Chapter 11
Generating Farm-Validated Variety Recommendations for Climate Adaptation

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11.1 Introduction

Choice of crop varieties plays an important role in climate adaptation (Ceccarelli et al. 2010). One of the most important options farmers have to adapt arable farming to future climates is adjusting the crop varieties they use to new climates as they emerge (IPCC 2014). Also, a portfolio of two or more varieties can substantially buffer the impact of climate variation between seasons (Nalley and Barkley 2010; Di Falco et al. 2007).

Several barriers, however, stand in the way of a more effective use of intra-specific crop diversity for climate adaptation. Variety recommendations are often based on station trial data—hardly reflecting variety performance in low-input agriculture—and are seldom based on climate analysis (Abay and Bjørnstad 2009). This means farmers often reject the new varieties they try because of poor performance (Ceccarelli and Grando 2007). In addition, many varieties are released based on their potential for broad adaptation. This approach offers a good average potential yield over many localities but will not maximise yield at any given place (Ceccarelli and Grando 2007). In addition, breeding rarely relies on genebank material, focusing instead on elite varieties with limited allelic diversity. Genebanks hold thousands of varieties of major crops that have (co-)evolved under natural and human selection for thousands of years and have the potential to host alleles for adaptation to various biotic and abiotic stresses (Vavilov and Dorofeev 1992). Yet, these promising, diverse materials are rarely used. Introducing sets of diverse materials into areas where modern varieties have not yet made an impact is a possible first step in

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support of climate adaptation. This does not only serve to identify initial populations for breeding programmes, but can also identify farmers varieties (or varieties bred for other areas) that may prove superior and can therefore be disseminated directly. For example, in Ethiopia we found in a durum wheat trial that the best farmer variety outperformed the best modern variety with a yield difference of 20% (Mengistu et al. 2018).

The use of improved or modern varieties (MVs) has limitations in Africa (Salami et al. 2010). MVs often require a high quantity of external inputs to fulfil their potential. On African low-input farms in high-risk areas, landraces may be chosen over MVs by local farmers because of their better adaptation, higher market value and better end-product quality (Ceccarelli et al. 2010). In addition, the cultivation of a small set of MVs over large areas lowers the genetic diversity at a landscape scale, with detrimental effects on the resilience of agro-ecosystems (Cabell and Oelofse 2012).

At present, both public and private efforts fail to insert varietal diversity for climate adaptation into local farming systems in a rational way (Ceccarelli 2015). On-farm testing is crucial to determine farmer knowledge and preferences (Mancini et al. 2017). Such tests can also identify suitable germplasm for breeding and can be linked to improved dissemination of the genetic material to local communities through more efficient seed systems (Thomas et al. 2012). Current on-farm testing is usually done with a limited set of elite materials, which are compared to the current market-leader variety. These trials require constant attention from technical personnel. As a result, the testing is relatively costly, especially in marginal areas where technical personnel must travel long distances. These trials are therefore kept relatively small and thus have limited statistical power. In some cases no formal statistical inference is done, and decisions are made based on tallies of farmer votes and simple averages of yield data. These trials allow the release of a small number of varieties backed by limited evidence of their value under farm conditions (Abay and Bjørnstad 2009).

For climate adaptation of African smallholder agriculture, a different approach is needed. The best approach would be a hybrid system in which the quantitative aspects of conventional trials are combined with the benefits of participatory on-farm methods. This would ensure that a diverse range of useful genetic material reaches farmers. A system in which farmers play a more active role would accelerate genetic gain and access to variety diversity, thus contributing to system resilience (Badstue et al. 2012).

In this chapter, we present a possible solution to a number of the problems of on-farm trials: the triadic comparisons of technologies, or “tricot”. Following a citizen science philosophy, this approach increases farmer ownership of trials and uses smart, simple data collection formats to help scale on-farm testing (van Etten et al. 2016). The tricot approach involves cost-effective, large-scale, repeated participatory evaluation of varieties under farm conditions using novel material from national gene banks or other sources (advanced lines from breeding programmes, varieties bred for other areas). Van Etten et al. (2016) provide a detailed discussion on how the tricot approach simultaneously builds on and differs from previous participatory approaches in crop improvement. The approach was designed to overcome a number of specific challenges in participatory crop improvement, including the need for scaling, cost reduction, data standardisation, and taking into account heterogeneity in environments and farmer preferences.

The tricot approach is especially suited for climate adaptation. Combining the resulting geo-referenced variety evaluation data with environmental data and climatic data, the approach distinguishes different responses of crop varieties to seasonal climatic conditions. The data can then be translated into concrete variety recommendations that reflect current farm conditions, stabilise yields, and track climate change over time. We illustrate the approach with an example, using simulated (yet realistic) data.

11.2 Analyzing Data from On-Farm Trials Using the Tricot Approach

We performed a series of simple simulations to illustrate the methods and results of the tricot approach. In our simulation we use realistic data that mimic the data collected in a number of countries, including India, Nicaragua, Honduras and Ethiopia. Farmers provide feedback based on different traits. These traits are selected together with farmers and technical personnel in focus groups. The traits can include yield, pest and disease resistance, phenological characteristics, plant vigour and more.

In the trials, each farmer receives three different varieties and is trained on how to set up the experiment in terms of plot layout and management. They plant the seeds, and, as the crop grows, they rank the varieties for each of the traits. Farmers do not know the names of the varieties in their set, which are randomly allocated to them from a larger portfolio, generally at least 10–20 per trial, at times previously selected from a much larger set—up to 400 in a recent application in Ethiopia (Mancini et al. 2017). Farmers are asked to fill out the forms during the season based on the traits they are evaluating. At the end of the season, farmers complete the forms by providing their assessments of productivity and the quality of the final product, as well as an overall performance judgment (Steinke and Van Etten 2016; Van Etten et al. 2016). The entire process is supported by the digital platform ClimMob (http://climmob.net/), which takes the user through a structured process of trial design, electronic data collection, analysis and automatic reporting.

The overall performance of crop varieties was analysed using Plackett-Luce trees, using R software (Hothorn and Zeileis 2015; Zeileis et al. 2008; Turner et al. 2018). Publicly available soil and climate data can be linked to the trial dataset by using location data (latitude and longitude) and the planting date of each farm. The Plackett-Luce model can use these data to distinguish between groups of environments with different patterns of variety performance.

We simulated two examples. In each, 500 farmers ranked a set of 3 varieties taken from a set of 20 varieties. Varieties are assigned in a randomised and balanced

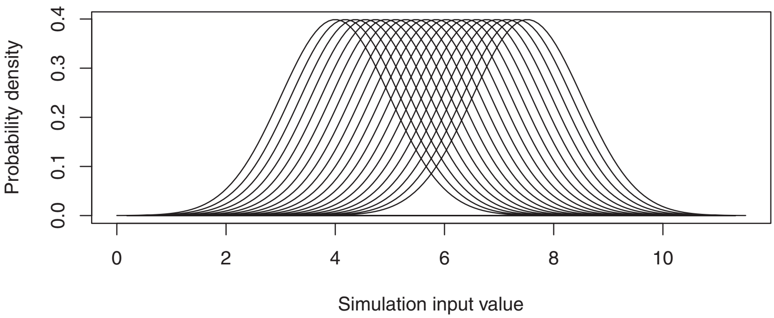

Fig. 11.1 Probability distributions used for the simulation for 20 varieties. Normal distributions with standard deviation of 1 and means separated by an interval of 0.185 (value from Steinke et al. 2017 for "challenging trait")

way. In Example 1, farmers draw random values from a normal distribution separated by a small interval and rank the varieties based on these values (see Fig. 11.1). This simulates the error that farmers make, following our findings on the accuracy of farmer observations in these trials for a relatively difficult trait (Steinke et al. 2017). An interesting feature of this ranking approach is that it also works for more elusive traits that depend on farmers' preferences, such as the taste of the product or farmers' overall evaluation of each variety, which is eventually what determines variety adoption.

In Fig. 11.2, the results of the first simulation can be seen. The original input values of the simulation are on the x axis and the Plackett-Luce model estimates are on the y axis. As the graph shows, the PL model is able to reconstruct the values very closely, with a correlation of 0.994 with the original values. In a few cases, the model does not retrieve the right order. Variety 13 is ranked lower than Variety 12 and Variety 18 is ranked lower than Variety 17. In other words, only 10% of the varieties are shifted by one position. There is very little information loss. However, there are important features that reveal the limitations of the PL model. The y scale represents the log-odds of winning from Variety 1, the variety arbitrarily chosen as our reference. The scale of the model parameters does not have an absolute zero. Variety 1 has a parameter value of zero, but any other variety can be chosen as the reference variety. In reality the underlying mean value for Variety 1 is 4. The original value cannot be retrieved from the model. In other words, the index given by the PL model has a meaning only relative to the other varieties, even though there is a strong linear relationship with the underlying latent variable.

In Example 2, we added a complication in that 250 of the 500 farmers experienced a drought condition, which made two varieties increase their mean. However, there is also an error in the measurement of the drought condition. We then applied a Plackett-Luce tree model to this artificial dataset, to visualise how it distinguishes between the two groups of farmers and their variety rankings. Also, we show how to derive variety recommendations from the model outputs to respond to climate risk.

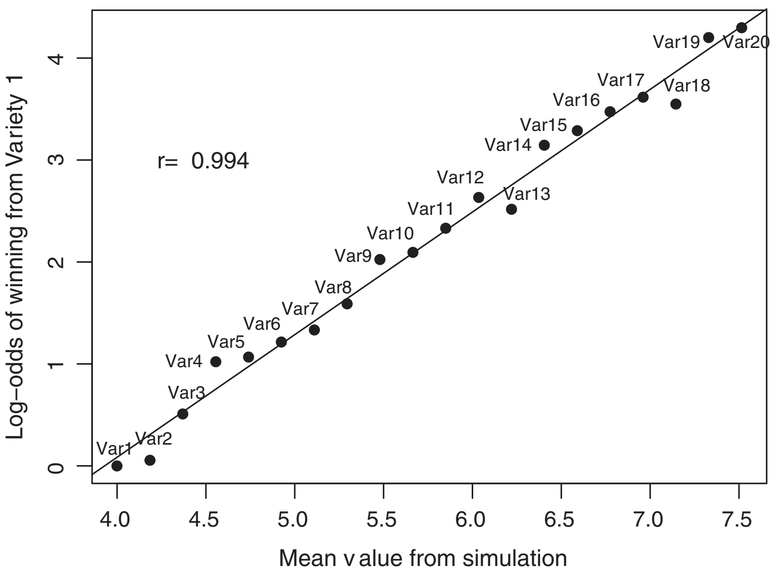

Fig. 11.2 Results of Example 1. Relation between simulation input values and Plackett-Luce output values. Based on a simulation of 500 farmers, each ranking 3 varieties out of a set of 20

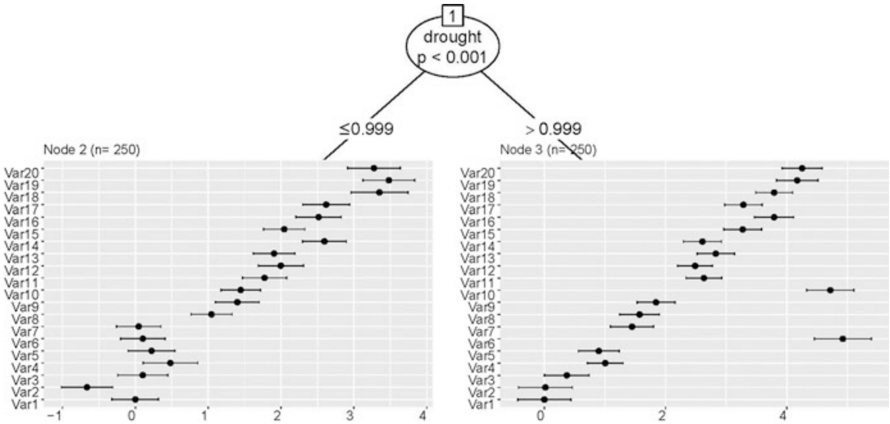

Fig. 11.3 Results of Example 2. Half of the farmers were selecting under a drought condition, in which Varieties 6 and 10 excelled. The Plackett-Luce tree distinguishes correctly between the two groups

In Fig. 11.3, we show the results of a Plackett-Luce tree, applied on data with a covariate representing seasonal rainfall. The Plackett-Luce tree determines how to use the drought variable to split the data.

In real analyses, we derive covariates from a geospatial weather dataset, using the GPS point of each farm and the planting date to retrieve data from the right place and time. We then generate multiple variables from these data (number of consecutive dry days, number of days with temperature above a certain threshold, total rainfall accumulated, etc.). We also use variables related to the terrain and soil. The Plackett-Luce model picks the best predictor and determines the best point where to split the data (for example, making a group with less than four consecutive dry days and another group with more than 4 days).

In our second example, the model splits the set of farmers in two equal groups. In the simulation, 250 farmers were assigned to each condition. It correctly identifies the drought resistant varieties—Varieties 6 and 10—which jump out in the right part of the graph. The graph also shows 95% confidence intervals around the parameter estimations, which give an idea of the certainty we have that the varieties are really different.

The results of our simulation illustrate how the tricot approach can distinguish between different varieties and has the power to evaluate the variety by climatic conditions. In a simulation of different environmental conditions, it is clear that the performance of the different varieties varies based on those basic climatic conditions. This influences the evaluation of the farmers, who provide different feedback.

11.3 Deriving Variety Recommendations from On-Farm Trials

The outputs from the Plackett-Luce model and the Plackett-Luce tree are shown on a log-scale in reference to winning from a particular variety. These values are a bit abstract, but as shown in Fig. 11.2, the values are linearly related to the underlying trait values. The PL model can also produce probabilities of winning from all other varieties for each of the varieties, which are easier to interpret. These values can be used to construct portfolios of varieties.

We illustrate variety portfolio construction with an example. To construct robust portfolios, we use theory from financial asset management, adapting the method of Dembo and King (1992) to relative losses (probabilities of being the best). The method is closely related to Conditional Value at Risk (Testuri and Uryasev 2004). This is a state-of-the-art metric now widely used in banks, which was previously applied by Sukcharoen and Leatham (2016) to variety portfolio construction.

For simplicity, we focus on a smaller example, with four varieties in two seasonal climate scenarios. In Table 11.1 we show a possible output from a Plackett-Luce tree, which can be interpreted as a payoff matrix for the construction of robust portfolios.

We generated another table from this, Table 11.2, showing the relative opportunity loss. We obtained these values by dividing the values by the highest value in each column, to first get the so-called competitive ratio. We subtract the competitive ratio from 1 to get relative opportunity loss values. Different types of seasonal

Table 11.1 Imaginary example of probability of winning from all other varieties for two different seasonal climate scenarios

Variety	Dry (P = 0.6)	Wet (P = 0.4)
Var1	0.30	0.25
Var2	0.27	0.27
Var3	0.25	0.25
Var4	0.18	0.23

Table 11.2 Relative opportunity loss of each variety in each seasonal climate

Variety	Dry (P = 0.6)	Wet (P = 0.4)
Var1	1–0.30/0.30 = 0.00	1–0.25/0.27 = 0.07
Var2	1–0.27/0.30 = 0.10	1–0.27/0.27 = 0.00
Var3	1–0.25/0.30 = 0.17	1–0.25/0.27 = 0.07
Var4	1–0.18/0.30 = 0.40	1–0.23/0.27 = 0.15

Table 11.3 Regret calculation for a portfolio of 50% Variety 2 and 50% Variety 3

Variety	Dry (P = 0.6)	Wet (P = 0.4)	Expected regret
Var2 (0.5 share)	0.6 * (0.10 * 0.5)2 = 0.0015	0.4 * (0.00 * 0.5)2 = 0.0000	0.0015
Var3 (0.5 share)	0.6 * (0.17 * 0.5)2 = 0.0042	0.4 * (0.07 * 0.5)2 = 0.0006	0.0047
Expected regret	0.0057	0.00055	0.0062

climate happen with different probabilities. In our example, we have determined with long-term weather data or seasonal climate forecasting that the probability of dry conditions during the growing season is 0.6 and of a wet condition 0.4.

From this table, we can calculate the expected regret for a particular portfolio of varieties. We square the regret per variety per scenario to give more emphasis to higher regret values, following Dembo and King (1992). For example, a portfolio with 50% Variety 2 and 50% Variety 3, would give a regret of 0.0062 (Table 11.3).

Expected regret will never become zero, because we can never beat a perfect forecast by choosing a good portfolio. But we can get very close. We can pick an optimally robust portfolio by minimising the expected regret. We can calculate the proportions of each of these varieties in an optimally robust portfolio through a simple optimisation, which can be done in Microsoft Excel. In this case, the optimal portfolio has 67% of Variety 1 and 24% of Variety 2 (and small contributions from Varieties 3 and 4), achieving a regret value of 0.0014, more than four times less than the portfolio we looked at above. More study is needed to determine the best portfolio design method on the basis of this type of data. There are various ways to parameterise the model further. However, our main point here was to demonstrate that it is possible to construct rational variety portfolios from this type of data. This portfolio construction approach can also be used to construct crop portfolios for climate resilience.

11.4 Contribution of the Tricot Approach

Our simulation exercises show that the tricot approach is statistically robust and allows us to identify the varieties or portfolios of varieties that are preferred by farmers in different environments. Each farm constitutes a mini-experiment in which most of the conditions are not constant. The tricot approach does not try to eliminate the variability between farmers' management practices, soil types, seasons and preferences, but rather makes statistical use of such information to provide recommendations that work in each place and are robust to climate risk.

The approach can also determine if varieties perform differently under different environmental conditions. This has the potential to significantly contribute to the improvement of seed systems by allowing the delivery of varieties based on seasonal climate forecasts or on prevailing conditions in different environments. When working in a complex topography such as those found in Ethiopia, one can expect important differences in conditions among villages, depending on altitude, rainfall and other factors. The tricot approach can help to deliver the best seeds based on the actual climatic conditions of a particular village.

The tricot approach also can cover a higher number of varieties than usual on-farm testing approaches. It can engage with a larger community of farmers than a conventional participatory variety selection (PVS), and the larger number of farmers provides considerable statistical power, resulting in more data points. In addition, the tricot approach could be combined with genomic data to increase the predictive power of the model (Jean-Luc Jannink, personal communication).

Lastly, even without determining absolute levels of yield or other variables, the tricot approach can deliver variety recommendations for risk-reducing portfolios, which adds another tool for climate adaptation. In the literature, limited applications of crop variety portfolio design can be found, mainly for well-endowed production environments in the US and Mexico (e.g., Nalley and Barkley 2010, among others). Our simulation shows that it is possible in principle to generate crop variety portfolio recommendations for marginal environments through participatory trials at scale.

11.5 Implications for Development

Under the current agricultural model, climate change will cause a reduction of yields for many crops in many parts of Africa. Farmers in these environments need accelerated seed-based innovation to cope with climate change. It seems logical, therefore, to diversify in ways that will enhance productivity at any given locality by quickly delivering varieties that are tested by the farmers. Such an approach will significantly increase the adoption rate. As Ceccarelli (2015) has argued, success of plant breeding should be measured based on the technologies that are adopted by the farmers and not by the number of released varieties.

Modern plant breeding has not yet reached many marginal environments and is unlikely to reach them in the next couple of decades through conventional approaches. Research has shown that all over the world, farmers often prefer to grow traditional varieties despite the availability of more productive technologies (Jarvis et al. 2011). The reasons for this include the traditional varieties' better adaptation to prevailing climatic and soil conditions, taste preferences, market preferences, nutritional value, resistance to pests and diseases, and reduced risks. Many times new technologies are not adopted because of costs or lack of accessibility—or simply because they do not match farmers' needs.

Engaging farmers directly in the development of new technologies has many benefits (Beza et al. 2017). It decentralises crop improvement efforts, reduces costs, enhances the efficiency of plant breeding, and shortens the time frame for new varieties to be released. It also increases adoption rates, and allows the adoption of a portfolio of varieties that will enhance resilience in the face of climate unpredictability. Perhaps most importantly, it will maximise yields at any given location rather than promoting a good average variety.

Another significant advantage is the use of material conserved in national or international gene banks. This injects into the production systems novel alleles for adaptation to a number of stresses, biotic and a-biotic, that are lost when only elite lines are used in the process of breeding. Many of the farmers' varieties conserved in the gene banks have been exposed to different pests and pathogens and different climatic conditions, and as a result have developed alleles that allow them to adapt to a multitude of conditions. The gene banks, designed mainly as recipient of material to be eventually distributed by breeders, need to rethink their role and become a source of new traits for farmers and production systems. A shift in the functioning of the gene banks is already underway in Ethiopia and Uganda, where gene banks are delivering material to the farmers and are helping to manage community seed banks.

Once such genetic material is out in the production system, the new alleles in the varieties selected by farmers may prove very important for breeders. If the varieties are also investigated using genotyping approaches, this would allow the identification of quantitative trait loci (QTLs) for relevant traits and promote marker-assisted participatory breeding.

The tricot approach has the potential to contribute to making seed systems more dynamic when demand and supply are put in contact—e.g., using the ClimMob platform—and more diversified because more varieties per crop will be delivered in a location-specific way. A more integrated seed system will allow both informal and formal contributions to the sustainability and resilience of farming system. It also creates the space for an intermediate seed system in which local seed cooperatives or community seed banks are involved in the production of preferred seeds that are identified through the tricot approach. Legislation is being developed in Africa (including in Tanzania, Uganda and Ethiopia) in which seed production rules are designed to allow those local actors to multiply and sell seeds of certain varieties of a sufficiently good quality (Quality Declared Seeds or QDS). This legislation favors the promotion of varieties developed using the tricot approach. Also, variety release procedures could benefit from scaled on-farm testing using the tricot approach.

How does this work contribute to Climate-Smart Agriculture? Climate-Smart Agriculture means different things to different people (Chandra et al. 2018). The smartness in our approach does not come through technical prioritisation exercises that guide investments towards certain "climate-smart" agricultural practices that are guaranteed to confer climate-related benefits. We have serious doubts about this approach. The Green Revolution settled on seeds largely because more knowledge-intensive approaches were more difficult to realise in the absence of well-developed extension systems (Fitzgerald 1986; Harwood 2009). As a result, "smartness" had be put into scientifically-bred seeds as the vehicles that would reach farms. Farmers would not need to learn, they simply had to start using the new seeds. This worked, but it worked best where the ground was already prepared, in production areas that most resembled modern temperate-climate agriculture, where agriculture was commercial in outlook, used high levels of inputs or irrigation water, and worked in relatively homogeneous environments (Fitzgerald 1986). Mechanisation and increased use of bulky fossil inputs characterised these farming systems, rather than knowledge intensification.

In our approach, which focuses specifically on marginal areas, we do not pretend that agricultural science can inject smartness into farming using seeds or other "climate-smart" technologies as the vehicle. "Climate-smart technologies" do not exist literally, if at all. It is subject to the fallacy of misplaced concreteness. In the end, smartness is about how people do things, how farmers are involved in constantly assessing the local appropriateness of technologies, how farmers, extension agents and researchers create new linkages that enhance information generation and exchange, and how these different ways of doing are then leading to new types of knowledge, seeds, and technologies. These end products may symbolise people's collective smartness, but do not replace it. The desired smartness (or better, wisdom) emerges as a systemic property of reconfigured seed and knowledge systems in which knowledge and technology is generated and exchanged in ways that are in pace with accelerated climate and socio-economic change, more equitable, and more attentive to environmental and social diversity and needs.

References

Abay F, Bjørnstad A (2009) Specific adaptation of barley varieties in different locations in Ethiopia. Euphytica 167(2):181–195. https://doi.org/10.1007/s10681-008-9858-3

Badstue ALB, Hellin J, Berthaud J (2012) Re-orienting participatory plant breeding for wider impact. Afr J Agric Res 7(4):523–533

Beza E, Steinke J, van Etten J et al (2017) What are the prospects for large-N citizen science in agriculture? Evidence from three continents on motivation and mobile telephone use of resource-poor farmers participating in "tricot" crop research trials. PLoS One 12(5):e0175700

Cabell JF, Oelofse M (2012) An indicator framework for assessing agroecosystem resilience. Ecol Soc 17(1):18. https://doi.org/10.5751/ES-04666-170118

Ceccarelli S (2015) Efficiency of plant breeding. Crop Sci. https://doi.org/10.2135/cropsci2014.02.0158

Ceccarelli S, Grando S (2007) Decentralized-participatory plant breeding: an example of demand driven research. Euphytica 155(3):349–360. https://doi.org/10.1007/s10681-006-9336-8

Ceccarelli S, Grando M, Maatougui M et al (2010) Plant breeding and climate changes. J Agric Sci 148(6):627–637. https://doi.org/10.1017/S0021859610000651

Chandra A, McNamara KE, Dargusch P (2018) Climate-smart agriculture: perspectives and framings. Clim Pol 18(4):526–541

Dembo RS, King AJ (1992) Tracking models and the optimal regret distribution in asset allocation. Appl Stoch Model Bus Ind 8(3):151–157

Di Falco S, Chavas JP, Smale M (2007) Farmer management of production risk on degraded lands: the role of wheat variety diversity in the Tigray region. Ethiop Agric Econ 36(2):147–156

Fitzgerald D (1986) Exporting American agriculture: the rockefeller foundation in Mexico, 1943–53. Soc Stud Sci 16(3):457–483

Harwood J (2009) Peasant friendly plant breeding and the early years of the green revolution in Mexico. Agric Hist 83(3):384–410

Hothorn T, Zeileis A (2015) partykit: a modular toolkit for recursive partytioning in R. J Mach Learn Res 16:3905–3909 Available from: http://jmlr.org/papers/v16/hothorn15a.html

IPCC (2014) In: Core Writing Team, Pachauri RK, Meyer LA (eds) Climate change 2014: synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change. IPCC, Geneva 151 pp

Jarvis DI, Hodgkin T, Sthapit BR et al (2011) An heuristic framework for identifying multiple ways of supporting the conservation and use of traditional crop varieties within the agricultural production system. Crit Rev Plant Sci 30(1–2):125–176. https://doi.org/10.1080/07352689.2011.554358.

Mancini C, Kidane YG, Mengistu DK et al (2017) Joining smallholder farmers' traditional knowledge with metric traits to select better varieties of Ethiopian wheat. Sci Rep 7(1). https://doi.org/10.1038/s41598-017-07628-4

Mengistu DK, Kidane YG, Fadda C et al (2018) Genetic diversity in ethiopian durum wheat (*Triticum turgidum* var durum) inferred from phenotypic variations. Plant Genet Resour 16(1):39–49

Nalley LL, Barkley AP (2010) Using portfolio theory to enhance wheat yield stability in low-income nations: an application in the Yaqui Valley of Northwestern Mexico. J Agric Resour Econ 35:334–347

Salami A, Kamara AB, Brixiova Z (2010) Smallholder agriculture in East Africa: trends, constraints and opportunities. African Development Bank, Tunis Available from: http://core.ac.uk/download/pdf/6590805.pdf

Steinke J, van Etten J (2016) Farmer experimentation for climate adaptation with triadic comparisons of technologies (tricot). A methodological guide. Bioversity International, Rome

Steinke J, van Etten J, Mejía Zelan P (2017) The accuracy of farmer-generated data in an agricultural citizen science methodology. Agron Sustain Dev 37:32

Sukcharoen K, Leatham D (2016) Mean-variance versus mean–expected shortfall models: An application to wheat variety selection. J Agric Appl Econ 48(2):148–172

Testuri CE, Uryasev S (2004) On relation between expected regret and conditional value-at-risk. In: Rachev ST, Anastassiou GA (eds) Handbook of Computational and Numerical Methods in Finance. Birkhäuser, Boston, pp 361–372

Thomas M, Demeulenaere E, Dawson J et al (2012) On-farm dynamic management of genetic diversity: the impact of seed diffusions and seed saving practices on a population-variety of bread wheat. Evol Appl 5(8):779–795. https://doi.org/10.1111/j.1752-4571.2012.00257

Turner H, Kosmidis I, Firth D, van Etten J (2018) PlackettLuce: plackett-luce models for rankings (R package). https://cran.r-project.org/package=PlackettLuce

Van Etten J, Beza E, Calderer L et al (2016) First experiences with a novel farmer citizen science approach: crowdsourcing participatory variety selection through on-farm triadic comparisons of technologies (tricot). Experimental Agriculture, Online. https://doi.org/10.1017/S0014479716000739

Vavilov N, Dorofeev VF (1992) Origin and geography of cultivated plants. Cambridge University Press, Cambridge, UK

Zeileis A, Hothorn T, Hornik K (2008) Model-based recursive partitioning. J Comput Graph Stat 17(2):492–514