels. This is captured by the statistically significant SDs of the estimated coefficients. At the aggregate level (all regions, column 1), the RPL model indicates heterogeneity for grain yield level 3 (3,500 kg/ha, significant at 10 %) and drought tolerance level 2 (15 days, significant at 1 %). Cross-regional results further reveal heterogeneity for grain yield in Koulikoro (2,500 kg/ha, significant at 5 %) and Sikasso (3,500 kg/ha, significant at 10 %). In the Ségou region, heterogeneity is observed for drought tolerance of 15 days (significant at 5 %) and seed purchasing cost of 450 CFA/kg (significant at 10 %). No significant heterogeneity was found in the Kayes region. These heterogeneous preferences may reflect differences in farm locations (e.g., upper vs. lower lands), seasonal rainfall, drought frequency, and household resource endowments. For instance, larger households may prioritize higher yields to meet family food needs, while smaller households may place greater emphasis on drought tolerance. Such factors likely explain the observed variations across attributes and levels in the RPL model. The results also reflect trade-offs made by respondents during the choice process, underscoring the relevance of the WTP estimates for the CL and RPL models in Table 4.

Table 4 presents farmers' WTP for attributes of improved and climate-resilient sorghum varieties, as estimated in the CL and RPL models. The WTP was calculated only for attribute levels that were statistically significant in each model, following Equation (7). Overall, farmers exhibited the highest WTP for the higher grain yield attribute (3500 kg/ha) in both models at the aggregate level (all regions) as well as across individual regions (relative to the reference of 1500 kg/ha).

**Table 4**
Willingness to pay (WTP) for the CL and RPL models.

| CL model | | | | | RPL model | | |
|---|---|---|---|---|---|---|---|
| Attribute levels | WTP | WTP | WTP | WTP | WTP | WTP | WTP |
| | All regions | Kayes | Koulikoro | Sikasso | All regions | Koulikoro | Sikasso |
| **Grain yield** | | | | | | | |
| 2,500 kg/ha | 1.6722 | 1.2139 | 1.6912 | 1.0896 | 1.7794 | 1.6439 | 0.9938 |
| 3,500 kg/ha | 2.4462 | 2.7260 | 2.3463 | 2.0528 | 2.6884 | 1.6846 | 2.1458 |
| **Drought tolerance** | | | | | | | |
| 15 days | 0.8400 | 1.7332 | 1.0600 | | 0.8855 | 0.8303 | |
| 20 days | 1.0029 | 2.1587 | 0.4873 | 1.1161 | 0.9975 | 0.4184 | 0.9563 |
| **Grain storage** | | | | | | | |
| 8 months | 0.7876 | 0.8269 | | | 0.8070 | | |
| 10 months | 1.2861 | 1.7284 | 1.4243 | | 1.3383 | 1.4946 | |
| **FBOs** | | | | | | | |
| yes | 0.2328 | | | | 0.2556 | | |

Source: Authors calculated with estimated coefficients from CL and RPL models

This finding aligns with that of Singbo et al. [37], who also reported strong farmer preferences for higher yielding improved sorghum varieties in Mali. For the drought tolerance attribute, respondents showed the highest WTP for 20 days of tolerance (relative to 7 days) in both aggregate and regional models, with the exception of the Koulikoro region. In Koulikoro, farmers instead displayed the highest WTP for 15 days of drought tolerance in both models. This difference may indicate that farmers in Koulikoro typically experience shorter drought spells than those in other regions. Similar patterns of WTP for drought tolerant attributes were reported by Miriti et al. [25] and Regassa et al. [60] in studies on improved sorghum and groundnut varieties in Tanzania. Concerning grain storage capacity, the highest WTP was observed for 10 months of storage (relative to 4 months) in both aggregate models. This result suggests that farmers are willing to pay for an additional month of storage capacity. Given the subsistence nature of sorghum farming and the central role of sorghum grain in household food security, farmers likely value long term storage as a key attribute. Finally, farmers exhibited higher WTP for membership in FBOs (relative to farming alone) in both models, but only at the aggregate level. This finding underscores the importance of establishing more innovation platforms or collective action networks for sorghum farmers in Mali.

## 4. Conclusion and policy implications

Participatory plant breeding requires the full involvement of farmers as key stakeholders in varietal development. This approach is essential for achieving sustainable adoption of improved and climate resilient sorghum varieties in Mali and across SSA. To meet this objective, farmer preferred attributes must be integrated from the earliest stages of breeding. This is particularly important for sorghum, a pro poor staple cereal crucial for rural household food security across most of SSA countries, including Mali. This study used a DCE to elicit farm household preferences for improved sorghum variety profiles in Mali, aiming to identify preferred attributes and estimate farmers' WTP for them. Key findings indicated that farmers preferred higher grain yields (3,500 kg/ha and 2,500 kg/ha, relative to a reference of 1,500 kg/ha), drought tolerance (20 days and 15 days, relative to 7 days), longer grain storage capacity (10 months and 8 months, relative to 4 months), and membership in FBOs. These results were consistent across both the CL and RPL models. Conversely, farmers showed negative preferences for higher seed costs or prices (750 CFA/kg and 600 CFA/kg, equivalent to 1.18 USD/kg and 0.94 USD/kg, respectively). Beyond the basic CL model, the RPL model revealed significant preference heterogeneity for the highest grain yield level (3,500 kg/ha) and for 15 days drought tolerance. The findings underscore that a singular focus on higher yield, which has long dominated sorghum breeding is insufficient to ensure farmer adoption of new varieties. Breeding programmes should also integrate climate resilience attributes, such as drought tolerance, to better align with farmers' needs. Combining improved yield with climate resilience could therefore enhance farmers' commitment to sustainable adoption. In light of these results, we recommend that future sorghum breeding initiatives prioritize farmer preferred attributes, including higher grain yield (3,500–2,500 kg/ha), drought tolerance (20-15 days), extended grain storage capacity (10-8 months), and support for farmer networking through innovation platforms. Incorporating these traits would strengthen farmers' climate resilience and increase the adoption rate of improved and climate-resilient sorghum varieties, thereby supporting sustainable agricultural intensification in rural Mali.

As a methodological note, this study employed a novel data collection tool, the "DCEtool" in R software, utilizing R Shiny package features. While this tool can generate more accurate choice data than conventional techniques, the resulting dataset does not readily allow for interaction effects with socioeconomic characteristics, which are commonly explored in multinomial or latent-class models. Additionally, as a stated preference approach, the choices expressed by farm households may not fully predict future adoption behaviour, due to the influence of uncontrolled contextual factors. A follow-up study tracking actual adoption decisions would help address this gap, though such research was beyond the scope of the present work given time and resource constraints. Furthermore, the precision of DCE estimates can be enhanced by incorporating prior coefficient values, typically obtained from the literature or from a preliminary pilot study. While this three-step design process is methodologically advantageous, it could not be implemented here due to the same practical limitations. We therefore recommend the use of such prior information in future research to improve the robustness of parameter estimates.

## CRediT authorship contribution statement

**Adama B. Coulibaly:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Félix Badolo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Jummai O. Yila:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Bourema Koné:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Funding acquisition. **Macdonald Bright Jumbo:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Funding acquisition. **Ayoni Ogunbayo:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Funding acquisition. **Kimseyinga Savadogo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Conceptualization.

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**Declaration of Competing interest**

The authors declared no conflicts of interest.

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## Appendix ASupplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jafr.2026.102701.

## Appendix A1. Households' characteristics

**Table A**
Households quantitative sociodemographic characteristics

| Quantitative | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Variables | N | mean | sd | min | max |
| Age (year) | 154 | 47.94 | 10.23 | 19 | 69 |
| Experience (year) | 154 | 16.10 | 8.261 | 2 | 35 |
| Household size (number) | 154 | 25.57 | 15.03 | 5 | 90 |
| Household dependents (number) | 154 | 9.73 | 6.20 | 1 | 30 |
| Household workforce (number) | 154 | 5.24 | 3.18 | 0 | 18 |
| Oxen (number) | 154 | 3.61 | 2.45 | 0 | 16 |
| Ploughing motors (number) | 154 | 0 | 0 | 0 | 0 |
| Tractors (number) | 154 | 0.00 | 0.08 | 0 | 1 |
| Market average distance (km) | 154 | 3.50 | 4.97 | 0 | 15 |
| Household monthly food expense (CFA) | 154 | 130,938 | 69,011 | 45,000 | 450,000 |
| Sorghum area (hectare) | 154 | 3.00 | 2.18 | 0.25 | 15 |
| Farm average distance (km) | 154 | 2.75 | 2.13 | 0 | 12 |

Source: Authors from survey data May 2022, SD: standard deviation, N: number of observations

**Table B**
Households qualitative sociodemographic characteristics

| Qualitative Variables | Descriptions | Percentages (%) |
|---|---|---|
| Gender | 1 if male and 0 for female. | 66 |
| Marital status | 1 = married, 2 = single, 3 = divorced, 4 = widowed; with respect to the following percentages. | 95; 3; 0; 2 |
| Education | 0 = illiterate, 1 = alphabetised 2 = french school, 3 = merdersa; with the following percentages. | 36; 43; 19; 3 |
| Main activity | 1 if the respondent's main activity is farming. | 100 |
| Affiliation to FBOs | 1 if yes and 0 otherwise. | 99 |
| Platform | 1 if the respondent is a member of any innovation platform and 0 otherwise. | 92 |
| Technology transfer | 1 if the respondent participated in any technology transfer in the previous year (2021) and 0 otherwise. | 92 |
| Farming equipment | 1 if the respondent declares that the household has completed farming equipment and 0 otherwise. | 92 |
| Cattle herd | 1 if the respondent declares that the household has a cattle herd and 0 otherwise. | 68 |
| Sheep herd | 1 if the respondent declares that the household has a sheep herd and 0 otherwise. | 81 |
| Goat herd | 1 if the respondent declares that the household has a goat herd and 0 otherwise. | 86 |
| Extension services | 1 if the respondent has access to agricultural extension services and 0 otherwise. | 100 |
| Off-farm work | 1 if the respondent practises off-farm work and 0 otherwise. | 77 |
| Fertiliser main source | 1 if subsidised and 0 for cash in the market. | 89 |
| Drought report | 1-5 drought occurrence times, 6 = drought occurrences above five times, 7 = no drought occurrence (the year 2021); for the following percentages. | 64; 6; 30 |
| Pest report | 1-5 times pest invasions, 7 = no pest invasions; for the following percentages. | 5; 95 |
| Yield perception | 1 = bad, 2 = acceptable, 3 = good, 4 = don't have an idea about it; with respect to the following percentages. | 24; 68; 7; 1 |
| Soil quality perception | 1 = bad, 2 = acceptable, 3 = good, 4 = don't have an idea about it; with respect to the following percentages. | 18; 73; 8; 1 |
| Fertiliser type | 1 = chemical, 2 = organic, 3 = both, 4 = none of them; with respect to the following percentages. | 14; 3; 79; 3 |
| Total | | N = 154 |

Source: Authors from survey data May 2022.

*Appendix A2. BIC value for RPL (2338) and BIC value for CL (2273)*

*Appendix A3Test of IIA assumption*

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| | CL fe | H_IIA | cm_nocst |
| asc | −3.410*** | | −3.410*** |
| | (0.331) | | (0.331) |
| gylevel2 | 0.862*** | 1.296*** | 0.862*** |
| | (0.0762) | (0.0787) | (0.0762) |
| gylevel3 | 1.261*** | 1.787*** | 1.261*** |
| | (0.0786) | (0.0797) | (0.0786) |
| dtlevel2 | 0.433*** | 0.787*** | 0.433*** |
| | (0.0755) | (0.0805) | (0.0755) |
| dtlevel3 | 0.517*** | 0.929*** | 0.517*** |
| | (0.0753) | (0.0793) | (0.0753) |
| gslevel2 | 0.406*** | 0.837*** | 0.406*** |
| | (0.0759) | (0.0794) | (0.0759) |
| gslevel3 | 0.663*** | 1.025*** | 0.663*** |
| | (0.0757) | (0.0784) | (0.0757) |
| fboslevel2 | 0.120* | | 0.120* |
| | (0.0633) | | (0.0633) |
| sclevel2 | −0.0646 | 0.308*** | −0.0646 |
| | (0.0880) | (0.0911) | (0.0880) |
| sclevel3 | −0.482*** | −0.239** | −0.482*** |
| | (0.0916) | (0.0975) | (0.0916) |
| sclevel4 | −0.549*** | −0.312*** | −0.549*** |
| | (0.0895) | (0.0992) | (0.0895) |
| Log likelihood | −1095.2709 | −1228.3961 | −1095.2709 |
| Pseudo R2 | 0.4674 | 0.4027 | 0.4674 |
| Observations | 5616 | 5616 | 5616 |

Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

## Data availability

Data will be made available on request.

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