What Are the Implications of Digitalisation for Agricultural Knowledge?

Julie Ingram* and Damian Maye

Countryside and Community Research Institute, University of Gloucestershire, Gloucester, United Kingdom

In this perspective paper we consider the implications of a digital transformation for agricultural knowledge, a subject which hitherto has received limited attention. We raise critical questions about how digital agriculture will intersect with established modes of knowing and decision-making. We also consider the implications for the wider Agricultural Knowledge and Innovation System (AKIS), specifically the roles and capabilities of those who provide advice to farmers, as well as those responsible for data analytics, and the organizations and institutions that link and support them. We conclude that new data driven processes on farm, as well as the changing AKIS dynamic under digital agriculture, bring new demands, relations and tensions to agricultural decision-making, but also create opportunities to foster new learning by harnessing synergies in the AKIS.

Keywords: digital agriculture, agricultural knowledge and innovation system, knowledge, smart farming, farmer, big data

INTRODUCTION

It is generally agreed that digital agriculture[1] will deliver a step change in efficiency, productivity and sustainability at the farm level and across the value chain (Aubert et al., 2012; Wolfert et al., 2017). Sensing systems and associated analytics can provide producers with better information to make more timely decisions with more predictable outcomes, while automating tasks using sensing technologies and machine learning can increase reliability. Rapid developments in the Internet of Things (IoT), cloud computing, robotics and Artificial Intelligence are accelerating the transition to smart farming and the promotion of big data and precision agriculture to improve agri-food sustainability. The expectation is that smart farming approaches will ultimately improve knowledge about an individual enterprise, or via efficient sharing and learning from data from multiple enterprises (Robertson et al., 2018).

However, although this "fourth agricultural revolution" brings the promise of multiple gains, it also brings with it technical, social, economic, ethical and practical questions, with significant implications for how commercial agriculture is structured, practiced and governed. Research to date is only just exploring the full ramifications of this so called "disruptive innovation" in relation to these aspects (Bronson and Knezevic, 2016; Jakku et al., 2016; Carolan, 2018; Klerkx et al., 2019; Rotz et al., 2019). One question that is not being fully addressed, however, is: what are the implications of digitalisation for agricultural knowledge?

---

[1]Digital agriculture typically involves both the collection and analysis of data to improve both on-farm and off-farm decision (Leonard et al., 2017), although here we refer to different forms of digitalisation in agricultural production systems.

Digital applications and platforms have the potential to dramatically change the way knowledge is processed, communicated, accessed and utilized. For farmers, digital applications will provide decision-making capabilities that were previously not possible, potentially leading to radical changes in farm management (Sonka, 2014; Wolfert et al., 2017). As smart machines and sensor networks increase on farms and farm data grow in quantity and scope, farming processes will become increasingly data-driven and data-enabled (Wolfert et al., 2017). This raises critical questions about how digital agriculture will require new capabilities, support decision-making and interact with, and potentially disrupt, established modes of knowledge processing.

There are significant implications for the whole Agricultural Knowledge and Innovation System (AKIS)[2], specifically the roles and capabilities of farmers, those who provide advice to farmers, as well as those responsible for data analytics, and the organizations and institutions that link and support them.

These considerations are important if we are to enable digital agriculture to be effectively implemented.

DIGTIAL AGRICULTURE AND KNOWLEDGE PROCESSES

Our understanding of knowledge in agriculture has evolved from regarding it as a transferable commodity to something more diffuse emerging out of technical and social interactions. This understanding underpins the AKIS concept and the multiple knowledge generation, exchange and utilization processes operating interactively between the heterogenous actors involved (Klerkx et al., 2012). Analysis of the potential impact of digital agriculture on the AKIS to date has tended to follow a supply-orientated narrative, examining, for example: digital services in extension (Steinke et al., 2020), social media usage, digital literacy and access (Bronson and Knezevic, 2016); and adoption of technologies (Pierpaoli et al., 2013; Barnes et al., 2019; Lowenberg-DeBoer and Erickson, 2019). Whilst these perspectives are insightful, we argue that digital agriculture requires us to fundamentally rethink these knowledge processes and to reflect on the consequences of a shift toward data-driven processes.

This perspective piece refers especially to conventional agricultural systems and draws on research primarily from developed countries. In this brief discussion inevitably we have to use shorthand terms for the different AKIS actors: farmers, advisers, researchers, etc. We acknowledge that these groups are not homogeneous and we know that farmers' interactions with, and access to, digital agriculture differs significantly depending on multiple farm, farmer and wider enabling factors (Barnes et al., 2019; Vecchio et al., 2020).

---

[2]The AKIS concept refers to complex arrangements and interactions between actors, knowledge organizations (agricultural research, extension, and education organisations) as well as the informal networks of heterogeneous actors (supply chains, policy makers etc).

DIGITAL AGRICULTURE, FARMER KNOWLEDGE, AND DECISION-MAKING

Decision Support - Analytical Capabilities

Digital agriculture offers the ability to utilize technology to convert precise data into actionable knowledge to drive and support complex decision-making on-farm and along the value chain. The promise is that, whilst past sources of knowledge were based on general knowledge often derived from research experiments, smart technologies will be able to offer on-farm, local-specific information to farmers (Poppe et al., 2015). As such, digital agriculture reflects a shift from generalized management of farm resources toward highly optimized, individualized, real-time, hyper-connected and data driven management (Van Es and Woodard, 2017).

Of the three pillars of digital agriculture: robotics, sensors, and Big Data analytics platforms, the latter is critical. The large amounts of data being currently generated on farms by, for example, yield monitors, are of little value unless they can be turned into useful decision support tools for farmers (Janssen et al., 2017; Weersink et al., 2018).

However, some scholars suggest that our capacity to collect large amounts of data outstrips our ability to convert it into usable information. Data analytics[3] and decision support are fundamental for fully-enabled digital agriculture, but to date the interpretation and use of data from smart technologies is not matching expectations (Leonard et al., 2017; Weersink et al., 2018) and the capability to effectively analyse these data to achieve promised improvements is limited.

Whilst there is evidence of uptake of GPS technologies that simplify the work (e.g., auto-steer systems) or passively collect data (e.g., yield monitors) (Lowenberg-DeBoer and Erickson, 2019), they signify "embodied-knowledge technologies" (Griffin et al., 2017) that require no additional skills to capture their value; in other words, they rely on the knowledge that farmers already possess regarding how to operate their machinery. This is distinct from the information-intensive technologies which use data collected from the farm as input into a decision support system that generates a prescription for the variable inputs. This distinction, some argue, explains the low uptake of variable-rate (VR) technologies which require new skills and decision-making models compared to the widespread adoption of GPS automated steering systems, yield monitors, and grid soil sampling (Weersink et al., 2018). Barnes et al. (2019) for example in a recent European survey noted this distinction in adoption patterns. Capalbo et al. (2017) point to the many cases where VR application of nutrients continues to be based on simple rule-of-thumb or empirical approaches.

Overall, it is felt that the difficulty of constructing, maintaining, analyzing, and sharing such data limits the opportunity to derive effective decision rules with high information value to producers Weersink et al. (2018). Given this, there is still a heavy reliance on the user to interpret the data. Studies have also found an increased learning load for farmers from using digital agriculture tools and the need to invest in

---

[3]Analytics is the capability available to analyse data (Shepherd et al., 2018)

human capital (Van Es and Woodard, 2017; Eastwood et al., 2019).

Apart from the difficulty of providing decision support, farmers, advisers and researchers are finding it hard to manage, interpret, or make use of their data as a result of their volume and complexity (Van Es and Woodard, 2017). Typically farmers do not need high frequency and precise data for every decision (Robertson et al., 2018) and have limited capacity to deal with data complexity (Lioutas et al., 2019).

Despite these challenges, there are multiple examples of technologies available, from farm management software solutions (e.g., AGERmetrix and FieldView™ in USA and Agrivi in UK) to decision support tools (e.g., FieldNET Advisor™ in the USA) (Kamilaris et al., 2017; Saiz-Rubio and Rovira-Más, 2020), that show how analytic capabilities are advancing.

However, limited decision support continues to reduce farmers' ability to meet the new demands of digital agriculture and can present significant adoption hurdles (Pierpaoli et al., 2013; Knierim et al., 2018). Whilst we cannot characterize the complex implementation problems of digital agriculture as solely due to limited capabilities in analytics and data use (Lowenberg-DeBoer and Erickson, 2019), it is evident that the optimism for digital agriculture is not yet matched by analytic capability within the AKIS.

Disruptions To Farmer Knowledge and Decision-Making

Although there is a suggestion that skilled agricultural workers have the highest probability of automation compared to other workers (Nedelkoska and Quintini, 2018), the extent to which this will support or replace decisions in farming depends on the technology. Sensors provide raw data (e.g., weather data), and smart devices (robotic vehicles, drone mounted cameras) will allow sophisticated farm management advice (Walter et al., 2017), while smart systems have the capability to execute autonomous actions (Budaev et al., 2019). For the former, human interpretive skills for decision making are still important, but for the latter the role of humans in analysis and planning is increasingly assisted by machines.

The nature and extent to which the human role shifts in the "sense–analyse–act" cycle in achieving actionable knowledge is debated. Whilst many agree that farmers' knowledge is not about to be replaced by algorithms, it is suggested that their involvement will be at a much higher intelligence level, leaving most operational activities to machines (Wolfert et al., 2017). This distinction between strategic and tactical action releases the farmer from mundane day-to-day monitoring although it also removes the opportunity for observational knowledge which contributes to experiential learning.

There is a perceived risk of increasing reliance on technical experts and the technology resulting in a loss of tacit knowledge if the cognitive processing of information is delegated to machines or algorithms (Jago et al., 2013; Shepherd et al., 2018). Arguably the farmers' experiential knowledge acquired over the years is at risk (Moschitz and Stolze, 2018). However, the opportunity for farmers to acquire a better knowledge of their production sites

and thus gain greater certainty when making decisions increases (Rösch and Dusseldorp, 2007). The use of digital technologies, such as sensors for monitoring animal behavior, can arguably also replace the lost knowledge of older generations (Moschitz and Stolze, 2018). Furthermore, new systems are expected to support handling a higher complexity as well as an increased local adaptation which may be beyond individual experiential knowledge (Aubert et al., 2012).

More fundamentally, decision-making and experiential processing commonly applied on farm have been supported in the past with descriptive and diagnostic tools and models explaining what and why things have happened. Digital agriculture heralds an era where these learning opportunities will be potentially diminished, in which the "what is known" is prioritized over the "capacity to know."

With respect to decision making, new sources of data are seen to create the opportunity to inform and drive a change in decision making from one that is typically characterized as being highly intuitive to one that is data driven and processed in real-time (Xin and Zazueta, 2016). This, many argue, requires a change in the mode of working for many farmers, transitioning from experiential decision-making to data-driven processes (Eastwood and Kenny, 2009; Nuthall and Old, 2018). However, in reality many farmers have been transitioning toward more data-driven decision-making processes for some time, integrating different information sources and drawing on different levels of analysis, using, for example, precision agriculture and DSS.

Insights from studies of DSS, reveal that they largely support, rather than replace, the decision maker; that farmers use DSS, not in a deterministic way to provide specific answers, but as learning tools (McCown, 2001; Baars, 2011; Lindblom et al., 2017). Experience with participatory design of DSS suggests that, a better appreciation of how farmers build tacit knowledge, the mind's store of decision rules and background information through repeated experience, may improve decision support for digital agriculture. In particular, understanding how this experiential processing can combine with analytical processing, where information is obtained through statistical description (Marx et al., 2007); Hansen et al. (2019), can help to overcome difficulties at the interface between data and decision-making. Working with farmers in developing technologies can also address the limited opportunities product developers have to ground truth information (Kamilaris et al., 2017). Although there are few examples yet of co-created digital technologies there is acknowledgment that farm management and information systems require a user-centric approach (Fountas et al., 2015; Van Es and Woodard, 2017).

THE CHANGING AKIS DYNAMIC UNDER DIGITAL AGRICULTURE

Farmers draw on multiple sources of knowledge and innovation support services in the AKIS (regulators, supply chain actors, conservation experts, NGOs, policy makers), however, for many, farmer networks and farm advisers remain key. Evidence to date

of the impacts of digital agriculture suggest potential shifts in these knowledge relationships.

Enabling or Disrupting Farmers' Knowledge Networks

Informal networks, between farmers and often including other actors, are one of main knowledge exchange mechanisms in farming communities which lead to learning and innovation (Leeuwis and Aarts, 2011; Ingram, 2015). The extent to which digital agriculture will disrupt or enable these network processes is an important consideration. Proposed smart systems, which promise to take and learn the best practices from advanced precise farmers, formalize and transfer their knowledge and support to other farmers in everyday decision making (Budaev et al., 2019) could arguably replace interpersonal networks. However, the potential for digital technologies to support collaborative knowledge creation has also been identified (Eastwood et al., 2012). ICT enables farmers to exchange information, benchmark their production against others, establish cooperation and peer review, and maybe even develop informal information systems that can complement more formal information systems (Wolfert et al., 2017). Many farmers have started to mobilize and organize themselves (e.g., in cooperatives, online communities) to create and share know-how, technologies and experiences, and big data understanding (Kamilaris et al., 2017; Carolan, 2018). Distributed sensing systems can form the basis for knowledge platforms for social learning (Robertson et al., 2018).

Innovation Support Services

With respect to support services, farm advisers have always been important as interpreters of data and information. The digitalisation of expert knowledge into decision support tools or via artificial intelligence has the potential to disrupt advisory services and change the adviser's role (Wolfert et al., 2017). Digital agriculture tools can provide farmers with analytical power and access to information previously unavailable (Ayre et al., 2019). This may mean advisers need to reassess their capabilities, practices, services and skills as they respond to new demands (Eastwood et al., 2017; Rijswijk et al., 2018). They may also need to create new networks with technology providers and R & D (Lundström and Lindblom, 2018). Although there is a potential role for technology suppliers to take on greater advisory support for farmers and act as knowledge "translators," they can often lack the farm systems expertise or knowledge networks to adequately support on-farm use (Eastwood et al., 2016). To address this problem, researchers propose a co-development approach for building the capability to use digital agriculture tools (Eastwood et al., 2019).

New Entrants and Changing Roles

The emergence of new suppliers of equipment, software and services, business models and networks creates a new dynamic within the incumbent AKIS. The public and private sector generally operate together to establish a wide variety of data, knowledge and institutional arrangements that together constitute "a decision making infrastructure" that supports

management in agriculture (Capalbo et al., 2017). This is evolving under digital agriculture with new disruptive entrants (e.g., digital technology companies) and various models of development and investment appearing, including new business models that challenge incumbent forms (Phillips et al., 2019). The changing roles of old and new software suppliers and the emerging landscape of data-driven initiatives, with the prominent role of big tech and data companies and research universities has been observed (Keogh and Henry, 2016; Van Es and Woodard, 2017; Wolfert et al., 2017). The dynamic between the new and established players is often framed by discussions of private-public data accessibility, ownership and governance (Bronson and Knezevic, 2016; Jakku et al., 2016); however, issues of knowledge are also key, and are redefining AKIS boundaries. The tensions and synergies between these new entrants and those in public bodies and universities are of particular interest. The former have limited understanding of agronomic principles but excellent market access, while the latter have the expertise and institutional learning which has provided the foundations for understanding the processes driving agricultural systems, through decades of experimental research and sophisticated modeling (enabling diagnostic understanding).

The opportunities for combining their different analytics are highlighted by Antle et al. (2017, p. 258) who point to synergies between the modeling community, which is strong on analytical capability, and the developers of user-related farm-level products. Harnessing big data and the analytical powers of models can also lead to what Capalbo et al. (2017) referred to as a virtuous circle which builds on both and will allow a new generation of models and decision support.

At a more fundamental level the arrival of new analytics raises the questions about knowledge and data-driven processes. Established R&D institutions applied analytical techniques associated with descriptive and diagnostic analytics which led to the effective application of what Sonka (2014) calls "Small Data." An important question for Sonka is: "how can the best aspects of the Small Data system be linked to the application of Big Data technologies?" Whilst he acknowledges that knowing, at increasing levels of precision, "what" happened in the field or in animal facilities does have value, he argues that knowing "why" is also key to agricultural applications.

This shift in analytics also has the potential to significantly impact the AKIS in other ways, moving us from "hindsight" to "foresight" (Shepherd et al., 2018). Digitizing agriculture will take these systems to predictive (what will happen) and prescriptive (how can we make it happen) analytics, which are future focused. This development again raises questions about where our understanding of the mechanisms underpinning these predictions and prescriptions lies.

CONCLUSION

New data-driven processes on farm as well as the changing AKIS dynamic under digital agriculture brings new demands, relations and tensions. However, there is also great potential to both build

on established ways of knowing and to foster new learning by harnessing synergies.

Morakanyane et al. (2017, p. 437) defined digital transformation "as an evolutionary process that leverages digital capabilities and technologies to create value." We would argue that these capabilities are crucial and extend beyond the digital domain *per se* to the knowledge capabilities of all actors in the AKIS. Enhancing capabilities at every level, from the farm and adviser level, to new technology and software providers and established researchers, will be important if digital technologies are to achieve their full value. Equally facilitating opportunities for combining different analytic approaches and capabilities should be supported. Fostering co-learning and collaboration in implementing new technologies should be an important strand for future development and research.

AUTHOR CONTRIBUTIONS

JI prepared the main draft. DM contributed material and ideas and edited the text.

ACKNOWLEDGMENTS

REFERENCES

Antle, J. M., Basso, B., Conant, R. T., Godfray, H. C. J., Jones, J. W., Herrero, M., et al. (2017). Towards a new generation of agricultural system data, models and knowledge products: design and improvement. *Agric. Syst.* 155, 255–268. doi: 10.1016/j.agsy.2016.10.002

Aubert, B. A., Schroeder, A., and Grimaudo, J. (2012). IT as enabler of sustainable farming: an empirical analysis of farmers' adoption decision of precision agriculture technology. *Decis. Support Syst.* 54, 510–520. doi: 10.1016/j.dss.2012.07.002

Ayre, M., Mc Collum, V., Waters, W., Samson, P., Curro, A., Nettle, R., et al. (2019). Supporting and practising digital innovation with advisers in smart farming. *NJAS-Wagen. J. Life Sci.* 90–91:100302. doi: 10.1016/j.njas.2019. 05.001

Baars, T. (2011). Experiential science; towards an integration of implicit and reflected practitioner-expert knowledge in the scientific development of organic farming. *J. Agric. Environ. Ethics* 24, 601–628. doi: 10.1007/s10806-010-9281-3

Barnes, A., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., et al. (2019). Exploring the adoption of precision agricultural technologies: a cross regional study of EU farmers. *Land Policy* 80, 163–174. doi: 10.1016/j.landusepol.2018.10.004

Bronson, K., and Knezevic, I. (2016). Big data in food and agriculture. *Big Data Soc.* 3:2053951716648174.

Budaev, D., Lada, A., Simonova, E., Skobelev, P., and Travin, V. (2019). Conceptual design of smart farming solution for precise agriculture. *Manag. App. Complex Syst.* 13, 309–316. doi: 10.2495/DNE-V13-N3-309-316

Capalbo, S. M., Antle, J. M., and Seavert, C. (2017). Next generation data systems and knowledge products to support agricultural producers and science-based policy decision making. *Agric. Syst.* 155, 191–199. doi: 10.1016/j.agsy.2016.10.009

Carolan, M. (2018). *The Politics of Big Data: Corporate Agri-Food Governance Meets "Weak" Resistance.* Routledge: Agri-environmental Governance as an Assemblage. 195–212.

Eastwood, C., Ayre, M., Nettle, R., and Rue, B. D. (2019). Making sense in the cloud: farm advisory services in a smart farming future. *NJAS-Wagen. J. Life Sci.* 90–91:100298. doi: 10.1016/j.njas.2019.04.004

Eastwood, C., and Kenny, S. (2009). Art or science?: heuristic versus data driven grazing management on dairy farms. *Exten. Farming Syst. J.* 5, 95–102. Available online at: https://search.informit.com.au/documentSummary;dn= 722662138426388;res=IELHSS

Eastwood, C., Rue, B. D., and Gray, D. (2017). Using a network of practice approach to match grazing decision-support system design with farmer practice. *Anim. Prod. Sci.* 57, 1536–1542. doi: 10.1071/AN16465

Eastwood, C. R., Chapman, D. F., and Paine, M. S. (2012). Networks of practice for co-construction of agricultural decision support systems: Case studies of precision dairy farms in Australia. *Agric. Syst.* 108, 10–18. doi: 10.1016/j.agsy.2011.12.005

Eastwood, C. R., Jago, J. G., Edwards, J. P., and Burke, J. K. (2016). Getting the most out of advanced farm management technologies: roles of technology suppliers

and dairy industry organisations in supporting precision dairy farmers. *Anim. Prod. Sci.* 56, 1752–1760. doi: 10.1071/AN141015

Fountas, S., Carli, G., Sørensen, C. G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., et al. (2015). Farm management information systems: current situation and future perspectives. *Comput. Electron. Agric.* 115, 40–50. doi: 10.1016/j.compag.2015.05.011

Griffin, T. W., Miller, N. J., Bergtold, J., Shanoyan, A., Sharda, A., and Ciampitti, I. A. (2017). Farm's sequence of adoption of information-intensive precision agricultural technology. *Appl. Eng. Agric.* 33, 521–527. doi: 10.13031/aea.12228

Hansen, J. W., Vaughan, C., Kagabo, D. M., Dinku, T., Carr, E. R., Körner, J., et al. (2019). Climate services can support african farmers' context-specific adaptation needs at scale. *Front. Sust. Food Syst.* 3, 1–16.

Ingram, J. (2015). Framing niche-regime linkage as adaptation: an analysis of learning and innovation networks for sustainable agriculture across Europe. *J. Rural Stud.* 40, 59–75. doi: 10.1016/j.jrurstud.2015.06.003

Jago, J., Eastwood, C., Kerrisk, K., and Yule, I. (2013). Precision dairy farming in Australasia: adoption, risks and opportunities. *Ani. Prod. Sci.* 53, 907–916. doi: 10.1071/AN12330

Jakku, E., Taylor, B. M., Fleming, A., Mason, C., and Thorburn, P. J. (2016). *Big Data, Trust and Collaboration: Exploring the Socio-Technical Enabling Conditions for Big Data in the Grains Industry.* Brisbane, QLD: CSIRO, 34.

Janssen, S. J., Porter, C. H., Moore, A. D., Athanasiadis, I. N., Foster, I., Jones, J. W. et al. (2017). Towards a new generation of agricultural system data, models and knowledge products: information and communication technology. *Agric. Syst.* 155, 200–212. doi: 10.1016/j.agsy.2016.09.017

Kamilaris, A., Kartakoullis, A., and Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. *Comput. Electron. Agric.* 143, 23–37. doi: 10.1016/j.compag.2017.09.037

Keogh, M., and Henry, M. (2016). *The Implications of Digital Agriculture and Big Data for Australian Agriculture.* Sydney, NSW: Australian Farm Institute.

Klerkx, L., Jakku, E., and Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: new contributions and a future research agenda. *NJAS-Wagen. J. Life Sci.* 90–91:100315. doi: 10.1016/j.njas.2019.100315

Klerkx, L., Van Mierlo, B., and Leeuwis, C. (2012). "Evolution of systems approaches to agricultural innovation: concepts, analysis and interventions," in *Farming Systems Research into the 21st Century: the New Dynamic,* eds I. Darnhofer, D. Gibbon, and B. Dedieu (Dordrecht: Springer), 457–483.

Knierim, A., Borges, F., Kernecker, M. L., Kraus, T., and Wurbs, A. (2018). "What drives adoption of smart farming technologies? Evidence from a cross-country study," in *13th European International Farming Systems Association (IFSA) Symposium, Farming systems: Facing Uncertainties and Enhancing Opportunities, 1-5 July 2018* (Chania: International Farming Systems Association).

Leeuwis, C., and Aarts, N. (2011). Rethinking communication in innovation processes: creating space for change in complex systems. *J. Agric. Educ. Exten.* 17, 21–36. doi: 10.1080/1389224X.2011.536344

Leonard, E., Rainbow, R., Laurie, A., Lamb, D., Llewellyn, R., Perrett, E., et al. (2017). *Accelerating Precision Agriculture to Decision Agriculture: Enabling*

Digital Agriculture in Australia (Narrabri, NSW: Cotton Research and Development Board).

Lindblom, J., Lundström, C., Ljung, M., and Jonsson, A. (2017). Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. *Precis. Agric.* 18, 309–331. doi: 10.1007/s11119-016-9491-4

Lioutas, E. D., Charatsari, C., La Rocca, G., and De Rosa, M. (2019). Key questions on the use of big data in farming: an activity theory approach. *NJAS-Wagen. J. Life Sci.* 90–91:100297. doi: 10.1016/j.njas.2019.04.003

Lowenberg-DeBoer, J., and Erickson, B. (2019). Setting the record straight on precision agriculture adoption. *Agron. J.* 111, 1552–1569. doi: 10.2134/agronj2018.12.0779

Lundström, C., and Lindblom, J. (2018). Considering farmers' situated knowledge of using agricultural decision support systems (AgriDSS) to foster farming practices: the case of CropSAT. *Agric. Syst.* 159, 9–20. doi: 10.1016/j.agsy.2017.10.004

Marx, S. M., Weber, E. U., Orlove, B. S., Leiserowitz, A., Krantz, D. H., Roncoli, C., et al. (2007). Communication and mental processes: experiential and analytic processing of uncertain climate information. *Global Environ. Chang.* 17, 47–58. doi: 10.1016/j.gloenvcha.2006.10.004

McCown, R. (2001). Learning to bridge the gap between science-based decision support and the practice of farming: evolution in paradigms of model-based research and intervention from design to dialogue. *Aust. J. Agric. Res.* 52, 549–572. doi: 10.1071/AR00119

Morakanyane, R., Grace, A. A., and O'Reilly, P. (2017). Conceptualizing digital transformation in business organizations: a systematic review of literature. *InBled eConference*, 21.

Moschitz, H., and Stolze, M. (2018). "How can we make sense of smart technologies for sustainable agriculture? A discussion paper," in *International Farming Systems Association 13th European IFSA Symposium* (Chania: International Farming Systems Association).

Nedelkoska, L., and Quintini, G. (2018). Automation, skills use and training. *OECD Social, Employment and Migration Working Papers* (202).

Nuthall, P., and Old, K. (2018). Intuition, the farmers' primary decision process. A review and analysis. *J. Rural Stud.* 58, 28–38. doi: 10.1016/j.jrurstud.2017.12.012

Phillips, P. W., Relf-Eckstein, J.-A., Jobe, G., and Wixted, B. (2019). Configuring the new digital landscape in western canadian agriculture. *NJAS-Wagen. J. Life Sci.* 90–91:100295. doi: 10.1016/j.njas.2019.04.001

Pierpaoli, E., Carli, G., Pignatti, E., and Canavari, M. (2013). Drivers of precision agriculture technologies adoption: a literature review. *Proc. Technol.* 8, 61–69. doi: 10.1016/j.protcy.2013.11.010

Poppe, K., Wolfert, J., Verdouw, C., and Renwick, A. (2015). A european perspective on the economics of big data. *Farm Policy J.* 12, 11–19.

Rijswijk, K., Klerkx, L., and Turner, J. (2018). "Digitalisation of agricultural knowledge providers: the case of New Zealand," in *European International Farm Systems Association Symposium* (Chania: International Farming Systems Association), 1–5.

Robertson, M., Moore, A., Henry, D., and Barry, S. (2018). Digital agriculture: what's all the fuss about? Available online at: https://blog.csiro.au/digital-agriculture-whats-all-the-fuss-about/

Rösch, C., and Dusseldorp, M. (2007). Precision agriculture: how innovative technology contributes to a more sustainable agriculture. *GAIA-Ecol. Perspect. Sci. Soc.* 16, 272–279. doi: 10.14512/gaia.16.4.9

Rotz, S., Duncan, E., Small, M., Botschner, J., Dara, R., Mosby, I., et al. (2019). The politics of digital agricultural technologies: a preliminary review. *Sociol. Ruralis* 59, 203–229. doi: 10.1111/soru.12233

Saiz-Rubio, V., and Rovira-Más, F. (2020). From smart farming towards agriculture 5.0: a review on crop data management. *Agronomy* 10:207. doi: 10.3390/agronomy10020207

Shepherd, M., Turner, J. A., Small, B., and Wheeler, D. (2018). Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture' revolution. *J. Sci. Food Agric.* doi: 10.1002/jsfa.9346. [Epub ahead of print].

Sonka, S. (2014). Big data and the ag sector: more than lots of numbers. *Int. Food Agribus. Manag. Rev.* 17, 1–20. doi: 10.22004/ag.econ.163351

Steinke, J., van Etten, J., Müller, A., Ortiz-Crespo, B., van de Gevel, J., Silvestri, S., et al. (2020). Tapping the full potential of the digital revolution for agricultural extension: an emerging innovation agenda. *Int. J. Agricu. Sust.* 1–17. doi: 10.1080/14735903.2020.1738754

Van Es, H., and Woodard, J. (2017). Innovation in agriculture and food systems in the digital age. *The Global Innovation Index 2017: Innovation Feeding the World* (Ithaca, NY; Fontainebleau; Geneva). 97–104.

Vecchio, Y., Agnusdei, G. P., Miglietta, P. P., and Capitanio, F. (2020). Adoption of precision farming tools: the case of italian farmers. *Int. J. Environ. Res. Public Health* 17:869. doi: 10.3390/ijerph17030869

Walter, A., Finger, R., Huber, R., and Buchmann, N. (2017). Opinion: smart farming is key to developing sustainable agriculture. *Proc. Natl. Acad. Sci. U.S.A.* 114, 6148–6150. doi: 10.1073/pnas.1707462114

Weersink, A., Fraser, E., Pannell, D., Duncan, E., and Rotz, S. (2018). Opportunities and challenges for big data in agricultural and environmental analysis. *Ann. Rev. Resour. Econ.* 10, 19–37. doi: 10.1146/annurev-resource-100516-053654

Wolfert, S., Ge, L., Verdouw, C., and Bogaardt, M.-J. (2017). Big data in smart farming–a review. *Agric. Syst.* 153, 69–80. doi: 10.1016/j.agsy.2017.01.023

Xin, J., and Zazueta, F. (2016). Technology trends in ICT–towards data-driven, farmer-centered and knowledge-based hybrid cloud architectures for smart farming. *Agric. Eng. Int. CIGR J.* 18, 275–279.