Product Use Testing in Agriculture

2024-11-26

Contents

Chapter 1

About

Guide for user-centred testing in agriculture

Chapter 2

Introduction to the tricot approach

Jacob van Etten, Jonathan Steinke, Kauê de Sousa

The *tricot* approach (triadic comparison of technology options) is a participatory [van Etten et al., 2016], decentralized method where participants test three randomly assigned options on their use context. Using citizen science, it integrates participatory insights and site-specific data to guide breeding and agricultural innovation. Scalable and cost-effective, tricot empowers farmers and enhances crop diversity and resilience.

2.1 The 10 steps of a tricot experiment

2.1.1 Step 1: Preparation

Researchers define a set of comparable technology options to test. For example, they decide to compare crop varieties with each other, or different fertilizer types, or irrigation technologies. They will provide the necessary materials (inputs or other) to project implementers (organizations that will reach farmers). Typically, about 8-12 technology options (comparable items) are included in the trial to be tested.

2.1.2 Step 2: Design

The implementing organization uses the ClimMob (climmob.net) free online software to design the project. This digital platform has been specifically created to manage tricot projects, from designing the experiment to data collection and analysis. The use of the digital platform streamlines the process. ClimMob offers the following benefits: 1. ClimMob helps to avoid mistakes by introducing

7

QR codes and electronic forms; 2. ClimMob provides a dashboard to monitor progress; 3. ClimMob reduces or eliminates the effort spent on digitalizing data collected on paper; 4. ClimMob creates automatic reports with analytical results, avoiding the usual lengthy process of data cleaning and analysis; 5. ClimMob provides clean, formatted data that can be easily downloaded for further analysis with existing tools, for example, combining with weather data. The tricot project will only work well if ClimMob is used from the very start and implementers are trained in its use. After designing the project, the implementers prepare trial packages, which include experimental quantities of three randomly selected technology options generated by the ClimMob platform.

2.1.3   Step 3: Recruitment

The implementers recruit dedicated farmers interested in improving their farming through the use of new technologies.

2.1.4   Step 4: Distribution

Farmers are trained in the tricot approach and on how to collect data. Each farmer receives a trial package of three technologies to be tested.

2.1.5   Step 5: Execution

Farmers use their trial packages to apply the new technology options separately, on small plots next to each other, in a mini-trial on their own farm. To avoid any bias, they are not aware of the names of the crop varieties or other technology options they are testing. These are revealed to them only after the data has been collected.

2.1.6   Step 6: Observation

Every farmer is responsible for their own trial and makes various easy observations about their three options over the course of the season. For example: Which variety had the highest or the lowest yield? The farmers record these observations on an observation card.

2.1.7   Step 7: Compilation

The local designated field agents collect and compile the observation data from the tricot farmers, either in person or by phone. They record the information digitally and send them on to the implementing organization. For this, they can use the free 'ODK Collect' smartphone app, which is connected to the ClimMob software.

2.1.8 Step 8: Analysis

The implementers compile and analyze the data from the trials, using the ClimMob online software, to identify which technology options showed the best performance and under which conditions.

2.1.9 Step 9: Feedback

The implementers provide feedback to every participating farmer: the names of their three technology options, which options were most suited to their farm (out of the three options tried by them and out of all the options tried by farmers throughout the project), and where to obtain them.

2.1.10 Step 10: Evaluation

Tricot is an iterative process: after every project cycle, researchers, implementers and farmers collaboratively evaluate how the process may be improved in the next cycle.

Chapter 3

Planning a tricot experiment

3.1 Problem Identification

- Defining research questions and objectives.
- Understanding the target farming system.

3.2 Stakeholder Engagement

- Roles of researchers, extension agents, local facilitators, and farmers.
- Building partnerships (e.g., with NGOs, genebanks, seed companies).

3.3 Resources and Budgeting

- Required materials (e.g., seeds, observation tools, digital platforms).
- Time and financial planning.

Chapter 4

Standard operaring procedures

Marie-Angélique Laporte, Almendra Cremaschi

An experimental protocol provides a standardised overview of the basic information that will be collected during a crop tricot trial. The protocol provides an overview of the data collection moments during the trials and the variables and traits collected at each data collection moment. Farmers evaluate varieties in their on-farm trials and provide comparative observations by ranking the varieties based on their performance throughout their growth and post-harvest qualities including taste and consumption preferences.

Chapter 5

Socio-economic sampling

Béla Teeken, Jill Cairns

5.1 Assuring experienced participants

A common weakness in standard participatory variety selections is that farmers are chosen without eye for their experience and the specific work they are doing and to which local social category they belong. Where this is considered usually very broad general categories are used such as age and sex., occupation, level of education, farm size. Furthermore, when gender is brought in focus, the practice is mainly on having both men and women farmers in equal numbers evaluating the trials, disregarding their specific expertise or experience in farming. Another problem is that often farmers get chosen who feel comfortable talking and interacting within the sphere of a scientific evaluation, which emphasizes experience in reasoning and talking. This often excludes very skilled persons that however are not able or are normatively not allowed to communicate these skills and knowledge through language. But even if the respondent is good at talking it still does not include the tacit knowledge, the embodied skill and knowledge that people have. Breeders are however interested in detailed concrete hands-on information if they want to align with a demand led breeding approach such as the stage gate breeding approach that is now introduced in the CGIAR public sector breeding. Within the current reform to a stage gate breeding approach it is also crucial to get feedback from not only farmers but also processors/prepares and marketers who turn the RTB crop into an edible quality food product.

To overcome these issues while choosing the TRICOT participants, we therefore work with a so-called purposive sampling using a task group approach with an explicit gender dimension. This gender dimension is not only important within the light of gender equity but is also very practical and concrete if we want to

15

know the expertise and experience people have with regards to work related to the RTB corps because often tasks related to the RTB crop are gendered: certain tasks are often carried out be a specific sex. Important to note here is that a task group is not necessarily a group that works together but a category of people of the same social segment that carry out similar tasks related to the crop. A task group approach is also in line with a much more performative way of participation instead of only a deliberative one (Richards, 2007) . In such a performative approach people who are verbally not strong or are not allowed to speak up are included and approached more self-evidently and tacitly, because they have been identified as a specific task group within a locally defined and thus relevant social group or intersection of different groups.

From a demand led perspective breeders are interested in good information on the suitability of improved varieties within the livelihoods of the users and therefore want to know the user preferred crop characteristics. To get good information it is therefore important to get this from experienced people that are skilled in farming but also with regards to processing of the crop into the food products and their quality as well as the marketing of the crop. Importantly storability of food products as well as fresh roots tubers and bananas are important in the last instance. E.g if men are are hardly involved into processing cassava into gari , a breeder will not be interested much in men's preferences with relation to processing because they will not always be able to give correct hands on experience-based knowledge because they do not possess the skill. Men in this case might have indirect knowledge about it (e.g. through their spouses), but certainly not the embodied skills.

A bad example of how participants got chosen is a farce case where someone wanted to work with mango farmers and ended up with only male participants of which non had a mango tree field. When later confronting these participants with this, the village chief and his friends all claimed to have a mango tree in their backyard. It is obvious that a tricot with such participants will not yield the best information.

Locally Relevant Social Group*	Share of Local Population (oral or record share) [B1.4a]	Language (record language) [B1.4b]	Associated Livelihood(s) or Crops [B1.4c]	Tasks Related to Cassava (Women)	Tasks Related to Cassava (Men)	Better Off Group(s) (Yes=1, No=2) [B1.4d]	Politically Active & Influential Group(s)? (Yes=1, No=2) [B1.4e]
i. Ilaje (originally from Ondo state)	1000	Yoruba dialect	Fishing, selling of fish			2	2
ii. Agatu (Immigrants from Benue state)	500	Agatu	Farming (subsistence and cash crops), farm labourer. Includes cassava	Farming (weeding, harvesting), processing, marketing	Farming (weeding, planting, harvesting), marketing of fresh roots	2	2
iii. Markurdi (Immigrants from Benue state)	100	Tiv/Igede	Farming (subsistence and cash crops), farm labourer. Includes cassava	Farming (weeding), processing, marketing	Farming, marketing of fresh roots	2	2
iv. Hausa	10	Hausa	Trading, fishing			2	2

Locally Relevant Social Group*	Share of Local Population (oral or record share) [B1.4a]	Language (record language) [B1.4b]	Associated Livelihood(s) or Crops [B1.4c]	Tasks Related to Cassava (Women)	Tasks Related to Cassava (Men)	Better Off Group(s) (Yes=1, No=2) [B1.4d]	Politically Active & Influential Group(s)? (Yes=1, No=2) [B1.4e]
v. Cotonou (Immigrants from Benin republic)	50	Fon/Ewe	Farming (subsistence and cash crops), particularly cultivate vegetables, tomatoes, and peppers. Includes cassava	Farming (planting, weeding), processing, marketing	Farming and occasional processing	2	2
vii. Fulani	150	Fululde	Cattle rearing			2	2
viii. Yoruba	18145	Yoruba	Farming (food and cash crops), trading. Includes cassava	More of processing, some farming (weeding), firm marketing	Farming, marketing of fresh roots	1	1

Chapter 6

Geographic sampling

Joost van Heerwaarden, Jacob van Etten

Chapter 7

Target product profiles

Chapter 8

ClimMob software suite

Brandon Madriz, MrBot Software

8.1 Introduction to ClimMob

8.2 Data collection and submission

Chapter 9

Implementation

Setting up experiments. For OFT, best practices in planting and maintaining the plots. For consumer testing, best practices in handling the samples. Preparing the packages for distribution.

Chapter 10

Feedback and dissemination

Feedback session to participants. Follow up and reporting.

Chapter 11

Data analysis

11.1 Integrating farmer-generated data and agro-climatic data for crop variety selection"

In this example, we demonstrate a possible workflow to assess crop variety performance using decentralized on-farm testing data generated with the tricot approach [de Sousa et al., 2024]. We use the `nicabean` dataset, which was generated with decentralized on-farm trials of common bean (*Phaseolus vulgaris* L.) varieties in Nicaragua over five seasons (between 2015 and 2016). Following the tricot approach, farmers tested three randomly assigned varieties of common bean on their farms as incomplete blocks of size three (from a set of 10 varieties). Farmers assessed which of the three varieties had the best and worst performance in eight traits (vigor, architecture, resistance to pests, resistance to diseases, tolerance to drought, yield, marketability, and taste). Additionally, farmers provided their overall appreciation of the varieties, i.e., which variety had the best and worst performance overall, considering all the traits.

Here, we use the Plackett-Luce model, jointly proposed by Luce (1959) [Luce, 1959] and Plackett (1975) [Plackett, 1975]. This model estimates the probability of one variety outperforming all others (worth) for a given trait, based on Luce's axiom [Luce, 1959]. The model is implemented in R by Turner et al. (2020) with the PlackettLuce package [Turner et al., 2020].

The `nicabean` dataset is a list with two data frames. The first, `trial`, contains trial data with farmers' evaluations ranked from 1 to 3, with 1 being the highest-ranked variety and 3 the lowest-ranked variety for a given trait and incomplete block. These rankings were previously transformed from tricot rankings (where participants indicate the best and worst) to ordinal rankings using the function `rank_tricot()`. The second data frame, `covar`, contains the covariates

associated with the on-farm trial plots and farmers. This example requires the PlackettLuce, climatrends, chirps, and ggplot2 packages.

To begin the analysis, we transform the ordinal rankings into Plackett-Luce rankings (a sparse matrix) using the `rank_numeric()` function. We iterate over the traits and add the rankings to a list called R. Since the varieties are ranked in ascending order (1 being the highest and 3 the lowest), we use the argument `ascending = TRUE`.

11.1.1   Correlation between overall appreciation and the other traits

Using the function `kendallTau()`, we can compute the Kendall tau (τ) coefficient [Kendall, 1938] to identify the correlation between farmers' overall appreciation and the other traits in the trial. This approach can be used, for example, to assess the drivers of farmers' choices or to prioritize traits for testing in the next stage of tricot trials (e.g., a simplified version of tricot with no more than four traits to assess). We use overall appreciation as the reference trait and compare the Kendall tau values with those of the other eight traits.

The Kendall correlation indicates that farmers prioritized the traits yield ($\tau = 0.749$), taste ($\tau = 0.653$), and marketability ($\tau = 0.639$) when assessing overall appreciation.

11.1.2   Performance of varieties across traits

For each trait, we fit a Plackett-Luce model using the function `PlackettLuce()` from the package of the same name. This enables us to continue analyzing the trial data using other functions available in the gosset package.

The `worth_map()` function provides a visual tool to assess and compare variety performance across different traits. The values represented in a worth map are *log-worth* estimates. From a breeder or product developer perspective, the function `worth_map()` is a valuable tool for identifying variety performance across multiple traits and selecting crossing materials.

11.1.3   The effect of rainfall on yield

To examine the effect of climate factors on yield, we incorporate agro-climatic covariates into a Plackett-Luce tree model. For simplicity, we use total rainfall (Rtotal) derived from CHIRPS data [Funk et al., 2015], accessed in R through the `chirps` package [de Sousa et al., 2020a]. Additional covariates, such as temperature, can also be incorporated into a Plackett-Luce tree using packages like `ag5Tools` [Brown and de Sousa, 2022] or `nasapower` [Sparks, 2018] as proposed by the studies of van Etten et al. (2019) [van Etten et al., 2019], de Sousa et al. (2021) [de Sousa et al., 2021] and Brown et al. (2022) [Brown et al., 2022].

The CHIRPS data is requested via the `chirps` package, and the returned data should be formatted as a matrix. Note that this process may take several minutes to complete.

We compute the rainfall indices for the period from the planting date to the first 45 days of plant growth using the `rainfall()` function from the climatrends package [de Sousa et al., 2020b].

To link the rankings to covariates, they must be coerced into a 'grouped_rankings' object. This is done using the `group()` function from the PlackettLuce package. For this example, we retain only the rankings corresponding to yield.

Now we fit a Plackett-Luce tree with the climate covariates.

The following is an example of the plot generated using the `plot()` function in the gosset package. The functions `node_labels()`, `node_rules()`, and `top_items()` can be used to identify the splitting variables in the tree, the rules applied at each split, and the top-performing items in each node.

11.1.4 Reliability of superior varieties

The function `reliability()` can be used to compute the reliability estimates [Eskridge and Mumm, 1992] of the evaluated common bean varieties in each of the resulting nodes of the Plackett-Luce tree. This helps identify varieties with a higher probability of outperforming a variety check (Amadeus 77). For simplicity, we present only the varieties with a reliability score ≥ 0.5.

The results show that three varieties marginally outperform Amadeus 77 under drier growing conditions (Rtotal ≤ 193.82 mm), while two varieties demonstrate superior yield performance under higher rainfall conditions (Rtotal > 193.82 mm) compared to the reference. This approach is valuable for identifying superior varieties tailored to different target population of environments.

For instance, the variety ALS 0532-6 exhibits weak performance in the overall yield ranking but outperforms all others in the subgroup with higher rainfall conditions. Combining rankings with socio-economic covariates could further enhance the identification of superior varieties for specific market segments, as proposed by Voss et al. (2024) [Voss et al., 2024]

11.1.5 Going beyond yield

A more comprehensive approach to assessing the performance of varieties involves using "overall appreciation," as this trait is expected to capture the performance of a variety not only for yield but also for all other traits prioritized by farmers. To support this hypothesis, we use the `compare()` function, which applies the method proposed by Bland and Altman (1986) [Bland and Altman, 1986] to assess the agreement between two different measures. Here, we compare overall appreciation and yield. If both measures completely agree, all the varieties should be centered at 0 on the Y-axis.

The chart reveals no complete agreement between overall appreciation and yield. For instance, variety SX 14825-7-1 exhibits superior performance for overall appreciation compared to yield. By examining the *log-worth* estimates in the worth map, we can argue that the superior performance of this variety is likely influenced by traits such as taste, marketability, and disease resistance. However, these aspects were not captured when assessing yield alone.

11.1.6   Conclusion

This vignette demonstrates a detailed workflow for analyzing tricot data in the context of on-farm testing trials. By integrating farmers' evaluations, agro-climatic covariates, and trait-specific performance metrics, the analysis provides valuable insights into the performance and adaptability of bean varieties across diverse environmental and socio-economic contexts.

Key findings reveal that while yield remains a critical trait, other traits such as taste, marketability, and disease resistance significantly influence farmers' overall appreciation of varieties. The use of Kendall correlation highlighted the traits most strongly associated with farmers' preferences, while the worth maps and Plackett-Luce models provided a clear visualization of variety performance across traits. Furthermore, the analysis of rainfall effects using Plackett-Luce trees underscored the importance of agro-climatic factors in determining the relative performance of varieties, enabling the identification of genotype-by-environment interactions.

The vignette also emphasizes the value of using "overall appreciation" as a comprehensive indicator of variety performance. Comparing this measure with yield alone demonstrated the limitations of focusing exclusively on yield, as traits such as taste and marketability can significantly enhance variety appeal.

Finally, the reliability analysis and tree-based exploration of rainfall effects provide insights for breeding programs and product development. These tools enable researchers and practitioners to identify superior varieties tailored to specific target population of environments and market needs. By combining statistical rigor with participatory approaches, this workflow supports more effective and farmer-centric decision-making in crop improvement.

This vignette illustrates how decentralized data, participatory methods, and advanced statistical models can work together to enhance breeding and selection strategies for common bean and other crops.

Chapter 12

Stories

Chapter 13

Appendices

13.1   On-farm testing protocol

Bibliography

J. Martin Bland and DouglasG. Altman. Statistical methods for assessing agreement between two methods of clinical measurement. *The Lancet*, 327 (8476):307–310, February 1986. doi: 10.1016/s0140-6736(86)90837-8. URL https://doi.org/10.1016/s0140-6736(86)90837-8.

David Brown and Kauê de Sousa. *ag5Tools: Toolbox for Downloading and Extracting Copernicus AgERA5 Data*, 2022. URL https://agrdatasci.github. io/ag5Tools/. R package version 0.0.2.

David Brown, Sytze de Bruin, Kauê de Sousa, Amílcar Aguilar, Mirna Barrios, Néstor Chaves, Marvin Gómez, Juan Carlos Hernández, Lewis Machida, Brandon Madriz, Pablo Mejía, Leida Mercado, Mainor Pavón, Juan Carlos Rosas, Jonathan Steinke, José Gabriel Suchini, Verónica Zelaya, and Jacob van Etten. Rank-based data synthesis of common bean on-farm trials across four central american countries. *Crop Science*, 62(6):2246–2266, October 2022. ISSN 1435-0653. doi: 10.1002/csc2.20817. URL http://dx.doi.org/10.1002/csc2.20817.

Kauê de Sousa, Jacob van Etten, Jesse Poland, Carlo Fadda, Jean-Luc Jannink, Yosef Gebrehawaryat Kidane, Basazen Fantahun Lakew, Dejene Kassahun Mengistu, Mario Enrico Pè, Svein Øivind Solberg, et al. Data-driven decentralized breeding increases prediction accuracy in a challenging crop production environment. *Communications biology*, 4(1):1–9, 2021.

Kauê de Sousa, Jacob van Etten, Rhys Manners, Erna Abidin, Rekiya O. Abdulmalik, Bello Abolore, Kwabena Acheremu, Stephen Angudubo, Amilcar Aguilar, Elizabeth Arnaud, Adventina Babu, Mirna Barrios, Grecia Benavente, Ousmane Boukar, Jill E. Cairns, Edward Carey, Happy Daudi, Maryam Dawud, Gospel Edughaen, James Ellison, Williams Esuma, Sanusi Gaya Mohammed, Jeske van de Gevel, Marvin Gomez, Joost van Heerwaarden, Paula Iragaba, Edith Kadege, Teshale M. Assefa, Sylvia Kalemera, Fadhili Salum Kasubiri, Robert Kawuki, Yosef Gebrehawaryat Kidane, Michael Kilango, Heneriko Kulembeka, Adofo Kwadwo, Brandon Madriz, Ester Masumba, Julius Mbiu, Thiago Mendes, Anna Müller, Mukani Moyo, Kiddo Mtunda, Tawanda Muzhingi, Dean Muungani, Emmanuel T. Mwenda, Ganga Rao V. P. R. Nadigatla, Ann Ritah Nanyonjo, Sognigbé N'Danikou, Athanase Nduwumuremyi, Jean Claude Nshimiyimana, Ephraim

Nuwamanya, Hyacinthe Nyirahabimana, Martina Occelli, Olamide Olaose-bikan, Patrick Obia Ongom, Berta Ortiz-Crespo, Richard Oteng-Fripong, Alfred Ozimati, Durodola Owoade, Carlos F. Quiros, Juan Carlos Rosas, Placide Rukundo, Pieter Rutsaert, Milindi Sibomana, Neeraj Sharma, Nestory Shida, Jonathan Steinke, Reuben Ssali, Jose Gabriel Suchini, Béla Teeken, Theophilus Kwabla Tengey, Hale Ann Tufan, Silver Tumwegamire, Elyse Tuyishime, Jacob Ulzen, Muhammad Lawan Umar, Samuel Onwuka, Tessy Ugo Madu, Rachel C. Voss, Mary Yeye, and Mainassara Zaman-Allah. The tricot approach: an agile framework for decentralized on-farm testing supported by citizen science. a retrospective. *Agronomy for Sustainable Development*, 44 (1), January 2024. ISSN 1773-0155. doi: 10.1007/s13593-023-00937-1. URL http://dx.doi.org/10.1007/s13593-023-00937-1.

Kauê de Sousa, Adam H. Sparks, William Ashmall, Jacob van Etten, and Svein Ø. Solberg. chirps: API Client for the CHIRPS Precipitation Data in R. *The Journal of Open Source Software*, 5(51):2419, 2020a. doi: 10.21105/joss.02419. URL https://doi.org/10.21105/joss.02419.

Kauê de Sousa, Jacob van Etten, and Svein Ø. Solberg. *climatrends: Climate Variability Indices for Ecological Modelling*, 2020b. URL https://CRAN.R-project.org/package=climatrends. R package version 0.2.

K. M. Eskridge and R. F. Mumm. Choosing plant cultivars based on the probability of outperforming a check. *Theoretical and Applied Genetics*, 84(3): 494–500, July 1992. ISSN 1432-2242. doi: 10.1007/BF00229512. URL https://doi.org/10.1007/BF00229512.

Chris Funk, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, James Rowland, Laura Harrison, Andrew Hoell, and Joel Michaelsen. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2:150066, dec 2015. doi: 10.1038/sdata.2015.66. URL http://dx.doi.org/10.1038/sdata.2015.66.

M. G. Kendall. A new measure of rank correlation. *Biometrika*, 30(1-2):81–93, 06 1938. ISSN 0006-3444. doi: 10.1093/biomet/30.1-2.81. URL https://doi.org/10.1093/biomet/30.1-2.81.

R. Duncan Luce. *Individual Choice Behavior*. Courier Corporation, 1959.

R. L. Plackett. The Analysis of Permutations. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 24(2):193–202, 1975.

Adam H Sparks. nasapower: A nasa power global meteorology, surface solar energy and climatology data client for r. *The Journal of Open Source Software*, 3(30):1035, oct 2018. doi: 10.21105/joss.01035.

Heather L Turner, Jacob van Etten, David Firth, and Ioannis Kosmidis. Modelling rankings in R: the PlackettLuce package. *Computational Statistics*,

2020. ISSN 1613-9658. doi: 10.1007/s00180-020-00959-3. URL https://doi.org/10.1007/s00180-020-00959-3.

Jacob van Etten, Eskender Beza, Lluís Calderer, Kees Van Duijvendijk, Carlo Fadda, Basazen Fantahun, Yosef Gebrehawaryat Kidane, Jeske Van De Gevel, Arnab Gupta, Dejene Kassahun Mengistu, D. A. N. Kiambi, Prem Narain Mathur, Leida Mercado, Sarika Mittra, Margaret J. Mollel, Juan Carlos Rosas, Jonathan Steinke, Jose Gabriel Suchini, and Karl S. Zimmerer. First experiences with a novel farmer citizen science approach: crowdsourcing participatory variety selection through on-farm triadic comparisons of technologies (tricot). *Experimental Agriculture*, 55(S1):275–296, 2016. doi: 10.1017/S0014479716000739.

Jacob van Etten, Kauê de Sousa, Amílcar Aguilar, Mirna Barrios, Allan Coto, Matteo Dell'Acqua, Carlo Fadda, Yosef Gebrehawaryat, Jeske van de Gevel, Arnab Gupta, Afewerki Y. Kiros, Brandon Madriz, Prem Mathur, Dejene K. Mengistu, Leida Mercado, Jemal Nurhisen Mohammed, Ambica Paliwal, Mario Enrico Pè, Carlos F. Quirós, Juan Carlos Rosas, Neeraj Sharma, S. S. Singh, Iswhar S. Solanki, and Jonathan Steinke. Crop variety management for climate adaptation supported by citizen science. *Proceedings of the National Academy of Sciences*, 116(10):4194–4199, feb 2019. ISSN 0027-8424. doi: 10.1073/pnas.1813720116. URL http://www.pnas.org/lookup/doi/10.1073/pnas.1813720116.

Rachel C. Voss, Kauê de Sousa, Sognigbé N'Danikou, Abdul Shango, Lys Amavi Aglinglo, Marie-Angélique Laporte, Eric C. Legba, Aristide Carlos Houdegbe, Danfing dit Youssouf Diarra, Aminata Dolo, Amadou Sidibe, Colette Ouedraogo, Harouna Coulibaly, Enoch G. Achigan-Dako, Aishi Kileo, Dickson Malulu, Zamira Matumbo, Fekadu Dinssa, Joost van Heerwaarden, Jacob van Etten, Amritbir Riar, and Maarten van Zonneveld. Citizen science informs demand-driven breeding of opportunity crops. July 2024. doi: 10.1101/2024.07.31.605211. URL http://dx.doi.org/10.1101/2024.07.31.605211.