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Improving data management and decision support systems in agriculture

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Developing decision-support systems for crop rotations

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1 Introduction

The simplification of ecosystems for a package of improved seed, synthetic fertilizer and irrigation-driven yield improvement is a design paradigm that has dominated agricultural development (Ramankutty et al., 2018). There are inherent trade-offs in this model. Currently the world comfortably produces enough basic energy to feed all its inhabitants (Food and Agriculture Organization of the United Nations, 2011; Ng et al., 2014). At the same time agricultural lands cover ~38% of the world's land surface area (Foley et al., 2011), contribute to 22% of yearly anthropogenic greenhouse gas emissions (Smith et al., 2014), account for 92% of the human water footprint (Hoekstra and Mekonnen, 2012), result in erosion of ~35 Pg yr^{-1} of soil (Quinton et al., 2010), and lead to widespread nitrate and phosphate pollution (Vitousek et al., 1997), and drive biodiversity loss of 20–30% of local species richness (Newbold et al., 2015). It is now recognized that many of these environmental externalities, in turn risk yield losses to climate change, and pest outbreaks, reducing resilience of the food systems on which humans depend (Bellwood, 2018; Lesk et al., 2016; Ramankutty et al., 2018).

In recent decades, the agricultural sector has fine-tuned the model of optimizing yields through increased efficiency or 'more crop per drop'. These

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advances have been aided through the improved use of inputs. However these increases in efficiency have not been enough to halt the negative environmental impacts of agriculture on people and planet. This continued degradation has led to calls from food system scientists to move away from simple technological intensification (using synthetic fertilizers, pesticides, improved seeds and water) towards ecological intensification (e.g. the use of diverse crop plantings which help recycle or fix nutrients, manage water and pest outbreaks), as the major pathway towards a more sustainable agricultural future (Coomes et al., 2019). There is some evidence that the transition to sustainable intensification is already taking place in many landscapes (Pretty et al., 2018).

Ecological intensification through increasing the diversity of crops in rotations, cover cropping, intercropping, or increasing non-crop habitat on farmlands, has long been promoted as a major solution to counter the negative impacts of agriculture on environmental and human health (Bommarco et al., 2013; Kremen et al., 2012). This promotion comes from the finding that increasing plant diversity in time and space can increase water-use efficiency, reduce nitrogen leaching, regenerate soils, increase pollination, reduce losses to pests, reduce greenhouse gas emissions, increase nutritional quality of foods and increase the stability of production to climate change (Isbell et al., 2017; Mariotte et al., 2018; Renard and Tilman, 2019). However the composition of elements for the design of ecological systems is not trivial and the benefits of diversity found in ecological studies have largely been studied in separation from the economics of farming. Recent studies which study both show that significant financial trade-offs often exist with managing diverse farming systems (Rosa-Schleich et al., 2019).

The decline in the diversity of crops found on larger farms is tightly linked to the economics of farming and labour. There is a strong inverse relationship between the size of a country's economy and the percentage of people employed in agriculture. Lack of labour forces, an upward shift in farm size, mechanization and a downward shift in the complexity of agricultural ecosystems and the number of crop species grown, are all interlinked. As scale and capital investment increases, the burden of knowledge management, and risk, also increases, further forcing an increase in specialization and a reduction in crop diversity and an increase in continuous cropping cycles (Awokuse and Xie, 2015; Ramankutty et al., 2018; Ricciardi et al., 2018). The focus on optimizing yields in monoculture, with limited focus on ecological intensification, is reflected in modern decision-support systems used by farms for management today. Ecologically based decision-support tools are largely non-existent.

At the core of developing tools for managing more diverse farms, including crop rotations, lies a complex information challenge. Crops interact with each other, their above- and below-ground symbionts (e.g. fungi, bacteria, pollinators and pests), climate, soils, the landscape and farm-management

decisions, in extremely context-dependent and site-specific ways. This makes data-driven agronomy and digital extension services difficult and uncertain even in the simplest of agrosystems. Advisory for complex and diverse cropping systems is further exacerbated by a lack of data on local conditions, and lack of data on the outcomes of particular species interactions in response to a wide range of ancillary and seasonally varying factors, a lack of generalizable ecological theory and the gap between economics and ecological inquiry.

In this chapter I will look at the current challenges and opportunities for designing farm-level decision-support tools for diversified agriculture, with a specific focus on developing tools for crop rotations. I will cover the aspects of key information challenges, ecological theory, agronomic models, encoding farmer decisions, finishing the chapter with principles for design pulling together insights from these cases, and future trends and directions.

2 Key information challenges

The landscape of decision-support systems for improved rotations, should be understood within a broader challenge faced by data-driven agronomy itself and the state of play currently in developing predictive tools for aiding farmer's decision-making. The challenges faced in diverse cropping systems add a layer of complexity to these broader challenges through increased heterogeneity of information that needs to be handled. Below are the major information challenges facing data-driven agronomy with a particular focus on optimizing for multiple sustainability objectives.

1 **Information overload.** In the age of big data, the potential for information overload is overwhelming. Farmers, extension agents and researchers contend with agricultural data from the proliferation of sources such as: low-cost sensors; novel satellite data streams; trial databases; weather data; machine data; biodiversity data; market data; supply chain-transparency data; certification data; climate data; farmer-safety data; food-safety data and interest in developing long-term farm-, national- and global-scale datasets across these streams. This leads to cognitive overload, limited time for record keeping and 'analysis paralysis', hindering the use of important information for decision-making.
2 **Data gaps and harmonization.** While there is a growing abundance of data streams, data collection, aggregation and management are costly. This often results in a lack of coverage for some regions, or limited coverage of some variables resulting from aims of isolated data collection initiatives. Data is also collected at varying levels

of granularity, in disparate formats, structures, and through varied protocols, and is of varying degrees of quality. Where data exists, there are often compatibility issues between data sets and no formally agreed or accepted ontologies for translating between data collection efforts.

3 **Tool isolation.** Currently, there is a disconnected ecosystem of sustainable agriculture tools and sustainability assessment frameworks, resulting in a landscape dotted with duplicated efforts, isolated clusters of tools lacking interoperability (e.g. decision tools that are incompatible with on-farm record-keeping software, or carbon calculators which are not integrated with financial accounting software). There are few formal efforts to develop modular services that are plug and play, which ensures the development of decision-support tools involves high up-front costs.

4 **Validation.** Many decision-support systems do not carry estimates of validation of their performance for the indicators they aim to help optimizing for, whether that be improving farmer incomes or reducing pest outbreaks. This lack of validation has led to a wide number of tools with no benchmark as to their reliability. This is exacerbated by the fact that many existing decision-support tools are static and cannot be easily updated based on advancements in farming technology and management innovations, or novel data streams.

5 **Privacy.** The collection and dissemination of data on farmer decision-making processes and on-farm outcomes carries important privacy concerns. Knowledge of how farmers perform on environmental, economic or social outcomes is valuable information that if disclosed to third parties can put farmers at risk of legal action, extortion or financial loss. Taken together with the lack of standards for tool validation, privacy concerns diminish trust in tools.

6 **Inequalities in access.** Information is power. Yet access to information and decision-support tools is mediated by economic or cultural status. The availability and access to digital technology services is unequal globally, and many of the world's poor farmers are currently excluded from the benefits provided by commercial and public decision-support tool providers. At the same time there is an inequality in access to traditional knowledge, and farmer expertise, on outcomes of farm management decisions on sustainability outcomes, and cultural barriers that enforce the integration of traditional knowledge sources with mainstream science.

7 **Supply-driven design.** Cool uses of new data streams and flashy hardware or software interfaces for farm management decision support can be found in abundance, but careful human-centred design of decision-support systems that tackle specific and significant problems faced by farmers are lacking. This is particularly problematic where

disciplinary gaps between natural scientists, engineers and social scientists exist, and ultimately results in the development of tools with poor usability, with low uptake and adoption. There is a need to develop demand-driven design principles and work with farmers directly to design the tools to solve their problems.

3 Ecological theory

Over the last two decades a rapid growth in the ecological study of the costs of benefits of growing different combinations of plants on plant health emerged. We now have strong experimental evidence that plants can culture soils to the benefit or detriment of other plants, either through nutrient depletion, releasing toxic metabolites, or through the recruitment of beneficial or pathogenic symbionts in the root zone (Bever et al., 2012; Inderjit et al., 2011; Van Der Putten et al., 2013). Ecologists call these dynamics between plant interactions, 'plant-soil feedbacks' (PSF), which they study for their roles in ecosystem succession, invasion and species coexistence (Callaway et al., 2004; Klironomos, 2002; Van Der Putten et al., 1993; Schnitzer et al., 2011), but really they are similar in many ways to crop rotations.

One of the theories that has been tested by ecologists is an old idea (recognized as far back as Charles Darwin) that more closely related plant species are likely to share pests and pathogens (Gilbert and Webb, 2007; Webb et al., 2006). This idea of sharing of pests and pathogens led researchers to think that plants that are more closely related will have more negative interactions with each other through the soil (Brandt et al., 2009; Burns and Strauss, 2011; Liu et al., 2012; Sedio and Ostling, 2013). However, the most comprehensive assessment to date found that this pattern is not general – and fails to hold across a large range of flowering plants, life histories, life cycles and even within groups of recently diverged species (Mehrabi and Tuck, 2015), suggesting that using relatedness to predict which plants will do better in rotations may be of limited use (Mehrabi and Tuck, 2015; Ingerslew and Kaplan, 2018).

Newer advancements in ecology have hypothesized that fast-growing resource-exploitative species ('fast species') with highly decomposable tissues replenish nutrients quicker and have higher fertilizing effects on soil than slow-growing resource conservative species. Positive effects of fast species on the growth of subsequent plants could be explained by their fertilizing effects and soil chemistry legacies of high plant-available N, or due to proliferation of microbes involved in nutrient mobilization in fast soils (Baxendale et al., 2014; Grigulis et al., 2013; Ke et al., 2015). However there are a number of other processes associated with fast species such as the proliferation of pathogens (Veresoglou et al., 2013), losses of beneficial fungi (Grigulis et al., 2013; Hoeksema et al., 2010; Orwin et al.,

2010), phytotoxic effects of highly decomposable tissue inputs (Bonanomi et al., 2011, 2006) and disruptions or lags to recycling of plant materials (Hobbie, 2015), which would drive plant-soil feedbacks in the opposite direction, with plants performing worse on soil cultured by faster species. Separating out the effects of each of these factors will require targeted experimentation.

While ecologists still struggle to pin down reasons why species perform better or worse when grown in sequence, case-by-case insights have been developed which can help specific agricultural systems. For example, in limiting negative effects of below-ground pests, such as nematodes, fungi or bacteria (Mariotte et al., 2018; Silva et al., 2018), and through maximizing positive effects of plants which build symbionts with microbes in the soil and enhance nutrient-use efficiency (Bender and van der Heijden, 2015), or increase above-ground resistance to pests (Pineda et al., 2017). Some of these case studies are particularly important, such as with take-all in wheat, where new genetic varieties have been identified which create pathogen-suppressive soils and can be rotated with more susceptible varieties, reducing yield losses by 3 t/ha^{-1} (Mehrabi et al., 2016). It is this depth of understanding of the ecology of soil biology that makes the research on plant-soil-feedback mechanisms so appealing with the idea that one day we may be able to engineer soils to help agricultural systems perform better by manipulating soil biology.

4 Agronomic models

Alongside ecological research on plant-soil-feedbacks is agronomic research on 'soil sickness', a phenomenon which results from continuous cropping of the same species on soil. Crop rotation is the central method used by humans to overcome the observed yield declines seen with successive monocultures (Bennett et al., 2012; Dick, 1992; Lawes, 1895; Raaijmakers et al., 2009). Much empirical work has been conducted on which sequences of crops lead to optimal outcomes.

One well-known agronomist rule of thumb is the use of N_2-fixing plants in rotations. Recent synthesis shows benefits to rotations for cereals rotated with grain legumes, with yield increases of approx. 29% relative to continuous cropping of cereals. However these benefits are only observed in systems where nitrogen application rates are low, becoming negligible in systems with N applications > 150 kg/ha (Cernay et al., 2018). The benefits of legume rotations in low-input systems, and their benefits for farmer livelihoods have been documented elsewhere in specific country case-studies (Snapp et al., 2010), but scaling these benefits to high input synthetically fertilized systems, in, for example, the EU or North America to reduce dependency on N inputs is less clear.

A range of other agronomic meta-analyses have been conducted on the benefits and costs of rotations for pest control, product quality, input use reduction, production stability, improvement in soil organic carbon and soil quality, biodiversity, greenhouse gas emissions and economic profitability (Beillouin et al., 2019). In some meta-analyses the benefits of rotation for specific outcomes are reported to be clear, although often crop differences are masked by pooled analysis across systems and crop types. For example, organic systems have been reported to have higher yield and profits relative to conventional rotations when grown in longer and more diverse rotations (Crowder and Reganold, 2015; Ponisio et al., 2015). Longer rotations have also been reported to produce strong positive effects on microbial richness (Venter et al., 2016) and enhanced microbial N and C and microbial activity (Lori et al., 2017).

The benefits of rotation can vary immensely by crop and system type. For example greenhouse warming potential and emissions intensity of soybean and maize rotations is greater than in continuous maize crops, but lower in smaller grain crop combinations of barley and pea compared to continuous barley (Sainju, 2016). While in some crops, the effects seem clearer, for example, in canola in North America diverse rotations for every 3–4 years are required to maintain yields (Assefa et al., 2018), in many other cases the responses are highly contextual, because the benefits of rotation depend on interactions between crop species combinations and environmental conditions. For example, in wheat systems wheat yields after break crops are on average 0.5–1 t/ha more productive after oats, and 1.2 t/ha more productive after grain legumes, than continuous crops, but the benefits only hold for the first 2 years of break crop, and are less beneficial after 3 years except in drought (Angus et al., 2015).

In addition to problems of generalizability of empirical data, meta-analyses of agronomic models of 'soil sickness' also do not report the predictive skill of particular crop associations for specific outcomes (e.g. yield, biodiversity, climate mitigation, biodiversity impacts, etc.) , and there are significant biases in geographic and system-level coverage. A recent systematic review of 99 meta-analyses assessing diversification, including studies of rotation, found that the majority of reported benefits of crop diversification covered only 10 key crops: pea, cowpea, bean, soybean, oat, rice, sorghum, barley, wheat and maize, with most studies based in North America and Europe (Beillouin et al., 2019).

Despite these shortcomings, the accumulation of experimental agronomic data is pushing us to a space where, if the coverage of systems and crop types increases, we may be able to make empirically based predictions of the likely outcomes of different rotation sequences in the near future. Data-driven models of optimal crop rotation pairs could therefore be within reach, even if general ecological theory does not yet exist to ground it. Incorporation of these

empirical data, with insights from operations research-based optimization studies, alongside formalization of farmer decision-making, and mechanistic modelling for rotations, remains a new frontier of this work (Box 1).

Box 1 A plethora of approaches

A number of statistical, rule-based, mathematical, and mechanistic models have been developed for aiding recommendations of crop sequences for crop rotations (Beillouin et al., 2019; Dury et al., 2012). These models have in general not been integrated or widely adopted by farmers or extension agents. These models include:

- Recommendations for rotations based on rules set by experts, which cover all theoretical permutations of crops, then filter sequences based on thresholds for outcomes of interest (e.g. nitrogen leaching, soil erosion, weed and pest management), which may be calculated from simple spreadsheet or crop-simulation models parameterized by field trials, and ranked based on likely economic benefits (Bachinger and Zander, 2007). These models help to formalize the inclusion of multiple objectives in models where little data exists, although, as currently formulated, they are inflexible in dealing with non-linear or complex crop or sequence plans (Castellazzi et al., 2008).
- Recommendations for sequences based on empirical observations for particular crop pairs or groups. As covered in Section 4, a number of trials have been compiled into meta-databases which cover the known relationship between particular crop interactions and particular outcomes from an agronomic perspective (Beillouin et al., 2019). These models can be used as a basis to make recommendations for specific crop selections. However currently the scope of recommendation is limited in crop type and geographic coverage.
- Recommendations based on the maximization of a set of single or multiple objectives (e.g. gross margins, profits, labour, land, market demand, water, waste, food supply, pesticide use), given particular a priori constraints. These constraints include yields dependent on previous crops (El-Nazer and McCarl, 1986), fixed known allocations of land per crop (Detlefsen and Jensen, 2007), forbidden crop sequences (Haneveld and Stegeman, 2005), pre-desired planting principles (Forrester et al., 2018), known demand and stocking lengths (Costa et al., 2014) or incorporation of spatial constraints such as blocks holding homogenous management practices (Akplogan et al., 2013). Coefficients in these models can be modelled probabilistically to account for the influence of stochastic factors such a climate feedbacks (Itoh et al., 2003). While these models have tackled the optimization problems of rotation recommendations, they

are time-consuming to set up and are bounded by study-specific constraints and objectives.

- Recommendations based on mechanistic models. Mechanistic or process-based crop models can incorporate dynamic responses of outcomes of interest to external factors, such as climate and markets. Platforms for simulating different realizations of process-based models have been developed (Bergez et al., 2013) that allow for running simulations of the impacts of choice of rotations on outcomes such as water use (Chacoff and Aizen, 2006), yields and nitrogen dynamics (Kollas et al., 2015). The major problem with process-based models for rotation modelling is the lack of representation of biotic interactions between crop species, data on specific non-major crops, soil chemistry dynamics, particularly with organic matter, and interactions with specific management practices (Kollas et al., 2015).

There is a clear need to combine insights across these different modelling approaches into the next generation of decision-support systems for rotations. We need a better observation of farm management data, more biologically realistic mechanistic models, adaptive recommendations based on personalized time-varying constraints and real-time data on climate, markets and pest outbreaks. To ensure adoption, these models must be integrated into culturally and technologically accessible interfaces designed in iterative participatory processes with farmers.

5 Encoding farmer decisions

Ecologists, agronomists and economists' representations of how farmers make decisions on rotations represent different ways of knowing about the world, which may not represent each other or model the way farmer makes rotation decisions. Academics have documented models of farmer decision-making in disparate fields, but how close has this brought us to effective decision support?

Economic models designed to maximize utility have been built around survey-driven decision trees developed with farmers to understand how farmers cope with risk (Adesina and Sanders, 1991), and in visualization of cropping choice outcomes for illiterate farmers (Collins et al., 2013). Notably however, there is a lot of contention about the usefulness of purely rational economic models in representing real-world decision-making. Operational decision-making theory is one school of thought that may help to overcome this by attempting to understand the mental models of farmers when they are undertaking rotations, documenting the process of information selection by farmers and exploring methods of dealing with time variant objectives (Martin-Clouaire, 2017)

A key branch of studying farmer behaviour to date has been founded on the idea that decision-making can be encoded into a set of conditional IF-THEN statements, which together represent a 'model for action' derived from both objectives of the farmer and plans of schedules to realize those objectives. This method has been particularly useful in mapping out the temporal and spatial dynamics of farmers crop-planning decisions, and have been used for encoding vastly different farming systems, for example, in locations such as France and Cameroon governed by very different social and biophysical contexts (Aubry et al., 1998; Dounias et al., 2002). Spatial representations of these models for action have also been undertaken (Dury et al., 2013), and there have recently been efforts to join economic models with these methods, along with biophysical crop models as a way to model short-, medium- and long-term components of decision-making (Robert et al., 2018).

A complementary approach, recognized in the early 1980s by anthropologists (Chibnik, 1980), is the use of statistical learning to try and understand patterns in farmer decision-making, without depending on explicit encoding of farmers intentions or plans. This purely relies on inferring likely constraints on decision-making from realizations of plan execution. There is currently untapped opportunity to use of modern statistical methods to understand the heterogeneous nature of farmer decisions, particularly for rotations. This will be aided if time series of management decisions can be obtained, and likely offers a powerful basis for developing personalized decision support.

While these methods are useful, perhaps the most overlooked step in understanding farmers' models for optimal crop sequences selection is to put more time into understanding farmers' ways of knowing. This is typically achieved by employing methods of qualitative data collection and observation, such as interviews, surveys and ethnography developed in anthropology and sociology. Farmers' own ways of knowing about rotations help illustrate existing concepts and tools used for planning, and can help build an understanding of what farmers think grow well together – and why (Mohler and Johnson, 2009). Expectedly farmers also hold a breadth and depth of information not incorporated or reconciled with formal scientific literature (Bentley and Thiele, 1999). The integration of both farmers' traditional and emergent knowledge of what crops work best together, as well as the knowledge of the well-being generated from decision processes made outside those optimizing financial gain, remains perhaps the largest gap in our understanding of developing effective decision-support systems in farming.

6 Design principles

The fundamental hurdle facing data-based decision-support systems for rotations is not so much a technical feat that you can solve at your computer,

as it is access and adoption of tools you build. Solving this challenge requires a clear understanding of what farmers' key pain points are with respect to managing their farm and their rotations, and creating useful solutions to these problems. Some tips are given below:

Safeguard interests. Data-driven agronomy is a fast-moving field, and due to many commercial interests in this area, farmers are bombarded with surveys and market research aimed at building tools for decision support, which can be extremely extractive in nature and lead to survey fatigue. You should work with farmers with whom you have strongly aligned interests and a long-term commitment also. Decision-support tools should be designed and to empower users through data and knowledge and to safeguard against the risks posed by overreliance and loss of resilience, traditional knowledge or adaptive capacity. You will need to think about the ethics of your project, have clear protocols to minimize risk and have your data management plans approved by a recognized ethics board. You should have strong privacy and data-sharing agreements in place.

Know your user. Understand the population of farmers you want to work with through surveys, in depth semi-structured interviews, focus groups, design workshops and ethnographic methods such as non-participatory observation. Focus on the broader normative stance, preferred knowledge sources and formats, demographics, institutional context, political context, what makes individuals that you are working with tick, why they farm, what their greatest issues are and what the broader constraints in realizing their objectives as a farmer are. We are not focussed on rotations here but a more general understanding of the user group.

Define a model. Get a deep view on how your farming group currently models rotations, which can substantially differ from ecological, economic and agronomic representations of how academics or researchers like to model how farmers make decisions about sequential cropping patterns. How do they currently map out their rotations? Do they use spreadsheets, wheel diagrams, pen and paper, mental maps based on weather, or celestial-based cues? Intuition? And when do they make their plans, which actors play roles and constrain their option space, and what kinds of decisions happen in and out of season? Have they tried other solutions to deal with this problem in the past, and how did they arrive at their current solution? Do they see rotation selection as a problem that needs solving, or are there more important things on their agenda they would rather have help with?

Focus in. Many complementary methods exist for digesting and prioritizing data generated through working with farmers, for example, through affinity diagrams, card sorting, content analysis, persona development, journey mapping, network analysis, decision trees, fuzzy cognitive mapping and so on. Using such analytic methods to simplify the goal of the tool development

to focus in on one main problem to solve for your farmer group, while maintaining the nuances of the subsets of problems required for solving that problem, is a major milestone in the design process.

State and test your assumptions. All along the development cycle you will find yourself making assumptions about the ways farmers operate. It is important to explicitly state these assumptions. They should be built with your farmers directly, and as new assumptions arise they should be tested through future engagements. The development of usable decision-support tools will be marked by rapid iterations across ideas and assumptions that are tested and validated continuously.

Be forward looking. Sometimes it is not possible to develop decision-support systems or features due to lack of empirical data – this is particularly the case for crop sequence decision-support systems for vegetable crops. This may require a re-focus on features that are not top of your agenda as a crop rotation specialist or developer – and may even seem tangential. It is your job to understand which features are of key utility to the farming objectives and to build tools which service their needs – which can mean offering short-term utility in financial management, or lifting paperwork burden for certifications, but at the same time generating the data required for a rotation feature to be built and delivered to farmers at a later date.

Check the market. Once you have focussed in, it makes sense to do comparative analysis of existing solutions offered to solve rotation choice problems, or subsets of the problem such as crop planning tools, both in terms of their features and their information architecture. If you have the resources conduct user testing on these alternative solutions to identify what your user group does and does not like about them, this will help you define a clearer idea of which design is likely to work for you.

Interoperate. It makes little sense to develop a standalone decision-support tool, for example, for crop rotations – because decision-making in agricultural systems results from the integration of multiple sources of information, and processes. If farmers have existing tools and models for financial management, or labour management, fertilizer management, or other farm activities, then your rotation tool should be able to speak to those models. A common ontology and the development of translators between alternative semantic representations of farm objects and models are essential, and you should be using existing work as building blocks for your operation where they exist (e.g. standardized crop lists and trait information with taxonomically accepted names, weather data, soil data, plant and pest-trait databases).

Optimize. Bad rotation choice decisions can impact negatively on the environment and human health efforts should be made to provide an understanding of the trade-offs that a given choice of sequence will likely have, so that informed, rather than prescribed, decisions can be made. It

is unlikely that all of the criteria a farmer is using to make choices will have available data and, so a focus on key proxies for main variables of importance (e.g. nutrient balance, water balance, yield, pesticide use etc.) here is a good starting point.

Personalize. Farming systems and individual farmer's models of how their farm works are incredibly diverse. The only solution to deal with this problem of multiple possible combinations of social, biophysical and value-based factors is to develop personalized rotation sequence decision-support services. These services by their nature are data hungry, and this means design has to account for data gathering as a key feature. The utility in personalized services is that they can readily account for adaptive and flexible shifts in farmers' operations, decisions and learning processes.

Make accessible. One of the key challenges with developing decision-support tools for the majority of farmers worldwide is the large inequality in the distribution of technology availability, access and utilization to different farmers – whether in service coverage, mobile phone ownership, internet access, the cost of data, and education, age culture, or language barriers which limit the usage of these services. Developing a solution that overcomes this inequality in decision support deserves a central place in the development of new decision-support tools.

7 Outlook

Crop rotations are a formative component of agricultural practices and are a key path towards improving multiple farming outcomes, for people and the planet. Improved decision-support systems for crop rotations therefore hold great potential for improving food system sustainability. New opportunities exist to gather and collect on-farm data at unprecedented temporal and spatial resolution and frequency. These developments herald an age of personalized decision-support tools able to provide adaptive recommendations for multiple sustainability indicators, based on real time data on climate, markets, and pests. Realizing this opportunity requires multiple information challenges be solved. Researchers will need to link insights from the development of alternative models for crop rotation across diverse disciplines and subject fields, to design tools that are interoperable with the wider farm data ecosystem, and that are built to both gather data and internally validate predictions over time. All of these efforts must be combined with improved human-centred design, participatory methods that seek to understand farmer's way of knowing, and a long-term view to development that builds lasting partnerships with farmers, improves access and trust, empowers users through ownership of their data and maintains farmers agency in the design and governance of the decision-support ecosytems that serve them.

8 Where to look for further information

This chapter covered a lot of material and you might be wondering where to go from here? Much is covered in the references, with the exception of the design thinking. However there are some good books and resources to get you started, such as: IDEO's Human Centred Design Toolkit (https://www.ideo.com/post/design-kit); as well as books such as The Design Thinking Playbook (https://www.design-thinking-playbook.com/playbook-en) and This is Service Design Doing (http://www.thisisservicedesignthinking.com/).

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