Where AI adds value to agronomic and crop decision-making now, and where might this technology be in 5 years?

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Take home message

- Artificial intelligence (AI) will add value to different agronomic decisions differently
- Prioritise quality-assuring yield and management data from on-farm experiments to help enable AI in agronomy
- Expect some AI-enabled beta (test) agronomy products from GRDC projects to be available in 2024 and keep an eye on the May-June Groundcover supplement for more information.

Background

GRDC has a significant portfolio of R&D in AI in agronomy. The intent of this paper is to provide a practical and non-exhaustive overview of where AI currently adds value to agronomic decision making and where the technology is likely heading in the Australian market in the near to midterm based on scientific, commercial, and regulatory factors.

This paper is brief and qualitative in nature because a Groundcover supplement scheduled for release in May-Jun 2024 will discuss this subject in more depth, along with results from GRDC's broader portfolio in 'on-farm' applications of digital agriculture and automation.

Where does AI add value to agronomic decision making?

AI is likely to add value to different agronomic decisions differently. That's a key message from this paper. A helpful way to think through the contribution to AI in agronomic decision making is in one of three categories:

1. Informing decisions
2. Guiding decisions
3. Prescribing decisions

This is not meant to be used as a formal or fixed distinction, but to provide some guard rails for understanding how AI can add value to decision making now and into the future.

Where does AI add value now?

Informing decisions

Some forms of AI are adept at retrieving, synthesising, and summarising vast amounts of information. Large Language Models (LLMs) such as Chat GPT by Open AI, Bard by Google, and Llama 2 by Meta AI are popular examples. For example, sourcing information on the optimum planting time for a specific variety in your location, its disease ratings, and its certifications to inform variety selection. Most LLMs have multi-model capabilities, meaning they can ingest and analyse multiple types of input data such as text, images, numerical data, etc. The capabilities of LLMs are evolving rapidly and their future influence on agronomic decision making could be profound. For now, they're worth experimenting with to make the job of sourcing and synthesising information much easier, but note they have biases, errors, and their terms of use need to be carefully understood.

Guiding decisions

Many agronomic decisions can be guided by access to good data, as in accurate biophysical data provided at the right spatial resolution in a user friendly and cost-effective manner at the right time.

For example, information on the flowering time of a given variety for a given location and emergence date; the PAWC and depth to constraints across a paddock; plant available water at *x* depth in *y* paddock or zone; spatial distribution of weed emergence in fallow and to some extent, in-crop, etc. These are all examples of current capabilities enabled by the coupling of AI with relevant domain expertise.

Sometimes the influence of AI is easily apparent, but often it's used 'behind the scenes' within a broader workflow for sourcing, processing, and analysing multiple sources of data. Here are some examples of AI at work across the GRDC portfolio developing agronomic data layers to guide decision making (Table 1). Note this is a just a snapshot and by no means an exhaustive list.

Table 1. Examples of how AI is used to create insightful agronomic data that can guide decisions.

GRDC project code	Domain	Use-case	Example of how AI adds value
UOM1806-001RTX	Crop phenology	Predicting variety-specific flowering time	To predict parameters required for APSIM Next Gen to simulate flowering time using genetic data
UOS2205-006RTX	Frost and heat (Abiotic stress)	Predicting yield loss from frost and heat events in major crop types	To develop analytics methods that use historical precision ag, crop physiological, environmental, and remotely sensed data to predict the impacts of frost and heat events at different stages of development in different crop types and environments
UOS2206-009RTX	PAWC and soil constraints	Mapping spatial variations in PAWC and the depth to soil constraints	To develop analytics methods that use soil sampling data, soil surveys, environmental and remotely sensed data in combination with digital soil mapping techniques to map spatial variations in PAWC across a paddock and map the 'effective' rooting depth based on the depth to soil constraints.
UOS2002-001RTX	Plant available water (PAW)	Mapping and monitoring plant available water at different depths in the profile and across zones	To develop analytics methods that use soil sampling data, soil surveys, environmental and remotely sensed data (optical and microwave) in combination with soil water balance models to estimate the PAW content at different depth profiles at different points in time across a farm, paddocks, or zones in a paddock
BCS2307-001RTX	Weed management	Mapping post-emergent weeds for site-specific herbicide applications	To detect the location of weeds from drone-based imagery for input into sprayers with section control or individual nozzle control for site-specific application of post-emergent herbicides
DFL2304-001RTX	Disease management	Detecting the occurrence of foliar diseases	To analyse satellite imagery for the purpose of mapping the incidence of crop foliar diseases to inform fungicide management

A few of these projects are just getting started, but many will have initial protypes/beta products made available in the spring of 2024 following 4-6 years of applied research and development and ongoing engagement with growers and agronomists across Australia. Keep an eye on the May-Jun Groundcover supplement for more information.

Prescribing decisions

This is where AI in agronomy is most frequently hyped and perhaps most infrequently realised. A pertinent example is with mid-season nitrogen decisions in winter cereals across Southern Australia. It can be a complex decision given there are multiple variables interacting in different ways across different sites and seasons. Nonetheless, AI can have significant, strategic impacts in prescribing a course of action, but there's often a requirement to couple large volumes of quality on-farm data with relevant domain expertise, precision agriculture technologies, and a long-term outlook. The experience with the Future Farm project (CSP1803-020RMX) is a good example.

Working with leading growers across Australia to implement and sample large-scale strip trials and analyse multiple data layers in different ways, the team developed a method to predict the economically optimum N-rate that more than halved the recommendation error associated with a simplified mass balance approach (Colaço *et al.,* 2024). See Figure 1 for a summary figure sourced from Colaço *et al.,* 2024. This method is being evaluated further at scale in multiple crop types and environments with growers across Australia in partnership with a private company. While the results are very impressive, the requirement for data is intensive and the approach is contingent on implementing N-rich and N-nil strips using precision agriculture technology.

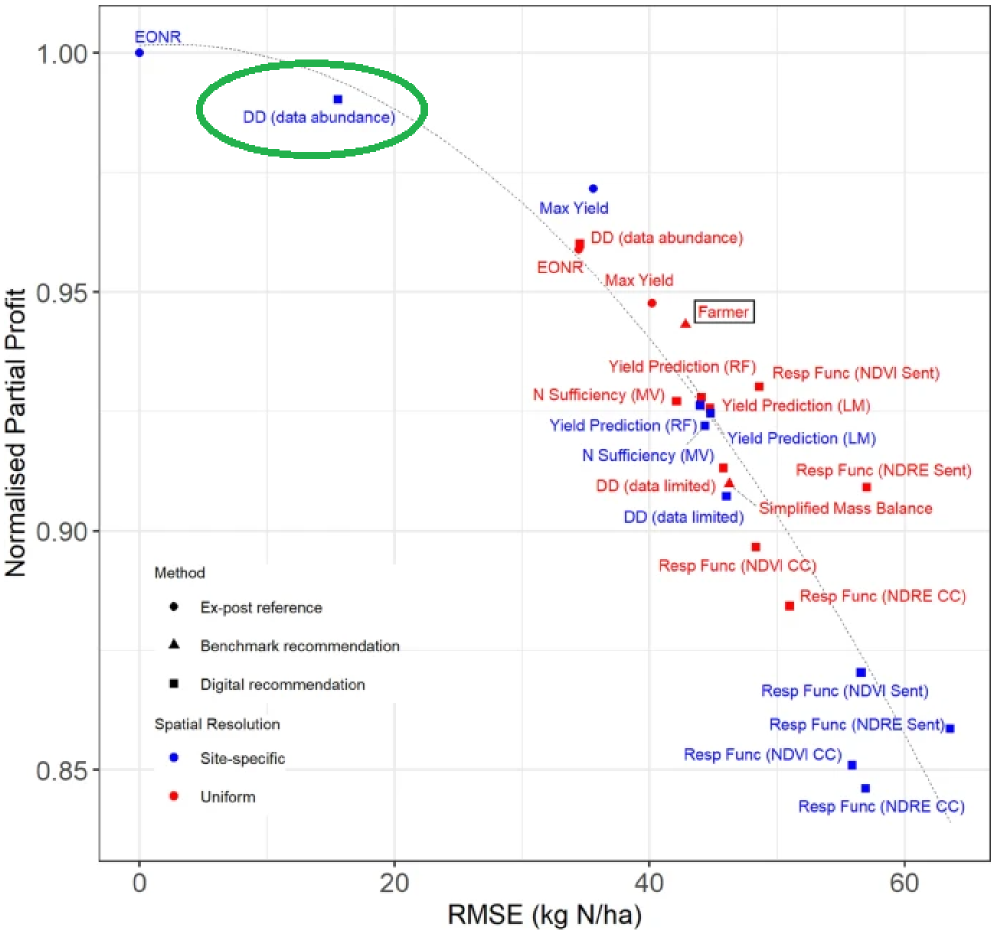

Figure 1. Error by profit biplot showing the average results of various N recommendation methods across 21 large scale on-farm trials in Australia, sourced directly from Colaço *et al.,* (2024). The RMSE stands for root mean squared error is a measure of accuracy. The lower the RMSE the better. Normalised partial profit is a relative measure of how profitable the N recommendation was. The higher the better. The method circled in green is the best-performing one and enabled by AI. Again, see Colaço *et al.,* (2024) for more information.

In summary, AI for prescribing complex decisions is doable and very powerful, but it's not easy. A key enabler of this approach is collated on-farm data and easy to use digital tools for collating yield and agronomic management data as well as results from large-scale on-farm experiments like strip trials. There are prior, powerful examples of this at work.

The power of on-farm experimentation for enabling AI in agronomy

For example, Bayer's Fieldview^{TM} platform has a powerful set of predictive agronomic tools for corn growers in the US. Fieldview provided digital tools for growers to implement simple strip trials and collect yield data from those strips alongside relevant agronomic management information. Aggregating that on-farm data at scale and combining it with their in-house small-plot database, genetic insights, and data science expertise provided an opportunity to build, test, and refine powerful predictive agronomic models that are both scalable and locally accurate. A blog post from the Climate Corporation (Bayer's Fieldview) back in 2018 provides a simplistic overview of the power or digital tools in the context of AI and agronomy (Eathington, 2018). For a more revealing description that highlights the power of collated on-farm data and on-farm experiments, it's worth reading through a patent filing from the Climate Corporation titled Digital modelling and tracking of agricultural fields for implementing agricultural field trials (Climate Corp, 2020).

Of course, many growers and agronomists already implement and learn from many types of OFEs. But quality assuring the yield data collected from those OFEs, collating it alongside management information, and creating a networked database of OFEs for analysis is often the missing piece. That's often key to realising the power of AI in agronomy. In addition to supporting product development in AI in agronomy, OFE provides a powerful basis to support peer-to-peer learning and fostering of farmer-researcher relationships (Lacoste *et al.,* 2022).

Digital tools are key facilitating both shared discovery between growers, agronomists, and researchers and collection of the quantitative geospatial data required to power AI-based agronomic models. There are many products available in the Australian market to help Australian growers implement and collect geospatial data from on-farm experiments, such as PCT Agcloud's strip trial tool and the Field Trial Module from SMS Advanced by AgLeader®. There are also different methods available to analyse treatment responses from large-scale on-farm experiments (e.g., Lawes et al., 2012 and Rakshit et al.) and published examples of the potential value of OFEs in different domains (Yan *et al.,* 2002; Virk and Witcombe, 2008; Kandel *et al.,* 2018).

The impact of commercial drivers and market structure

While there's significant potential for AI in agronomy, commercial drivers often restrict the pace of development of AI in agronomy in the Australian market. Australia is a relatively small market on the global stage for digital agronomic analytics products and services. That mitigates the private investment into developing and scaling new innovations in AI and agronomy. While Australia has some excellent precision ag analytics companies operating in our market, the business case for investing in advanced agronomic analytics products for wheat, barley and canola in Australia often doesn't stack up the way it does for say corn and soy growers in North and South America.

Where might this technology be in 5 years-time?

While this is difficult to predict given the pace of technological progress and some uncertain regulatory issues related to generative AI, there are some general observations worth noting:

Expect new AI-enabled products and services to hit the market from GRDC investments

GRDC has been investing in high-value use cases in agronomy and AI in multiple areas. By focussing on the high-value use-cases with a long-time horizon, GRDC's partners have able to couple their domain expertise in crop physiology, agronomy, soil science, nutrition, abiotic stress, and other areas to develop new products and innovations in AI and agronomy. We're excited to see many of them hit the paddock in and around spring 2024. Keep an eye on the May-Jun 2024 Groundcover supplement for more details on those projects, and where we're heading with our 'Grain Automate' program of RD&E that's focussed on machine autonomy and intelligent systems; areas heavily enabled by AI.

Expect data from on-farm experiments to have a strong influence in AI and agronomy

Modern machine capabilities and data analytics tools make it easier than ever to implement large-scale on-farm experiments (OFEs) using precision agriculture tools. OFEs provide a rich basis of quantitative data across sites and seasons to help train and calibrate AI-based products for sub-paddock scale applications. As we head toward leveraging the power of AI for more complex agronomic decisions, OFEs are likely to be a linchpin in developing those products and services, and in helping growers and agronomists build confidence in those products.

Expect LLMs to advance rapidly barring regulatory and legal constraints

The AI arms race among big tech companies such as Microsoft, Google, Meta (Facebook) is accelerating the pace at which AI tools become available to a wide breadth of users. At Agritechnica last year Bayer and Microsoft announced an update to Microsoft Azure Data Manager for Agriculture that included news of large language model APIs in Azure Data Manager for agriculture (Thomas, 2023). LLMs are also making coding tasks more accessible to non-software engineers, opening possibilities to easily automate bespoke data and/or agronomic analysis tasks, and many other applications.

GRDC's investment strategy in AI and agronomy

GRDC has been focussing on high value use-cases that require complex science and commercial innovation to bring to market. That often involves investing upstream in applied R&D where the power of AI can be combined with relevant domain expertise, and where we can partner with companies that work closely with growers and agronomists to develop user-friendly AI products and services that really meet the need on-farm. We're excited to see the fruits of that long-term strategy deliver benefits on-farm and at scale in 2024 and beyond.

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