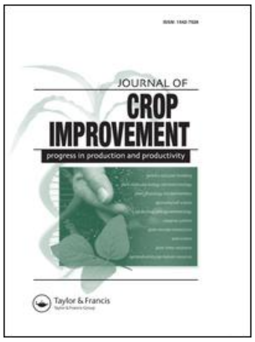

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Gamification of farmer-participatory priority setting in plant breeding: Design and validation of "AgroDuos"

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ABSTRACT

Participatory methods to characterize farmers' needs and preferences play an important role in plant breeding to ensure that new varieties fulfill the needs and expectations of end users. Different farmer-participatory methods for priority setting exist, each one responding differently to trade-offs between various requirements, such as replicability, simplicity, or granularity of the results. All available methods, however, require training, academic skill, and staff time of specially qualified professionals. Breeding and variety replacement may be accelerated by empowering non-academic organizations, such as NGOs and farmer organizations, to carry out farmer-participatory priority setting. But for this use context, currently no suitable method is available. A new method is needed that demands relatively low skill levels from enumerators and respondents, engages farmers without the need for extrinsic incentives, and gives statistically robust results. To achieve these objectives, we followed principles of "gamification" in the design of AgroDuos, a choice experiment that resembles a card game and that involves pairwise ranking of variety traits. We tested the method in a pilot with 39 farmers in Honduras to define their trait priorities for common bean (*Phaseolus vulgaris* L.). To validate our results, we independently carried out conjoint analysis, an established method for priority setting in plant breeding. We found that AgroDuos produced valid and useful results while enabling rapid, easy, and engaging data collection. Challenges persist concerning local adaptation and data analysis by non-specialist staff, which may be resolved in the future by providing templates and online support.

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Citizen science; conjoint analysis; farmer preferences; gamification; Honduras; plant breeding; priority setting

Introduction

The use of farmer-participatory methods in plant breeding is now widely established, although not standard practice everywhere (Ceccarelli, Guimarães, and Weltzien 2009). Given continuously changing pressures on farming and the immense diversity of farmers' needs and preferences, participatory methods promise to accelerate breeding and increase adoption of

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/wcim.

new varieties (Ceccarelli 2015; Dawson, Murphy, and Jones 2008; Joshi et al. 2012). However, breeding programs have limited resources that require effective allocation, so one important stage of farmer participation is the definition of breeding priorities (Li et al. 2013; Weltzien and Christinck 2009). Participatory priority setting can be used to inform breeders about clients' preferences for the targeted selection of parent lines or on-station selection of crosses (Ashby 2009; Sperling et al. 2001). In many cases, farmer-participatory priority setting is part of a methodology that also involves farmers in other steps of the breeding process (Li et al. 2013).

Different methods for client-oriented trait prioritization are in use, involving varying degrees and forms of farmer participation (Witcombe et al. 2005). The most common methods include participatory rural appraisal (Gebretsadik et al. 2014; Sibiya et al. 2013), ranking and rating of traits or entire plants (Asfaw et al. 2012; Vom Brocke et al. 2010), and stated-choice experiments using multi-criteria decision making (Achot et al. 2014; Asrat et al. 2010). All approaches represent different solutions to the trade-offs between multiple requirements, including replicability, participation, scalability, ease and speed of execution, cognitive simplicity to participants, and granularity of results (i.e., the ability to analyze results by different groups of farmer, beyond the aggregate sample). Having different emphases, each method combines unique strengths and limitations. Participatory rural appraisal emphasizes deliberation and can reveal highly granular results, but this also requires good facilitation skills and significant time. Quantitative methods, on the other hand, emphasize replicability. Ranking methods, including revealed-choice experiments, such as on-farm selection of plants, are rapid, adaptable to local context, and a relatively easy exercise both for enumerators and for respondents. By involving relatively few farmers, however, they risk masking granularity of results, covering internal diversity of farmers' preferences and leading to suboptimal breeding strategies. Stated-choice experiments can include many respondents and allow for high granularity of results but are more demanding in time and user skill and expose respondents to higher cognitive load that may skew results.

All the mentioned methods, however, require fairly high levels of specific training, academic skills, and sometimes significant financial resources to implement research and to keep participants engaged. For breeding programs and development agencies, time invested into training, as well as highly qualified staff time, may be limiting resources to adequately carrying out participatory priority setting. These restrictions may result in only partially participatory decision making and subsequently ineffective allocation of breeding resources. With breeders often facing resource constraints for participatory research—what if research programs could reach out and empower non-academic stakeholders in agricultural development, such as farmer organizations, to implement robust priority setting for plant breeding in an easy, replicable way?

Existing experience with farmer organizations as forefront actors in plant breeding suggests that supportive institutions and often donor support are needed for long-term sustainable outcomes (Humphries et al. 2015; Joshi et al. 2012; Pope 2013). However, both may not always be available, so simpler methods that can be employed without in-depth training and with limited financial resources are also needed. With appropriate methods, farmer-participatory priority setting could take up a "citizen science" approach and be entirely carried out by local non-scientific professionals and organizations collaborating with formal researchers (see McKinley et al. 2017). Crowdsourcing breeding priorities by citizen science may then save resources and speed up both centralized and decentralized breeding endeavors by improved agenda setting. Such a method would need to (i) pose relatively low requirements to skill levels and be easily implementable by NGO staff, farmer organizations, or agricultural students, (ii) give robust results that can be easily interpreted without needing profound scientific background knowledge, and (iii) engage participants without requiring explicit incentives and instead deriving motivation from the method itself. To promote the engagement of volunteers and incentivize participation, many citizen science projects have designed data collection and/or data analysis in a "gamified" way, often emphasizing "playful experience" (Bowser et al. 2014; Ponti, Hillman, and Stankovic 2015).

The objective of our study was to design and validate a method for priority setting in client-oriented plant breeding that fulfills these criteria. We drew upon the individual strengths of existing methods to design a solution that satisfies the multiple requirements to a method of farmer-participatory priority setting in the best way. We formulated various requirements as design criteria and made corresponding design decisions in an attempt to respond to the multiple trade-offs in an optimal way. To test the new method, we implemented it with farmers in Honduras, focusing on trait prioritization for common bean (*Phaseolus vulgaris* L.). To compare with the current state of the art, we also executed conjoint analysis, which is an established method in this context (Asrat et al. 2010; Bett et al. 2011; Tano et al. 2003). We observed how farmers engaged with each method and compared the quantitative results. We discuss our new method in the light of this validation, evaluating whether it meets our own design criteria.

Material and methods

Design criteria

Drawing from the individual strengths of existing methods and grounded on the requirements to a simpler method than current ones, we defined eight design criteria to guide the development of a new, simple, and adaptable method for farmer-participatory trait prioritization. We present our design criteria in Table 1.

Design decisions

We viewed each design criterion as a set of options inspired by the characteristics of current methodologies for farmer-participatory trait prioritization. Based on these options, we made interrelated design decisions for all criteria in order to best respond to the numerous requirements such methods face.

Replicability

To ensure replicability, we chose to design a choice experiment focusing on stated preferences. In contrast to qualitative methods, such as participatory rural appraisal, choice experiments follow a strict and replicable guideline and provide quantitative results, which can be compared with previous results and the results of alternative methods for priority setting. Our focus on stated preference involves creating hypothetical options. Methods using revealed preferences would limit the prioritization of new traits not currently present in locally known crop varieties, such as disease resistance.

Ease of enumeration

Our aim was to minimize enumeration effort. We therefore designed a method that NGO staff, citizen scientists, or university students can use in farming communities without requiring specific, in-depth training or special

Table 1. Criteria used in the design of a new method for farmer-participatory priority setting.

Design criterion	Explanation
Replicability	The method should follow a stringent, replicable guideline and should provide quantitative results.
Ease of enumeration	Data collection should enable enumerators with moderate skill level to use the method without time-intensive training.
Ease of participation	Data collection should be simple and self-explicatory to respondents and not require specific skill, knowledge, or training.
Speed	The method should enable rapid, resource-efficient data collection from a large number of participants.
Adaptability	The method should be easily adaptable to local context and work at any location as well as with any number of participants.
Engagement	Data collection should engage participants without requiring extrinsic incentives.
Granularity of results	Interpretation of results should allow detailed insights into respondents' preferences, specifying more than just a general overview.
Ease of interpretation of results	Analysis and interpretation of results should be simple enough to enable (i) users with moderate skill level to carry out analysis in a quick manner and without specific training and (ii) the enumerators to interpret and feedback results with low effort.

material requisites. We created a “choice game” with extremely simple “rules” and designed a set of “playing cards.” In the new method, enumeration of the choice experiment consists in facilitating “gameplay” and recording choices in a simple binomial structure.

Ease of participation

To enable large-scale participation across context and avoid excluding any potential participants, we attempted to make data collection as simple as possible for respondents and applied two strategies to this end. Firstly, we chose to minimize cognitive load per required discrete choice by confronting respondents with simple trade-offs. Instead of asking participants to choose between several multiattribute profiles, we reduced decision making to preference choices between just two traits at a time, in multiple, successive pairwise comparisons. This pairwise choice structure gives the name to the method: “AgroDuos”. Secondly, we assumed low levels of literacy by using simple pictograms to express traits and trait levels.

Speed

We decided to design data collection in the form of a group activity, thus enabling enumerators to record choices from multiple respondents simultaneously. This feature of our method saves much time compared with one-on-one methods, which include most implementations of conjoint analysis. Group processes, however, can lead to participants mutually influencing each other and biasing the results. We designed the dynamics in such a way that they ensured independent decision making.

Adaptability

We intended to design a method that is adaptable, to make it usable in many different contexts and with any number of participants. We accounted for these requirements by developing a generic stated-choice method. The method can be used for many applications where prioritization of multiple alternatives is required. In our pilot of the method, we used seven variety traits that had been previously defined in a local program of participatory crop improvement, resulting in 21 pairwise choices. In other contexts (different countries, crops, traits, or trait levels), the method can be easily adapted by using different pictograms. The number of pictograms to be used in the card deck is flexible, too: any pool of n variety traits may be employed, requiring two pictograms per trait, and resulting in $\binom{n}{2}$ choices.

Engagement

We attempted to take the engagement of respondents into account by providing an entertaining, intrinsically motivating activity. Recent literature suggests "gamification" is a powerful strategy to foster participant motivation in non-game contexts (Deterding et al. 2011). To enhance an experience of fun, we decided to design data collection in the form of a card game that respondents play. The game mixes elements of common playing cards, the *memory* game,[1] and *lotería*, a pictorial *"bingo"* particularly popular and well known in Central America and Mexico. *Lotería* is common at Honduran village fairs and is associated with joy and conviviality. In our method, farmers express preferences through an activity that resembles playing *lotería* along with other participants, so we expect to provide a pleasurable activity that is not tedious to participants. Although the game may be unknown in other parts of the world, it is equivalent to *bingo*, a widely known game that is easy to understand, so we do not expect this fact to limit adaptability. Also, other local card decks or games could be adapted in a way similar to how we adapt *lotería* here.

Granularity of results

In designing the method, we gave priority to analytical tools that allow distinguishing groups of respondents that share similar preferences. Choice data produced by pairwise comparisons between individual traits can be fit with the Bradley-Terry model (Bradley and Terry 1952). The model can be combined with recursive partitioning, which makes it possible to identify groups among respondents with significantly distinct preference profiles (Strobl, Wickelmaier, and Zeileis 2011). The identification of different preference profiles would allow defining multiple, alternative breeding strategies, for example, addressing different groups of farmers by selecting different parent populations, or performing this selection with various groups of farmers, thereby increasing overall fit of new crosses to clients' needs. These methods are explained in more detail below.

Ease of interpretation of results

We chose to analyze choices with the Bradley-Terry model because results of this model can be visualized in an easily interpretable manner. We used recursive partitioning to divide the set of participants in sub-groups with similar preferences or choices (Strobl, Wickelmaier, and Zeileis 2011).

Implementation of the choice experiment

Experimental design

Our method is inspired by Hansen and Ombler's (2008) PAPRIKA method of multi-criteria decision making by pairwise ranking. PAPRIKA is an adaptive

[1]Also known as *concentration, match match*, or *pairs, memory* is a children's game that consists in spotting pairs of equal images within a large set of cards by disclosing only two cards at a time. Beginning with random disclosures first, players need to remember the location of items to win the game.

method implemented in interactive software. By assuming transitivity (i.e., consistency in the answers of respondents), it avoids asking for all $\binom{n}{2}$ pairwise comparisons between n options. For example, if option A is ranked over B, and B over C, PAPRIKA will omit the comparison between A and C, assuming that A is ranked over C. For our context, we avoided the need for an adaptive, digital procedure by including all possible pairwise choices in the experiment but reducing the number of choices that need to be made by (i) limiting the number of traits to two per choice situation and (ii) limiting the number of attribute levels to two ("high" and "low"). This also reduced cognitive load per decision.

Our simple setup, including seven traits, resulted in a manageable number of $\binom{7}{2} = 21$ pairwise choices. In each pairwise choice, participants had to indicate their stated-preference between two hypothetical varieties. These were characterized by the same two traits (e.g., yield and pest tolerance). But the levels of these traits presented a trade-off, for example, "High yield, but susceptible to pests" versus "Low yield, but tolerant to pests" (Figure 1, step 4). Respondents were required to choose their preferred option in all 21 pairwise comparisons by analyzing the trade-off between the two traits. We converted these choices to wins and losses for each of the traits. In the example, if the participant picks the first option, *Yield* wins from *Pest tolerance*.

Game design and implementation

Our research took place in the context of a participatory crop improvement program focusing on red common bean in Honduras (Humphries et al. 2015; Rosas, Gallardo, and Jiménez 2003). Our selection of seven bean variety traits for the choice experiment followed local on-farm variety trials (Steinke 2015; van Etten et al. in press), in which our respondents had evaluated varieties of bean for these traits (see Table 2). Local experts, together with farmers, had previously identified these traits as most important selection criteria through focus group discussions. Therefore, we could safely assume that farmers had an adequate understanding of these traits.

For the quantitative traits *Yield* and *Market value*, we determined locally reasonable high and low levels together with local experts. For the other, qualitative traits, we simply indicated a "Good" and a "Poor" level (Table 2). We designed simple pictograms to express traits and trait levels of hypothetical varieties. Each hypothetical variety was represented in the style of a playing card (see Figure 1, step 4). We designed 21 pairs of cards, resulting in a card deck of 42 individual cards. Each pair of cards can be easily recognized because it shows the same image on the back sides. These images were taken from a traditional Mexican design of *lotería* (see above). Images include "the devil", "the mandolin", or "the melon" (see Figure 1, step 1). These are all

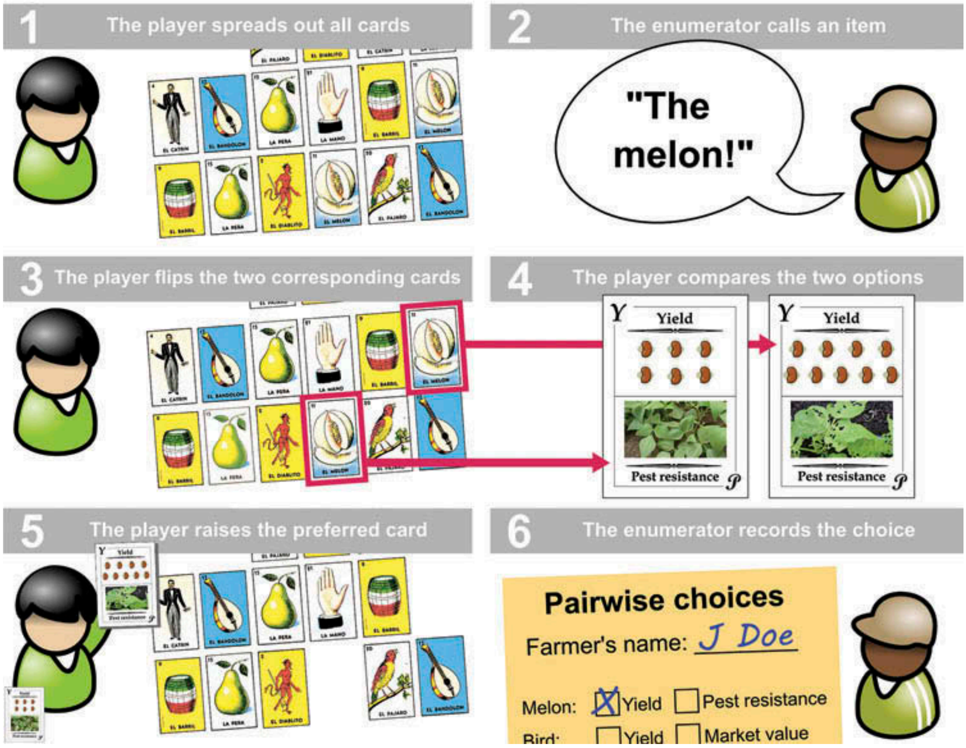

Figure 1. Visualization of AgroDuos gameplay, according to the procedure described in the text. Step 1 shows a selection of *lotería* images used for the back sides of AgroDuos playing cards. Step 4 shows an example of the trait trade-offs presented by the AgroDuos front sides, between *Yield* and *Pest resistance*.

Table 2. Trait levels used in AgroDuos and stated-choice experiment for conjoint analysis.

Trait	Low level	High level	Experiment
Disease resistance	Susceptible	Tolerant	A
Market value	600 L†/Q‡	900 L/Q	A
Pest resistance	Susceptible	Tolerant	A
Plant architecture	Crawling	Upright	B
Plant vigor	Bad	Good	B
Taste	Bad	Good	B
Yield	12 Q/Mz§	18 Q/Mz	A, B

†L = Honduran Lempira, about 0.05 US Dollar
‡Q = Quintal, about 46 kg
§Mz = Manzana, about 0.7 ha

distinctive items and easily recognizable for participants. Using this deck of cards, AgroDuos gameplay and data collection was done according to the following procedure.

(1) Several players can play AgroDuos at the same time. Each of the players randomly spreads out a full set of cards on a table, with their back sides (*lotería* images) facing up.

(2) The enumerator draws a *lotería* item and calls it out, as the numbers are called in bingo (e.g., "The melon!").
(3) Among their card set, each player searches for the two cards with the same image (e.g., the two "melon" cards), and flips them over.
(4) For every player, the front sides of a pair of cards presents a trade-off between two crop traits (see Figure 1, step 4). This is the same trade-off for all players. The enumerator briefly explains the trade-off and requests players to choose the preferred option out of the two hypothetical varieties.
(5) Each player selects a card and raises it in the direction of the enumerator without showing it to the other players or speaking about their choice. No passes or ties are allowed. The pair of cards is then put aside.
(6) The enumerator records the players' choices on a sheet.
(7) Steps 1 to 6 are repeated until no cards are left in front of players, i.e. until all 21 pairwise choices between crop traits have been recorded from each player.

Data analysis

We used the Bradley-Terry model to analyze the data produced by the AgroDuos game (Bradley and Terry 1952). This model estimates from the data the "worth" or relative importance of different traits. This model can be used with "recursive partitioning" to assign the participants to sub-groups with similar preferences or choices (Strobl, Wickelmaier, and Zeileis 2011). The algorithm uses participants' characteristics as "splitting variables" to make these groups. For example, the model can evaluate if women and men have different preferences, using gender as the splitting variable. If the difference in preference is significant, the model creates two groups: men and women. This works not only with categorical variables, such as gender, but also with continuous variables, such as age. In this case, the algorithm searches along the continuous variable for the splitting point that gives maximum model improvement. If the model finds that this difference is statistically significant, it splits the set of participants into two sub-groups. It creates one sub-group with participants above the splitting point (e.g., participants older than 30 years) and the other group below the splitting point (e.g., participants younger than 30 years). If the model finds different groups, it recursively repeats the analysis for the resulting groups until it finds no more significant differences. The result is a regression tree structure with binary splits.

In our analysis, we apply this model to farmers' trait preferences (response), using age and household size as continuous, and gender and region as categorical splitting variables. We set minimum group size to two respondents, to avoid the identification of sub-groups that consist of a single farmer who may have an unrepresentative opinion.

We used the R environment (R Core Team 2016) for data analysis. We fit Bradley-Terry models to farmers' pairwise choices of traits with the *psychotree* package (Strobl, Wickelmaier, and Zeileis 2011). We fit one Bradley-Terry model without including splitting variables, and one Bradley-Terry model with recursive partitioning to the same data, including the four variables mentioned above as splitting variables.

Comparison with conjoint analysis in breeding research

To assess the results of AgroDuos, we compared it with an alternative method for farmer-participatory priority setting, conjoint analysis by ordered probit. We carried out conjoint analysis with a similar group of respondents. Conjoint analysis is a common method in marketing research, but it has also become established as a tool in animal and plant breeding (Achot et al. 2014; Asrat et al. 2010; Bett et al. 2011; Sy et al. 1997; Tano et al. 2003). To determine the relative importance of different traits for farmers' overall varietal preference, conjoint analysis applies a Lancasterian utility framework. Lancaster's (1966) theory of consumer demand assumes that consumers derive utility not from a good itself but rather from its underlying properties. Thus, the utility of any good consists in the sum of the part-worth utilities of the good's attributes and may be decomposed into these partial utilities by experiment. Utility can then be written as a multivariate function of the respective attribute levels (Asrat et al. 2010; Sy et al. 1997).

In applications to plant breeding, various genetic traits of a variety are regarded as independent properties with specific, user-dependent part-worth utilities, which add up to the overall utility of the variety. In stated-choice experiments, test persons are asked to choose their preferred option among different hypothetical varieties, which differ with respect to various genetic traits (e.g., yield, earliness, and market price) (see Asrat et al. 2010). Conjoint analysis assumes a respondent's preference choice for or against a hypothetical variety can be explained by a function of its trait levels and the relative importance attributed to each trait by the respondent. So, after collecting choice data, a multivariate function is fit to farmers' choices by ordered probit. The model estimates coefficients to all included variables (traits). These coefficients represent the contribution of the level of each trait to model output (i.e., preference or non-preference of the specific hypothetical variety).

The simple model expresses the utility of selecting profile i in choice set X for farmer f as

$$U_{iXf} = \mathbf{T}\boldsymbol{\beta}_{iX} + \varepsilon_{iXf} \tag{1}$$

where $\mathbf{T}$ is a vector of crop traits, $\boldsymbol{\beta}_{iX}$ is the farmer-specific parameter vector including a profile-specific constant accounting for trait levels, and ε_{iXf} is an error term.

The probability that farmer f will choose profile i over profile j in choice set X can be written as

$$P_{iXf} = P\left\{\mathbf{T}\boldsymbol{\beta}_{iX} + \varepsilon_{iXf} > \mathbf{T}\boldsymbol{\beta}_{jXf} + \varepsilon_{jiXf}; \forall j \neq i\right\} \tag{2}$$

By fitting a utility function to empirical data by logistic regression, parameter values for $\boldsymbol{\beta}$ can be estimated. These values inform about the marginal utility of each trait.

Stated-choice experiment

We set up a stated-choice experiment and generated data by asking farmers to state their preference between multiple sets of two hypothetical varieties of bean, which differed in their levels of the tested traits. We adapted the experimental design from Tano et al. (2003). We created 16 choice sets, each consisting of two hypothetical varieties characterized by different levels of the same traits (Table 2). To avoid the high cognitive effort required by choosing between variety profiles that include all seven traits, we split the experiment in two parts: Each experiment (A and B) included four traits, with *Yield* included in both experiments to enable linking the utility functions using the coefficients of *Yield* (Table 2). We used the *AlgDesign* package (Wheeler 2014) in R (R Core Team 2016) to create a full factorial design of $2^4 = 16$ different variety profiles per experiment (i.e., combinations of high and low levels of the four traits) (Louvière, Hensher, and Swait 2000). We used the resulting fractions to define the attribute levels for the first profile in each choice set and created the alternative profile by using complementary trait levels (see Table 3 for an example).

To speed up data collection, we reduced the number of choices needed from respondents by applying an orthogonal fractional design (2^{3-1}). This leads to multiple combinations of only eight profiles instead of 16. An orthogonal fractional design treats all variables (traits) as independent and reduces the number of experiments required to define the main effects of the variables but does not take into account higher-level interactions (Bunch, Louviere, and Anderson 1996).

Table 3. Example of a choice set in experiment A of conjoint analysis.

Trait	Variety 1	Variety 2
Disease resistance	Tolerant	Susceptible
Market value	600 Lempiras per sack	900 Lempiras per sack
Pest resistance	Susceptible	Tolerant
Yield	18 sacks per Manzana	12 sacks per Manzana

We collected data from 25 small-scale farmers by presenting them with a fraction of eight choice sets from each experiment A and experiment B and asking them to select the preferred variety from within each choice set. We recorded responses and fit two utility functions, model A and model B, to data, using *glm* of the *stats* package in R (R Core Team 2016). We validated the models by comparing their likelihood ratio with critical Chi-square values.

To calculate the relative importance of each bean trait for the sample of respondents, we converted the part-worth utility estimates to relative importance values (Ψ) by using the following formula:

$$\Psi_i = \frac{\Delta U_i}{\sum \Delta U} \quad (3)$$

where ΔU_i is the part-worth utility estimate of marginal increase in trait i and $\sum \Delta U$ is the sum of marginal part-worth utility estimates throughout all traits.

We then generated Ψ-values for all traits from both models by setting the values for *Yield* to 1 in both models. We did not explore the effects of covariates in the conjoint analysis.

Data collection

We collected data in November and December 2014 in 9 rural communities characterized by small-scale farming in four regions of Honduras: the departments Yoro, Lempira, Intibucá, and the region around Lake Yojoa, belonging to various departments. All respondents were collaborating farmers with two Honduran rural development NGOs, and their selection was determined by the NGOs' ongoing extension activities and farmers' daily time availabilities. No explicit sampling criteria were applied.

For the experimental implementation of our new method, we "played" AgroDuos at 11 occasions, with groups of one to six farmers simultaneously, and recorded 39 farmers' choices. We also collected four household variables from participants as potential covariates of trait prioritization: two continuous variables, age and number of household members, and two categorical variables, gender and research region.

For the conjoint analysis, we tried to achieve a group of respondents that was similar to the respondents for AgroDuos, as it was not possible to have all farmers participate in both experiments for reasons of time. We collected 25 farmers' choices for the conjoint analysis. Nine of these farmers also participated in AgroDuos. We found the samples for AgroDuos and conjoint analysis did not significantly differ with respect to age or number of household members ($\alpha = 0.95$). In addition, both experiments provide a similar distribution of respondents by region. However, the share of women among respondents to AgroDuos (46%) was significantly higher than for the conjoint analysis (4%).

Results

Quantitative analysis of AgroDuos data from pilot implementation

The Bradley-Terry model produced worth estimates for the traits *Disease resistance, Plant architecture*, and *Taste* that were significantly higher than those for *Yield. Market value, Pest resistance*, and *Plant vigor* have values close to *Yield*, and the worth estimates are not statistically significant from each other (Table 4).

The Bradley-Terry model with recursive partitioning split the sample in three sub-samples by region but did not split the sample by gender, age, or number of household members. These results are presented in Table 5 and visualized by the regression tree in Figure 2.

The three farmer segments have highly distinct trait priorities. Farmers from Lempira set priorities that differ from the preferences of all other farmers ($p < 0.001$), and the priorities of farmers from Intibucá differ from those of farmers from Yoro and the Lake Yojoa area ($p = 0.011$). Within each segment, defined by a terminal node in the regression tree, individuals' preferences are homogeneous insofar as any further partitioning does not improve model fit.

We used *Yield* as reference in the Bradley-Terry model and observe that *Yield* was attributed highest priority in Lempira, but second-lowest priority in Intibucá, and lowest priority in Yojoa and Yoro. Given the small sample size and resulting large standard errors in Lempira, only *Plant vigor* can be identified as valued lower than *Yield* ($p < 0.05$). In Intibucá, *Disease resistance, Plant architecture*, and *Taste* are given significantly higher priority than *Yield.* In Yojoa and Yoro, this is true only for *Disease resistance* and *Plant architecture.* All in all, we observe patterns in trait priorities that are fairly similar throughout three regions: In Intibucá, Yojoa, and Yoro, *Disease resistance* and *Plant architecture* are highly prioritized traits, while *Yield* is given low priority throughout the three regions. Interestingly, we observe almost inverse trait priorities among farmers in the fourth research region, Lempira. Although worth estimate differences between traits are not significant in the case of Lempira, the general pattern of preferences contrasts sharply with the

Table 4. Parameter estimates of Bradley-Terry model to farmers' pairwise choices (n = 39) by AgroDuos.

Trait	Worth estimate, scaled to unity	Standard error	Z value	p (>|z|)
Yield	0.1084			
Disease resistance	0.1529	0.1738	1.980	0.0477*
Market value	0.1204	0.1735	0.607	0.5441
Pest resistance	0.0974	0.1745	−0.610	0.5417
Plant architecture	0.2136	0.1767	3.840	0.0001***
Plant vigor	0.1241	0.1734	0.779	0.4358
Taste	0.1832	0.1750	2.999	0.0027**

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$
Model Log-Likelihood: −551.60

Table 5. Parameter estimates of Bradley-Terry model of farmers' pairwise choices by AgroDuos, with recursive partitioning (n = 39).

Trait	Worth estimate, scaled to unity	Standard error	Z value	$p(>\|z\|)$	Log-Likelihood of sub-model
Node 2					−27.1
Yield	0.2904				
Disease resistance	<0.0001	3587.3428	−0.0061	0.9952	
Market value	0.2411	0.6108	−0.3043	0.7609	
Pest resistance	<0.0001	4421.3888	−0.0091	0.9928	
Plant architecture	0.2007	0.6119	−0.6037	0.5460	
Plant vigor	0.0266	0.8435	−2.8327	0.0046**	
Taste	0.2411	0.6108	−0.3043	0.7609	
Node 4					−75.4
Yield	0.0365				
Disease resistance	0.2141	0.5054	3.5020	0.0005***	
Market value	0.0257	0.4873	−0.7213	0.4707	
Pest resistance	0.0687	0.4675	1.3548	0.1755	
Plant architecture	0.3023	0.5267	4.0154	0.0001***	
Plant vigor	0.0504	0.4670	0.6937	0.4878	
Taste	0.3023	0.5267	4.0154	0.0001***	
Node 5					−387.7
Yield	0.1018				
Disease resistance	0.1705	0.2093	2.4618	0.0138*	
Market value	0.1291	0.2082	1.1400	0.2543	
Pest resistance	0.1263	0.2082	1.0372	0.2996	
Plant architecture	0.1819	0.2100	2.7631	0.0057**	
Plant vigor	0.1467	0.2084	1.7533	0.0796	
Taste	0.1436	0.2084	1.6515	0.0986	

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

results from the other regions: *Disease resistance* was given low priority, while *Yield* and *Market value* were preferred most strongly.

Trait priorities from conjoint analysis

We present the results of the conjoint analysis in Table 6. There are two main effects models (A and B) for the whole sample of respondents (n = 25). In model A, all four traits significantly influence the model outcome at the 5% significance level. In model B, *Plant vigor* showed no significant contribution to model fit, which is why we re-estimated a model B', dropping *Plant vigor* as covariate. The relative importance values we calculated using formula (3) are shown in Table 7. We observe that traits related to avoidance of disease-induced losses contribute much stronger to variety preference (*Disease resistance* and *Plant architecture* alone: 51.2%) than traits related to gross value potential (*Market value* and *Yield* alone: 3.7%).

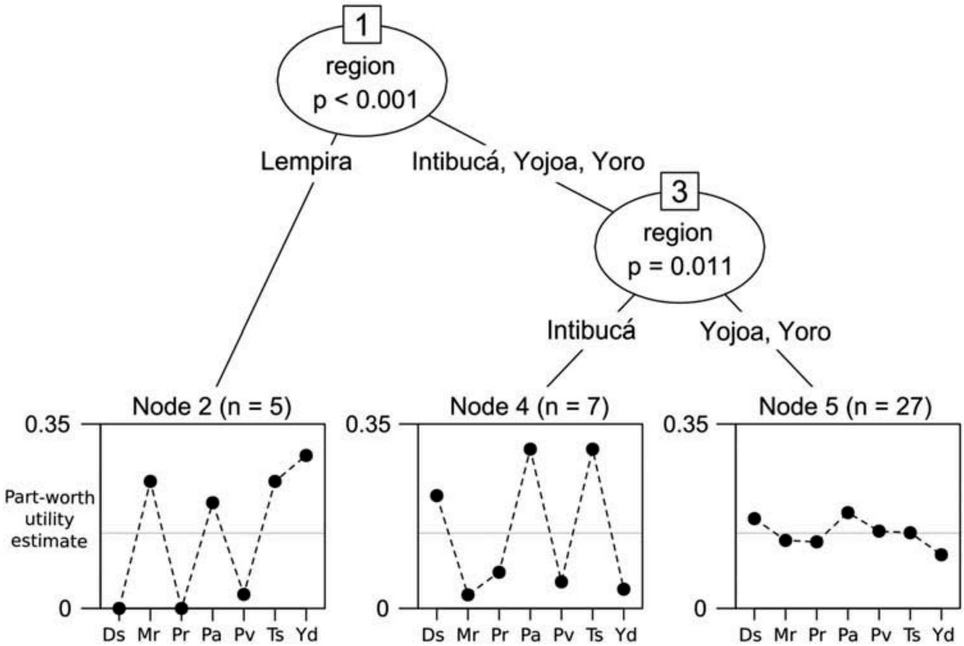

Figure 2. Recursive partitioning of Bradley-Terry model of farmers' pairwise choices (n=39). Ds = Disease resistance, Mr = Market value, Pr = Pest resistance, Pa = Plant architecture, Pv = Plant vigor, Ts = Taste, Yd = Yield.

Table 6. Main effect model estimates for effects of levels of variety traits on farmer preference for variety profiles in conjoint analysis. Values are regression coefficients (standard error in brackets). Model B′ is an improvement of model B by dropping *Plant vigor*.

Variable	Model A	Model B	Model B′
Constant	−5.2257 (0.9403)***	−4.0422 (0.7290)***	−4.0422 (0.7044)***
Disease resistance	1.8231 (0.2406)***		
Market value	0.0034 (0.0008)***		
Pest resistance	0.9986 (0.2303)***		
Plant architecture		1.4077 (0.2545)***	1.3866 (0.2511)***
Plant vigor		0.2816 (0.2248)	
Taste		1.9683 (0.2611)***	1.9363 (0.2567)***
Yield	0.0841 (0.0368)*	0.1527 (0.0393)***	0.1523 (0.7044)***
Likelihood ratio (LR)	$\chi^2(4) = 102.4^{\dagger}$	$\chi^2(4) = 110.4^{\dagger}$	$\chi^2(3) = 108.8^{\dagger}$

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$
$^{\dagger}p(\text{LR}>\chi^2) < .001$

Table 7. Relative importance of variety traits by conjoint analysis, in percent.

Trait	Model A	Model B′	Overall
Disease resistance	62.7		31.3
Market value	0.1		0.1
Pest resistance	34.3		17.2
Plant architecture		39.9	19.9
Taste		55.8	27.9
Plant vigor		–	–
Yield	2.9	4.3	3.6
Total	100	100	100

Game implementation

We observed the outcomes for the five design criteria that we had used to design data collection: ease of enumeration, ease of participation, speed, engagement, and ease of interpretation of results.

Ease of enumeration

We had designed the method for easy implementation by NGO staff or extension workers. We observed good understanding and easy handling on the part of local staff.

Ease of participation

Use of simple pictograms and trade-off pairs consisting of only two traits resulted in easy participation, and the activity was well understood and executed correctly by all respondents. Because participants' pairwise choices were not disclosed to other players, peer pressure affecting choice can be assumed to be absent.

Speed

Data collection with AgroDuos usually took longer than data collection for conjoint analysis (around 60 and 30 minutes, respectively). But parallel data collection for AgroDuos from up to six respondents per single exercise saved time and, altogether, allowed quick collection of preference data from many participants.

Engagement

AgroDuos proved to be a fun activity to participants, who generally maintained a joyful and playful attitude yet took decisions seriously, sometimes hesitating and pondering over choice.

Ease of interpretation of results

Although we did not experimentally assess the ease of autonomous interpretation of results with local staff, we observed that two NGO field agents who contributed to the research found the tree-like segmentation structure and the two-dimensional plots representing trait worth estimates (see Figure 2) demanding but not too difficult to interpret.

Discussion

Farmers' trait priorities detected by AgroDuos

With our design and implementation of AgroDuos, a game-like choice experiment, we were able to quantify how 39 smallholder farmers in Honduras prioritize seven traits of common bean. By recursive partitioning, we identified three regional farmer segments with different preferences.

Our findings suggest that a majority of farmers in three out of four regions prefer increased avoidance of disease-induced crop losses to improvements in productivity or marketability. Both genetic disease resistance and an erect plant architecture, the two most highly ranked traits, contribute to the goal of reducing disease-induced losses. Bad plant architecture means that bean pods tend to be in contact with the moist soil where they are easily infected. In the three regions taken together, *Disease resistance* and *Plant architecture* account for 38.6% of variety preference. This is higher than the expected 28.6% ($^2/_7$) if all traits were given equal priority.

This result does not indicate that farmers have no interest in improvements in marketability and productivity. Rather, farmers are willing to accept the below-average levels in *Yield* and *Market value* that we had defined for the low trait levels. That is, they are willing to forgo gross output or income, for the sake of avoiding genetic worsening in traits related to yield stability (*Pest resistance, Plant architecture*) and culinary quality (*Taste*). As it appears, currently reachable ranges in yield and market price are satisfactory when external conditions are favorable (i.e., no significant disease-induced losses) and varieties can realize their potential. Consequently, farmers do not prioritize genetic improvements in these traits over improvements in traits that contribute to ensuring harvest under adverse conditions.

Trait priorities in Lempira, however, contrast strongly with the results from the other three regions. Details in farming history, climate, and local economy distinguish Lempiran agriculture from farming in the other regions and may explain contrasting priorities. Unlike farmers at the other sites, at the time of research, farmers in Lempira had little experience with cultivating common bean and had generally achieved low yields or strong crop losses, using varieties that had been introduced to the area just few seasons before. In addition, arid climate and low yield levels of other staple crops such as maize and sorghum contribute to lower levels of income and weaker market integration compared with the other research sites. The combination of few years of experience with bean cultivation and low levels of precipitation may have led to low perception of disease risk, while low levels of both farm income and bean yield may have contributed to strong demand for the development of high-yielding, "cash crop" bean varieties.

Comparison of AgroDuos and conjoint analysis

Our use of conjoint analysis confirms the results from AgroDuos. For the full samples of respondents, both methods identified *Disease resistance, Taste*, and *Plant architecture* as the three highest-priority traits, while *Yield* and

Market value play a generally minor role for variety preference at currently attainable levels. Conjoint analysis confirms our observation from AgroDuos that, overall, increased avoidance of disease-induced losses has higher priority than increased gross value potential. Different gender proportions between the two samples did not lead to discrepancies between the two methods. In other studies, women farmers' preferences have been associated more strongly with consumption and processing traits in some cases, while men tended to emphasize productivity (Defoer, Kamara, and De Groote 1997; Oakley and Momsen 2005). In our study, however, we did not observe this pattern, and *Taste* ranked second with either method. Our use of conjoint analysis allows concluding that the design and implementation of AgroDuos indeed generated plausible and useful insights into farmers' priorities in bean breeding.

Insights into the use of AgroDuos

Segmentation of preferences was possible with AgroDuos and revealed strongly diverging priorities by region. This may be crucial information for plant breeders. For example, providing farmers in Lempira new germplasm that was selected or developed based on the aggregate results of the four regions would likely lead to limited impact there.

Segmentation techniques are not unique to the Bradley-Terry model and can be used with stated-choice methods like conjoint analysis, too. Yet one reason for choosing Bradley-Terry models with recursive partitioning during the design process of AgroDuos was that this would also enable partitioning by *continuous* variables, defining splitting points by optimal model improvement (for examples see Strobl, Wickelmaier, and Zeileis 2011; Strobl, Kopf, and Zeileis 2015). Although our data did not allow segmentation of trait priorities by age or household size, in future implementations of AgroDuos and resulting data sets, recursive partitioning may detect segmentation of farmers' varietal preferences by continuous variables, such as farm size, annual farm income, or altitude.

Deciding appropriate levels for the traits included in choice is a crucial element in the design process of AgroDuos. This was shown to be particularly challenging for qualitative traits. For example, many farmers associated "Disease susceptibility" with complete crop loss. As a consequence, their willingness to accept low (but not zero) levels of quantitative traits, such as market price, was high, facing the idea of complete crop loss to diseases. An important lesson from our experiment is that enumerators in AgroDuos will need to "calibrate" trait levels in order to avoid the impression that trait levels correspond to the extremes of a continuum. Changing the phrasing may help, for example, "Low/Medium risk of disease losses" instead of "Tolerant/Susceptible to diseases." Alternatively, it may be useful to quantify risk in a realistic way, for example, “Losing half the harvest if the weather is bad” versus “Losing a quarter of the harvest if the weather is bad.” AgroDuos should use currently typical trait levels as its point of departure because it is intended as a tool for plant breeding and current trait levels are the “baseline”. Therefore, we suggest that in future implementations, the lower trait levels should, wherever possible, be average values, instead of below-average values, as we had used. We expect this approach to reveal farmers’ priorities in breeding more accurately than in our experiment, where farmers had to choose between hypothetical situations that implied genetic improvements of one trait but frequently meant genetic worsening of the other trait.

Engagement of farmers and citizen scientists from local organizations was generally achieved by the provision of playful experience through AgroDuos. In the future, motivation may be enhanced by adding immediate feedback and discussion of basic results. For example, enumerators may identify the two overall most important traits for all participants in an event of data collection with AgroDuos via simple tally counts of wins of each trait in pairwise choices. Ensuing group discussions among AgroDuos players are likely to increase engagement with AgroDuos as well as social capital and may strengthen social relations of enumerators and citizen scientists.

At the current stage, practical use of AgroDuos by non-academic users still faces a number of challenges. Design of the card game required illustrative icons for each of the seven traits, which may be time-intensive and requires skill to generate. While, in theory, the game can be adapted to investigate farmers’ trait priorities for any crop or livestock species, this means a large database of icons will be needed for easy adaptation to the research context. Besides picking and designing icons, correct assignment of front to backsides of playing cards was a critical issue in creating the card deck. We suggest a ready-made online tool could facilitate users’ design and production of their own AgroDuos card set. Here, users would merely pick the traits to be included from a large data bank and add potential custom traits. The platform would suggest trait icons but also let users choose from an icon database and would then generate a printer-ready set of playing cards with all required pairwise choices.

Another restriction relates to statistical analysis. The use of our R script is straightforward for experienced R users, but data cleaning, data import, and dealing with any error messages may pose an obstacle to many non-academic users without investments in training and staff time. Standardized data entry via smartphones or tablet computers (Hartung et al. 2010) and server-based remote data analysis can be a solution. Creating an online service for data analysis, digesting a standardized format, would also enable presenting results by more illustrative Bradley-Terry trees than Figure 2 and increasing the ease of interpretation for science-illiterate users, for example, by dropping p-values, avoiding abbreviations, and placing the names of partitions right above their respective plot. Van Etten et al. (in press) report positive experiences with a three-stage process for citizen science: (i) structured survey design with a user-friendly internet platform, (ii) data collection with mobile devices, and (iii) remote data analysis with the same internet platform. Creating a similar system for AgroDuos involves initial effort but may boost practical usability and empower rural NGOs and farmer organization to implement their own participatory research on breeding priorities.

Conclusions

This study presents the design and application of a novel method for farmer-participatory trait prioritization for plant breeding. In order to speed up variety replacement in the light of restricted resources for research, particularly limiting time-intensive, but vital farmer participation, our objective was to create an easy method that can be implemented by non-academic actors with limited financial resources and that does not require intense training or profound background knowledge. The method should be implementable by farmer organizations or NGOs to inform research on farmers' breeding priorities.

We took inspiration from existing methods to design a simple method that gives robust results and engages participants through gamefulness. By taking decisions in multiple design criteria in creating the new method, we generally achieved our objectives. We found that AgroDuos is replicable, allows rapid and easy data collection, engages participants by providing a fun activity, and leads to sufficiently granular, robust results. It seems that the method does not require lengthy training or detailed skills for successful implementation and can be employed by grassroots organizations to inform breeding. Nonetheless, challenges remain in order to make our prototype truly available for extra-academic, citizen science research. Further effort is required to reduce training needs for the adaptation of the method to local context as well as data analysis.

At its current development stage, probably AgroDuos is best used in combination with other methods in a two-stage process. After defining the most relevant variety traits and respective levels by participatory rural appraisal or other qualitative tools with a small number of households, our method can be used to up-scale farmer-participatory priority setting and account for larger inter-household variability by segmenting preferences by virtually any variable, via recursive partitioning. In the future, the game-like choice structure of AgroDuos may also be used for other uses than plant breeding, such as the targeted introduction of different improved varieties or the prioritization of other agricultural technologies.

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