

Chapter 24

Digital agriculture

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Introduction

Since about 2010 there has been an explosion in the interest and expectations for data-driven agriculture, often dubbed ‘digital agriculture’. Digital agriculture is often used interchangeably with the term ‘smart farming’, which refers to the use of data to inform farm decisions and then automation and actuation to execute those decisions. Several technological drivers have converged to bring about this interest (Koch 2017):

- advances in, and availability of, cheaper sensor networks and the Internet of Things (IoT, Atzori *et al.* 2010);
- big data analysis (Wolfert *et al.* 2017);
- availability of connectivity at a decreasing cost per bit; and
- inter-operability of devices.

Effectively, farmers are becoming enabled to make use of farm business data that was previously impossible or impractical to collect and analyse. For the purposes of this chapter we restrict our attention to the use of data to inform farm decision making, including the broader definition of smart farming that includes the idea of taking data beyond the farm gate to inform decisions by regulators, financial institutions, agribusiness and governments. Digital agriculture is broader than ‘precision agriculture’, which is traditionally defined as matching farm operations to variable conditions, especially with the use of spatially-aware technologies and data (Robertson *et al.* 2012).

The advent of global navigation satellite systems (GNSS), including the widely known United States (US) global positioning systems (GPS), and yield monitors heralded the beginnings of precision agriculture. The core idea of precision agriculture was that collection and analysis of spatial information would allow more efficient production. More recently there has been heightened interest and associated hype around digital agriculture. This is being driven by a range of forces and was initially centred in the US. The primary opportunities have arisen by the confluence of several factors:

- First, the cost of collecting data is declining as new technology and sensors become available. Machinery is increasingly ‘smart’, is sensorised and able to communicate digitally;
- Second, the computing platforms and services such as the cloud are becoming ubiquitous, providing natural platforms with both the required storage and computational power to deliver digital agriculture services;
- Third, existing agricultural companies are going digital to ensure their future relevance and to open new data streams to exploit in the development of new products and services; and
- Fourth, there is a range of successful digital business models being imported into the agriculture space. For example, Google has shown that access to data about users can provide information to sell to advertisers, as well as information to tailor the experience to individual users. Some digital agriculture companies are trying to replicate this model. Other companies in agriculture are proceeding to implement decision-support techniques which are well developed in business analytics (*e.g.* dashboards) to provide situational awareness to managers.

These factors combine with the relative lack of maturity of the industry to produce a complex range of products in the market that seek to provide new sensor technology mounted on drones, services to support information cloud-based platforms, integrate information to support more refined decision

making, more complex business models that link producers and suppliers. Some do a mixture of all of these. There is also a variety of start-ups in this space that will pivot their business models to attempt to find a profitable configuration. Some products are only regionally specific and lack transferability, and others are focussed on specific farm management tasks without consideration of how they impact on other parts of the farm system, if at all.

As digital applications are developed for the agricultural industry, there will be a spectrum for the use of these data-intensive technologies and the degree to which the collection and actuation of farm tasks are automated. As the number of steps increases between data acquisition and task execution, this increases the complicated nature of the task. For example, in the simplest case, GNSS-guided farm machinery has only three steps between the use of the data-generating technology and the action: a GNSS-enabled vehicle is geo-located; this in turn guides auto steer, which results in a controlled driving pattern. Such cases are typified by embodied technologies that can directly increase efficiency or productivity as soon as they are used and require little or no human control or oversight. By way of contrast, a more complicated case of the application of fertiliser nitrogen to various sub-field zones in a cereal crop involves collection of spatial information, definition of management zones, selection of nitrogen fertiliser rates, encoding the variable rate controller to apply the prescribed rates, and application of the prescribed rates. Various biophysical and economic variables, with their own inherent uncertainty, need to be accounted for along the way. In these cases the digital technologies are not embodied in the technology being applied and require some kind of decision support tool to convert information to knowledge in a more complicated and challenging adoption scenario.

This chapter focuses on those digital agriculture applications where data are used to support farm decisions, through the use of decision support tools. We discuss the role of decision support tools, their state in Australian agriculture and data requirements. We consider the rise of ‘platforms’ and what a desirable future for decision tools might look like. We finish by considering the future requirements for digital agriculture from a farmer perspective.

The role of decision support tools

Decision support is the process of improving decision-making by providing some combination of information and analytics to a decision-maker. Most sources of rural data need to be mediated through some form of decision support if they are to benefit managers. In order to make the information or knowledge available, a decision support tool requires some kind of user interface; the interface is commonly implemented using information and communication technologies (ICT), but this is not a necessary feature. Figure 1 illustrates a typical agricultural decision support workflow, using the Yield Prophet® tool as an example.

Monitoring and diagnosis

Some decision support tools are designed to provide new information about the current state of plants, animals, land, water and infrastructure; the integration of this information into a decision-making process is left to the user. These tools provide value to a decision-maker by improved understanding of current conditions, often by deriving a diagnostic system parameter that would otherwise be inaccessible and/or relatively costly to the decision-maker. Tools provided with many spatial sensing products (e.g. yield monitor maps, mapping of canopy temperature or cover from unmanned aerial vehicle [UAV] data) are in this category.

An emerging opportunity in this category is the imperative to produce safe, quality, sustainable and ethical products embodied in volunteer traceability systems. Such systems speak of each participant in a commodity supply chain being able to provide information on ‘one step forward, one step back’ along the chain as a minimum requirement. For producers, this ‘one step back’ component could include inputs, management regimes, and environmental metrics.

Rural decision support software can have a range of different purposes. The following list is expanded from that provided by McCown (2002b):

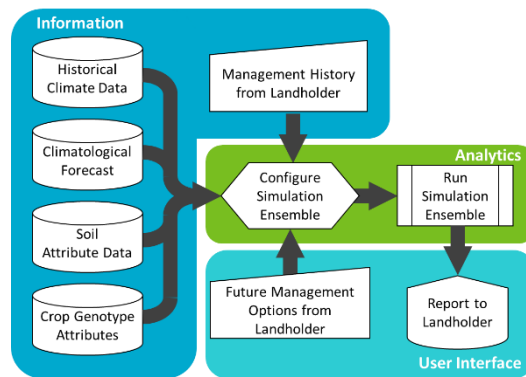


Figure 1. Information flows in the Yield Prophet® tool, showing the key components: information, analytics and a user interface.

Analysis of options in highly structured tasks

Tools with this purpose are the most widespread agricultural applications. They contribute value to the decision-making process by using powerful analytics to estimate the future outcomes of alternative actions, often in conjunction with a monitoring step, and they typically focus on a small number of variables that are relevant to the task. The intended user is typically a producer or an advisor, but can also be regulators. Perhaps the best-known example of this ‘decision calculus’ tool in Australian agriculture is Yield Prophet® (Birchip Cropping Group; Hochman *et al.* 2009), in which the user can explore the likely consequences of several specific crop management decisions such as cultivar choice or nitrogen fertiliser rates, based on probabilistic estimates of their consequences for crop yield (see Chapter 23).

Provision of prescriptions

Tools with this purpose share the same underlying rationale and logic as those in the previous category, but differ in that they select a single recommended action. A simple example of a prescription tool (control decisions for silverleaf whitefly in cotton) is shown in Figure 2. Some prescription tools, such as the FieldView™ tool delivered by the Climate Corporation in the US, are designed to produce ‘packages’ of prescriptions that cover multiple decisions – and the interactions between them – simultaneously. Local climate information is used to calculate a day-degree sum; this is combined with in-field sampling to derive a single recommendation for action.

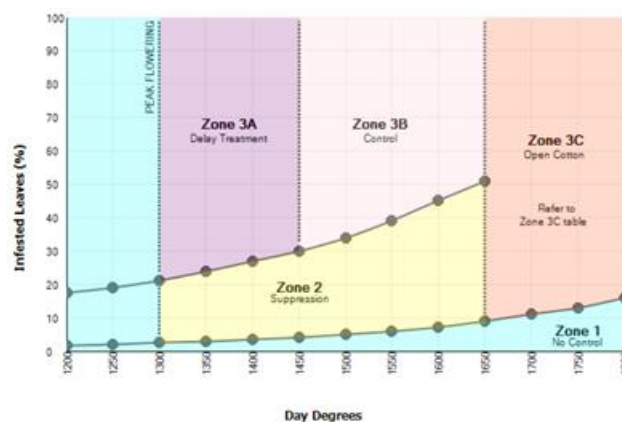


Figure 2. A simple prescription tool: silverleaf whitefly control recommendations from CSIRO’s CottAssist tool (Cotton Research and Development Corporation and CSIRO, 2015)

Use in consulting

These tools are based on ‘versatile simulators’ (McCown 2002b), *i.e.* complex simulation models designed to mimic system function and performance, cost-effectively. A problem is defined by the ultimate user (a producer, policy maker, or some other actor). An advisor then applies the simulator to the problem and its particular circumstances. The analysis process differs from other tools in that the task is typically not well-structured, so that the set of possible decision options emerges from an iterative process of asking ‘what-if’ questions; the consultant acts as the interface between a ‘hard systems’ and a ‘soft systems’ approach. These tools are generally designed to provide information about a wide range of potentially-relevant variables. The GrassGro® decision support tool for grazing systems (Moore *et al.* 1997) was explicitly re-designed to operate in this mode (Herrmann and Zurcher 2011).

Meeting external regulatory demands

In situations where standards for environmental conservation and safety are sought, decision support systems can be used in two ways. Documented compliance by farmers with the recommendations from a tool that embodies the current understanding of best management practice can demonstrate effective self-regulation (the CottAssist® tools are used in this way by the cotton industry). Alternatively, regulatory bodies can use decision support tools to evaluate whether proposed rural activities are acceptable, such as the widespread use of the OVERSEER™ nutrient budgeting tool (Wheeler *et al.* 2006) by regional planning authorities in New Zealand (Freeman *et al.* 2016).

The current state of decision support in Australian agriculture

A great many decision support products have been developed for Australian rural industries, dating back to the SIRATAC® system in the 1970s (Hearn *et al.* 2002). The 2007 Australian Farm Software Directory produced by the Queensland Department of Primary Industries identified ~75 distinct decision support tools, excluding software primarily designed for information recording. This variety is also seen in other countries (*e.g.* Rose *et al.* 2016 located 395 tools in the UK); it reflects the diversity of rural industries and the continuing development of new data streams and technologies. Some tools started as management information systems to which analytics have been added; some have been developed by machinery providers to add value to monitoring information; some are extensions of research models, often resulting from projects funded by rural R&D corporations (RDCs); yet others (*e.g.* the MLA Feed Demand Calculator® and the recently-released AskBill™ product for the sheep industries) were initiated by RDCs or Cooperative Research Centres (CRCs) in response to a perceived industry need.

While apps have proliferated it has been more difficult to identify documented cases where impact in the use of decision tools has occurred with end users. Robertson *et al.* (2015) recorded 11 cases where crop simulation models played a pivotal role in research, development or extension activity, and led to a demonstrable impact with decision makers (farmers, advisors, breeders). Many of the examples originated from the northern, subtropical grains region (see Chapter 23). This is a cropping region with high climate variability and a diverse farming system where growers have a wide range of crop and fallow options. It is also the historical base for the group that developed the Agricultural Production Systems sIMulator (APSIM, Holzworth *et al.* 2014). The unifying theme of all 11 examples is that models were used to integrate and quantify the effects of climate, soil and management in evaluating a new option for a farmer or plant breeder. Models were used to extrapolate field results beyond site and season specificity and, in doing so, built confidence for the decision maker in the reliability of the option.

Diverse analytic techniques

As a result of their diverse purposes and origins, a wide range of analytic techniques are embedded within the currently-available decision support tools. Because of the uncertain nature of the Australian climate, decision support tools that forecast outcomes tend to rely on biophysical simulations of varying levels of complexity, *e.g.* Yield Prophet®, hydroLOGIC® for cotton (Richards *et al.* 2008) or

AskBill®. At its simplest, however, the analytic process can involve the computation and presentation of a summary statistic (*e.g.* degree-day counts, as in the federally-funded CliMate™ app, or the normalized difference vegetation index). Other tools are based on straightforward algebraic calculations based on user-input data and/or tables of generic data; many examples of this type have an explicitly financial focus, such as the VegTool® gross margin comparator for vegetable production. There are also tools that rely on predictive equations generated from statistical analysis of experimental or other field data, *e.g.* the LambAlive® tool (Donnelly *et al.* 1997).

More recently, machine learning techniques are being employed to develop predictive equations for use in agricultural decision support. The most widely-publicised example is the work of Climate Corporation in North America, where predictive analytics are used to provide cropping prescriptions to grain growers using local climate, soil, yield and other information. Machine learning approaches rely on the collation of large, consistent datasets of outcomes (*e.g.* crop yields) that can be related to other large, consistent datasets of potential predictors. The dearth and relative inaccessibility of such predictors in Australia must therefore be resolved if they are to find widespread application in Australian agricultural production. As well as offering the potential for improved prediction of outcomes in task-analysis tools, however, machine learning offers the prospect of analytics that can update themselves as farming practices shift, through the ongoing (and automated) collection of data and re-estimation of predictive equations. The emergence of IoT sensors that provide highly-time-resolved data (*e.g.* microclimate/soils sensors) and new algorithmic approaches is challenging the notion of the minimum data required to train an artificial intelligence (AI) system. The requirement is smaller than intuitively assumed – especially when data are shared into the AI platform from multiple sources, such as sensors deployed across a landscape that experience a multitude of dynamic ranges and integrated with spatial remote sensed information from mobile, aerial and/or satellite systems.

Dissemination channels in transition

The earliest agricultural decision support tools in Australia were delivered by models linked to main-frame computers (Hearn *et al.* 2002) but nearly all tools developed during the 1980s and 1990s were designed for use on a stand-alone personal computer. Spreadsheet implementations have historically been common; for many tool producers, the quality-assurance drawbacks of a spreadsheet have been outweighed by the familiarity to users of the spreadsheet interface.

In recent years, however, migration of agricultural decision support to the Internet has taken place. At its simplest, existing tools have been hosted on their providers' websites, to improve their findability and accessibility. Yield Prophet® was an early Australian example of server-based computation delivered via a Web page; the attraction of this technical approach is the ubiquity of the Web browser as a channel. In parallel, some long-established tools (*e.g.* GrazFeed®, Freer *et al.* 1997) have been re-implemented as apps for use on portable devices.

Given the advantages for developers and the widespread uptake of the necessary devices, it might be expected that this shift toward app-based or web-based delivery of decision support will soon be complete. Over the medium term, however, automation of agricultural husbandry may well result in a need to decentralise the analytics for small-scale, tactical decisions onto the machinery that is carrying out the tasks; examples might include determining whether a weed is worth killing, or the automatic drafting of livestock into different paddocks. What this will mean for the overall process of decision-making, and the extent to which automation can work with copies of centrally-maintained algorithms versus the extent to which local machine learning will need to take place, is as yet unknown.

Technical challenges to successful adoption of decision support in Australia

Historically, gaining widespread adoption of decision support tools has been a difficult task. This phenomenon – the 'problem of implementation' – is not limited to Australia (Rose *et al.* 2016) nor to agriculture (McCown 2002b). As a result, successful decision support systems in Australia have generated significant industry benefit through relatively small user bases, often by leveraging the networks of influential actors such as agricultural advisors. For example, Yield Prophet® has been

applied to just under 1000 paddocks across the country since 2002. A notable exception is the CottAssist suite of tools, which by 2019 appears to have generated almost 100% uptake over a 10-year period.

Technical challenges for decision support developers include:

- High fixed costs of development caused by diverse populations of potential users – especially with respect to their objectives in farming, the difficulties in accessing and re-using publically-held data, and the lack of consistent interfaces to on-farm data records;
- Limited context-specificity despite this being critical to landholders, caused by the coarse spatial resolution of public environmental data (especially soils and weather) compared with other OECD countries and, once again, the lack of ready links to on-farm data;
- High climatic variability compared with most other developed countries, resulting in a need to communicate probabilistic information in many contexts; and
- Need for high-quality user interfaces because potential users are time-poor and because much of the useful information that decision support can provide is complicated. Digital literacy and confidence amongst would be users is also a challenge that needs to be met (at least in some way) by developers. Surveys by Zhang *et al.* (2017) and Dufty and Jackson (2018) reported approximately one-third of farmers identified a lack of skills as a constraint on their uptake of new ICT tools.

Decision support in ag-tech: the rise of ‘platforms’

The perception of commercial opportunities in digital agriculture has resulted in an explosion of platforms on the market. Rather than starting from computer models and interfaces designed by agricultural scientists and targeted at particular decisions, these new platforms are based on ideas and models that have been successful in other digital industries.

Despite all being marketed as platforms, new software tools are actually highly diverse, reflecting different views of where the opportunities (both real and perceived) lie in the rural sector. At least four broad types of platform are emerging in the North American, and to a lesser extent in the Australian, rural industries:

- Aggregated views of information: these tools are similar in purpose to traditional monitoring/diagnosis tools, but present a decision-maker with multiple data streams (*e.g.* presenting current weather and forecasts, soil moisture and commodity prices side-by-side). These applications provide situational awareness and are analogous to the use of ‘dashboards’ to provide synthesised management information in government and industry. The weakness of these products is their inability to integrate information in an analytical sense.
- Mobile apps: are based on simple, easy-to-use interfaces and are targeted at very particular problems (*i.e.* they are a new way of delivering analysis of options for highly structured tasks). They are often linked with other technology such as drone-mounted or in-field sensors. Examples include the NSW Drought Feed Calculator® and the The Yield™ app for irrigation in horticulture. These tools exploit the ubiquity of smartphones and the well-developed ecosystem to market and deploy apps. The major impediment to using them in Australia is broadband coverage. A 2016-17 ABARES survey of 2,200 Australian broadacre, dairy and vegetable farmers confirmed that the overwhelming majority (96%) owned and used ICT assets as part of their farm business, ostensibly in support of decision making, and 95% were connected to the internet (Dufty and Jackson 2018). This is consistent with the survey conducted by Zhang *et al.* (2017) that identified 94% of 1000 producers surveyed had an internet connection for their business with the largest proportion (55%) relying upon the mobile phone network, and 30% of respondents rely upon landline, ostensibly ADSL/ADSL2+ for internet connectivity. The ubiquity of smart phones and tablets has likewise seen a veritable explosion in the number of decision supporting ‘apps’ available to producers; with listings for producers provided by numerous peak bodies and advisory groups (*e.g.* Roberts 2012; Ag Excellence Alliance 2014). Roberts (2012) provides a listing of 88 ‘useful’ apps and 2 years later The South Australian Ag Excellence Alliance

(www.agex.org.au) released the second edition of “Smart Phone Apps for Smart Farmers” which describes 414 apps.

- Federated analysis platforms: are based on gaining access to data from multiple enterprises and using it to learn to predict, or to benchmark, commercially important quantities such as prices of inputs, commodities, or yields. The resulting analytics can, in principle, be used for any of the purposes described above. These applications mimic the classic ‘big data’ model where the flow of data permits continuous improvement of the analytics. In Europe and the US, their success is critically dependent on the availability of publicly-curated soils and weather information. Variants of such platforms can also provide privileged access to suppliers and markets; in these cases, the platform can mimic the CostCo™ business model in which membership provides access to improved buying power.
- ‘Pure’ platforms: these are platforms in the narrow sense; their purpose is to provide software infrastructure through which multiple third parties can transact business, exchange data and access digital and professional services. They typically include cloud-based storage, standard data formats and access control; access is on a subscription basis. Platforms are powerful tools and if successful can become dominant players. There are preliminary indications that major software companies are developing pure platforms for agriculture often translated from application in a different sector.

We note that some applications contain elements from more than one pattern, and that a given company’s business model may evolve from one mode to another. For example, the Climate Corporation’s FieldView product is a federated analysis platform, but Climate appears to be evolving toward delivering a pure platform.

What might a desirable future for decision support look like?

Analytics and automation reinforce one another We envisage a future where small decisions are automated, freeing decision-makers to focus on the bigger picture. Platforms like UAVs and terrestrial robots can both monitor and act in response to threats to a production system. Like self-steering vehicles in which the controlling software lies within the GNSS-enabled agriculture vehicle, the algorithms that classify disease and pest risks and take corrective actions can reside on the device – a device that can communicate and interact to enable automatic responses.

Value extracted from the full diversity of analytics One element of a desirable future is that the new machine-learning techniques find their full expression; another is the improvement of predictions made with more-traditional simulation approaches through the use of model-data fusion techniques. In both cases, effective means are required to collate information about on-farm activities and outcomes. Barriers to market entry of new analytic approaches – in particular barriers to accessing training data – should be as low as possible, to encourage participation by firms that are new to Australia or to agriculture.

Fixed costs of decision support development and deployment are lowered From the point of view of decision support developers – regardless of the ways their work is deployed – a desirable future includes a range of FAIR cross-sectoral data that are available on acceptable terms (The FAIR principles – Findable, Accessible, Interoperable, Reusable – are described in Wilkinson *et al.* (2016)).

In addition, it will be essential that certain widely-usable computations be available on a FAIR basis as well: examples include ‘harness’ software for carrying out model-data fusion to estimate current conditions on a piece of land, and methods to estimate and present the uncertainties in a prediction of future outcomes on that piece of land.

Sustained, targeted investment in analytic capabilities for Australian agriculture is an essential requirement to deliver the value of cross-sectoral data. For example, updating (model-independent) information about the changing plant and animal genotypes used here is likely to be necessary: the North American business model, where the genetics and the analytics are owned by the same

commercial entities, is unlikely to emerge in Australia in the medium term. A commitment to FAIR principles on the part of analytics providers should be a minimum pre-condition for public investment.

To exploit FAIR agricultural data and analytics at least cost, we envisage that they will need to be made available as services that are accessed across the Internet (the ‘everything as a service’ approach). This will require investment by custodians to devise and implement interfaces to the necessary services; this process is already well advanced in the soil information space, and to some extent for remote-sensing data.

In a service-oriented environment, the process of acquiring the pieces of a software tool becomes much simpler, but assuring the quality of the software package becomes more complex. In our desirable future there will be one or more “staging services” available to tool developers; these services will simplify handling the technical aspects of trust, especially access control (*i.e.* who can use this information or computation?) and provenance (*i.e.* where did these numbers come from?).

Better and different analytics reach decision-makers If the current limitations to data access and re-use can be overcome, we see a wide range of opportunities to improve (or supersede) existing decision support software. Table 1 provides examples of these possibilities.

Table 1. Some possible future decision support software in a world with improved management of rural data and analytics

	IMPROVEMENTS TO EXISTING TOOLS	NEW KINDS OF TOOLS
Monitoring and diagnosis	<ul style="list-style-type: none"> Higher resolution, more-frequent, maps of crop/forage/tree using metrics that are better suited to diagnosing specific problems and opportunities 	<ul style="list-style-type: none"> Production/financial benchmarking services that are based on wider panels of properties, take local context into account and are available closer to real time Simple crop development monitoring for diverse horticultural crops that includes medium-term forecasts Product traceability systems that integrate with on-farm management activities/data
Analysis of options in highly structured tasks	<ul style="list-style-type: none"> Forecast-based husbandry decision support (<i>e.g.</i> <i>Yield Prophet</i> or <i>AskBill</i>) predict with reduced uncertainties, resulting in increased confidence in decisions, powered by reduced need for manual inputs by users 	<ul style="list-style-type: none"> Variable-rate planning for fertiliser and water inputs that balances farmer objectives and constraints against conditions sensed at small scales ‘Intelligent assistants’ for one-off decisions that are based on textual knowledge-bases as well as numeric data
Provision of prescriptions	<ul style="list-style-type: none"> Automatic feeding of livestock based on their day’s intake as well as currently-monitored attributes such as yield potential 	<ul style="list-style-type: none"> Entry of North American ‘prescription agriculture’ providers to Australia not limited by data supply
Use in consulting		<ul style="list-style-type: none"> Annual land use allocation decisions on cropping and mixed farms supported by provision of multiple information streams
Regulatory compliance		<ul style="list-style-type: none"> Access to EU markets or to price premiums supported through monitoring and interpretation of farm-scale environmental conditions

In addition, we believe that as the fixed costs of developing decision tools fall, landholders themselves will be able to take advantage of the services we describe above to develop their own analytics tools. Examples might include being able to send crop-monitor data to a consultant without a second thought; building specific data streams or analytic modules into business-specific dashboards; using public weather and soil data when analysing on-farm experiments; or reducing the costs of carrying out on-farm experiments as part of a local collective.

Data requirements for digital agriculture

Soil information Unlike the US and some European countries (where publically available sub-farm scale soil maps have been produced), Australia has not had a long-term and detailed soil survey program. Some broad-scale and consistent mapping is available in some jurisdictions and soil information (and streams of soil data) is now available from farm and agribusiness based on proximal and remote sensing technologies. A major step forward was achieved in 2015 with the release of the Soil and Landscape Grid of Australia (Grundy *et al.* 2015).

Changes in the structure of private actors in the agricultural advisory system, increased soil-information capacity in agribusiness and increased capacity on-farm to collect and monitor soil status is now providing new opportunities in soil-information supply and demand in the private sector. For example, there is potential for locally based soil data marketplaces; especially if the data streams available from farm machinery, soil sensors and appropriately interpreted proximal and remote sensing are included. Here we envisage local and intense soil information available on-farm or across farm communities being used by a wide range of actors.

Weather and climate The official and co-operative weather observation networks of the Bureau of Meteorology (herein the Bureau) provide a wide range of real-time data feeds from across Australia, contributing to more than one billion observations processed by the Bureau forecast models every day. The network has varying levels of quality and maintenance regimes, tailored for various purposes, which are captured in the metadata for every record. Beyond the official Bureau network of weather stations there are many private weather stations and networks collecting data. Techniques are now being designed to add these third-party networks to the Bureau suite to both improve the national modelled observations and to take existing weather forecasts and records and calibrate them to the paddock of interest where sufficient weather records are available.

Gridded products of historical weather have been developed to study climate trends throughout Australia. To obtain a grid of historical weather information, point observations are used and then varying techniques such as interpolations or dynamic models can be used to ‘fill in the gaps’.

Any forecast product is generated by considering the relationships between known observations over time, and uses physics to project those relationships into the future. Operational weather forecasting is provided by the Bureau, which also enables third parties to develop and maintain forecast services. To create its official forecasts, the Bureau combines runs from a suite of models, weighted according to recent and historical performance, to create a consensus forecast twice per day.

For many operational decisions, including crop choice and input management, forecasts are needed for the next six months at a local scale. One way to do this is to generate statistical outlook models using past climate records. Analogue years are chosen from the past according to larger climate states such as El Nino Southern Oscillation (ENSO). In recent years dynamical seasonal climate models are becoming skilful enough to be used in agricultural decision making (Rodriguez *et al.* 2018). These models are run at a lower spatial resolution and provide predictions for up to nine months ahead (see Chapter 25). Unlike weather forecasts, however, they provide a probabilistic picture of the future that must be interpreted accordingly. We are now at a cross roads in the statistical vs dynamical model approaches for climate forecasting in agriculture. Both methods have their advantages and are increasingly being combined to provide indications of the unfolding seasonal climate.

Remote sensing The primary uses of remote sensing (RS) imagery in agriculture have been in the detection and mapping of classes of land cover of interest (and their changes over time) and the

measurement of ‘greenness’ – with accompanying estimates of foliage cover and Leaf Area Index. To date, this information has been at a coarse spatial resolution, typically using indices such as the normalised difference vegetation index (the ratio between near infrared and red reflectance). Landsat is the oldest Earth observing mission and has an extensive history of use in agriculture. It started in the 1970s, but came into widespread use around 1982, and is still operating. Landsat has been the imagery of choice because of its application at paddock and sub-paddock scales, the historical record dating from the early 1980s, and its 16-day frequency. Blending activities are becoming more common where Landsat is being combined with Sentinel-2 and the temporal detail of MODIS (two overpasses per day).

New and increasing numbers of RS sensors and platforms are becoming available, most importantly those from the national space agencies (government), the private sector, particularly the miniaturised satellites and sensors (mounted on aeroplanes, drones or UAVs). This new-generation of satellite sensors is providing both high spatial resolution and high repeat frequencies, making it feasible to detect changes in time at paddock and sub-paddock-scales. Many useful applications in agriculture of hyperspectral or radar imagery have been demonstrated, but the low repeat frequencies, coarse spatial resolutions, and/or limited geographical coverage have historically limited their use. This is changing; *e.g.* the European Sentinel-1 satellite includes a synthetic aperture radar sensor and has a revisit time and coverage useful for agriculture and particularly suitable for regions with high cloud cover. Such spatial resolution and revisit frequency does not on its own resolve the issue of local specificity of many of the derived data products, and the need for broad scale transferability remains.

The trend towards increasing numbers of sensors and platforms with higher spatial, temporal and spectral resolutions will result in increasing data volumes. This will pose challenges for the flow, storage and processing of massive volumes of spatial data, in order for it to be useful and timely for farm operations. Several initiatives are providing users with large amounts of remotely sensed imagery ready to be used in analyses. Private providers are changing from business models where they sell imagery to one, to where they provide access to a cloud platform where the user can apply standard processing algorithms or even develop their own. The future will involve an increase in bespoke satellite missions that have specific foci, using constellations of micro-satellites that are cheap, and provide full and rapid coverage for a narrow and specific set of observations.

Farm management data Data on farm operations, crop yields, soil tests, and machinery and staff performance and workflows are collected directly by farmers in a diverse array of manual, semi-automated and automated means. Data reside in a variety of analogue and digital formats, thus limiting analytics and use in decision support tools. Contemporary farm management software has a focus on land use planning, task scheduling, allocating and monitoring, and basic performance recording. Rarely is dynamic information such as weather, soil moisture, machinery performance or crop development stage integrated, and even if it is, the associated analytics are rudimentary.

Being able to link such on-farm dynamic information with relevant public data sources (*e.g.* soils, climate, and remote sensing imagery) will enable more sophisticated analytics and notifications for tactical intervention. At a more strategic level, the ability for farmers to conduct ‘natural experiments’ using machine learning on historical farm information to arrive at optimised management regimes for each paddock and season based on *their* data rather than an abstraction of such in a decision tool is an exciting prospect.

In a response to big agribusiness developing ‘pure’ platforms in the US (see above) there is the emergence of the notion of data aggregation by groups of farmers to maintain control of farmer-derived data, while unlocking greater analytical power. There is also the prospect of creating a data asset that could be monetised, although this has yet to be widely validated in the market.

Telecommunications

Discussion of digital agriculture with the farming community inevitably involves the issue of telecommunications, both on- and off-farm. This includes the dimensions of connectivity from the farm gate to the outside world, but also connectivity within the boundaries; namely from sensors and

technologies deployed across the farm land to a point where it can be taken to the outside world. A survey of farms and farmers by Lamb *et al.* (2017) revealed that farms vary widely in terms of meeting the needs of its deployed data generating technologies, its physical communications environment (topography and land systems, access to external connectivity), the requirements for on- or off-farm data analysis, the particular management platform that the data are interacting with, and the ways the information is provided back to the farm management team for decision making and how it is used. Historically (> 5 years ago) this could have been attributable to a lack of widespread, well understood, 'standard solutions' in the market place. This has changed with the emergence of experienced providers of 'end-to-end' telecommunications solutions for farmers and on-farm devices and link technologies conforming to accepted, established industry standards.

The role of telecommunications in supporting a digital agriculture future is not necessarily technology constrained; if a farm has access to the mobile network somewhere on the farm, or National Broadband Network into the farm house then there is technology available to beam it to where it is needed. Entirely new, innovative, methods of extending connectivity over remote regions are in the R&D pipeline. Others have been around for some time and overlooked. At the same time there has been a significant increase in the development of end-to-end telecommunications technologies and services offered to producers. So-called 'second-tier' telecommunications providers offer their own transmission backhaul capability and in some cases associated cloud-based services. Second-tier providers will help extend the value and potential of existing telecommunication networks.

There are several possible communications pathways to and from remotely connectible devices on farm and these are largely dictated by the volume of data to be communicated, the speed it is to be transmitted, and also whether it is necessary to transmit the data live or whether some form of latency is acceptable. This applies equally to whether data are being sent to a remote device (*e.g.* for the purposes of actioning a command such as releasing a gate or door latch in a shed, switching on heaters, lights or pumps and panning and zooming a remote camera) or whether data are being sent back from a device such as a weather station, remote camera, or a plethora of other plant, soil, water, environmental, animal or asset sensors.

In summary, while limited and patchy telecommunications coverage is a 'hot button' issue for farmers with respect to digital agriculture, many innovations are becoming available that can be matched to the range of 'use cases' on farm. This will continue to evolve at the same time as the public telecommunications network improves coverage.

Farmer-centric imperatives to maximise the value from digital agriculture systems

Here we posit eight imperatives we believe should be borne in mind by those designing and marketing digital agriculture solutions for farmers. These imperatives are informed by theories of technology adoption in agriculture (*e.g.* Rogers 2003) and reinforced by our many interactions with farmers who are implementing digital systems on their farms.

1. Make it easy for me to collect the data

Digital agriculture solutions are based on collecting data. Farmers are time poor and juggle competing demands. They prioritise the most important tasks and will not go to great lengths to collect data unless highly valuable. If information can be automated or collected while conducting another (routine) task then this increases the likelihood of use by farmers. One example is collecting crop yield maps while harvesting, made easy by yield monitors being factory-fitted to harvesters.

2. Too much information can confuse and does not clarify

Digital systems have enormous power to generate high volumes of data. This comes at the risk of overwhelming the decision maker with too much information. Hayman (2004) noted that relationship between more information and improved decision making is not proportional; there is a critical amount of information which is helpful, after which more information can become unnecessary or confusing.

3. I do not need high frequency precise data for every decision

The attraction of digital technologies is that they provide the opportunity to collect information at high spatial resolution and high frequency. For example, many commercially available soil water sensors can log soil water status in intervals of minutes; grain monitors and satellites can record yield and plant biomass to tens of square metres; and GNSS collars on livestock can locate individuals to within a few metres. High frequency/precision information is useful to farmers if it matches the decision time frame or can be aggregated to a scale matching the decision requirement and if management levers can be deployed to similar level of precision. Where information is too frequent and does not match the management decision, it is likely to be under-utilised or at worst, confuse the decision-making.

4. Minimise the steps between data collection and providing me with some knowledge I can use

The fewer the steps in processing between data collection and decision-making the more adoptable will be the digital technology. As the number of steps increases between data acquisition and task execution the complicated nature of the task increases. The number of ancillary variables required to make a confident decision also increases, particularly when converting information to knowledge. Uncertainty increases as the influence of climate, market, logistical or regulatory conditions increase. The corollary is that adoption will be limited in more complicated cases, or where the enabling technology is difficult to access, learn, operate or extract information from. Many of the digital solutions currently in the marketplace require multiple steps between data collection and actionable knowledge.

5. An extrapolation or a forecast helps me more than just a sensor measurement.

A follow-on imperative to 4. is that it is tempting to assume that output from sensors and subsequent analytics provides all that a decision-maker needs. However, most sensor output, no matter how elegantly summarised, needs extrapolation or a forecast that goes beyond the bounds of the data. One of the most useful ways to turn sensed data streams into actionable information is through extrapolation and forecasting. Data collected at sparse points in time or space may require interpolation to fill the gaps, or extrapolation to completely different circumstances such as a soil type, season or management regime. In the face of uncertain climate or market conditions, a forecast of possible scenarios can help evaluate the consequences of various courses of action based on current information. An example is the value added to a soil water measurement by using a weather forecast with a soil water balance model to predict how long that water will last before the next anticipated rain/irrigation, and the associated consequences for plant growth.

6. Help me test and improve my own heuristics, not replace them

Farmers apply deep knowledge formed through experience in the form of heuristics (or rules) to decisions. Farmers use their experience to build a mental construct that allows them to predict what might happen next and react accordingly. The most effective learning-based approaches to improve farmer practice are based on innovative and participatory adult learning methods that build on farmers' heuristics. These involve guided practical field-based investigations through which land users learn for themselves how to address challenges through observation, testing and monitoring of different treatments. Digital technology can assist this learning process by reducing the costs to farmers of knowing what is going on in their fields. Through timely updates of the system status they can adapt to uncertain conditions in a flexible manner.

Because farmers have their own mental constructs of how they think their system 'works', the 'objective' information coming from various sensors is often filtered through a range of subjective factors. These sit within a wider set of socio-cultural influences, including family and rural values, local industry norms and expectations and the behaviour of neighbours.

7. Sensors and analytics are unlikely to tell me everything I need to make a decision

The promotion of the benefits of digital agriculture often comes from an industrial perspective, informed by process control thinking. In industrial settings, the role of a system manager's intuition, beliefs, risk attitude and valuation of competing benefits is less prominent than on a farm. One mistake made by vendors of digital solutions for farmers is the stereotyping of the farmer as a technician, and the farming community as a market for technical-based recommendations. Rather, as McCown (2001) has pointed out, the farm is a socio-ecological system where there is complex interplay between a

‘management’ system and a ‘production’ system with psychosocial and cultural factors at play. An emerging opportunity is to capitalise on the growing use of social media by farmers to canvas views and seek input from fellow farmers on decisions and issues. Such content, when analysed and meshed with ‘hard’ data from decision tools, internet searches and the like could provide a powerful source of farmer-validated information to support decisions.

8. Connectivity is important, but not for every decision

A major barrier cited for the widespread use of digital technologies on farms is the lack of broadband connectivity in the field. Voice connectivity is rated as the highest reason for farmers wanting farm-wide connectivity. The second most cited is ‘watch and respond’ whereby farmers can monitor (say from the house, tractor or livestock yards) in order to respond in a timely and appropriate way. The need for comprehensive connectivity needs to be critiqued in terms of the likely use cases for digital systems in the field. For example, connectivity will be important if data need to be processed, analysed and provided in an executable format for tactical decisions ‘on the spot’. However, there are many applications where data can be captured and then processed, analysed and modelled later, when there is a reliable connection to the internet. The advent of cheap and low powered communications systems that provide broad coverage, such as LoRaWAN™ are seen by many farmers as an acceptable communications solution for sensor networks.

Conclusion – looking ahead

Farming will be increasingly data-driven. This will be fuelled by advances in weather and climate forecasts, more dynamic and timely information on the state of soils and crops, and linkages with farm management software to improve operational efficiency, safety and transparency. Large volumes of data will be able to be generated by cheap, ubiquitous sensors. This raises concerns about whether the quality of such data will be out-weighted by the sheer volume of data being generated.

Biggest strides will be made in the short term by improving the quality and accessibility of foundational datasets such as weather and climate, soils and topography, and remote sensed imagery. Further into the future, coupling these data with a growing stream of private data, much of it farmer-derived, will stimulate services from a wider range of providers, and maybe even ‘DIY analytics’. Routine tasks will be automated, and data and analytics bought to bear on more complex decisions.

Greater ubiquity, automation and accessibility of decision tools means they are likely to reach a far greater audience. Digital tools will touch a wider range of actors who interact with, and service, farmers – agronomists, farm consultants, banks, insurers, marketers, input suppliers, bulk handlers, and consumers. Data will have multiple applications and potentially multiplied value when aggregated with others’ data. We envisage digital systems enabling farmers to respond to increasing pressures and opportunities for regulatory compliance, product provenance and best management practice.

Digital agriculture is in the middle of a heightened ‘hype’ phase. Lessons need to be heeded in the history of adoption/dis-adoption of decision support tools. Home-grown rather than imported solutions are likely to succeed in the market due to Australia’s unique farming environment and socio-cultural context. Farmers will insist on being enabled to learn and refine the management of their farms using their data, rather than being presented with prescriptions generated by closed loop data-technology systems.

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