158. On-farm experimentation and machine learning in the development of intelligent decision systems in agriculture: a synthesis of the Australian Future Farm project

A.F. Colaço[1,*], R.G.V. Bramley[1] and B. Whelan[2]
[1]*CSIRO, Waite Campus, Urrbrae, SA, Australia; *present address: University of São Paulo, Piracicaba, SP, Brazil; andre.colaco@usp.br*
[2]*The University of Sydney, Eveleigh, NSW, Australia*

Abstract

In the context of fertilizer management, machine learning (ML) has been restricted to predicting crop and soil parameters used as input to generalized recommendation frameworks. Consequently, while input information has improved, fertilizer recommendations still rely on simplistic agronomic rules. This work presents outcomes from the 'Future Farm' project, established to re-examine and improve the way in which digital technologies are used to inform decisions about input management, focusing on nitrogen fertilization. Results indicate that effective data-driven decisions combine ML with site-specific crop response information from on-farm experimentation, avoiding the generalized agronomic rules inherent to current recommendation methods.

Keywords: data-driven, fertiliser recommendation, N management

Introduction

Since the early development of precision agriculture (PA) in the 1990s, decision tools used for site-specific nutrient management have largely relied on traditional agronomic recommendation frameworks to calculate fertiliser application rates. For example, a common strategy to generate variable rate fertiliser prescriptions has been to input information from soil fertility maps into formulas available in commonly used recommendation charts, which are based on generalized response functions (e.g. Colaço and Molin, 2017). This type of approach has been long criticized (Bullock *et al.*, 2002 and Colaço *et al.*, 2020) because it fails to consider the local crop responsiveness to applied nutrients, which is a key element of site-specific management. Similarly, most sensor-based approaches for nitrogen (N) management have also relied on generalized agronomic approaches to calculate fertiliser rates (Colaço and Bramley, 2018). A common strategy has been to employ a nutrient mass balance (or 'nutrient budget') calculation in which sensor-based yield predictions are used as a proxy for nutrient demand (Raun *et al.* 2005). However, aside from the generally weak yield prediction models generated from a single sensor input (Colaço and Bramley, 2019), other elements of the nutrient balance framework, such as the total available nutrient in the system or the fertiliser use efficiency are often not measured nor estimated, so fixed values are assumed. As a result, these factors combined can compromise the accuracy of the final recommendation (Colaço *et al.*, 2021). Overall, the lack of adequate decision support tools to make use of the digital data provided by PA technology has been a critical barrier for the advancement of site-specific management and of PA more broadly.

During the last decade, agriculture has seen an increase in the use of data science techniques, particularly machine learning (ML), to help improve on-farm decisions (Liakos *et al.*, 2018). However, in the context of fertiliser management, ML has not been used as a driver for the decision per se, but as a tool to predict crop and soil parameters that are needed as input to the same generalized recommendation frameworks as described above (Figure 1a). For example, great effort has been put into crop yield prediction using ML (Chlingaryan *et al.*, 2018, Van Klompenburg *et al.*, 2020).

However, a study by Colaço *et al.* (2021) has shown that despite significantly improved yield predictions by ML, its use through simplified nutrient balance N calculations did not result in more accurate recommendations due to assumptions in the framework regarding other key input information. In general, the effort to improve agronomic parameter prediction through ML has been generally undertaken without a critical consideration of the limited ability of current agronomic decision tools to make appropriate use of such information.

Effective integration of machine learning into decision support tools

An approach to better integrate ML techniques into decision support tools for fertiliser management has been proposed by Colaço *et al.* (2021). This work used a 20-year plot-based N trial for wheat in Oklahoma, USA – originally used by Raun *et al.* (2005) – to develop the concept of a decision framework in which multivariate data relating to crop development, soil moisture and climate were modelled directly against optimal N rates obtained from historical N trial information (Figure 1b). As such, this data-driven framework avoids simplistic mechanistic calculations of N requirement and uses an empirical data-driven approach to directly arrive at an optimized decision. As a result, the N recommendation error dropped by half when compared to an application based on the historical average optimal N rates (Figure 2). This approach was also superior to the application based on a nutrient balance framework and yield estimation with ML (Y_{est}ML in Figure 2).

In Figure 2, 'Control' indicates the application of the historical average optimal N rates; 'Y_{est}', a recommendation based on a nutrient mass balance calculation of N requirement in which yield potential was predicted using mid-season NDVI (normalized difference vegetation index) and linear regression; 'ResF', a recommendation derived from a mid-season NDVI response function; 'Y_{est}ML' the same as the 'Y_{est}' recommendation but using multiple variables and machine learning for the yield prediction; 'DD': a data-driven approach where multiple variables and machine learning were used to directly predict optimal N rates.

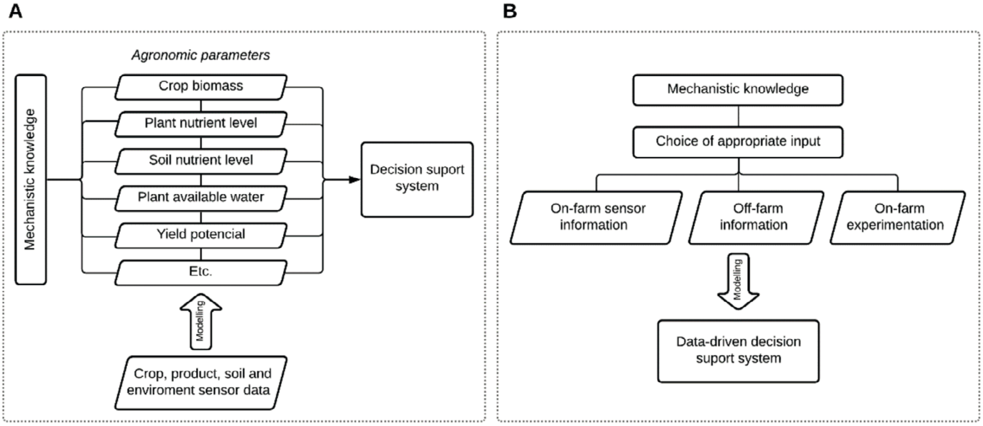

Figure 1. Two paths to the use of digital data and modelling for decision support systems: (a) the conventional approach focused on the estimation of crop and soil parameters as input to existing mechanistic decision support systems, and (b) an alternative framework using on- and off-farm digital information and on-farm experimentation as direct input to data-driven agronomic recommendations (Colaço *et al.*, 2021).

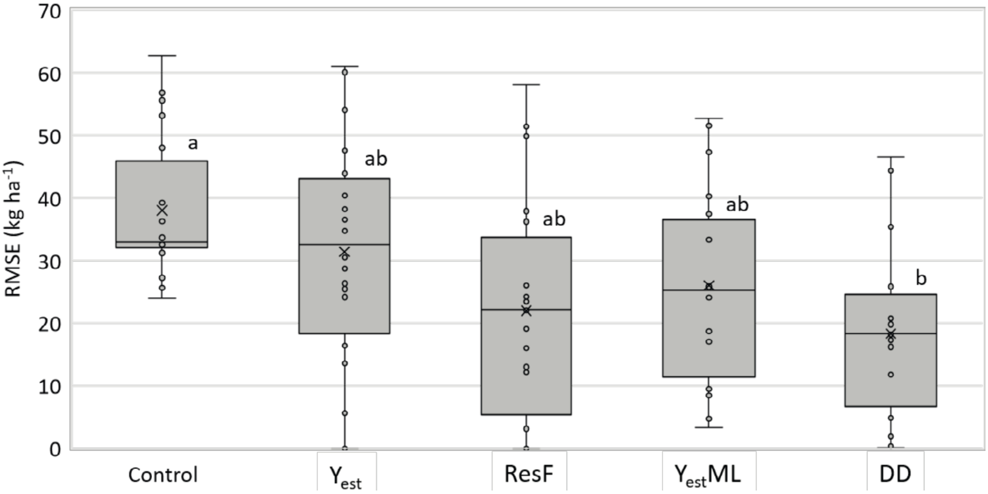

Figure 2. Nitrogen fertiliser recommendation error arising from different recommendation methods in a 20-year wheat experiment in Oklahoma, USA (Colaço *et al.*, 2021).

The role of on-farm experimentation for decision systems development

After the initial concept development using a single plot trial, the data-driven approach described above was tested in a larger field program based on on-farm experimentation (OFE) conducted in Australia as part of the 'Future Farm' project (Colaço *et al.*, 2022, 2024). The project was established to re-examine and improve the way in which digital data are used to inform decisions about input management and to provide a way of automating the process from data acquisition, through analysis, to the formulation and implementation of decision options. The focus for the project was improvement in the efficiency and profitability of applied N use and, in particular, increased farmer confidence in N decision making.

The field program comprised over 20 field scale OFE trials established in commercial fields of wheat and barley between 2018 and 2021, covering a range of soil types and weather conditions across Western and South Australia, Victoria and New South Wales. Each experiment included strips of high ('rich'), low ('zero') and intermediate ('field') N rate treatments that were harvested by combines equipped with on-board yield and protein monitors (Figure 3). Important features of all of these trials were that they were laid down with the farmers' own equipment during their normal operations, and that the 'field' rate of N used was that chosen by the farmer using their existing norms. As such, the OFE were all farmer-centric (Bramley *et al.*, 2022; Lacoste *et al.*, 2022), and notwithstanding the involvement of researchers, were targeted at enabling farm business decision optimization through increased confidence in decision-making on the part of the farmers hosting the trials.

The main goal of the trials was to enable the observation of economically optimal N rates (EONR) along the length of the strips (Figure 3). The EONR was obtained in increments of 10 m along the length of the strip trial using a moving window regression approach. Each regression was conducted using N rates as the independent variable and partial profit as the dependant variable (Figure 3). Partial profit was calculated as the expected gross income minus the expenditure on N. The EONR was given as the N rate that maximized partial profit using a quadratic function (Figure 3).

The second objective of the trial was to provide a range of scenarios from which field data could be collected for the development of sensor-based N recommendation approaches for mid-season application. Four types of digital variables were collected in each trial: field history variables (e.g.

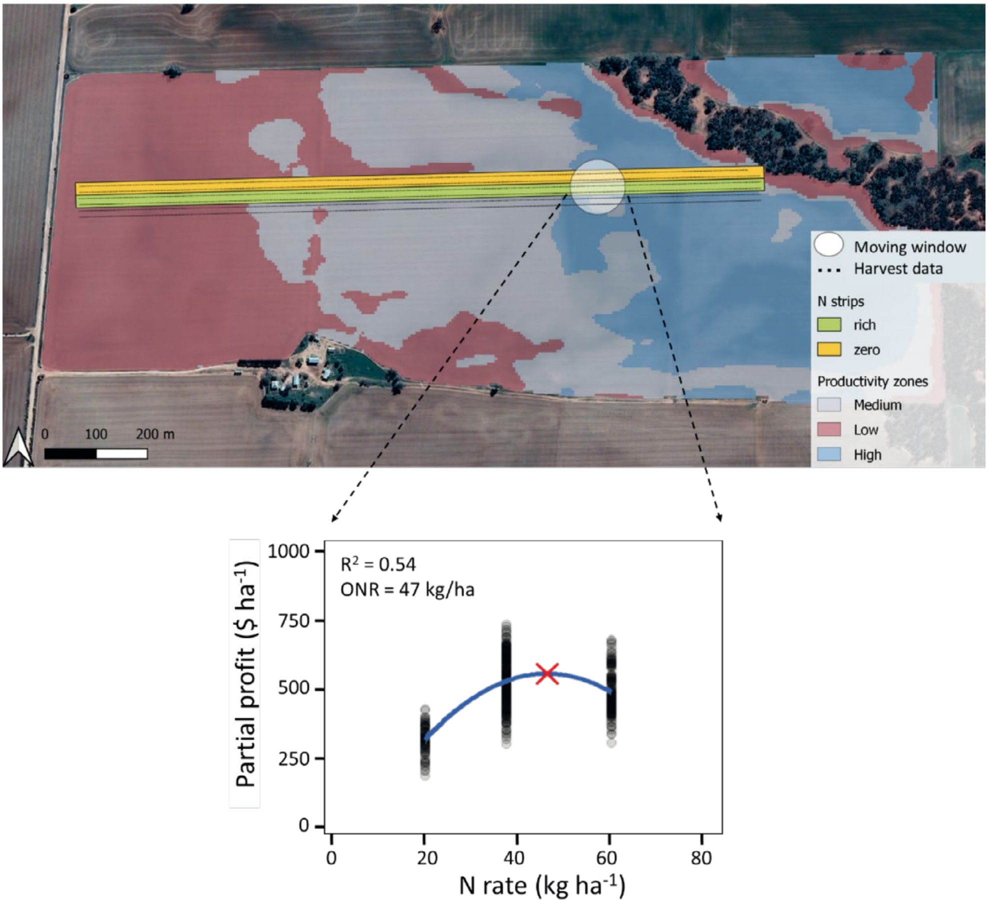

Figure 3. Experimental strip design implemented in a 100-ha barley field near Booleroo Centre, South Australia, 2021, and a moving window analysis of crop response to N application. The graphs illustrate the local response curve and the economically optimal N rate (EONR is depicted as a red cross) generated from data within one of the moving windows along the length of the strip trial (adapted from Colaço *et al.* 2024).

historical average yield), in-season crop status variables (e.g. NDVI), soil features (e.g. soil texture) and weather variables (e.g. daily rainfall and temperature). Different combinations of these data were then used as input to a range of decision frameworks for variable and fixed N rate recommendations. These methods were either developed in the project itself (the data-driven approach described above and others) or were benchmark methods traditionally used in both PA and non-PA systems. Colaço *et al.* (2024) provide further detail. The actual application rate used by the farmer was also included in the analysis for comparison. The different recommendations were then compared against the known EONR obtained along the length of each trial. Results for each recommendation method were given as the average root mean squared error (RMSE) of the recommended N rate against EONR and the average profitability of such recommendation. The expected profitability of a recommendation was obtained by inserting the recommended rate into its respective partial profit response function (Figure 2). Partial profitability was normalized (normalized partial profit; NPP) between 0 and 1, where 1 represented the partial profit of the EONR.

Somewhat surprisingly – or not – results showed that the existing farmer N management practice outperformed most recommendation methods tested (Figure 4). Moreover, current univariate sensor-based algorithms underpinned by simplistic agronomic decision frameworks ('Yield Prediction', 'Response Func' and 'N sufficiency' in Figure 4) nearly matched the performance of farmer management at the whole field level. However, due to inherently large error, recommendations derived from such technology were better implemented as the average for the field (i.e. uniform management) rather than site-specifically, which is contrary to the intended use of such tools and much associated PA research on the use of current commercially available sensor-based N tools. It is important to note that, similar to the findings of Colaço *et al.* (2021), using multivariate approaches that incorporate machine learning (ML) to enhance yield predictions – when these predictions are then used as inputs for a simplistic N balance calculation ('Yield Prediction RF', Figure 4) – did not improve the accuracy of the recommendations. In fact, this was comparable to using a simpler yield prediction based on linear regression and NDVI information ('Yield Prediction LM', Figure 4). This clearly demonstrates that the primary limitation of this approach lies in the recommendation process itself, not in the yield prediction. It also suggests that efforts invested in more advanced analytical techniques (such as ML) are wasted when they are coupled with simplistic recommendation formulae. The only method with potential to reduce recommendation errors, and thereby increase farmer confidence in the decision, and to increase farmer profitability was the data-driven approach (DD in Figure 4) in which multiple digital variables were modelled directly against EONR. However, this result was obtained for a scenario in which information about current field and season were well represented in the historical dataset used to train the model ('DD abundance' in Figure 4). That is, this method was heavily reliant on extensive historical on-farm digital databases. When limited information for the current field and season were available to the model – i.e. the model was trained only with information from different fields and seasons – results were similar to those obtained by other more simplistic methods.

Overall, the results strongly point to a key enabler for the construction of digital databases for data-driven decision tools being the implementation of OFE. More specifically, on-farm trials should be automated and embedded into normal farm operations so that large crop response datasets can be collected effortlessly across multiple farms and seasons. In addition, to foster farmer engagement, OFE must be 'farmer-centric', that is, an OFE framework must promote farmer involvement in the process and focus on solving problems for the farmer so that value can be immediately perceived upon adoption (Lacoste *et al.*, 2022, Bramley *et al.*, 2022).

Exploring different trial designs from the one presented is also encouraged. This work used a simple strip design for the OFE trials to facilitate farmer engagement in the project. However, as long as farmer engagement is not affected, more sophisticated designs – for example, highly replicated trials (Cook and Bramley, 1998; Bullock *et al.*, 2019) – could be considered as they could contribute to more N rates being used to improve the generation of local crop response functions (Trevisan *et al.*, 2020). Nonetheless, in considering such complex designs, the trade-off between trial complexity and farmer utility and pragmatism will need careful consideration (Bramley *et al.*, 2022). It is also worth noting that a simple strip trial provides valuable crop response information that can be used in the same season the trial is conducted. In fact, both the studies by Lawes *et al.* (2019) and Colaço *et al.* (2021) demonstrated that the most important variables for optimal N rate prediction using a random forest model were those obtained from an on-farm trial conducted during the same season as the recommendation. This is not possible with more complex designs, such as the checkerboard trial promoted by Bullock *et al.* (2019), because the trial occupies the entire field. As such, the information provided by the trial can only be used in future seasons, when, of course, the seasonal conditions may be quite different. In other words, there is significant virtue in the simplicity of a strip trial.

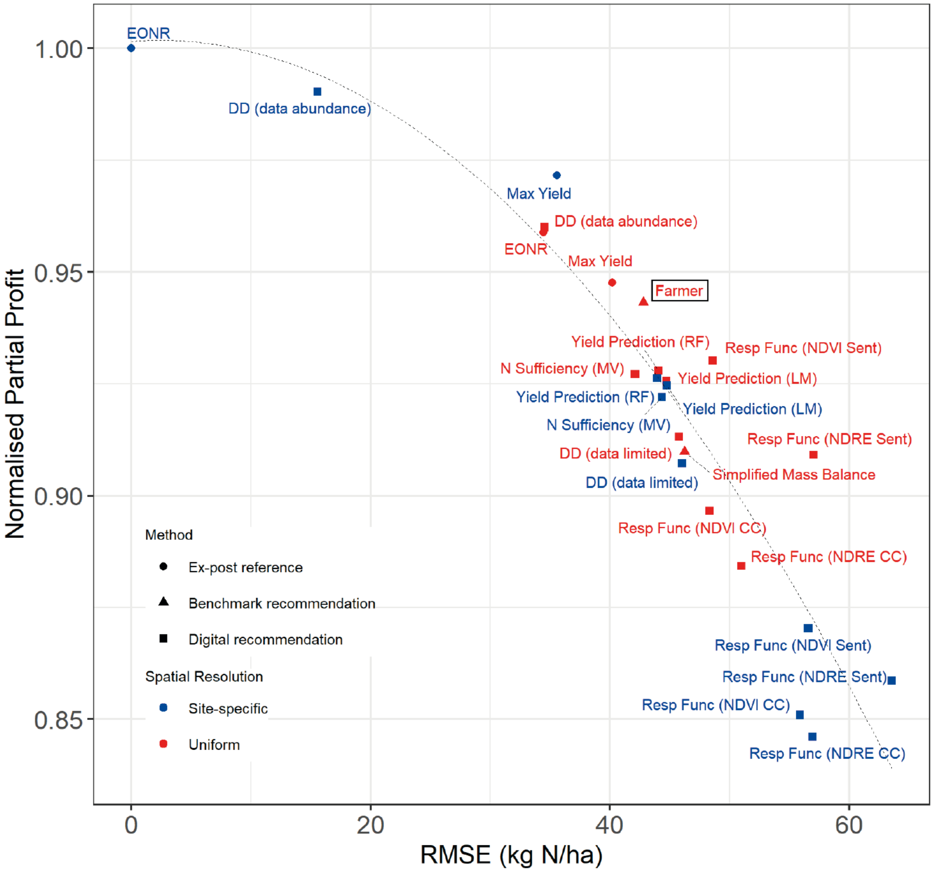

Figure 4. Error by profit biplot showing the average results of various N recommendation methods across 21 large scale on-farm trials compared to observed economically optimal N rate (EONR) (Colaço *et al*., 2024). 'Ex-post reference' were the observed optimum N rates after harvest for maximization of either partial profit (EONR) or grain yield (the 'Max Yield' method). 'Benchmark recommendations' were methods traditionally used by farmers and consultants. 'Digital recommendations' were those based on field digital data. Detailed description of each method is available in Colaço *et al.* (2024).

Final considerations

On-farm experimentation, multivariate digital data and ML are critical for effective data-driven decisions. However, due to the empirical nature of the data-driven approach presented, and the minimal agronomic domain knowledge embedded in it, the model is crucially reliant on an extensive historical dataset. That is, the success of this approach relies on availability of sufficient on-farm data that reflect crop response to inputs in such a way that it covers the range of variation in expected field and season conditions in which the model will be used. To tackle this challenge, OFE adoption needs to be promoted. This will be achieved through effective business models for OFE and careful thinking around the value-proposition of OFE for stakeholders. At the same time, future scientific work on model development should investigate the interaction between the geographical coverage of the data and derived models, and the amount of data needed to build effective models. Techniques to embed mechanistic knowledge and agronomic decision rules (for example, using crop simulation modelling) into empirical ML models are also worth exploring, as they could potentially reduce the data requirements and expand model applicability across more variable scenarios.

In conclusion, this work shows how modern data mining techniques can be used for purposes beyond the prediction of agronomic parameters, to effectively integrate decision optimization in agriculture using OFE. The lessons presented here show a promising pathway for digital on-farm technology, artificial intelligence and OFE to drive production systems closer towards season- and site-specific optimization.

References

Bramley, R.G.V., Song, X.S., Colaço, A.F., Evans, K.J., & Cook, S.E. (2022). Did someone say "farmer-centric"? Digital tools for spatially distributed on-farm experimentation. Agronomy for Sustainable Development, 42, 105. https://doi.org/10.1007/s13593-022-00836-x

Bullock, D.S., Boerngen, M., Tao, H., Maxwell, B., Luck, J.D., Shiratsuchi, L., Puntel, L., & Martin, N.F.. (2019). The data-intensive farm management project: Changing agronomic research through on-farm precision experimentation. Agronomy Journal, 111, 2736–2746. https://doi.org/10.2134/agronj2019.03.0165

Bullock, D.S., Lowenberg-DeBoer, J., & Swinton, S.M. (2002). Adding value to spatial managed inputs by understanding site-specific yield response. Agricultural Economics, 27, 233–245. https://doi.org/10.1016/S0169-5150(02)00078-6

Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Computers and Electronics in Agriculture, 151, 61–69. https://doi.org/10.1016/j.compag.2018.05.012

Colaço, A.F., & Bramley, R.G.V. (2018). Do crop sensors promote improved nitrogen management in grain crops? Field Crops Research, 218, 126–140. https://doi.org/10.1016/j.fcr.2018.01.007

Colaço, A.F., & Bramley, R.G.V. (2019). Site–year characteristics have a critical impact on crop sensor calibrations for nitrogen recommendations. Agronomy Journal, 111(4), 2047–2059. https://doi.org/10.2134/agronj2018.11.0726

Colaço, A.F., & Molin, J.P. (2017). Variable rate fertiliser for citrus: a long term study. Precision Agriculture, 18, 169–191. https://doi.org/10.1007/s11119-016-9454-9

Colaço, A.F., Pagliuca, L.G., Romanelli, T.L., & Molin, J.P. (2020). Economic viability, energy and nutrient balances of site-specific fertilization for citrus. Biosystems Engineering, 200, 138–156. https://doi.org/10.1016/j.biosystemseng.2020.09.007

Colaço, A.F., Richetti, J., Bramley, R.G.V., & Lawes, R.A. (2021). How will the next-generation of sensor-based decision systems look in the context of intelligent agriculture? A case-study. Field Crops Research, 270, 108205. https://doi.org/10.1016/j.fcr.2021.108205

Colaço, A.F., Whelan, B., & Bramley, R.G.V. (2022). Better targeted, more precise fertiliser decisions as a counter to rising fertiliser prices – focussing on 3 of the 6 Rs. In: South Australian Grains Research Update, Adelaide, 8 February 2022. Grains Research and Development, Canberra, ACT. Available online at https://grdc.com.au/resources-and-publications/grdc-update-papers/tab-content/grdc-update-papers/2022/02/better-targeted,-more-precise-fertiliser-decisions-as-a-counter-to-rising-fertiliser-prices-focussing-on-3-of-the-6-rs

Colaço, A.F., Whelan, B., Bramley, R.G.V., Richetti, J., Fajardo, M., McCarthy, A., …, & Lawes, R.A. (2024). Digital strategies for nitrogen management in grain production systems: lessons from multi-method assessment using on-farm experimentation. Precision Agriculture, 25: 983–1013. https://doi.org/10.1007/s11119-023-10102-z

Cook, S.E., & Bramley, R.G.V. (1998). Precision agriculture—opportunities, benefits and pitfalls of site-specific crop management in Australia. Australian Journal of Experimental Agriculture. 38, 753–763. https://doi.org/10.1071/EA97156

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., …, Hall, A. (2022). On-farm experimentation for global agriculture transformation. Nature Food, 3: 11–18. https://doi.org/10.1038/s43016-021-00424-4

Lawes, R.A, Oliver, Y.M, & Huth, N.I. (2019). Optimal nitrogen rate can be predicted using average yield and estimates of soil water and leaf nitrogen with infield experimentation. Agronomy Journal, 111, 1155–1164. doi:10.2134/agronj2018.09.0607

Liakos, K.G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674

Raun, W.R., Solie, J.B., Stone, M.L., Martin, K.L., Freeman, K.W., Mullen, R.W., …, Johnson, G.V. (2005). Optical sensor-based algorithm for crop nitrogen fertilization. Communications in Soil Science and Plant Analysis, 36(19–20), 2759–2781. https://doi.org/10.1080/00103620500303988

Trevisan, R.G., Bullock, D.S., & Martin, N.F. (2020). Spatial variability of crop responses to agronomic inputs in on-farm precision experimentation. Precision Agriculture, 22, 343–363. https://doi.org/10.1007/s11119-020-09720-8

van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: a systematic literature review. Computers and Electronics in Agriculture, 177, 105709. https://doi.org/10.1016/j.compag.2020.105709