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In pursuit of responsible innovation for precision agriculture technologies

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ABSTRACT

Agricultural decision support systems (DSSs) are hardware and software tools that utilize big data collected from satellites and drones, ground-based sensors, and analyzed with machine learning algorithms to provide site-specific farming recommendations. Despite the promise of DSSs to address many challenges of the farm economy, there are social and ethical concerns that need to be addressed. Utilizing a mixed-methods approach that consisted of focus group discussions and a follow-up survey questionnaire, we highlight the experiences and affectations of heterogeneous food system actors from Vermont and South Dakota. We find that DSSs transform agricultural knowledge production, reconfigure labor arrangements and unevenly distribute benefits and burdens among farmers. We suggest that agritech developers implement inclusive and deliberative processes when redesigning DSSs to engender ethical, equitable and sustainable improvements to food production systems. Inclusive processes of open deliberation are modalities of responsible innovation, tasked with mitigating frictions within socio-technical systems.

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Introduction

Food and agriculture systems in the US are undergoing a technological and sustainability revolution (Rose and Chilvers 2018). Precision agriculture (PA) employs data-based agricultural technologies and practices with localized farm data to generate site-specific farm recommendations (Banerjee, Bandyopadhyay, and Acharya 2013; Bongiovanni and Lowenberg-DeBoer 2004; Rossel and Bouma 2016; Smith 2018). Under the broader ambit of PA, agricultural decision support systems (DSSs) are becoming increasingly popular for translating agronomic and climate sciences to crop, livestock, and dairy farmers. However, DSSs are not new to agriculture. Since the 1970s, DSSs have emerged from the rapid development of computing and electronics, which have allowed agricultural machines to perform operations efficiently (McCown, Hochman, and Carberry 2002; Zhai et al. 2020). More recently, DSSs are integrated with current technologies like the Internet of Things (IoT), big data, artificial intelligence (AI), cloud computing and remote sensing to transform environmental and agronomic farm data into 'precise' and 'accurate' farming recommendations (Kamilaris, Kartakoullis, and Prenafeta-Boldú 2017; Rose et al. 2016). By providing targeted farming recommendations to farmers, DSSs enable a 'farming by the foot' approach that can facilitate an increase in farm productivity, reduce greenhouse gas emissions (GHGs), decrease farm management costs, and advance coordination across the food system value chain (El Bilali and Allahyari 2018; Balafoutis et al. 2017; Bongiovanni and Lowenberg-DeBoer 2004). Farmers in India and Colombia are adopting DSSs, such as Microsoft's Cortana Intelligence Suite, to assist in determining optimal planting dates for crops (López and Corrales 2018) and unmanned drones are translating agronomic information into maps that are visualized on DSSs to locate and remove weeds from fields (Lottes et al. 2017; Fennimore 2017). Proponents of PA claim that widespread use of data-driven DSSs will streamline the decision-making process in agriculture as these systems are based on empirical data and not guesswork.

Yet the prevailing narrative about PA that presents DSS as a techno-scientific fix to the challenges of agricultural decision-making must be treated with caution (Rose and Chilvers 2018). Innovation in DSSs depends on several activities, such as the collection and processing of big data, development of new cyber infrastructures, data sharing platforms, and machine learning algorithms, all of which have their own social and technical challenges. While some food system actors are excited about being empowered by big data technologies, others are equally concerned about the ownership, privacy and use of their data by corporations or regulators (Finn and Donovan 2016; Jakku et al. 2019; Salah et al. 2019). The design, development, use, and regulation of DSSs follow a complex and dynamic trajectory involving many different actors and organizations within the food system – e.g. farmers, farm advisors, researchers in the industry and universities, policy makers, regulators – each of whom is positioned differently in the PA value chain, giving them unique experiences and affectations with the technologies (Gutiérrez et al. 2019; Klerkx et al. 2012). We contend that open and inclusive deliberations on the unintended and undesired implications of DSSs involving social actors across the food system value chain can inform guiding principles for designing and governing new DSSs and associated technologies (e.g. big data, machine learning algorithms, AI) that are ethical, equitable and effective for farming and non-farming communities. In this paper, we utilize a responsible innovation (RI) framework to ask the following research question: *What are the experiences and affectations with DSSs of various food system stakeholders?* Through the RI framework, lived experiences of a range of agricultural stakeholders can help inform and shape future innovation and governance of agricultural DSSs. Developers of future PA technologies can benefit from anticipating and including concerns and needs of heterogeneous actors in the food system. As farm labor becomes more deeply integrated with PA technologies, sustaining yields of crops and capital necessitates socially responsible user engagement.

This article is organized into six sections. The second section is a literature review of the (a) social dimensions of DSS technologies and (b) responsible innovation. The third section describes our methodological approach, consisting of focus group discussions and survey questionnaires. The fourth section explores research participants' perceptions and experiences with DSSs. The fifth section discusses the broader implications of this study and makes a case for a responsible innovation approach that includes open deliberation among user groups to improve upon DSS technologies. The sixth section concludes the paper with a summation of findings and a recapitulation of our central thesis.

Literature review

Farmers' adoption of DSSs and changes to their knowledge, meanings, and social identities

Social science scholarship on DSSs has focused predominantly on the challenges pertaining to its uneven adoption among farmers (Lindblom et al. 2017; Lundström and Lindblom 2018). Lindblom et al. (2017) associate the low reception of DSSs among farmers as a result of the lack of engagement between technology developers and farmers. The former often fail to regard the levels of knowledge and actual needs of the farmers who are the end-users of the technology (Ogunyiola et al. 2022). The issues of perceived complexities of DSSs, ambiguous data inputs requirements, and low adaptability to peculiar farm situations can cause low motivation for farmers and farm advisors to learn and adopt novel practices. Commentators suggest that an easier data entry process, the ability for farmers to attend to multiple fields simultaneously, and user-centered designs can allow DSSs to complement instead of conflict with farmers' existing decision processes. Proponents of DSSs proclaim that adopting it would require less 'hands-on' management and more data-driven analysis (Eastwood, Chapman, and Paine 2012). In turn, farmers and farm advisors may need new skills to create, interpret, and establish recommendations based on a DSS-based yield map derived from 50,000 or more individual ecological measurements. Yet equipping the workforce with the necessary skill-sets to effectively utilize DSSs has associated challenges such as high training and equipment costs, poor broadband internet availability in rural areas, lack in mathematical skills among undergraduates, and comfort and trust issues among farmers (Rotz et al. 2019; Hennessy, Läpple, and Moran 2016).

The socio-technical transition to DSSs in agriculture is reconfiguring farmers' social practices, such as knowledge, meanings, work tasks, and social identities (Gardezi and Stock 2021; Gardezi and Bronson 2019; Carolan 2017; Burton, Peoples, and Cooper 2012; Marinoudi et al. 2019; Vougioukas 2019). Unlike previous technological transformations in agriculture, DSSs are not only replacing mechanized farm work (e.g. moving heavy equipment) but can also perform tasks that require human intuition and cognition (Huang, Rust, and Maksimovic 2019). While DSSs can enhance human-machine partnerships and open avenues for greater workforce augmentation, these tools can disrupt existing farming knowledge and create 'spaces where the tacit knowledge of old analogue systems is being lost' (Carolan 2017, 825). The critical social science literature on PA highlights how some of the 'smart' tools can change a farmer's role. Agritech's influence over the political economy of agriculture has enabled the proliferation of discourses that position future farmers not as cultivators but as 'an algorithmically assisted subject,' a reconfiguration of agrarian labor that 'casts farmers as office managers' (Tsouvalis et al. 2000, 913). Visions of a 'ghost farm' or farming without people dominate current discourses on the future of food, indicative of agritech's ascendant cultural hegemony. Depiction of a world of farmerless farms are being fed to the public through high-level visioning documents (Syngenta 2017) and even children's TV shows, such as the Magic School Bus Rides Again (Ghost Farm 2018). Building on emerging studies that have examined how these tools can create new – and exaggerate existing – social and ethical risks for farming and non-farming communities (Fielke, Taylor, and Jakku 2020; Van der Burg, Bogaardt, and Wolfert 2019; Gardezi and Stock 2021; Fraser 2019), we examine how DSSs are reconfiguring existing farming practices and challenging farmers' social identities (Gardezi and Stock 2021; Gardezi and Bronson 2019; Carolan 2017; Burton, Peoples, and Cooper 2012; President's Council of Advisors on Science and Technology 2012).

Growing power disparities between food system actors

The social and political effects of agricultural DSSs are not limited to the disruption of farm work. Big data and machine learning algorithms are vital components of DSSs. Critical data studies and food studies scholarship has demonstrated the inequitable impacts of big data on the relationships of power between actors in the North American food system (Bronson and Knezevic 2016; Crawford, Miltner, and Gray 2014). This scholarship shows that technology and its development is as much a technical feature as it is a social construction that may be imagined by a powerful minority of actors and organizations in the food system (Bronson and Knezevic 2016). DSS hardware and software developers selectively collect (via ground or aerial-based sensors) specific agronomic and environmental data while ignoring other potential data sources of food systems (Stock and Gardezi 2021). Agritech's choices about data collection and processing are neither amoral nor value-neutral but have serious implications for food production systems and natural resource governance (Winner 1986; Crawford and Boyd 2012). Agritech's decisions determine which aspects of food and livestock production systems are monitored, and which ones are not. For instance, many agritech firms produce a greater variety of fine-scaled machine learning models to predict nutrient recommendations for large-scale farms that grow corn and soybean, but very few models do the same for small cash crops (e.g. specialty fruits and vegetables), thereby perpetuating monocropping and reducing agricultural biodiversity. The uneven prioritization of DSSs to support large landholders over smaller ones may replicate and perpetuate existing social frictions in agriculture, specifically between small-scale and diversified production systems, such as various types of agroecological systems and large-scale monoculture farming systems (Bronson 2020; Klerkx and Rose 2020). There are secondary consequences of technological inequity that disproportionately harms older and lesser-educated farmers, some of whom are less likely to adopt DSSs (Lindblom et al. 2017; Rose et al. 2016). Stock and Gardezi (2021) contend that through PA technologies, agritech firms engage in biopolitical modalities that selectively 'make bloom and let wither' specific plants, pests and people throughout the food production system. Technological inequity and ecological homogeneity in agricultural systems may become more prevalent unless innovators and regulators of DSSs consciously ensure that these technologies are socially inclusive and responsive to the environmental demands for greater biodiversity.

Growing power disparities between food system actors is a historically recurring phenomenon in the U.S. agriculture sector. We situate DSSs (as a technology of PA) within this long genealogy of power asymmetries and technological disruption in food production systems. Scholars have for several decades examined and highlighted the growing power imbalances between small and large-scale farmers and farmers and large agribusinesses (Friedmann 2009; Friedmann and McMichael 1987). In the case of genetically modified organisms (GMOs), for example, regimes that protect the commercial interests of large agribusinesses through intellectual property rights has brought benefits to some farmers from improvements to their crop yields, but had reinforced stronger dependencies between farmers and powerful agribusinesses (Stucke and Grunes 2018). In a similar vein, the current PA innovation ecosystem enables large agritech corporations to consolidate proprietary data and intellectual property from not only seed and chemical patents, but also through digital platforms that enable capital accumulation for these firms predicated on the (dis)possession of farmers' data (Fraser 2019; Bronson 2019; Stock and Gardezi 2022). For example, John Deere's proprietary tractors use numerous environmental sensors that generate data for the entire farming system, including farmers' preferences and actions, which are protected through intellectual property rights that prevent the farmers from accessing, controlling or possessing this information (Carolan 2017; Rotz et al. 2019). Agritech firms require farmers to subscribe to proprietary DSSs that use farmers' environmental data to make recommendations such as how to manage irrigation systems, how to match climatic conditions to agricultural inputs, and how to purchase supplies and sell products (Carolan 2017; Rotz et al. 2019; Stock and Gardezi 2022). Some farmers have expressed concerns from opaque data sharing agreements offered by the industry and have urged the state to do more to address this unwanted byproduct of PA (American Farm Bureau 2016). For instance, Stock and Gardezi (2021) found that 84.6% of PA users were concerned about their data being used for regulatory purposes, while 65.4% feared that corporations will use the data for their benefit and not the farmers (see also: American Farm Bureau 2016). Many farmers using PA technologies contend that agritech firms dispossess data about their food production systems when users are engaging with the technologies as a capital accumulation strategy (Fraser 2019). This user engagement then undergoes 'commodification via datafication' (Miles 2019) – the data is bundled into user profiles, monetized, sold to other firms, and used to advertise new products to users (Fraser 2019). As we demonstrate in this paper, learning from these perceptions and experiences are key to designing more socially responsible digital agriculture technologies. We assert that the socio-technical transition to agricultural DSSs ought to address some of the socially and politically sensitive issues such as data privacy, trust, access, and the future of rural society.

Responsible innovation: guiding principles for steering toward socially and ethically viable agricultural DSSs

Previous technological transformations in agriculture, such as the development of harmful chemicals during the first Green Revolution (Carson 1962) and debates about the health and ethical implications of GMOs (Macnaghten 2015) highlight that agricultural technology can generate benefits, but also cause risks to society and the environment. As a result, emerging technologies can be met with resistance from users and civil society groups, especially when they lack clear institutional structures and governance arrangements (Hajer 2003) or do not meet up to the societal expectations regarding their broader social and environmental impacts (Macnaghten and Chilvers 2014). Managing an innovation ecosystem for emerging technologies (i.e. DSSs) is complex because the processes of innovation, governance and use exceeds the influence of an agritech firm, a regulator, or a farmer (Eastwood, Klerkx, and Nettle 2017b). The application of big data and AI to DSSs helps utilize data from various sources and provides farmers with advice for supporting their decision-making under uncertain scenarios and circumstances (Wolfert et al. 2017). Yet, the focus on developing new DSSs in recent years has outpaced policymakers' abilities to design effective regulatory frameworks that can properly govern the social implications of big agricultural data and AI. Social actors in the DSS value chain can have widely different priorities, motivations and values pertaining to how these tools ought to be designed, developed, tested, evaluated, used, and regulated (Regan et al. 2018). For instance, the benefits and costs to farmers of their use of DSSs may differ from those of farm advisors because farmers and advisors can have different positions and roles in the agricultural supply chain – advisors are intermediaries who broker agronomic or financial information (e.g. Lemos et al. 2014). In information and communication technologies (ICT), the 'problem of many hands' (Johnson 2012) is common because processes of innovation are distributed or divided between numerous different individuals or organizations that only produce a small component of the larger functioning technology (Jirotka et al. 2017). This complex web of organizations within agricultural technology innovation and governance systems can devolve into a problem of 'organized irresponsibility' (Beck 1995), insofar as there can be ambiguity about who is responsible for addressing the social and ethical implications of DSS and to whom are these actors accountable (Owen, Macnaghten, and Stilgoe 2012).

Against this socio-technical dilemma, the responsible innovation (RI) framework aims to transform current modes of innovation governance to make science and technology more responsive and reflexive of its social, ethical, and environmental commitments (Owen, Macnaghten, and Stilgoe 2012; Von Schomberg 2013). The RI framework proposes that innovation ought to be designed, developed, evaluated, and governed not only on the basis of its economic viability, but also how it attends to environmental and social demands for greater equity and justice (Von Schomberg 2013). Reliance on technical assessments cannot be the only departure point for addressing innovation's potential future implications on people and landscapes. Instead, a variety of stakeholders, including experts and laypersons must – in a collective conversation – ask what *they* want technologies to do and whose interests will these innovations serve. Previously, the RI framework has been applied to investigate the innovation processes of several emerging technologies, such as nanotechnology (Fisher and Rip 2013), geo-engineering (Stilgoe, Owen, and Macnaghten 2013), and synthetic biology (Tucker and Zilinskas 2006).

In agriculture, scholarship has used a RI lens to examine the emergence of collective responsibility (or irresponsibility) in the digitalization of food production systems and value chains (Bronson 2019; Eastwood et al. 2017a; Jirotka et al. 2017; Rose and Chilvers 2018; Barrett and Rose 2020; Klerkx, Jakku, and Labarthe 2019; Van der Burg, Bogaardt, and Wolfert 2019). Barrett and Rose (2020) found that in the UK media and policy documents, the benefits of PA were amplified through the rhetoric about potential productivity gains and improvement in the environment, but little attention was paid to PA's social consequences. Against this background, other studies have emphasized the need for innovation governance that enables multiple actors to responsibly coproduce socio-technical transitions in agriculture (Rose et al. 2021). Barrett and Rose (2020) and Klerkx, Jakku, and Labarthe (2019) suggested some possibilities for policymakers to comprehensively examine the risks and benefits of PA, with the overarching goal of enabling these technologies to work with – and for – different farming communities. Eastwood et al. (2017a) extended an existing RI framework by Stilgoe, Owen, and Macnaghten (2013) to investigate how innovations in the smart dairy farming sector could become more responsive to societal and environmental demands. They proposed that more open and inclusive conversations with a wide range of agricultural stakeholders could identify areas of contestation and consensus on these technologies and help steer the direction of innovation (Eastwood et al. 2017a). The purpose of these conversations should not only lead actors and organizations to anticipate the expected and unintended consequences of PA, but also to activate a more direct and active role in co-producing or co-shaping the future of agriculture in more desirable ways (Van der Burg, Bogaardt, and Wolfert 2019). The RI framework urges social actors and organizations to not only deliberate on the products of science and innovation (*what is it?*) and its purpose (*why do it?*), but also its unintended and undesired implications for society and the environment (Owen, Macnaghten, and Stilgoe 2012, 28). When applied to PA, RI for DSSs would be built on the premise that the societal implications of these technologies are co-produced and mutually shaped. Hence, the social and cultural values influence the process of designing, using, and evaluating DSSs affect the construction of social values and meaning of agriculture.

We propose that more open and deliberative conversations with a range of agricultural stakeholders could inform more responsible innovations of DSSs. RI enabled DSSs can be more attentive to concerns of and create opportunities for a wide variety of food system actors, to minimize the controversies that DSSs may embroil in the near future (such as the conflicts around GMOs). This research builds on this body of scholarship in RI to examine how various food system actors across two geographically heterogeneous regions in the US (South Dakota and Vermont) anticipate the implications of the DSSs in restructuring crop, livestock, and dairy production systems. Probing these implications can reveal the socio-technological scaffolding of DSS tools; the kinds of sociopolitical and technological worlds that have contributed to the development and configuration of DSSs and the likely distributional effects of these technologies on people and the environment. Understanding how DSSs may be rescripting the agri-food sector can avail opportunities for reconfiguring innovation and governance approaches for DSSs to become more ethical, socially inclusive and sustainable.

Methods

This section explains the steps used for participant recruitment, participant characteristics and study area, and the procedures used for data collection and analysis.

Participant recruitment

We utilized a snowball sampling technique to select participants representing different sections of the PA space, including (1) software and hardware developers, (2) state and county extension specialists, (3) non-profit and government agencies and (4) crop, livestock, and dairy farmers. A purposeful sampling approach enabled us to effectively recruit participants who could provide us rich and contextual information for answering questions pertaining to PA's social and ethical implications (Patton 2002). Potential participants were initially contacted through emails and follow-up phone calls and 65 participants were able to confirm their attendance. In total, 52 people were able to participate as research subjects. The number of participants from each category is summarized in Table 1 below.

Table 1. Number of FGD participants. (Table view)

Participants	South Dakota	Vermont	All participants
Farmers	4	2	6
NGO/government regulators	10	5	15
Academia/extension	14	8	22
Technology developers	6	3	9
Total	34	18	52

Note: Some participants had multiple roles. For instance, some extension agents also farmed part-time. For this reason, participants' primary occupation was used for grouping them into one of the four categories.

Study setting

Vermont and South Dakota are ideal locations for such a comparative study due to the wide variance of their social, political, and environmental aspects of agriculture. For instance, Vermont has a majority of small and medium scale farms while South Dakota contains a majority of medium and large-scale farms. The average acreage in Vermont is 176 acres compared to 1459 acres in South Dakota (USDA 2019). Further, Vermont farms tend to be family-owned, organic, mixed cropping/grazing-based while South Dakota has mostly industrial scale and conventional monocropping farming systems. With a total of 719 certified organic farms in 2017, Vermont had more organic farms than any other state per capita. Participants from these locations reflect this heterogeneity, representing different types of agriculture (corn and soybean versus diversified small crops and dairy), small open-access and large-scale technology developers, and non-farm non-profits that espoused unique socio-political values. The two states provide an interesting comparison of the heterogenous socio-demographic and biophysical conditions that provide a useful context into diverse food, fuel, and fiber production systems.

Procedure and data collection

We utilized a mixed-methods approach, consisting of six homogenous focus group discussions (FGDs) and a follow-up survey with stakeholders across the food system value chain. Fieldwork for this study was conducted between October and December 2019 in Vermont and South Dakota, USA. Appropriate human subjects research approvals were obtained under SDSU IRB-2103006-EXP. Field work was conducted in two phases. During the FGDs, participants deliberated on the risks and benefits of PA tools, such as DSSs, AI, big data, and machine learning algorithms for agronomic and financial decision-making in crop, livestock and dairy production systems. Participants also discussed the effectiveness of existing PA education and ways in which traditional and non-traditional education can prepare farmers and technical support personnel for careers in PA. Participants reflected through FGDs to articulate their perspectives and experiences vis-à-vis the development, use, or regulation of PA technologies. Some questions asked during the FGDs include: (a) What information is needed to make PA successful? What are the knowledge gaps that would aid PA? (b) How do you feel about the potential of big data in agriculture? (c) How do you think automation will change farming? (d) How do you think the adoption of PA will affect the livelihood of rural communities? We audio and video recorded all FGDs to assist with transcription. To ensure anonymity of name, affiliation and location, all participants were given unique codes. A follow-up survey questionnaire was completed by 52 FGD participants. The survey elicited participants' attitudes, beliefs, and perceived risks and benefits of PA technologies. Survey questions were designed to triangulate information from the FGDs on the overall benefits and risks associated with PA to farmers and farm workers (Arbuckle 2019; Creswell et al. 2003).

Analysis

This study adopted a qualitative interpretive method to analyze FGDs, allowing the emergence of concepts based on perspectives guiding this study (responsible innovation, data ownership, accessibility, sharing and control, power (re)distribution; impacts on human life and society framework). The qualitative approach was chosen to understand how participants understand social phenomena, with the emergent realities associated with their social lives. The interpretive approach allowed for exploring and interpreting distinct contributions and perceptions of stakeholders in the US food systems on the emergence of PA. An inductive approach to coding was used to read and interpret FGDs and develop codes and themes that emerge to answer our research question. In addition to the inductive approach, a deductive approach to coding was also utilized. Combining inductive and deductive approaches to coding can be seen as a hybrid coding process that allows themes to emerge from the data, literature, and theoretical frameworks that guided this study (Fereday and Muir-Cochrane 2006). This hybrid approach to coding has been used recently by Jakku et al. (2019) to code interview data on the benefits and opportunities of smart farming among Australian grain industry stakeholders.

A codebook was developed following the procedure outlined by Macqueen et al. (1998). Data were re-read, and initial coding was performed on FGDs. The initial coding allows for multiple pages of textual data to be reduced to important and manageable segments that can be further used in analyzing the data in the next stage (Bailey 2006). After the initial coding, axial coding was performed to identify and combine codes that emerged from the larger classifications that included multiple codes. In the third step, selective coding was applied, where themes emerged from the axial coding process following the labeling important textual segments with codes and combing codes that incorporate similar codes and categorizing them into themes. The themes that emerged were further refined and modified in the fourth step, reflecting the FGD transcripts. The codebook generated after this process was applied to the remaining FGDs. The qualitative program NVivo QSR 12 software was used to organize and manage the coding process, update the codebook, and document the description of themes and codes. Supplementary document renders Tables 1 and 2 to describe the analytical coding process used in this paper. Quantitative survey data was analyzed through standard descriptive statistical techniques.

Results

In proposing DSSs as techno-scientific solutions to social and environmental problems, PA developers described the interactions they expect to occur between emerging PA technologies and society. While study participants invoked social and ecological issues to motivate PA research, these discussions were quickly subsumed by the possibilities and perils offered to society by the technology. The depictions of the interaction between DSSs and society in these discourses often followed a technologically determinist path, where participants envisioned greater DSS use to improve social outcomes for the users. Yet many other participants highlighted that agricultural DSSs are disrupting social, economic, environmental and technological relationships in the agriculture sector. These technologies can pose wide-ranging repercussions for a network of agricultural stakeholders.

Knowledge production and intellectual property

Some participants explained that agricultural DSSs are disrupting existing competencies and experiential knowledge for a range of agricultural stakeholders. Processing AI-based models require the collection, curation, and analysis of large data sets. Most farmers in South Dakota or Vermont do not possess the capacity to store or analyze large datasets. For instance, a non-profit worker from South Dakota reflected on her interactions with farmers: ‘A lot of times they lay out a bunch of memory cards [with large data sets stored in them] in front of you – “well, here it is” – they haven’t done anything with it.’ The process required for moving from data to information and knowledge is changing the requirements for skills in agriculture. For example, a University Extension worker in Vermont perceived a ‘skilled farmer’ as someone who embraced data science: ‘The best farmers are observational data collectors, every single minute of every single day. They may not perceive themselves as data scientists, but information collectors.’

The reality, however, is different. The average age of a farmer in the US is 60 years and most of them are hesitant about how to adapt to rapidly changing farm work. A Vermont farmer remarked:

> So now, are we just layering additional requirements on what it takes to be a farmer? Now, you've got to be really good at technology and we all know the troubles we have when you come in in the morning and your computer doesn't boot up. You know, add your drone and your tractor with GPS, and then you spend your whole day on the line with tech support?

A South Dakota farmer lamented that many of the DSS-based recommendations required them to make significantly new investments and changes to their farm operation:

> They [agritech] can throw all the yield map analysis and all the soil analysis at us, but if they are not able to translate that into software or peripherals that will make *my* plan to run, none of it does me any good. The gap I see is the transition from having the information to making it work.

As one South Dakota farmer highlighted: ‘I would say mercy on the tools. I wish the industry would stop developing things and start figuring out how to use them, because it is pointless.’

Overwhelmingly, farmers feel as if they are losing autonomy over the equipment they purchase, insofar as their consent agreements prevent them from repairing their PA equipment. Regarding this issue, a technology developer in Vermont that developed robots for the dairy industry said: ‘Our model is similar to other large agricultural equipment developers that you have to be a certified qualified tech to work on a robot, you can’t touch it yourself and it requires a trade person to work on it. So I mean, we kind of have the same concept with John Deere as far as accessibility to the equipment, and a lot of that goes back to safety and proprietary, you know, investment, things that we've done that are secure.’ But then there’s not only the issue of repairing equipment, a farmer in South Dakota remarked:

> Maintaining the hardware isn't bad, it's all the subscriptions I got to pay every year to keep it running. It's the software that's more expensive in the long run than the hardware, and they know that. I mean Deere knows that, Climate knows that, Trimble knows that.

Reconfiguration of farm labor

Social applications of DSSs were mostly envisioned as a workforce augmentation strategy, or assisting farm workers in improving on existing tasks, but not replacing the farmer themselves. A PA technology developer in the Midwest defined DSSs as ‘supporting management decisions for improved resource-use efficiency.’ A South Dakota farmer explained: ‘They [agritech] are collecting yield data, lots of weather data, soil conditions data. The challenge is making that all work together. We need someone to analyze, someone in the middle that can actually move that through.’ Participants provided several interventions that could ease the process of workforce augmentation. One was to prepare farm advisors for a new kind of role, which was to interpret the recommendations coming out of an AI-based model, instead of relying on their own intuition or knowledge. A South Dakota farm advisor observed that there is

> still going to be a need for people that can explain the why [results of the model] to a grower who is looking to implement a practice … More recently, my job is to open the 'black box' up and explain to the farmer what it is inside it. Therefore, it is still important to have those boots on the ground.

Similarly, some participants imagined that the role of the farmer will change too, but remain important for ground-truthing or field-checking model recommendations. A South Dakota farm advisor noted that:

> I feel like the farmers' knowledge of the field and the history of it is really important, because they can pick out zones and areas of the field they know aren't producing well. That way we can make recommendations made by AI more suitable for farmers' fields.

However, not everyone imagined farmers to remain important in the near future. A Midwestern technology developer encouraged a future of farmerless farms:

> Our [firm's] concept is complete autonomy. Maybe it's called level five autonomy. It's the idea that a human does not need to physically sit in the machine. Today, when we farm, farmers are pushing hard in the middle of the night trying to get harvest done and they get tired out. But the [autonomous] machines will not get tired.

There seems to be a demand for a fully autonomous farming system as explained by a Midwestern PA technology developer:

> Some of the conversation we're having with our clients is that they want the easy button. It's like McDonalds. You know, the hamburger cooks itself and it's all just the recipe and all you need is a button pusher. You may not even require having any skill, really that is my perception.

Concern about who will get displaced as a result of digitalization troubled some of the workshop participants. A non-profit worker in the Midwest explained this sociological phenomenon:

> I want to comment on this idea that the advancement of technology in agriculture will promote workers and create opportunities for small farms. History tells us that doesn't happen. Small rural towns had all died in the previous technological transformation and what killed it was not the tractor, but that because of the tractor, you consolidated into larger farms that needed less labor. So, you want to be very careful when managing the transition to PA that you're not compounding that issue. Rather than more jobs, you're very likely looking at fewer jobs.

Indeed, the transition to preparing the agricultural workforce from an analog to a digital setting requires not only the fundamental rewiring of the labor force, but also examining this transition under the broader political economy of agriculture.

Data exclusions

Discussions on the effectiveness of workforce augmentation or better human-machine partnerships touched upon socially and politically sensitive issues such as data privacy, trust, and access. Indeed, most participants across the food value chain agreed that farmers lack confidence in the recommendations made by site-specific data (Figure 1). A South Dakota farmer explained their hesitance to trust recommendations made by their DSS:

> The field imagery that I got from Climate FieldView showed some areas of the field not doing so well [yield-wise]. And the plants they were calling as poor health, in fact yielded five bushel an acre better. I went into the field and found that it was just the shape of that corn plant that the field imagery was picking up and labeling as

> bad. It was just the shape. One was more upright and the other was more bent. It was picking up that difference and calling that plant health difference.

DSS technology developers and proponents of DSS argued that some of this uncertainty in the recommendations made by DSSs stem from the model's inability to accurately control for the variability found in natural systems. A Midwestern technology developer provided an explanation: 'Agronomy isn't black and white. There's a lot of grey area in that, and computers and technology have a problem in the grey area … Unless we're putting a bubble over a field, we can't control the environment.' Indeed, some of their recommendations is to do just that: collect data from each and every possible square inch of the field to visualize and interpret the ecological complexity of agriculture more reliably. A Midwestern technology developer's solution was to collect more data:

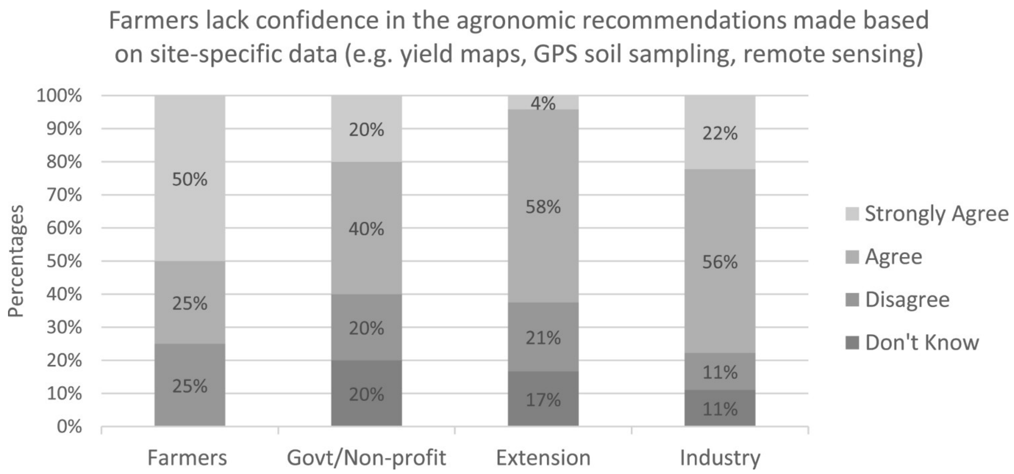

Figure 1. This figure illustrates data from the survey question: 'The following are potential challenges and/or concerns related to farmers' adoption of PA technologies. Please rate your agreement or disagreement with the following statements: Farmers lack confidence in the agronomic recommendations made based on site-specific data (e.g. yield maps, GPS soil sampling, remote sensing).' The data was disaggregated into four sections of the food system ranging from farmers to the industry. *Y*-axis shows the percentage of responses for each category of the survey question, ranging from 'Don't Know' to 'Strongly Agree.' There were no responses recorded under the category 'strongly disagree.'

> We need to measure probably every 10 square feet and maybe up to 100 square feet – do a soil test in every single one of those plots on the field. The only reason we can't do that right now is because the device is too expensive. It would be possible, however, if there was a way to produce low-cost biodegradable sensors. In fact, somewhere between three and ten years, the technology may be more affordable than we imagine.

Social differentiation

But other social actors in the food system are worried that agritech's technologically driven view of social progress may rely on the identification of social issues that are only amenable to interventions using DSSs. Deeper and systemic challenges pertaining to the political economy of agriculture may be ignored in this process. The present digital transformation in agriculture can disproportionately impact farms of different sizes and marginalized workers across axes of social difference. A South Dakota farmer questioned whether some of the PA tools were even effectual for small farmers: 'I mean, it is challenging to get a return on investment on some of these PA technologies if you don't have enough acres or volume to spread it over.' As shown in Figure 2, most participants agree that PA tools are effectual for large farms only. With respect to DSSs internal biases favoring largeholding farmers, smallholders feel increasingly marginalized in the political economy of agriculture. According to a non-profit worker in South Dakota: 'It becomes 'the big get bigger.' Look at our population; less than 2% of people are in the agriculture sector. So if we keep knocking more out of that 2 percent, the disconnect becomes bigger.'

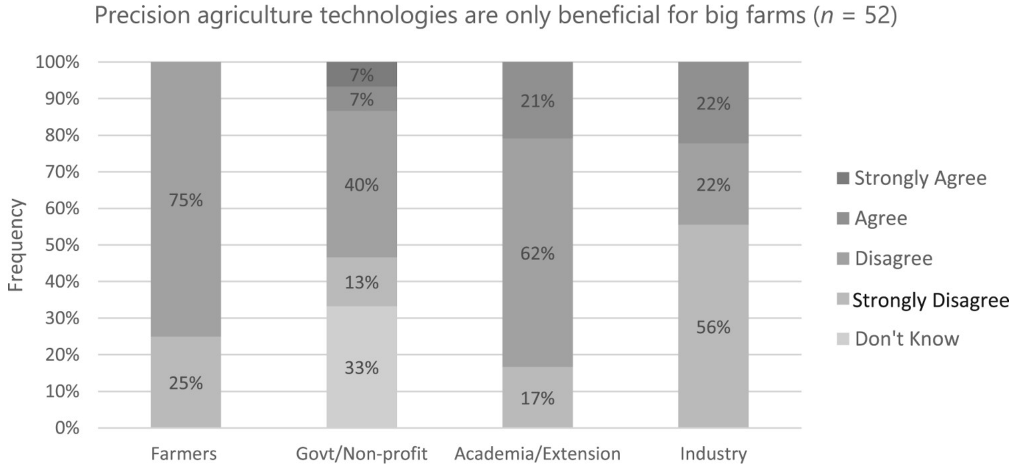

Figure 2. This figure illustrates data from the survey question: 'The following are potential challenges and/or concerns related to farmers' adoption of PA technologies. Please rate your agreement or disagreement with the following statements: PA technologies are only beneficial for big farms.' The data was disaggregated into four sections of the food system ranging from farmers to the industry. Y-axis shows the percentage of responses for each category of the survey question (e.g. Don't Know, Strongly Agree).

Just as some PA technologies are financially and technically ineffectual for large farms, these technologies are being developed with a specific kind of farming system in mind. A PA hardware developer in Vermont explained:

> In the industry, we're seeing, sort of, call it 'consolidation,' or monoculture emerging in the technologies as well. So, you know, row crops are the first target for PA because you have a ton of land you can manage all with the same method, all have the same big data set, to learn about it. And the small producers or the diverse producers are left out because it's not an attractive economic target. But it also reduces the resiliency to have people like John Deere or Monsanto or Syngenta, you know, playing such a large role in controlling so much production.

An extension agent from Vermont reiterated these worries of exaggerated corporate control of land and now AI:

> The business community has a full record of selling you things that are harmful. Think about opiates, DDT in agriculture. When the power gets concentrated, there's not a diversity in the economy, and there's not competition. That invites these kinds of problems. And that's what I get concerned about, within the AI industry of that concentration, of that concentration of data.

Ameliorating the negative impacts of corporate consolidation of farming systems and control over farming data will necessitate additional regulation of DSSs.

Currently, there are limited regulations on AI in agriculture and most of them are soft or informal regulation in the form of principles and guidelines that have been developed in the US and elsewhere. For instance, for AI, in general, Jobin, Ienca, and Vayena (2019) identified 11 ethical values and principles for AI, including: 'transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust, dignity, sustainability, and solidarity' (Jobin, Ienca, and Vayena 2019, 391). Ryan (2022) compared Jobin, Ienca, and Vayena's (2019) 11 ethical guidelines with their relevance and importance to AI in agriculture and found that some principles were fairly harmonious between agriculture AI literature and AI ethics guidelines in general, such as 'privacy' and 'responsibility.' The regulation of AI was a deeply important matter discussed by some focus group participants, including an academic from Vermont:

> In the agricultural community, concerns around privacy and trust issues are most heightened. There's a higher level of lack of trust in government. We need a Bill of Rights or AI Bill of Rights. We need to have clarity around AI and then there need to be universal standards, global standards that are negotiated through treaties.

> There's clear consensus on land ownership: Who owns what, when, where and how? And they need to get on it [for AI] ASAP. The challenge, I feel, is the genie is already out of the bottle. And so how do you stop and unwind on the rolling of a technology that's already in the market? Can you then have John Deere recall their tractors and change that up? Can you undo contract laws where farmers are signing off on genetically modified seed production and, basically, are now leasing their land to a global company?

Participants' affective responses captured within FGDs and subsequent survey questionnaire provide invaluable insights into the social dimensions of DSSs, grist for developing more responsible iterations of these technologies.

Discussion: leveraging agricultural stakeholder's lived experiences with PA to inform future innovation and governance of DSSs

DSSs are changing the nature of farming, redefining social practices and meanings in agriculture. At the same time, these hardware-software re-configurations augment farmers' ability to potentially achieve improved farming decisions. Our results show that participants across the food value chain are generally optimistic about the potential of these technologies to effectively integrate with farm work. Technology always puts humans into a dance with it, and it is through these interactions that the agency continues to move like a pendulum between humans and machines (Orlikowski 2005). Many commentators, such as Clark and Chalmers (1998) and Heersmink (2017), argue that technology extends human cognition to broader socio-technical systems and the strength of the human-artifact coupling or workforce augmentation requires not only reliable, dependable, and accessible technology, but also humans to '… develop new skills, share competencies, and negotiate for agency and autonomy' (Duus, Cooray, and Page 2018, 1). But developing new skills does not necessarily imply that farmers' tacit knowledge is ignored or considered obsolete. Instead, it would require carefully managing the integration between what is already known to workers and how DSSs can enhance that knowledge. Indeed, Lindblom et al. (2017) associate the low reception of agricultural DSSs to the disconnect between scientists and technology developers who do not regard the levels of knowledge and actual needs of the farmers who are the end-users of the technology. When considering the adoption of DSSs, developers should factor in the issues of observability, perceived complexities of DSSs, unfriendly user interfaces, ambiguous data input requirements, low adaptability to peculiar farm situations, irregular information updates, low motivation to learn and adopt novel practices, as well as unwillingness to entertain the possibility of having new advisors (Carberry et al. 2002; Hochman and Carberry 2011; Jakku and Thorburn 2010). Rose et al. (2018) note that a major reason for the success (or lack thereof) of DSSs can, however, be attributed to the participation and involvement of farmers in the design and development of technologies. Moving forward, DSS developers should program the technologies to recognize local knowledge and design the interface to facilitate the co-creation of knowledge. Community-based participatory approach to technology development can allow for creating novel DSS that integrates farmers' tacit, contextually specific information, and enables a powerful source of information to enrich AI models. Integrating farmers' experiential knowledge in AI models can also show respect to the farming community and has the potential to improve farmers' trust in DSS.

Several participatory approaches, such as a living laboratories approach, can be used for testing new DSSs technologies that can enhance users' trust and attend to broader environmental concerns. Living labs are environments, physical or otherwise, in which innovators, private and public entities and end-users collaborate in the creation and development of products and services (Schuurman, De Marez, and Ballon 2016). They are transdisciplinary and multi-methodological in nature, and consist of two essential principles: (1) end-users are co-creators of the product or service under development from stages of idea formation to implementation and evaluation; (2) the product or service is tested in a real-life environment with realistic conditions (Claude et al. 2017). Each party involved in a Living Lab provides unique value to the collaboration. Innovators typically supply the means to create the product or service. End-users co-create by providing insight into their needs and expectations of a given innovation and serve as evaluators for its continued improvement. Public agencies initiate market demand for the product or service of the Living Lab (Bergvall-Kareborn and Stahlbrost 2009), and other partnerships extend their expertise and ensure that expectations are met from all parties involved (Bergvall-Kareborn and Stahlbrost 2009). We contend that Living Labs could become more prevalent as a process of co-designing and co-evaluating new DSSs. We are already seeing the establishment of several living labs in the agricultural sustainability context in North America. For instance, the agricultural sustainability living labs at the AcadieLab (https://www.rang3.org/le-labo) and recent initiative by the Government of Canada launching its own Living Laboratory Initiative to promote user-centered approaches to farming technologies (http://www.agr.gc.ca/livinglab), are some ways in which early and iterative engagement in upstream design processes are bringing diverse users closer to the process of agricultural technology development. Similar initiatives in the European Union are being developed for social innovation in marginalized rural areas (see for example: https://liverur.eu/tag/simra/).

However, living labs are not simply a panacea for achieving social sustainability in agriculture (Van Geenhuizen 2019). Researchers and practitioners should ensure that these collaborative and generative innovation spaces can truly serve RI goals. Many living labs are brought to life for instrumental business value, such as to introduce new products to market (Bergvall-Kareborn and Stahlbrost 2009), rather than to achieve broader societal goals such as improving democratic participation or addressing ethical concerns related to new technologies. Van Geenhuizen (2019) discuss some of the limitations with existing living labs, and how these spaces can become more inclusive and purposive for achieving RI goals. They argue, for instance that a living lab should encourage participation of stakeholders with divergent interests and in this process acknowledge the unequal relations of power between and among them. RI goals can be achieved if the living lab is able to activate stronger and sustained level of support to those that are in a weaker position of power. The living lab should switch from its traditional focus on achieving project outcomes through means-goal effectiveness criteria, to broadening participation and positively impacting both farming and non-farming community. This requires setting up living labs to strive for other criteria of success that go beyond a single sector (agriculture) or outcome (economic profitability) to other ethical and normative principles of sustainability, like farm work safety, soil health, and rural quality of life. Framed around principles of responsible innovation, the Living Lab approach to designing DSSs may foster the production of equitable, ethical and ecologically sustainable PA technologies.

Attending to the broader notions of sustainability – beyond economic and environment – necessitates innovators and regulators of DSSs to become more responsive to society through ‘opening up the governance of science and technology to wider public values and internal reflection’ (Chilvers and Kearnes 2016, 8). In the last several decades, scholars in the social studies of science have sought to open spaces for engagement and dialogue on risks and benefits of science and technology (Rowe and Frewer 2005). Several theoretical and methodological frameworks, such as ‘post normal science’ (Funtowicz and Ravetz 1993), constructive technology assessment (Rip, Schot, and Misa 1995), ‘anticipatory governance’ (Guston 2000), and responsible innovation (Owen et al. 2013) have been proposed to ease tensions between innovation and the presence or absence of democratic participation. The RI framework attempts to create avenues for active engagement of the public in science and innovation. It demands innovators to seek novel approaches to public participation that require going beyond a simple calculation of economic and environmental risks and benefits to including elements of anticipation and speculative foresight involving non-technical communities of interest (Hellstrom 2003). Through well-crafted deliberation processes, social actors and organizations in the food system can anticipate diverse transition pathways – thereby adding alternatives to what is assumed to be normal. These arenas can help generate a range of perspectives, interests, and concerns of heterogeneous actors in the food system. Perhaps providing farmers the space to speak and the tools to create can prove to be a partial panacea to social frictions caused by PA.

Conclusion

The greatest predicament of modernity is that the development of new technologies in addition to producing benefits also produces risks. The benefits and risks of DSSs by advances in big data, IoT, and AI are not entirely predictable, and by virtue of their newness, have little or no historical precedent. Our results highlight that the implementation of DSSs in the world outside of the laboratory calls for a deeper understanding of the interactions between technology and society. On one hand, technologies shape the social and cultural processes of their production and use. On the other, the process of designing technology and governance mechanisms involves social as well as technical choices. Our results suggest that the innovation system is complex and some actors possess a dominant influence on the development, diffusion, management, and control of technology. Specifically, the agritech firms wield a disproportionate influence over the current political economy of agriculture. Their profitable technologies of PA are positioned as ‘smart’ responses to ecological crises within food production systems. Yet the proprietary configuration of PA technologies often dispossesses farmers of data and requires consistent capital investment, exacerbating agrarian distress among marginalized farmers. Agricultural DSSs are hardware and software technologies of PA that transform agronomic data gathered about the food production system into ostensibly ‘accurate’ farming recommendations. DSSs fall within a genealogy of PA technologies that unevenly distribute benefits and burdens throughout the value chain.

Utilizing a mixed methods approach that consisted of focus group discussions and follow-up survey questionnaire, we highlight the experiences and affectations of heterogeneous food system actors from Vermont and South Dakota. Farmers expressed concern about how proprietary exclusions of DSSs transform knowledge production and human-machine interactions. Farmers were dismayed by the potential for PA technologies like DSSs to render their labor redundant, reconfiguring the food production system into ‘ghost farms’ without humans. Biases internal to DSSs that favor large-scale monocropped farming systems produce social differentiation and exacerbate social power asymmetries throughout the value chain. Focus group participants were troubled by the lack of regulation around DSSs and envisioned new policies (e.g. PA ‘bill of rights) that protect users from agritech predation. Focus group discussions served as forums of open deliberation about DSSs. As such, participant responses could be used by PA developers to equitably and ethically redesign DSS technologies under the auspice of engendering data sovereignty for users. Likewise, our study extends this normative prescription to policymakers in pursuit of regulatory frameworks for PA. Inclusive processes of open deliberation are modalities of responsible innovation, tasked with mitigating frictions within socio-technical systems. The future of farming is unwritten; may authorship reside with farmers instead of machines.

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