Agronomy for Sustainable Development (2022) 42:105
https://doi.org/10.1007/s13593-022-00836-x

REVIEW ARTICLE

Did someone say "farmer-centric"? Digital tools for spatially distributed on-farm experimentation

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Accepted: 27 September 2022 / Published online: 21 October 2022

Abstract

On-farm experimentation (OFE) embeds the conduct of agronomic research within normal farm business operations such that experiments are driven by farmers' needs for business improvement, albeit enabled and facilitated by collaborating 'experts' in a process of co-learning. Because experiments are laid down using the farmers' own equipment in their own fields and at a scale that is consistent with the scale at which farm management decisions are made, it provides them with a salient, credible and legitimate means of creating knowledge for effective application that is valuable to the individual farmer in their field and farm, and potentially to neighbouring farmers in a region. Here, with a particular view to the potential application of OFE in Australian farming systems, we consider the synergies between OFE and the use of precision agriculture (PA) technologies such as yield monitors, crop and soil sensors, and variable rate application of inputs. Indeed, it is suggested that whilst the tools of PA greatly facilitate the conduct of OFE, it is arguably the case that OFE is an essential part of the optimal deployment of PA. We also address statistical issues associated with OFE conducted using PA, including the use of replication, randomization for experimental design, and concerns about spatial autocorrelation in data collected at the within-field scale. However, whilst farmers are generally disengaged from data analysis and place greater emphasis on the magnitude of gross effects and benefit:cost than on statistical significance, they nevertheless want robust and interpretable results. Accordingly, we identify some tools which facilitate simple assessment of alternative management actions across the range of variation in the production systems which farmers encounter. The need for farmer-trustworthy systems of data governance and data sharing amongst those engaged in OFE is also highlighted.

Keywords Precision agriculture · Farming systems · Spatial analysis · Trials

Contents

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1 Introduction

Farmers are under pressure; the world needs them to produce more food, and in Australia for example, despite recent improvements (2015–2020) to their terms of trade following a lengthy period (1995–2010) of decline (Zammit and Howden 2020), they frequently face marked 'shocks' to their cost structures. For example, the price of urea doubled in the period between May and October 2021 resulting in the ratio of the grain price to urea price being well over 2.5 t wheat per t urea (Whitelaw 2021b) compared to a long-term average of 1.26 (Whitelaw 2021a). Against this background, to maintain profitability and business viability, farmers must either increase yield (and/or quality), reduce expenditure on inputs or enhance the efficiency with which they make use of inputs. In short, they must find a way of improving productivity (Zhao et al. 2021) at the same time as maintaining the sustainability of the land resources on which we all depend; some have referred to this as *sustainable intensification* (Garnett et al. 2013). In recent discussions of Australian farm performance metrics, both Zhao et al. (2021) and Malcom (2021) have highlighted the importance of innovation to productivity growth. In other words, productivity growth and by inference, farm business sustainability, depends on research and development, whether it derives from innovation on the part of the farmers themselves or researchers working in universities or research institutes.

For the purposes of this paper, and consistent with the definition used by the #OFE2021 conference (https://ofe2021.com/manifesto), we define "on-farm experimentation" (OFE; Lyon 1996, Bramley et al. 1999; Adams and Cook 2000; Lacoste et al. 2022) as an approach to innovation in which farmers and researchers (or other "specialists" such as consultants) work in partnership to deliver both farm business improvement and advancement of agronomic and other scientific knowledge. Lacoste et al. (2022) characterise OFE as embedded within normal farm management and driven by farmer-initiated questions, the answers to which support farmers' own management decisions; thus, "farmer-centric". However, it is undertaken in partnership with specialists; that is, it is "farmer-centric" and "specialist-enabled", thereby promoting co-learning. Whilst OFE relies on the analysis of farm-specific data, it is scalable in that knowledge is created of local value to the farmer but also stimulates broader insight and potential application in other fields, farms, or regions. In this paper, we follow this same Lacoste et al. (2022) characterisation of OFE. Furthermore, and as noted by Lacoste et al. (2022), whilst precision agriculture (PA) is by no means an essential component of OFE, here we especially consider the value of using the tools of PA as OFE enablers, especially in relation to spatially distributed experimental designs (Bramley et al. 2013) as better alternatives to small plots in directing farm business improvement.

It may be readily observed that farmers like experimenting; they often try new things (e.g. a new fertilizer or crop variety, different sowing depths, or in a vineyard, different pruning methods or the use of an inter-row cover crop (Fig. 1)) and have likely been doing so for much longer than Agronomy has been recognised as field of research endeavour amongst the scientific community (Pretty 1991; Hansson 2019). It is therefore somewhat ironic that, even though farmer trials are primarily directed at farm business decision-making rather than scientific advancement, and that demonstrations of the richness in farm data are not hard to find (e.g. Lawes and Kingwell 2012; Bramley et al. 2019), researchers often regard farmers' trials with circumspection (e.g. Lyon 1996; Johnson et al. 2003; Piepho et al. 2011; Alesso et al. 2019) on the basis that treatments may not be replicated, that other elements of statistical rigour are missing, or that the results may not lead to improved scientific understanding. Yet these farmer trials are almost always conducted using the farmers' own equipment and at a scale that is relevant to the scale at which farmers must make and implement farm management decisions. Farmers perceive such trials (e.g. Fig. 1) as offering advantage over small plot-based randomized experiments (Griffin et al. 2008; Bramley et al. 2013), especially when the plot trials are conducted at locations other than their own farm, because as a source of advice for agronomic management, larger scale trials (Fig. 1) meet the requirements of salience, credibility and legitimacy (Cash et al. 2003). Critically, they generate the "actionable knowledge" (Evans et al. 2017) that is necessary to underpin decision-making. The re-emergence, re-alignment, and growth of effort between farmers and researchers in farmer-centric OFE, as described by Lacoste et al. (2022), is therefore important as it promotes a shift towards co-innovation in which experimentation is directed towards farm business improvement, with scientific or consultancy support provided, as required, by researchers or other specialists. The latter benefit through access to the OFE as a research resource and in the case of researchers, as a possible 'path to market' for their research. To build momentum in this area and move beyond more classical, researcher-driven approaches to participatory research (Petheram 2000; Carberry et al. 2002) to a *farmer-centric* model, researcher concerns at the credibility of farmer trials must be overcome. Likewise, farmer distrust of so-called experts (Rust et al. 2021), whose outputs may be perceived as lacking salience, credibility or legitimacy (Cash et al. 2003), needs to be addressed. Desirably, the number of farmers who regard OFE as 'business-as-usual' and who are willing to share their OFE data also needs to grow. Drawing especially on experience in Australian farming systems, this paper discusses these various issues with a particular focus on the role of PA and other elements of digital agriculture (DA; Shepherd et al. 2018; Hansen et al. 2022) in overcoming them. We begin by considering the synergies between OFE and PA/DA, address perceived statistical deficiencies in OFE conducted using PA, highlight some spatial analysis tools which enable analysis of OFE to the satisfaction of both farmers and researchers, and finish with some suggestions as to how OFE might be more readily adopted and implemented.

2 Precision agriculture and experimentation

Figure 2 shows yield maps collected in a 96-ha field over a 7-year period by an Eyre Peninsula (South Australia) farmer. It

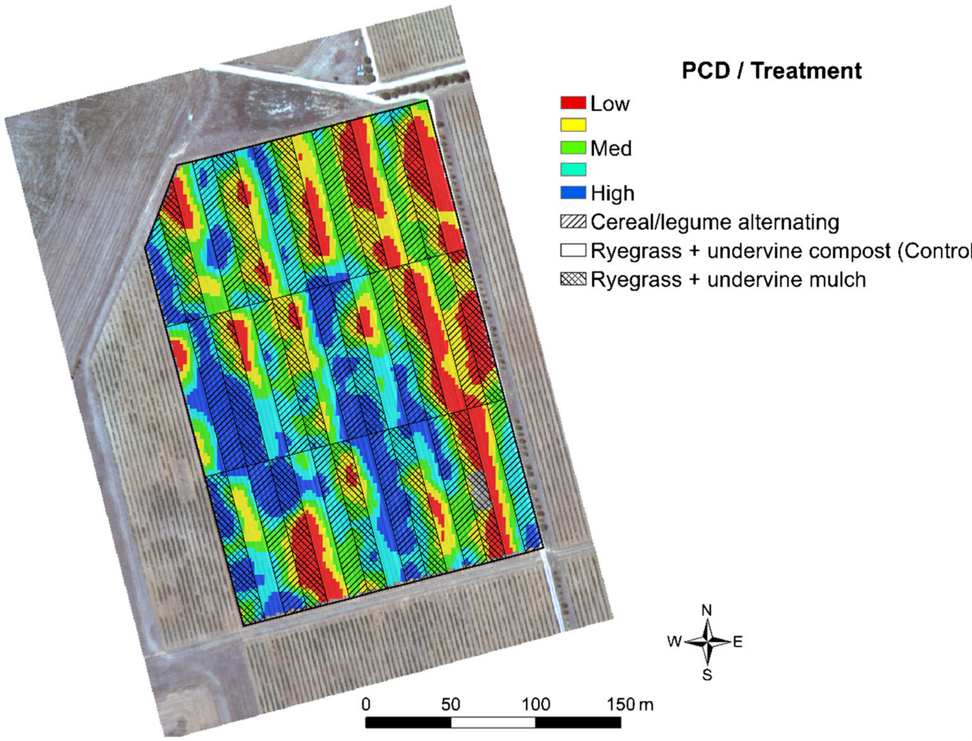

Fig. 1 True colour aerial photograph of an on-farm experiment conducted in a 4.8-ha vineyard planted to Merlot (*Vitis vinifera* L.) in the Clare Valley of South Australia, 2004–2007 (Panten et al. 2010, 2011). The experiment sought to evaluate alternative approaches to mid-row management intended to enhance vine vigour. Also shown is the *plant cell density* (PCD), otherwise known as the *simple ratio* (the ratio of infrared to red reflectance) obtained using airborne remote sensing, which provides an indication of vine vigour. With this image, the vineyard manager could go into the vineyard and align his observation of the different treatment effects and their variation to different parts of the block.

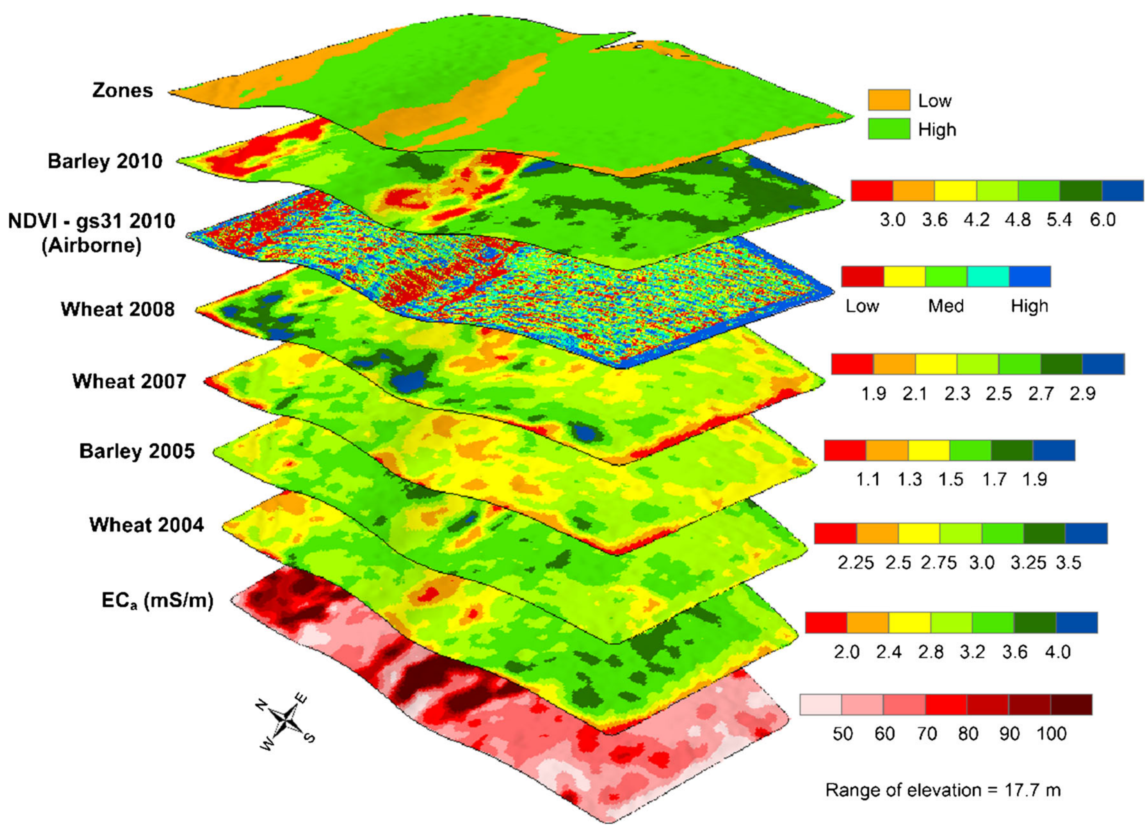

Fig. 2 Selected data collected by a farmer-adopter of precision agriculture in a 96-ha cereal field on the Eyre Peninsula of South Australia over a 7-year period (2004–2010). The yield maps, all of which have units of t/ha, were generated using data collected using a yield monitor on the harvester. Also shown is a map of apparent soil electrical conductivity (EC_a; mS/m) derived from a survey using an electromagnetic induction sensor in 2009, and an airborne image (0.76-m resolution) acquired mid-season in 2010. The data are draped over an elevation model derived from the kinematic GPS used for machine guidance on the harvester. All maps, including the zones derived from *k*-means clustering, were processed using PAT (Ratcliff et al. 2020). Note that the orientation of the north arrow is approximate only.

also shows an electromagnetic induction soil survey and mid-season airborne image that he purchased from service providers in one of the years, some management zones derived from these various map layers (Taylor et al. 2007), with all layers draped over a digital elevation model derived from the 20-mm accuracy GPS data generated and used by his harvester's guidance system. It is a deliberately old dataset to highlight the point that such data have been accessible for some time and that, notwithstanding lower rates of PA adoption than some might consider ideal (Bramley and Ouzman 2019; Ofori et al. 2020), most farmers operating modern farming systems nevertheless have ready access to such data if they want it. Key to the establishment of the management zones (Fig. 2) is temporal stability in the patterns of spatial variation in the yield maps and their alignment with both the high-resolution soil survey data and digital elevation model. In this example, sodic soils in the low-lying parts of the field, associated boron toxicity in the sub-soil, coupled with early season waterlogging in wet years, constrain yields in these areas. It is most likely that, due to farmer experience, the map layers shown in Fig. 2 do not present as a surprise to the farmer; he knows roughly which parts of the field are lower or higher yielding, but maps such as Fig. 2 delineate these areas more precisely and also provide rigorous quantification of their differences in performance (Cook and Bramley 1998). Whilst the knowledge generated through interpretation and understanding of the map layers in Fig. 2 is therefore potentially valuable to the farmer, it also poses a difficult question: how should he modify management in the different zones to reflect their different yield potential arising from their differences in soil and terrain? Perhaps the answer to this question might lie in an experiment? This is where the *farmer-centric* element of OFE (Lacoste et al. 2022) becomes critical because, with reference to Fig. 2, the scientific understanding of soil sodicity, boron toxicity, and waterlogging impacts on crop performance is already sound. What is needed here is not an experiment to quantify the impact of these constraints to production and their relative importance, but rather an experiment which underpins the improved business performance of this field within this farm. How, for example, should rates of mid-season nitrogen (N) be varied between the zones in order to optimise yield, grain protein, and/or return on investment in N at the end of the season? Such questions are those which confront the farmer with much greater immediacy than questions relating to scientific quantification of the factors impacting crop performance. They are why the *farmer-centric* element of OFE is so important. And if an experiment is to be conducted to inform the farmers' decision-making in relation to management of the field shown in Fig. 2, where should it be located and using what design? Clearly, a classical 'small plot' agronomic trial may not be the best way to underpin a business decision impacting this 96-ha field, and perhaps other parts of the farm, given the potential impact of trial location on the results obtained, their interpretation, and the merit of their extrapolation beyond the trial area (Bramley et al. 2005, 2013).

The development of so-called spatially distributed or whole of block experimentation was reviewed by Bramley et al. (2013). In brief, by taking advantage of the various PA technologies now available (variable rate controllers, remote and proximal sensing, yield monitoring, grain protein sensing, etc…), conducting experiments at scale in such a way that the range of underlying variation in the land on which the decision is to be made is included as an experimental tool, farmer experimenters can gain guidance towards decision optimisation. In effect, in addition to enabling better understanding of variation in crop performance, what the spatially distributed approach does is enable the farmer to take advantage of Krige's relation (Webster and Oliver 2007). Thus, the wider range of variation in a potentially useful explanatory covariate affecting treatment response over several hectares, compared to within a few small plots, can be used as the basis for extrapolating the experimental results to other parts of the field or farm. In the case of Fig. 2, elevation and the soil exchangeable sodium percentage, which is easily determined through routine soil testing, are examples of such covariates, yet neither might be expected to vary much within the area occupied by a typical small plot agronomic trial. Importantly, spatially distributed designs (e.g. strips, checkerboards) move away from the objective of a classical plot trial analysed using analysis of variance (ANOVA) and its derivates — to identify whether treatment *A* is better than treatment *B*. Instead, the spatially distributed approach recognises that both *A* and *B* may deliver benefit, but with the relative magnitude of their benefit varying in different parts of the field (Bramley et al. 2013). This was the philosophy underpinning the original checkerboard experiment (Cook and Bramley 1998; Cook et al. 1999; Adams et al. 1999), the 'adjacent strip' variety comparison experiments of Doerge and Gardner (1999) and the whole-of-vineyard floor management trial (6.8 ha) of Bramley et al. (2005) amongst other examples. None of these trials was analysed using classical Fisherian approaches (ANOVA etc; Fisher 1925) as the primary determinant of treatment effect. Instead, they employed map interpolation, with or without simple map algebra (Cook and Bramley 1998; Bramley et al. 2005), moving window regression (Cook et al. 1999), or more sophisticated machine learning methods (Adams et al. 1999). Anecdotally, they were regarded with varying degrees of scorn by classically trained agronomists and biometricians on the basis of lack of statistical rigour, even though in each case, the collaborating farmers were enthusiastic, especially in terms of the business-relevance of the trials; Marchant et al. (2019) provide a useful commentary on many of the statistical issues arising. Where there is strong agreement, however, is with the notion that PA greatly facilitates the conduct of OFE — both in the collection of experimental data and also in the laying down of trials using variable rate equipment (e.g. Bramley et al. 2013; Bullock et al. 2019; Marchant et al. 2019) — an idea that was implemented in the mid-1990s in the experiments of Cook et al. (1999), Pringle et al. (1999), Adams et al. (1999), and Adams and Cook (2000) and otherwise proposed by Reetz (1996) — i.e. more than 25 years ago.

3 Statistical analysis, statistical significance, and perceptions of experimental rigour

Two particular avenues of critique of both the early spatially distributed on-farm trials, and of farmer trials generally, were perceived flaws in experimental design relating to replication and randomization. In terms of replication, it is simply not possible to take the same soil or plant sample more than once. Thus, for example, destructive measurement of crop yield is very different to replicating measurements of the pH of the same solution. It is therefore of note that each of the yield maps in Fig. 2 is underpinned by approximately 18,000 yield records; in the context of the statistical robustness of these maps, each of these yield records is a replicate, albeit one with spatially autocorrelated replicates, which is why a yield map can be regarded as the simplest form of experiment — the uniformity trial. Similarly, in the case of strip trials used to underpin fertilizer decision-making (Lawes and Bramley 2012; Colaço et al. 2022 — see below), whilst an individual strip might be viewed as just one treatment, because it is laid out across the field and so crosses the range of underlying soil and topographic variation, one can have as many *virtual replicates* as are desired, albeit that these are subject to autocorrelation, with this replication achieved by taking multiple measurements, most likely using sensing technology, including yield monitors and crop canopy sensors. In other words, and in this context, a strip is not the same as one large plot.

Randomization is arguably a more vexed issue with some (e.g. Piepho et al. 2011; Bullock et al. 2019; Trevisan et al. 2021) insisting that spatially distributed designs adhere to the use of randomized treatments. On the other hand, what randomization might achieve if applied to an experiment designed to fine tune management of the field shown in Fig. 2 is open to question. The farmer knows perfectly well that the performance of the two zones is different and why, so has little to gain by randomizing experimental treatments across them. Similarly, in the case of the adjacent strip method of Doerge and Gardner (1999) and the checkerboard of Cook and Bramley (1998), the whole point of the non-randomized (but highly replicated) design is to enable side-by-side treatment comparison in all parts of the field. In the case of the checkerboard, this is possible in all directions, albeit with the issue of anisotropy possibly needing consideration in the case of yield monitor data obtained from such a trial (Marchant et al. 2019). How important such anisotropy might be when controlled traffic is used, such that machines always travel in the same path and in the same direction, is worthy of investigation.

Another area of concern in relation to experimentation using the tools of PA has been that the data generated by yield monitors and other digital technologies will almost certainly be spatially autocorrelated (van Es et al. 2007; Piepho et al. 2011; Alesso et al. 2019; Bullock et al. 2019; Marchant et al. 2019; Griffin et al. 2020; Trevisan et al. 2021). Indeed, were this not the case, yield maps such as those shown in Fig. 2 would not show spatial structure and so would not be of much value to a farmer. However, Alesso et al. (2019) have argued in the context of evaluating experimental results, that autocorrelation leads to an increase in so-called type 1 error rates (false positives), whilst Taylor and Bates (2013) and Tisseyre and Leroux (2017) have cautioned against the use of significance tests in correlation and ANOVA when data are autocorrelated, suggesting the use of corrections (e.g. Dutilleul 1993) to account for this. Whilst the merits of the statistical arguments on this issue are not questioned, the importance of their impact certainly can be. First, drawing on a large literature, McBratney and Pringle (1999) provide strong evidence that any multiple within-field measures of soil, and by inference crop attributes will be autocorrelated; the now much larger PA literature provides further weight of evidence of this. It might therefore be argued that correction for autocorrelation in *any* agricultural dataset is needed, not just those derived from PA/DA technologies or as a part of OFE. Second, the impact of autocorrelation is only an issue if a measure of statistical significance is required which, as discussed below, for *farmer-centric* OFE it may not be. However, across a range of disciplines, several authors (e.g. Matthews 2018; Amrhein et al. 2019; Wasserstein et al. 2019, and references therein) have advocated a move away from the use of tests of statistical significance because they can readily lead to misinterpretation of results, especially in the context, for example, of whether or not a drug exerts an effect (Amrhein et al. 2019); the effects of fertilizers or herbicides are similarly open to mis-interpretation. In this regard, Rowe (1994) provides a useful discussion of uncertainty.

Recently, Song et al. (2022b) sought to understand the motivations and behaviours of farmer experimenters and their consultants in the Australian wine sector across a diverse range of enterprise sizes and types. Twenty-nine out of 35 vineyard managers, and all 8 consultants interviewed made use of experimentation in some form each year, with common objectives being to improve grape or wine quality, reduce the costs of production or otherwise improve management operations in the vineyard. However, the primary aim of all of these vineyard trials was to improve confidence in operational decisions. (Note that, for the most part, these were not OFE under the Lacoste et al. (2022) definition as they were not specialist-enabled.) Yet, with the exception of a small number of growers who had access to technical support, this vineyard experimentation did not involve statistical analysis, and none of the growers reported considering statistical significance in their evaluation of trial results — including those who made use of statistical analysis. Instead, growers relied on simple comparisons between treatments, mainly because statistical significance and business significance are not the same thing. One grapegrower reported to Song et al. (2022b) that decisions about practice change following experimentation were based on "the efficacy and cost… did it work; how well did it work; how much did it cost ?" In other words, financial and experiential metrics, coupled with simple assessments of gross effects, were important determinants of actions being taken as a result of vineyard experiments. Nonetheless, and notwithstanding the low use of statistical analysis, growers expressed a desire for "robust results" and efficient approaches to experimentation that incorporate spatial information to underpin more informed decision-making (Song et al. 2022b). Griffin et al. (2008) and Thompson et al. (2019), working with grain growers in the USA, report broadly similar results. Spatial variability in land was recognised as a factor confounding trial results amongst the Australian grapegrowers interviewed by Song et al. (2022b) for whom access to or adoption of PA technologies was lower than is the case in the Australian grains sector (Bramley and Ouzman 2019; Bramley 2021). Therefore, tools which assist in the evaluation of trial results would clearly be valuable, as would experimental approaches and farm business analytics which recognise the reality of spatial variation in the land underlying vineyards and other farms (Oberthür et al. 2017; Song et al. 2022a).

4 Tools for spatial analysis of OFE

Notwithstanding general grower disinterest in statistics, the geostatistically based method of Bishop and Lark (2006) for analysis of "landscape scale" experiments was an important advance over analytical methods based on map algebra as it provided a means of attaching statistical significance to treatment effects assessed using some spatially distributed designs (Bramley et al. 2013). It therefore provided a counter to researcher perceptions of a lack of statistical rigour in such designs given that it enabled the statistical significance of treatment effects to be mapped in addition to the effects themselves. Illustrations of the use of this approach to experimental analysis are provided for broadacre cereals by Bishop and Lark (2007) and in vineyards by Panten et al. (2010), Panten and Bramley (2011, 2012) and Bramley et al. (2011). However, as discussed by Bramley et al. (2013), one problem with the Bishop and Lark (2006) method was that it employed a 'global' analysis, leading to two shortcomings. First, the matrix inversions involved meant that for a field such as that shown in Fig. 2, using data from a yield monitor (> 18,000 yield records) to analyse a trial conducted over the entire field with two or three treatments would be beyond the power of most desktop computers. Second, the 'global' analysis was inconsistent with the standard approach to yield mapping using 'local' kriging (e.g. Taylor et al. 2007), which is both a response to the computer power issue and also the likelihood that, in a field containing two or more contrasting soils with consequent differences in yield potential, the assumption of stationarity (e.g. Webster and Oliver 2007), a requirement for map interpolation by kriging, may not be met. The method of Jin et al. (2021) is an improvement on Bishop and Lark (2006) as it enables local analysis, with the size of the local neighbourhood determined using the method of Bakar et al. (2021). Both Jin et al. (2021) and Bakar et al. (2021) are enabled in *Precision Agriculture Tools* (PAT; Ratcliff et al. 2020) thereby providing a freely available open-source tool which can be used by growers, their advisors, and researchers in analysing spatially distributed OFE. Of course, whether the growers take notice of the statistical significance metrics offered by such tools is irrelevant. Implementation of the methods of Jin et al. (2021) and Bakar et al. (2021) in a tool such as PAT (Ratcliff et al. 2020) still provides growers, consultants and researchers with a useful map-based analysis tool for on-farm experiments with particular utility when digital technologies such as yield monitors or remotely sensed imagery are used to assess treatment effects. Importantly, they also provide an entry point for classically trained agronomists and their statisticians to such spatial analysis.

A possible objection to the whole-of-block approach has been that, especially for fertiliser response experiments using low or zero rates, such designs might lead to reduced revenues due to lost production, with small strip designs suggested as an alternative (Whelan et al. 2012). Another might be that since most adopters of PA tend to manage on a zone basis (e.g. Fig. 2; Whelan and Taylor 2013; Bramley and Ouzman 2019) rather than using continuous variable rate application of inputs, there might be less need to experiment in an entire zone or field than in representative parts of each zone. Thus, for example, Lawes and Bramley (2012) positioned 'N-rich' strips so that they crossed previously identified management zones in three fields in the Australian grainbelt and used a moving window analysis to assess the difference between the N-rich strip and adjacent farmer practice along the length of the strips. Whilst the *t*-test element of this work can be criticised on the basis that correction for autocorrelation (e.g. Dutilleul 1993) was not employed, its results were nonetheless similar to those obtained using a 'spatial ANOVA' which did account for autocorrelation (Lawes and Bramley 2012). More importantly, the moving window approach allowed the farmers involved to see both the magnitude of the gross differences between the strip and adjacent areas and to quantify a response index describing these. In addition to supporting decision-making relating to zone-based management, this moving window approach was valuable in highlighting the fact that contrary to frequent commentary, management zones are not "homogenous". More recently, Colaço et al. (2021, 2022) and Lawes et al. (2019) have concluded that such OFE is essential if optimization of N fertiliser management is the farmers' goal, with Lawes et al. (2019) and Colaço et al. (2022) also highlighting the utility of 'N-zero' in addition to 'N-rich' strips, even if these are short (Whelan et al. 2012) rather than running over the full length of the field (Lawes and Bramley 2012; Colaço et al. 2022). Moving window trial analysis is also available in PAT (Ratcliff et al. 2020).

5 Grower needs for OFE implementation

Whilst farmers commonly experiment, the use of more data-intensive experimentation as a 'business as usual' approach to improved agronomic management is yet to be realised given that the availability of time, labour, and unexpected events are frequent reasons for trials not being completed (Song et al. 2022b). Whilst the farmer-led, specialist-enabled nature of OFE as defined by Lacoste et al. (2022) may help to alleviate some of the pressures, such considerations dictate that OFE needs to be simple and/or easy for the farmer to implement. This is likely why both grapegrowers (Song et al. 2022a) and cereal farmers (Lawes and Bramley 2012; Colaço et al. 2022; Cho et al. 2021) see simple strips as attractive. In the case of vineyards, this will especially be the case in the absence of readily commercially available DA technologies that facilitate automation of vineyard operations. Equally, it is why the conduct of OFE as an inherent part of PA (Reetz 1996; Cook and Bramley 1998) was seen as attractive given the opportunity for the tools of PA to be used for automated trial establishment and measurement of treatment effects. However, current mainstream PA software lacks functionality for experimental analysis. Whilst it is expected that such analysis will primarily be the domain of either the farmers' agronomic consultant or a researcher partner supporting the OFE (Lacoste et al. 2022), experimental analysis may be facilitated for all participants by tools such as PAT (Ratcliff et al. 2020) and it is to be hoped that further development of such tools will continue. As a part of this, some exploration of the application of machine learning methods to OFE analysis (Adams et al. 1999; Colaço et al. 2021, 2022) may prove valuable.

Pannell et al. (2006) have highlighted that innovations are more likely to be adopted when they have a "high relative advantage" over current practice, and when they are readily "trialable"; that is, when they are easy to test and to learn about before adoption. In the context of farmer-centric OFE (Lacoste et al. 2022), 'trialability' is an obvious inherent element of the adoption process itself, whilst a clear purpose of OFE is to facilitate identification of the 'relative advantage' of a new approach to management. So, what might enable such practice to become a part of 'business as usual' for farmers who, as discussed, are disposed to try things anyway, and what might impede adoption? These are important questions given the suggestion (Lacoste et al. 2022) that the "restructuring" of the relationship between farmers and scientists promised through participatory processes has so far failed to materialise.

Rust et al. (2021) examined the information sources of farmers in Hungary and the UK who were considering innovations in sustainable soil management. They found, perhaps unsurprisingly, that farmers place most trust in other farmers. They also found that farmers place least trust in so-called experts, especially "agricultural researchers from academic and government institutions". The reality of this problem is readily supported by the observation of Bouma (2021) that, in identifying a role for Soil Science in realising the Sustainable Development Goals by 2030, Evans et al. (2021) failed to mention the role of farmers and landholders. Likewise, in identifying research priorities to overcome barriers to the benefits of DA being realised in New Zealand, Shepherd et al. (2018) acknowledged the need for a move away from reductionist approaches. However, their focus appeared more strongly aligned to partnership between researchers and technology companies than with the end-users of the technologies. Tsouvalis et al. (2000) reported dissatisfaction with companies developing PA technologies amongst UK farmers who felt ignored in this process, and more broadly, a mismatch can readily be identified between the objectives of digital technology developers and those of farmers (Rose et al. 2018; Bronson 2019; Jakku et al. 2019; Hansen et al. 2022). It is therefore somewhat surprising that, in a UK-based study aimed at identification of priority research questions for DA (defined in this case as the application of big data and precision technology systems in agriculture), Ingram et al. (2022) invited 148 stakeholders to participate in a survey, of whom only 8 (5%) were "Farmer representatives". Of the 40 who accepted the invitation and who were then asked to offer up research questions for consideration, only three were from the "Farmer representatives" cohort. Twenty-eight participants then prioritised the total of 195 research questions identified through a voting process, again with three of these participants being "Farmer representatives". This was followed by an online workshop in which the ideas were elaborated, on this occasion with four of the 25 participants being "Farmer representatives". Whether any of these "Farmer representatives" were actual farmers is unclear. However, by far the most represented group in this process were researchers, with the second most represented group being from DA companies (Ingram et al. 2022). In each of these examples, it might be suggested that acknowledgment of the need for salience, credibility and legitimacy (Cash et al. 2003) amongst farmer stakeholders has been a constraint to progress.

In contrast to the above examples, and in the context of a biosecurity management problem relating to pathogen incursions, Evans et al. (2020) suggest some valuable alternatives to the 'expert' presenting as such. They highlighted the need for scientists (and their host organizations) to take a wide view of the system in which the problem is situated and to adopt a "problem focus" rather than a "solution focus" to gain a deeper understanding of the issues being addressed, their context and the likelihood of different stakeholders reacting differently to the situation (c.f. experimental results). They would thus be better positioned for their expertise to be offered or sought when the farmer is most receptive in terms of timing, content, and mode of delivery. This approach is also in marked contrast to that which predominated at the recent International Conference on farmer-centric OFE (ISPA 2021) and presents as a significant area in which much value would accrue through scientists re-thinking their objectives in regard to on-farm trials and considering the desirability of these being *farmer-centric*. Thus, for OFE as envisioned by Lacoste et al. (2022) to succeed and progress, in addition to being driven by the farmers' questions (i.e. farmer-led), the insistence of some researchers on the use of complex methodologies for on-farm trials (e.g. Bullock et al. 2019; Cho et al. 2021) could desirably be softened so that OFE uses simpler designs which fit with normal farm operations (Colaço et al. 2022; Song et al. 2022a). Such an approach need not lessen the specialist-enabled element of OFE nor compromise the value to the specialist of participating. As Lacoste et al. (2022) make clear, OFE should be a process of co-learning between farmers and specialists. In summary, it is a process which depends on trust.

Finally, implicit in the farmer-specialist OFE partnership, and especially its scaling beyond the farm hosting the trial, is sharing of data amongst participants. However, a potential difficulty arises in the case of PA-based OFE relating to the numerous concerns around farm data ownership and privacy, and the potential for it to be captured by proprietary PA/DA systems and/or be used for purposes beyond those intended by the farmer (Jakku et al. 2019; Wiseman et al. 2019; Koch 2021). In Australia, the move towards development and adoption of a Farm Data Code (National Farmers Federation 2020) is a step in the right direction; it would be unfortunate if development of OFE were constrained by concerns as to where trial results might end up. On the other hand, the willingness of farmers to share data with other farmers and with researchers (Wiseman et al. 2019) bodes well for OFE; arguably their unwillingness to share with DA service providers does not. Accordingly, systems which facilitate this data sharing, but which recognise and are transparent about whose data are whose and what rights exist in regard to data access and re-use (Wiseman et al. 2019), would add value to the OFE process and contribute to its scalability. For example, whereas individual strip trials used to support N decision optimisation are only of immediate benefit to the farmer hosting the trial, the amalgamation of data derived from such trials into a single database could be valuable to the generation of improved models for farmer decision support (Colaço et al. 2021, 2022).

6 Conclusions and future directions

Farmer-centric OFE does not depend on digital technologies, but it seems clear that such technologies are a potentially significant enabler for OFE, given the time and labour constraints facing many growers. In the same way, OFE are likely significant enablers for the productive use of such technologies in farming system optimisation. Many of these technologies already exist for many cropping systems in the suite of tools which comprise PA. However, further development and sharing of methods for trial design and analysis, which are simple to use and deliver results in a manner that is consistent with the farm business objectives of OFE, would be valuable. A focus on the building of trust between researchers and farmers, along with recognition on the part of researchers that farm business improvement is of greater importance to the farmer than the advancement of science, will also be important. In successful OFE, these things will not be mutually exclusive. Overall, the data-driven and "evidence-based" nature of OFE (Lacoste et al. 2022) provides a means of reducing the metrical and translational uncertainty (Rowe 1994) of decision-making. Ideally, the OFE process needs to become embedded in normal operations such that it supports the farmer as they tackle the other uncertainties which mitigate against farm productivity growth.

Acknowledgements Preparation of this paper was supported by CSIRO and The University of Tasmania, with the input of RGVB and AFC also supported by the Grains Research Development Corporation (GRDC) as part of the *Future Farm* project (GRDC Project No. 9176493). However, it draws on research conducted over many years and funded by these organisations along with various Australian agencies of which GRDC, Wine Australia, and the Australian Department of Agriculture, Water and Environment have been to the fore. The input of many collaborating farmers across the grains and wine sectors over many years is especially acknowledged. Drs Rick Llewellyn and Roger Lawes (CSIRO) made helpful comments on an earlier version of the paper.

Authors' contributions All authors contributed to the discussion presented in this paper. The first draft of the manuscript was written by Rob

Bramley and Xinxin Song, André Colaço, Katherine Evans, and Simon Cook commented on this and subsequent versions. All authors have read and approved the final manuscript.

Data availability Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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