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Towards Incorporating Within-Field Variation into Spatial Agronomic Decision Processes

James Taylor

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MEMOIRE D'HABILITATION A DIRIGER DES RECHERCHES

TOWARDS INCORPORATING WITHIN-FIELD VARIATION INTO SPATIAL AGRONOMIC DECISION PROCESSES

James A. TAYLOR

CHERCHEUR EN FOUILLE DE DONNEES EN AGRICULTURE DE PRECISION - IRSTEA





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The defence of the thesis took place at SupAgro Montpellier on the 7th of June, 2019. The jury members were

Professor Phillip Vismara (Chair) – SupAgro Montpellier

Dr Gilbert Grenier – Bordeaux Sciences Agro (External Examiner)

Dr Aurelie Metay _ SupAgro Montpellier (Internal Examiner)

Professor Bruno Tisseyre – SupAgro Montpellier

Professor Jose Antonio Martinez Casanovas - The University of Lleida, Spain.

Dr Davide Cammarano – James Hutton Institute, Scotland, UK

Professor Christelle Gee – AgroSup Dijon was an external examiner but was unable to attend.

Please note, this has received a brief edit to correct grammatical and editorial errors. It differs slightly from the original submitted memoire, however, no additional sections have been added nor have any sections removed. References that are self-citations are indicated in bold within the text

This work is my own

James Taylor
September, 2019





Acknowledgements

Since receiving my PhD degree in December 2014, I have spent the past 14 years as a Research Fellow or Senior Lecturer in various research institutions around the world. It has been challenging at times, and not always easy with a young family, however I have had a fantastic experience wherever I have been so far.

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James Taylor
28/11/2018, Montpellier





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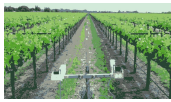
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1 - Introduction:

1.1 Background

The environment in which the majority of global crop production occurs is a variable environment¹. Only in closed situations, e.g. glass/greenhouse and growth chamber conditions, is it possible to control edaphic and meteorological variation. These conditions, however, only account for a fraction of global production area, for example there were 720,000,000 ha of cereals grown globally in 2016² compared with 498,000 ha of total greenhouse production in 2017³. Production variation occurs in both time and in space. Dryland (rain-fed) systems are particularly vulnerable to temporal variability, as production potential is strongly determined by the amount and timing of precipitation and any management to react to changing environmental conditions. The fluctuations in annual average wheat tonnage/ha from Australia and South Africa highlight this temporal variability (Fig. 1.1) at a national scale, but the same can be observed at enterprise, field and sub-field scales too. In Australia, where I started my research journey, national average dryland wheat yields can vary from $< 1 \text{ t}\cdot\text{ha}^{-1}$ to above $2 \text{ t}\cdot\text{ha}^{-1}$, and this is when averaging climatic conditions across an entire continent! Regional differences can be more extreme.

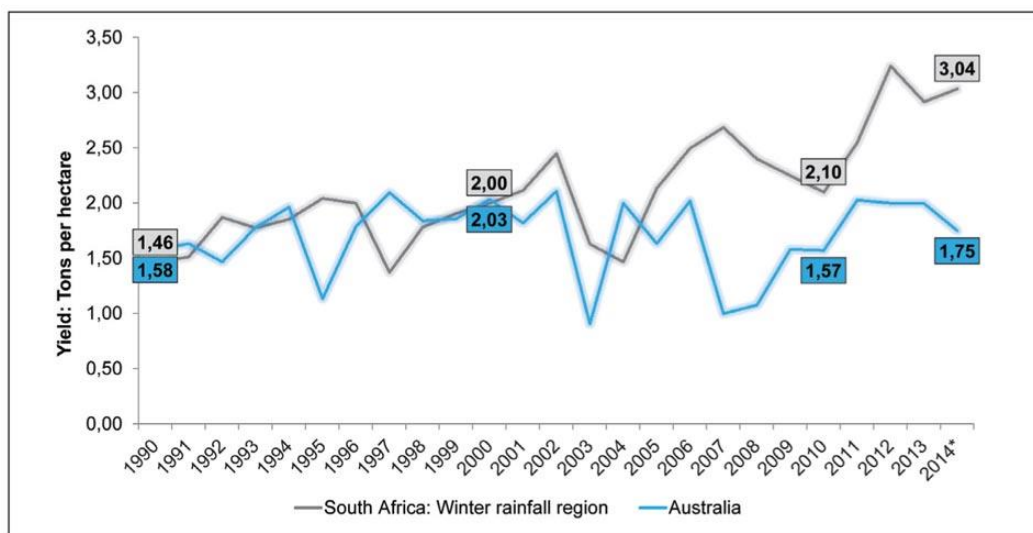
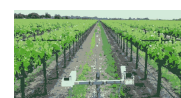


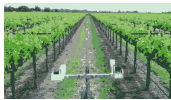
Figure 1.1 Graph of annual average dryland wheat yields from Australia and South Africa (1990 - 2015). Data obtained from BFAP 2014 and ABCS 2013. The graph is reproduced from the www.grainsa.co.za website.

¹ Only plant production systems are considered in this document. Variability in animal production, both indoor intensive and outdoor extensive systems is also important, and addressed in the domain of Precision Livestock Farming (PLF). While many of the variability concepts and technologies considered in the document have applications in PLF, they are only discussed in terms of cropping systems.

² Sourced from <https://data.worldbank.org/indicator/AG.LND.CREL.HA> (November 2018)

³ Sourced from International Greenhouse Vegetable Production – Statistics, 2018 Edition, Cuestra Roble Consulting, www.cuestaroble.com/statistics.html





Spatially within fields, production can exhibit even greater variation within a season. Yield monitoring from the early-mid 1990s has consistently revealed large patterns in yield variance in cereal systems (Fig. 1.2 shows some different examples of this).

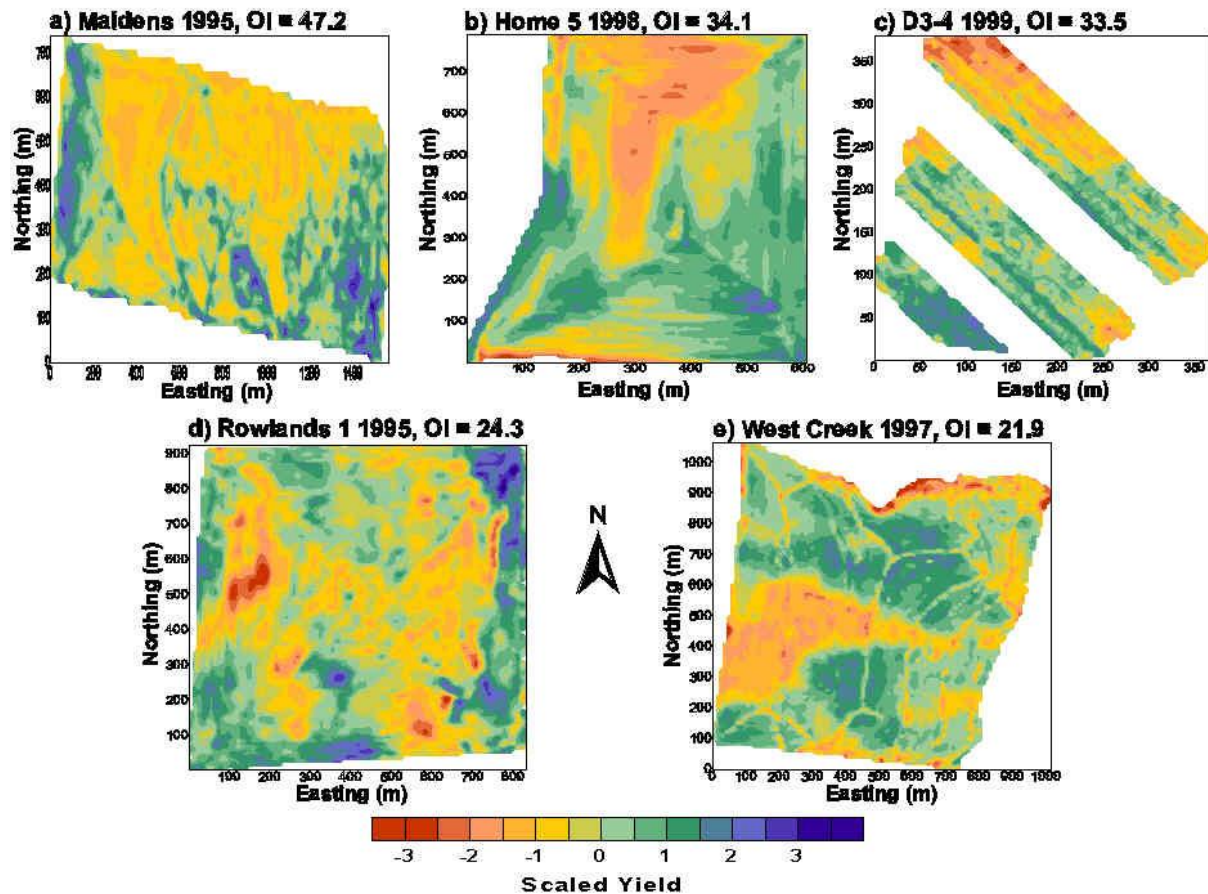
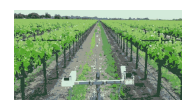
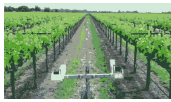


Figure 1.2 Examples of some early (1995-99) yield maps from Australia (reproduced from McBratney et al., 2000). Maps a), b), d) and e) are grain yield, c) is grape yield. Yields are scaled ($\mu = 0$) to present them on a common legend. Yields in the cereal systems tend to range from < 1 to > 5 t.ha⁻¹; grape yield ranged from < 10 to > 30 t.ha⁻¹.

Producers are therefore confronted with temporal variance (predominantly in climate) interacting with spatial variance (predominantly soil and/or management effects) in their production systems. Until fairly recently, it has not been possible to correctly characterise the spatial variance in soil and crop properties, let alone the spatio-temporal variance in production, *within* a field (Fig. 1.2 for yield examples). It has always been possible to determine temporal variance at a whole field-scale. Field records are generally well kept by growers and suppliers for accounting purposes. Thus, it has been field or farm-level information, and some ‘best guess’ information on near and long-term climate conditions, that has historically driven crop decisions with the aim of optimising management to the ‘average’ of a field. The development of, and recent explosion in, sensing systems, which are linked to global navigational satellite systems (GNSS) (e.g. GPS), that measure and geo-located plant growth,





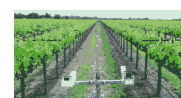
production attributes and soil properties has changed this situation. Growers and agronomists now have potential access to a wealth of high-resolution spatial data to help make management decisions. In the first instance, this should help to improve 'average' management, but the real opportunity lies in being able to make differential spatial and spatio-temporal management decisions at a sub-field level.

However, the opportunity to make more and better spatial decisions is also paired with the potential to make the wrong spatial management decision. Having access to more data does not directly translate to better (higher-resolution) decisions. There is a logical flow from data to information to decision that needs to be followed and adapted in the context of the end-user (growers/agronomists) and the target production system. In this context, the diversity in agricultural production, even just crop production, means a one-size fits all solution will rarely, if ever, be feasible. If the end-user cannot make a better decision, then the entire process (data collection, processing, data-fusion and interrogation) is redundant and worthless. This is a challenge that the precision agriculture community has always faced. Advances in sensing and communications mean that data exists (although it may still be incomplete or not exactly the right data needed). Methodologies to convert data and compress them into information layers are developed or developing rapidly. However, the leap to decisions is often still missing. If a decision exists, then the ability to enact the decision (an engineering problem) generally exists or can be quickly solved. The general process for PA implementation, which is a derivation of a process quality control cycle, is visualised in Fig. 1.3.

In situations where simple decision making is possible e.g. "Am I driving straight and at a fixed swath distance with an auto-steer tractor?", then the uptake of technology has been shown to be fast and effective. Agronomy is unfortunately rarely 'simple'; it is a biological process in a variable environment. There is a real challenge for agriculturists, engineers, computer scientists and the industry to make this work. Ideally, every time the circle in Fig. 1.3 is completed, an improvement in the decision and management process should be obtained. These are likely to be mostly incremental gains unless new disruptive technologies or methodologies are introduced that change the grower's ability to either sense, analyse, decide or apply.

The general background discussion above has used dryland (non-irrigated) cereal (wheat) production primarily as a 'classical' agronomy example. However, spatio-temporal variation in all cropping systems has been reported or is expected because management and environment is never 100% constant. Irrigated systems tend to be more resilient to annual variations in weather, especially drier years, but are unable to cope with excess precipitation, for example. Perennial crops, often irrigated and intensively managed, are affected by production and environmental conditions in the current year **and** the previous years. Therefore, how to determine the amount, the drivers and the decisions to manage crop production is a universal question in arable, horticultural and viticultural systems.

The term crop production in the introduction is deliberately ubiquitous, and slightly ambiguous in the previous statement. Site-specific crop management began with yield (quantity) management, because yield monitors were the first crop production sensing systems available. Crop quality is also important, and perhaps more so than yield in high quality production systems, and should also be considered in spatial decision-making.



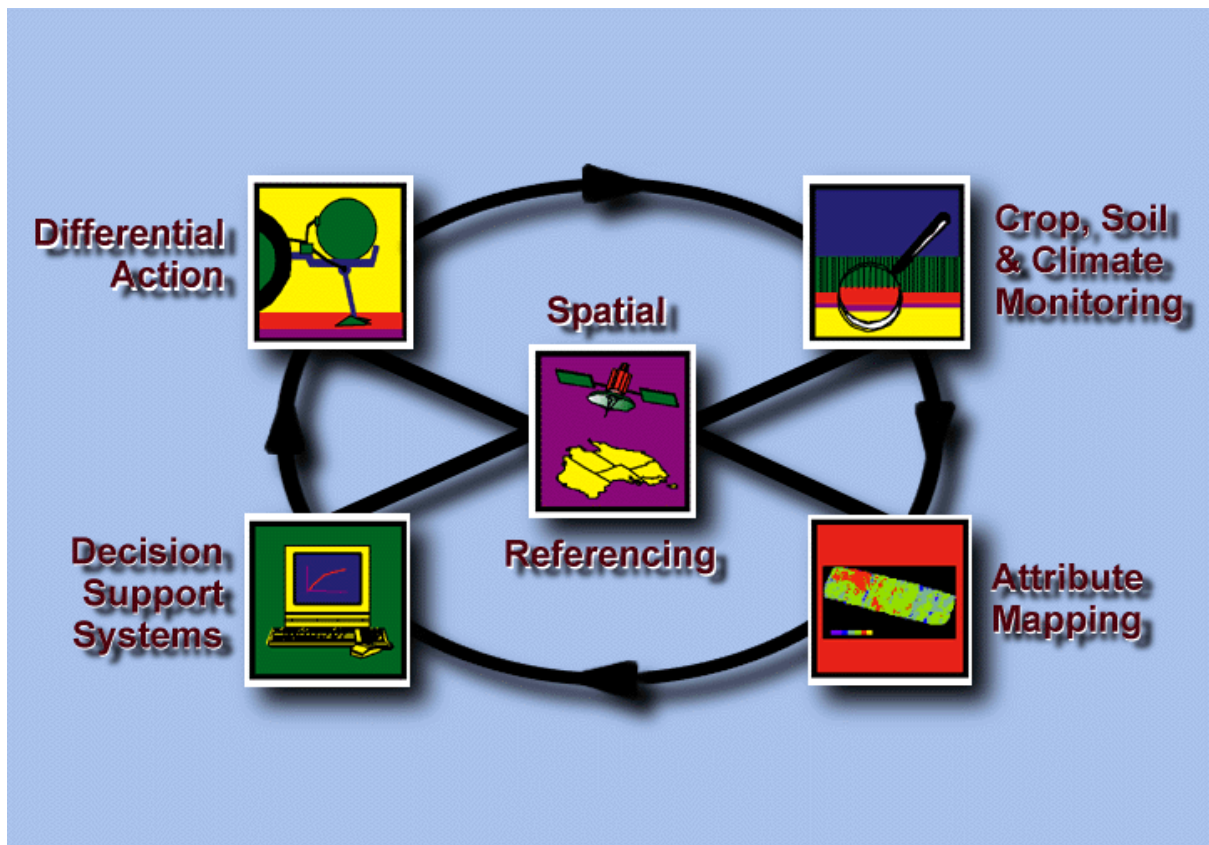
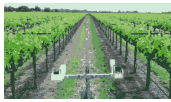
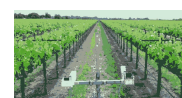


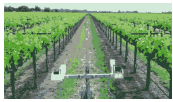
Figure 1.3 The Precision Agriculture wheel model showing the five main processes for a site-specific crop management system (reproduced from Precision Agriculture Laboratory, The University of Sydney, https://sydney.edu.au/agriculture/pal/about/what_is_precision_agriculture.shtml).

1.2 Outline of the Memoire

In this memoire I will present my journey and the knowledge that I have gained within the Precision Agriculture domain over the past two decades. The first section broadly introduces variation in cropping systems and serves as a very general introduction to the research domain.

Section 2 provides a more detailed overview of PA and develops some of the main issues and challenges that have been historically faced by PA practitioners. This includes clearly defining the domain and a recognition of the diversity and multi-disciplinary nature of PA. The role and importance of variability in production systems is then introduced along with the challenges in correctly and properly defining production variance. The final three parts of Section 2 turn the focus to how information, particularly multiple layers and multiple types of information, start to be translated into decisions. This shifts PA from a technical question on measuring and managing variation to a socio-technical innovation question on how technology is perceived and adopted and the potential disconnect between what scientists consider important and what commercial users want.





Section 3 further develops two key areas – the disconnect between academic research and commercial application (innovation) and the disconnect in the data that we have and what we want (in terms of data type and the quality). There is a deliberate focus on how PA technologies and methodologies are effectively translated into successful commercial services and what I have learnt about this from my various placements and from my attempts to define industry-facing protocols at various stages of my research career.

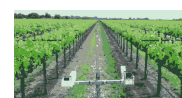
Section 4 provides an overview of how my research activities and publications that have (I hope) helped to address the issues raised in Sections 2 and 3. A focus is given to a large body of work that provides a descriptive reference base to observed spatial variation in yield and crop quality parameters in various annual and perennial systems. This is followed by the role and the evolution in zonation approaches over the past 2 decades and how these zones or management units have been used as a basis for more advantaged analysis to improve crop production knowledge and ultimately crop management decisions. The latter parts of Section 4 shift from natural, agronomic applications to more recent research that has started to interrogate and to build models to understand socio-technical aspects of PA. It develops ideas on how PA translation and adoption can be enhanced by better considering barriers and drivers of adoption.

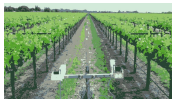
The last section, Section 5, outlines my own vision for the evolution of Precision Agriculture over the next decade. It outlines how Precision Agriculture needs to develop so that producers have a more ‘personalised’ agricultural decision system. It highlights key areas of research that I would like to pursue in my future career, and how advances in digital technology will help to achieve this research and translation. There are some concluding remarks.

Throughout the memoir, I have deliberately avoided the incorporation of mathematical notation. I have preferred to keep the discussion more general and not too specific for a broader audience. The cited references contain more specific details for those wishing to understand the derivation of the geostatistical approaches and models discussed. By convention, I have indicated in **bold** the references that are self-citations within the document. These are all listed in the Bibliography. A more detailed publication list is appended with my full publication list. The publication list contains work that is not cited in the document, particularly research that I have performed in soil science, rather than in PA, and teaching and industry-oriented publications.

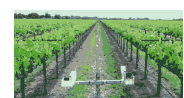
1.3 Personal Motivation

My journey into precision agriculture began within the domain of soil science, principally pedometrics and digital soil mapping (before the term was coined). Soil science always interested me through school, when soil erosion and the threat of land degradation was on the national conscious in Australia in the late 1980s. When I went to university to study agriculture, I naturally gravitated towards a major in soil science. I have always been (and continue to be) fascinated in the way that soil forms in a landscape and the variation that is observed. I was also interested in the mathematical way that this variation was being described and mapped. My interest in how and why soil varies in the landscape ultimately led to an interest in how soil variation within a field impacts and creates spatial variation in crop production. And so, I entered the domain of precision agriculture, initially with an honours thesis





describing spatial and temporal variation in wheat fields, then a PhD thesis on Precision Viticulture and Digital Terroirs. This was followed by a series of post-doctoral positions in precision agriculture and digital soil mapping, which led to a senior lectureship at Newcastle University and ultimately to Irstea and UMR ITAP. Throughout these endeavours, my research has always been strongly linked to industry needs and often I have been located on research stations and farms or working directly with growers and grower groups. It is a facet of Precision Agriculture that I love, bringing something new to the ancient art of agriculture while respecting the tradition and history behind production systems. I hope that it continues.





2 - Context of the Theme of Research to Date

2.1 The philosophy of precision agriculture

Precision Agriculture (PA) is still a relatively new term in global agriculture, although with the recent development of Digital Agriculture it is no longer the 'new kid on the block'. Precision Agriculture has its origins in grid soil surveying in the late 1980s in the USA (Pierce et al., 1994; Stafford, 1996). However its real birth came with civilian access to global navigation satellite systems (GNSS) and the development of on-combine and on-tractor sensing technologies. Linking the two generated an ability to map grain yield, a better appreciation of the inherent variation in yield (e.g. Fig. 1.2) and a desire to better manage this. In the 1990s, PA grew through a series of conferences and workshops and spawned its own specific academic journal in 2000 (Precision Agriculture Journal, Springer, New York, NY, USA). While the journal and many of the conferences continue as specialised PA forums, PA applications can now be found within more generic crop and agronomy forums, and it is now more common for PA articles to be found in 'mainstream' agriculture journals.

Definitions of PA are many and varied and reflect its diverse and diffuse origin. A legacy of its origin in soil sampling and mapping for crop nutrition is that in many definitions the 'Agriculture' in 'Precision Agriculture' tends to relate to cropping systems only. Suggestions that 'Site-Specific Crop Management' (SSCM) should be preferably used for PA applications in crop systems have been made (Robert et al., 1994; Plant, 2001). However, the term PA remains synonymous with cropping systems. Agriculture of course is much more than cropping systems. Animal-oriented studies however, tend to go by the term Precision Livestock Farming (PLF), rather than sit under the umbrella of PA. This is evident in Europe with both a biennial European Conference on Precision Livestock Farming (ECPLF) and a European Conference on Precision Agriculture (ECPA, which is strongly crop-oriented).

Table 1 gives some existing definitions for Precision Agriculture and their origin. Some are very specific while others are more general and inclusive. From my perspective, I tend to view PA in a more generic context and as a management philosophy rather than as a specific technological application. Precision Agriculture is about working out how to make better decisions, usually using emerging technologies. It is not based on any single or suite of technologies and innovations. It exists at the interface of innovation and agriculture, with the focus on improved resolution in spatial and temporal management. If it operates correctly, the PA of yesterday should be the 'normal' agriculture of tomorrow. The science and the community of Precision Agriculture should have 'evolved' into the next level of innovation and opportunity. Thus, it could now be considered that auto-steer tractors are no longer precision agriculture in many places, but part of good agricultural practice. Of course, GNSS-enabled equipment continues to be essential for many potential and developing PA applications.





Table 1.1 A summary of some key definitions of Precision Agriculture (and site-specific crop management) proposed over the past 25 years. The selected references represent the general range of definitions provided and not all cited definitions are given here.

Year	Definition	Source
1994	The intent of precision agriculture is to match agricultural inputs and practices to localized conditions within a field to do the right thing, in the right place, at the right time, and in the right way (Pierce et al., 1994)	Pierce, F. J., Robert, P. C. and Mangold, G. (1994).
1994 /1995	There is no broadly accepted definition of SSCM. We proposed the following: Site-specific crop management is an information and technology based agricultural management system to identify, analyze, and manage site-soil spatial and temporal variability within fields for optimum profitability, sustainability, and protection of the environment.	Robert P, Rust R, Larson W (1994)
1996	The targeting of inputs to arable crop production according to crop requirement on a localized basis.	Stafford, J. V. (1996)
1997	Precision agriculture is a management strategy that uses information technologies to bring data from multiple sources to bear on decisions associated with crop production.	National Research Council. (1997)
1997	Site-Specific Management is electronic monitoring and control applied to data collection, information processing and decision support for the temporal and spatial allocation of inputs for crop production. This technology is known by many names, including: precision agriculture, site-specific farming, prescription farming and variable rate technology (VRT).	Lowenberg-DeBoer, J., & Swinton, S. M. (1997)
1998	Precision agriculture is the application of a holistic management strategy that uses information technology to bring data from multiple sources to bear on decisions associated with agricultural production, marketing, finance, and personnel.	Olson, K. (1998)
1999	Precision agriculture is the application of technologies and principles to manage spatial and temporal variability associated with all aspects of agricultural production for the purpose of improving crop performance and environmental quality.	Pierce, F. J. & Nowak, P. (1999)
2000	Simplified, PA is the use of new information technologies together with agronomic experience to site-specifically: i) maximize production efficiency ii) maximize quality iii) minimize environmental impact iv) minimize risk.	McBratney, A. B., & Taylor, J. A. (2000)
2001	Site-specific management (SSM; also called, precision agriculture) is the management of agricultural crops at a spatial scale smaller than the whole field.	Plant, R. E. (2001)
2002	The term “precision agriculture” means an integrated information- and production-based farming system that is designed to increase long-term, site-specific, and whole farm Production efficiencies, productivity, and profitability while minimizing unintended impacts on wildlife and the environment	U S House of representatives. (2002)
2004	Precision farming is a systems approach to managing soils and crops to reduce decision uncertainty through better understanding and management of spatial and temporal variability.	Dobermann, A., Blackmore, B.S., Cook, S., & Adamchuk, V. I. (2004)
2005	One generic definition could be “that kind of agriculture that increases the number of (correct) decisions per unit area of land per unit time with associated net benefits”.	McBratney, A. B., Whelan, B., Ancev, T., & Bouma, J. (2005)
2010	Precision agriculture, or information-based management of agricultural production systems	Gebbers, R., & Adamchuk, V. I. (2010)
2012 (last update)	Precision agriculture involves the observation, impact assessment and timely strategic response to fine-scale variation in causative components of an agricultural production process. Therefore, precision agriculture may cover a range of agricultural enterprises, from dairy herd management through horticulture to field crop production. The philosophy can be also applied to pre- and post-production aspects of agricultural enterprises.	https://sydney.edu.au/agriculture/pal/about/what_is_precision_agriculture.shtml
2016	Precision Agriculture (PA) can be defined as the management of spatial and temporal variability in the fields using Information and Communications Technologies (ICT).	Fountas, S., Aggelopoulou, K., & Gemtos, T. A. (2016)





With this in mind, it is the definition of McBratney et al. (2005) that best defines PA for me.

“Precision Agriculture is that kind of agriculture that increases the number of (correct) decisions per unit area of land per unit time with associated net benefits.”

This definition does not specify system type (arable or perennial crops, animal, pastoral, etc...), nor does it link to specific technologies or methodologies. It emphasises that PA is about decisions. It is a philosophical statement that sets a goal for PA to make better decisions at finer spatial and/or temporal resolutions with the intent of making agriculture better. It is also (deliberately) ambiguous in how agriculture is made better i.e. it has ‘associated net benefits’. In an ideal application, these net benefits will be economic (production), environmental and social in nature, however it may be that only one or two are actually realised with any individual PA application. Collectively, a PA program should address all three aspects to ensure long term sustainability (economic, environmental and social) and enhanced food security. Typically the economic benefits are well understood and quantified (and easily derived in terms of monetary units), however the environmental and social benefits are poorly defined and quantified (Ancev et al., 2005).

Precision Agriculture has typically been advocated and employed in developed agricultural systems with higher levels of mechanisation. Applications into developing agricultural systems, including subsistence farming structures, are far fewer. However the philosophy of PA is as just applicable to small-scale and developing systems, even if the level of technological innovation in these systems is not as high. While mechanisation may be lower, management is often more (spatially) intense and can still be spatially varied, provided suitable tools for better decision-making are available. These of course need to be low-cost, user-friendly and effective, however there are globally increasing levels of disruptive technologies, notably smartphone and tablet technologies, which are providing a platform for PA applications in all types of agriculture systems (Lagos-Ortiz et al., 2018; Camacho and Arguello, 2018). The key, as alluded to previously, is of course to have the correct decision process for each type of system and for each location, i.e. a ubiquitous platform but a site-specific decision system.

2.2 PA - A multi-disciplinary domain

Achieving PA is no longer an agricultural science question. Precision Agriculture is about developing sensing systems to gather more or new data and information and decision systems to process and act on these systems. It is dependent on advances in many other disciplines to advance itself. At the core there will always be a need for good agricultural science but this operates around developments in sensing technologies (the domain of Electrical/Chemical engineers), data management and display (Computer Scientists), data analytics (Bioinformaticians and Statisticians) and PA machinery (Agricultural engineers). Precision Agriculture is a truly multi-disciplinary domain, especially when the social and economic components are added to the technical. With such multi- and inter-disciplinary needs, it is almost impossible for the complete PA skill set to be present in any single individual. Precision Agriculture must therefore exist within collaborations and multi-disciplinary teams, within which diverse groups (or individuals) support and enable each other.





This provides an enormous challenge for the PA community. Agriculture is not always seen as a ‘sexy’ area to work in. Neither does it command the financial power of many other industries (e.g. defence, mining, financial, etc...) where data analytics and engineering skills are equally sort after. There is a challenge for the PA community to attract and to retain people capable of crossing over between engineering, data analytics and agricultural science. This is not to expect such people to be an expert in all areas, but rather to have a fundamental understanding of how the other areas impact innovations in their main speciality. Biological systems, and particularly intrusive systems like agricultural production systems, are not intuitive systems for applications of pure sciences. It is a highly variable and often changeable environment in which practical applications and trade-offs are needed. This is often difficult for people unfamiliar with agriculture to understand, however it is these people (engineers, computer scientists etc...) that are needed to make PA work.

Precision Agriculture works when all aspects are integrated. Figure 1.3 shows the ‘PA cycle’, which follows a typical quality control cycle operating under the general approach of Plan → Act → Check → Plan → Act → etc... In Fig. 1.3 this has been slightly expanded to consider Monitoring (Check), Attribute Mapping and Decision Support (Plan) and Differential Action (Act). The cycle is made possible by the ability to geo-reference all actions and analysis using Global Navigation Satellite Systems (GNSS), such as GPS (the USA Department of Defense’s Global Positioning System). Monitoring is performed by a variety of sensing systems that utilise a variety of chemical, physical and spectroscopic approaches and are mounted on a variety of different platforms (from terrestrial fixed or roving platforms to satellite platforms). The conception and development of these systems usually requires non-agricultural scientific and engineering expertise. Mapping, analytics and decision support development must always be done with the production system in mind. Information and decisions need to be tailored to the limitations of production. However, the expertise to create these analytical and decision systems lies in computer science and informatics domains, not in agricultural science. The knowledge to populate the systems does lie with agricultural scientists and agriculturists. Once a decision is made, technology, particularly variable rate technology, is needed to act on the decision. This requires the development of software controllers and variable-rate machinery, i.e. electronic, electrical and agricultural engineers teamed with computer scientists and software developers.

This PA cycle, and any quality control cycle, is only effective at improving efficiencies if the cycle is completed and becomes a continuum where improvements are made with every rotation. From this perspective, there are no shortage of monitoring technologies available. The amount of data gathered is not-limiting, although there are still production variables that of interest that are not currently monitored. How raw data are processed into information, particularly single layer/variable maps, is generally well understood, although alternatives and advances continue. Likewise, controllers and hardware for variable rate applications and differential action are well developed and commercially available and quickly developed when a need is identified. The weak point in the cycle is the decision support step. Differential action will only be successful if the correct differential decision is given to the controllers. Decisions require information AND agricultural knowledge to be integrated and applied spatially.

Decisions in agriculture are reliant on the quality of data (and information) gathered, are affected by the economic and production goals of the system (farmer), are needed to be made in a spatially and temporally varying biological system and are dependent on previous and future management





decisions . In short, decisions are made in an imprecise systems with few situations where there is an absolute and correct decision. Optimising spatial decisions-making and demonstrating improved efficiencies is the biggest challenge to the further the development, acceptance and translation of PA.

2.3 The nature of variation in crop production.

Agricultural decisions are imprecise (not absolute) because the majority of agriculture exists within an open biological environment. When production interacts and reacts to variable environmental and biological conditions, production becomes temporally and spatially variable. From a PA context, the amount and nature of variation in a production system is a key determinant of the direction and opportunity for making decisions, determining the (absolute) quality of those decisions and imposing differential management (**Pringle et al., 2003**; Roudier et al., 2011).

In small-holder agriculture, qualitative PA is often practiced. Growers farm small areas that they interact with directly on a continuous basis and have a deep knowledge of the productivity across their (small) farm. This situation was the norm in developed agricultural economies before the mechanical and green revolutions of the 20th Century, and it still exists in many less developed agricultural economies (particularly parts of Asia, Latin America and Africa). Smallholder agriculture tends to respond to changes in productivity through manual interventions, but usually without quantitatively characterising the variation. For example, areas where seed germination is known to be lower may receive more hand-sown seed to promote a more even emergence. Input use efficiency has a quasi-optimisation process because of the knowledge of the grower in these situations and the general reliance on manual operations that can be adjusted based on existing knowledge.

The rise of mechanised agriculture and the green revolution led to farmers being able to farm larger areas, which included land they may have had no history with and limited knowledge of. The larger areas and use of machinery also decreased the time spent by the grower physically interacting with the land. In this new, larger production system, uniform (average) management of larger fields became the best economic model for crop production. Variation in yield and quality attributes was known to occur, but in the absence of historical knowledge and a lack of real-time information on exactly where and by how much production varied, the best solution became to farm to the average. Machinery was also geared towards large-scale average input applications. GNSS availability in the late 20th century changed the ability to locate information in fields, with some data traceable to within a few centimetres. This, coupled with development of crop sensors, meant that the location and amount of production variation and environmental variability could be recorded and analysed. Average, uniform management is no longer the most efficient model for modern crop production. However, recording this additional information comes at a cost, as does changing from a uniform to a spatially differential management system. The production efficiencies or other ‘associated net benefits’ must outweigh these additional costs for a producer to transition to differential management i.e. site-specific crop management may intuitively have a higher input use efficiency but it may not be more profitable than a ‘uniform’ management system and therefore not attractive to a farmer.

There are several ways that the nature of the production variation affects the ability of a farmer to react to this variability and to transition to PA management;





1. If the magnitude of production variation is low, then there is potentially little to gain from variable management. A field that varies between 3 and 8 t.ha⁻¹ with an average of 6 t.ha⁻¹ for a given crop will likely have more potential efficiency gains than a field that also averages 6 t.ha⁻¹ but with a range of 5.5 to 6.5 t.ha⁻¹. Applying an average input for a 6 t.ha⁻¹ crop is closer to optimal in all locations in the second field than the first.
2. If the observed variation is random, then regardless of the magnitude, it is not possible to respond to the variation. In most cases, variation is not random, but there are strong differences in the amount of trend and the size of coherent spatial patches between fields. Fields with larger spatial patches tend to be more suitable for differential management and more compatible with current variable-rate technologies.
3. Is the cause of the variation obvious and manageable? If the cause of the variation is not identifiable then it cannot be managed. Similarly, in some cases the cause of the variability may be known, but cannot be corrected by the farmer through management operations.
4. To what degree is the observed production variability 'independent'? This in itself has two facets- a) does the variable (e.g. yield) respond primarily to one level of input (e.g. N), or is it an interaction of multiple inputs (e.g. N x K x Irrigation), and b) does the variable have an effect on another aspect of crop production (e.g. if wheat yield is spatially managed does this impact spatial wheat protein (quality))?

Points 1 and 2 indicate how the (spatial) structure of variability can determine if progression into differential management is (likely) possible or not. Points 3 and 4 relate to the role that variation has in determining how decisions are made, and the implications of spatial decision making, if PA and differential management is to be implemented.

Points 4 also has implications for those building decision support systems as well as for those using them. Predictive models and crop simulation models are an increasingly important part of modern agriculture. Accurate and timely short and long-range predictions are invaluable for both managing and marketing agricultural production. Most of these models operate at large scales (regional, enterprise or field level). If they are to be spatialised or converted into spatial models, information on the expected variation is needed.

2.4 Spatial data fusion and decision systems in agriculture

High-resolution spatial data sets are relative new in agriculture and the way that the data and information are presented is still novel to many producers and industry actors. Interpreting maps of production attributes is not always intuitive (**Taylor and Whelan, 2013**). Individually, single biomass images, yield maps or soil maps are relatively easy for producers and agronomists to interpret and to superimpose their own knowledge onto. This is particularly true when there are clear management effects and/or environmental effects in the data/information. As more layers of data and information become available for a field, the ability to process the additional data/information diminishes. Figure 2.1 provides an illustration of this. It shows 7 different years of grain yield maps corresponding to different management decisions and to different climatic conditions. Each individual year is easily explained, however, when asked to simplify the maps and to integrate the multi-year data into a single map (e.g. a map of potential management units) the process becomes more difficult for the grower.





Which layers should be ignored? Which layers should be weighted as more important? This becomes more complicated if multiple years of biomass (canopy reflectance) imagery and soil maps are also added to the mix. It becomes even more complicated if some of the raw data are poorly presented or poorly mapped.

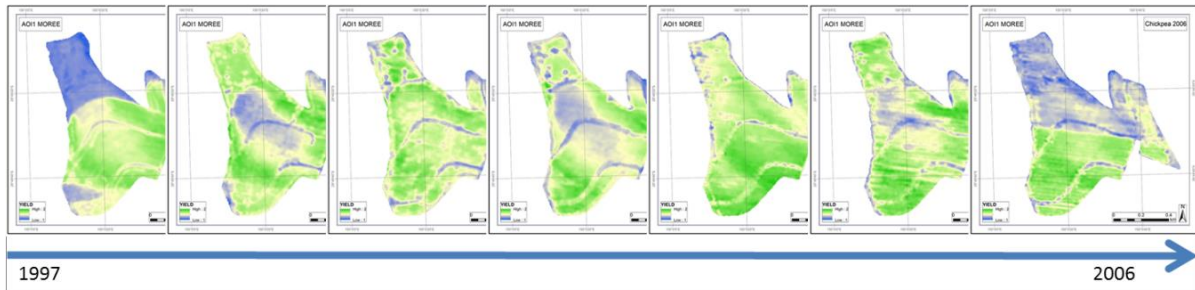


Figure 2.1 A time-series of yield maps from a field in North-western NSW, Australia. The 1997 and 2006 maps show distinct management patterns and the intervening years illustrate differing spatial patterns. Yield data are presented as standardised yield values. The variation in yield patterns associated with management but also with climate vs. soil effects in the field illustrate the difficulty that growers have in interpreting yield (and other production data) visually. (Data supplied by Mr. M. Smith and images adapted from **Blasch and Taylor, 2018**)

If precision agriculture is about better decision making, then it is paramount that the way data are presented, the way that data are transformed into information layers and the way that data and information are fused into a decision process is done correctly. The more confusion that is generated at the initial stages, the harder it is to arrive at a good decision at the end. Approaches to filtering (e.g. Blackmore and Moore, 1999), mapping (e.g. Whelan et al., 1996) and integrating data (e.g. Lark and Stafford, 1997) have therefore been key areas of research from the inception of PA. Without these basic building blocks, making decisions and therefore PA adoption and translation is not possible.

Filtering and mapping approaches continue to be updated (e.g. Sun et al., 2013, Leroux et al., 2018a), but the transformation of raw data into information layers is relatively well understood by academic and industry actors. How these data are then compressed, fused or simplified remains an issue for the industry. Methods, and well accepted approaches exist, however the on-going evolution in the amount and type of data available is constantly challenging the way that these data can be integrated and interpreted. Data fusion and the transfer of relevant information into decision systems remains a key area of development for PA. The more effective such methods are, the better the resulting decisions should be.

2.5 Adoption and translation in PA

Precision Agriculture is like any other advancement. Its movement from theory and development into application and translation follows the same laws/theory and pathways as other technological innovations (Koundouri et al., 2006). However, Precision Agriculture is about making better decisions,





it is not about a new method or a new technology (although in general these are the advances that are making higher spatial- and temporal-resolution decisions possible in agriculture). If the end-user cannot perceive a benefit in a new PA technology or methodology it will not be incorporated into management. Regardless of the quality of the technology/methodology, the benefit tends to come down to

- a) an ability to understand and make a different decision and,
- b) an ability to quantify the benefit of the new decision.

New and emerging technologies in agriculture tend to fall into two categories, i) embedded knowledge or ii) information intensive. Embedded knowledge technologies have no (or very little) additional skills or training needed to gain value from the value 'embedded' in the technology. In contrast, information intensive technologies require the end-user (grower or agronomist) to gain additional skills or training to gain value from the technology (Miller et al., 2018).

The difference in adoption between embedded knowledge and information intensive technologies can be very different and easily illustrated by two of the oldest and most recognised PA approaches;

- i) guided/autosteer tractors (embedded knowledge) and,
- ii) variable-rate nitrogen based on optical sensing (information intensive).

Guidance/autosteer tractors:

This is the most widely adopted PA technology in use today (See Fig. 2.2). In fact, it's prevalence in many systems would perhaps term it as a normal, everyday technology now. The decision process is a simple one – Am I driving straight and exactly a certain distance from my last swath/tramline (or exactly where I was driving last time/year in control-traffic systems)? IF the answer is 'yes' then the field operation is minimising overlap and saving input and fuel. When done without GNSS assistance, overlap is typically 3-8%. It is very easy for an end-user to determine the value of 3-8% of inputs relative to the cost of the guidance/autosteer system. However, when these autosteer systems first became available, they were very expensive, requiring a large capital outlay. Receiver technology was not as advanced and users needed expensive correctional signals or a local (expensive) base station to achieve accuracies of < 5 cm. Adoption was not high at this stage for autosteer, but guidance systems, where the GNSS provided help to the operator, were much cheaper and more common. These were less accurate but provided a benefit and a lower financial risk. In the past decade, high-accuracy GNSS receivers have dropped in price and the benefits of autosteer are so great that guidance systems are now rare and autosteer adoption is very high in many areas. In the first instance, this is because of a direct fiscal benefit with reduced overlap/control-trafficking, but increasingly there was a realisation that autosteer systems dramatically reduce stress and fatigue on the operator. They allow an operator to pay more attention to the operation (ploughing, drilling, fertilising, harvesting, etc...) and to more quickly identify issues thereby saving time and increasing efficiency. Operators can also potentially work effectively for longer (due to less fatigue), work at times of poor visibility (night-time, mist/fog, etc...) and in some cases the work can be done by less skilled operators. All this contributes to more timely operations that have a very large potential effect on production. Even though these societal benefits (e.g. less fatigue) cannot be fiscally quantified, growers are well aware of the advantage of returning home in a better state of mind and they do value this (social) benefit.



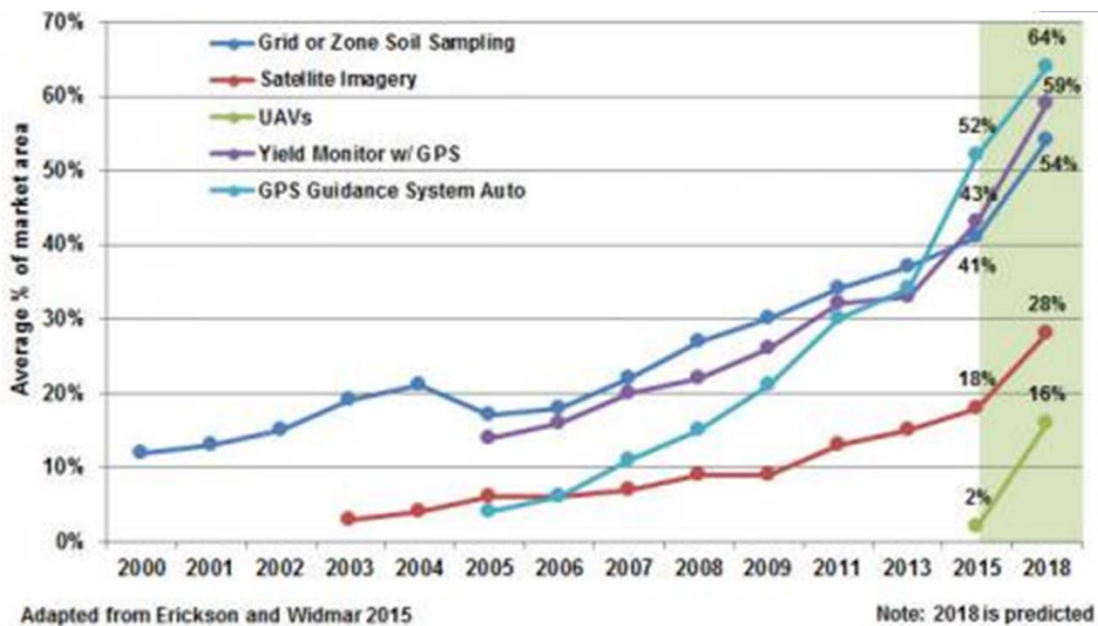


Figure 2.2 Adoption rates in the USA of key agri-technologies that facilitate Precision Agriculture (site-specific crop management). Reproduced from Sonka and Cheng (2015). Satellite imagery has multiple applications but the dominant use is for assessing canopy development to inform nitrogen fertiliser.

Variable rate application of nitrogen fertiliser (VRN):

The ability to apply variable rate nitrogen (VRN) has, like guidance/autosteer technology, been available to growers for 20+ years. It is highly desirable as the ability to optimise or improve nitrogen use efficiency is known to have a large effect on profitability. However, the adoption of VRN has been much lower than that of autosteer systems in arable cropping (Fig. 2.2) (Miller et al., 2018). The technology is mature. Optical sensing is able to determine vigour in crops and this can be linked to growth stage to determine if the crop is under- or over-performing (N deficient or sufficient). Regardless of whether the sensor is satellite, aerial or terrestrial (vehicle) mounted, an indication of vigour is returned on which a decision on fertiliser is made i.e. given that the vigour is under/over expectations, a certain amount of N is required in different places. This decision pathway is clear, however the actual decision - How much N is actually needed? - is very difficult and is usually site-specific. The N response in one field will differ to another field and similarly, the yield response to N in a field in year n may not be the same as in year $n+1$ in the same field. It is a variable environment. Without good (intensive) information, there is a strong possibility that a new and variable decision will be potentially erroneous. Therefore, average and/or historical N application rates are often used as growers perceive this to be the most risk adverse strategy to pursue. Nitrogen interactions are very complex and there is a large risk of doing the wrong thing. N management needs a lot of local knowledge and experimentation to arrive at a good decision process with which to direct the N-sensing and variable-rate fertiliser technology. In general, most growers do not have this or do not spend enough time gathering this information. They are therefore restricted to more generic approaches, which are potentially beneficial but certainly sub-optimal. The risk and the unclear decision system means that despite 20 years of promotion and clear potential benefits, variable rate N still remains a PA technology and not a 'normal' agricultural practice in most agricultural systems.





The two examples above provide an illustration of how and why PA services are (and are not) adopted. Any new PA service needs to contain as much embedded knowledge as possible to simplify the delivery and application of the service. Services that use so-called “black box” models are sufficient for the industry, as long as good spatial decisions are generated. Growers in general do not need to know the mechanisms of data/information/decision services, but will evaluate the quality of the end service. The information revolution associated with ‘Digital Agriculture’ has the potential to provide pathways to better support current information intensive technologies and in some cases transform them into embedded knowledge technologies. This should help with adoption and acceptance.

2.6 What does industry want? What can be delivered?

Precision Agriculture research must satisfy the demands of the industry. Many agri-technologies emerge from independent, fundamental research programs. The cross-over to agriculture is often related to the search for an alternative home for a technology. Development does not always directly address an agronomic issue, i.e. many innovations are a mature solution looking for a problem, rather than being co-designed to solve a known problem. A new technology doesn’t equal a new solution.

The PA community, both research and commercial, needs to be cognisant of these facts. There are limitations to the way that many physical and chemical principles operate within biological and farming environments. There are also limits on what can and cannot be directly measured. Producers may want specific information and science may only be able to provide proxy information. This limits the potential usefulness of the desired information. How well an ancillary data source approximates the desired data has a big impact on its usefulness. If the ancillary data are used for additional (secondary or tertiary) applications, such as an alternative input for a crop model, there is the potential for errors and uncertainty to be multiplied.

Furthermore, the ‘net benefits’ of a technology may not always be known, and if known, may be difficult to quantify. Understanding the limitations in the technologies, the methodologies, the data quality and the short and long-term ‘net benefits’ are essential when adopting PA. Inflated expectations will lead to misuse and mistrust in PA services among producers, and ultimately a rejection of the PA service. This is especially true if fiscal benefits are misrepresented. There is also always some form of trade-off between what is economically viable for a service provider to deliver and what the end-user (producer) is willing to pay. In many cases, PA services are simplified to meet expected pricing points, and are therefore sub-optimal compared to the expectations associated with research and trials.

In a few cases, new agri-technologies and services may be transformational i.e. change farming practices. However, in the majority of cases, technologies are developed or adapted to improve existing practices. Precision Agriculture is no exception and generally the on-farm application of PA is grounded in fundamental agronomy. Truly disruptive changes are difficult to implement at a large-scale, although of course not impossible. They must, however, show very clear increased profitability (and usually productivity) to be transformational. The green revolution and the acceptance of synthetic N fertiliser are examples. Robotics may be another example in the coming years. Most innovations however tend to be incremental in nature.



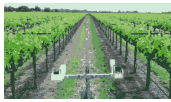


With incremental advancements in ‘conventional’ agronomic practices, there is still a need to provide a clear difference in ‘net benefits’, and particularly in efficiency and profitability, associated with the innovation. This may not be easy to quantify (Ancev et al., 2004; Walton et al., 2008; Rogers et al., 2016). Firstly, incremental advances may only generate incremental benefits. These may be hidden in the short-term by other externalities, e.g. unusual seasonal weather conditions or price shocks. Adoption tends to favour innovations showing immediate benefits. Profit and operating margins in agriculture do not always permit longer lead times for new approaches. Secondly, the ‘net benefits’ may be social or environmental in nature and have no discernible fiscal value to the producer (and are not transferable to some form of socio-environmental payment). Both of these relate to the end-user being able to justify a return on investment for a PA service or innovation.

Crop production is a system, specifically an agro-ecosystem. Commercial PA services have tended to focus on one aspect of the system that fits their business model and not the whole system. Growers however, want an integrated solution, a ‘system of systems’ solution, so that all aspects of production from cultivation to harvest are optimised with respect to all other operations. Such a solution is not currently available, although advances in digital agriculture are starting to provide concrete examples of this (Moisescu et al., 2018). This provides a conflict for PA service providers. Most are not large enough, or have enough expertise to deliver a holistic PA package that includes both hardware and software (data management) services. Commercial PA companies are therefore reliant on cooperation with other competitors within this space to provide the connectivity and interoperability to allow a third-party or an end-user to construct a ‘PA system’ from multiple PA services.

The potential difference between what can be sensed and modelled and what is ultimately able to be sensed/modelled is a key area for precision agriculture. Enhancing the transformation from data to information is paramount to being able to make the best decision and deliver the best possible service.





3 – Broad experiences with problems associated with Precision Agriculture:

3.1 Experiences to date (and what I have learnt).

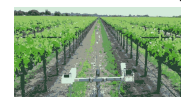
I began working in Precision Agriculture in 1997 when it was in its infancy. Over the past 20 years I have had the advantage of seeing how the Precision Agriculture domain and community has grown and evolved to fit different agricultural systems and in response to changes in existing agricultural systems. I began in cereal systems with an undergraduate Honours project (1997) and my first post-doctoral position (2003-2008) was also in Australian cereal systems. In between, I was part of the first push into Precision Viticulture in Australia (1999) and Precision Horticulture in New Zealand (2003).

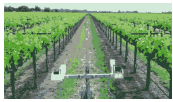
Precision Agriculture exists on the boundary where the theory of sensing, agricultural (and other) engineering, computer science and statistics interfaces with real-world agronomy and applications in agriculture. Precision Agriculturists need to be able to traverse this boundary and operate, either as an individual or as a collaborative team, in both academic and industrial spaces. Innovation and translation of any technology, including Precision Agriculture technology, is dependent on being able to link the science and theory correctly with a real-world need. Figure 3.1 illustrates this using the concept of Technology Readiness Levels. For academia, solving the scientific problem is the challenge (TRL 1-3), for industry, successful commercialisation is the desired outcome (TRL 7-9). In between there is a 'valley of death' (TRL 4-6). If this gap is not successfully bridged, in both directions, innovation and translation fails to happen. The TRLs 4-6 are not attractive to academic institutions as the science is applied and built on more fundamental scientific developments (TRLs 1-3 that carry more academic weight). Thus, research institutions prefer to operate as much as possible in TRLs 1-3. Nor are TRLs 4-6 attractive to commercial interests. Income is not being generated and commercialisation is not assured. It is the area of highest risk for an enterprise.

To complete the chain (remove the missing link in Fig. 3.1), the agri-tech sector needs people that can operate at the academia-industry interface and provide the human capacity to enable fluent agri-technology transfer. Precision agriculturists are key personnel in achieving this. They must also be supported by policy, financial incentives and infrastructure that promote technology transfer. Without both the missing link will remain disconnected.

3.1.1 Attempts to bridge the technological 'valley of death'

I would consider my position as a true 'precision agriculturist' (or precision agriculture scientist) who operates in the gap in Fig. 3.1. By this I mean that I am embedded in the domain. I am not a specialist, such as a molecular biologist, chemometrician, ecophysiologicalist, resource economist, etc..., who can dip into (and out of) the precision agriculture domain. Nor am I a specialist within any particular agricultural systems (cereal agronomist, field horticulturist, viticulturist, etc...). My interest lies in the spatial analysis and spatial applications associated with any agricultural data. As such, my research work tends to exist in the TRL 3-7 domain and has been spread over a wide variety of systems, including kiwifruit in NZ, grapes in Australia, France and the USA, apples in Italy, potatoes in the UK,





cereals in the UK and Australia and cotton in the USA and Australia. I do not develop technologies, my interest is in the how and the why of their operation in real agricultural environments. The opportunities that I have had to work in diverse systems and in various countries has certainly enhanced my understanding of how to bridge the gap between academia and industry.

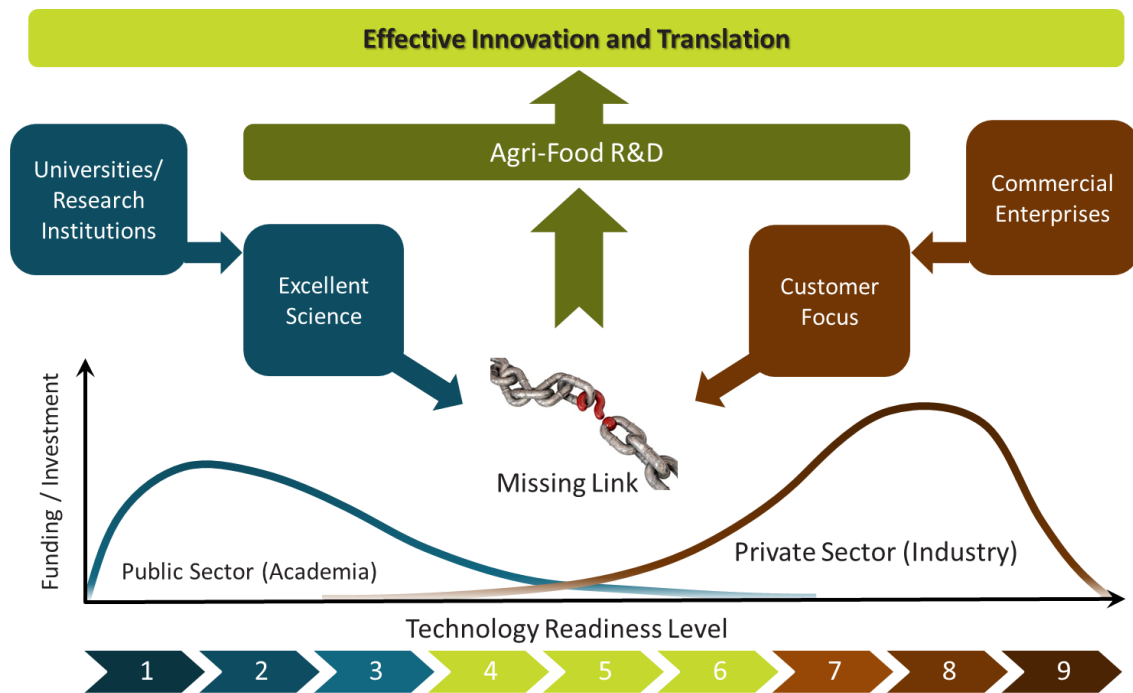
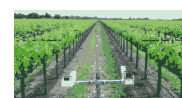
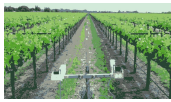


Figure 3.1 Schematic illustrating the preferred operational domains for academic institutions and industry enterprises and likely funding support using the concept of Technology Readiness Levels. The disconnect and lack of funding at intermediate TRLs is clearly indicated and provides a barrier to successful innovation and technology translation.

Evolving Protocols

One of my first publications (originating from my PhD) was a protocol to convert point soil pit data into continuous maps for vineyard mapping. This was work to use newly developed pedo-transfer functions (PTF) in an applied industry context (**Taylor and Minansy, 2006**). It was not to develop soil science, i.e. new PTFs, but to illustrate how they could be used with existing, current and historical data sets in Australian viticulture. The method is effective and produces more interpretable layers of information for vineyard design. However, while it managed to find its way into *The World Atlas of Wine* (Johnson and Robinson, 2001 p28), it was never adopted within the industry. This is mainly because the protocol was developed in a PhD student's (i.e. my) ignorance, in a university setting with academic supervision and no industry engagement. It was published in a soil science journal. It was not published or promoted at all within industry or commercial media. In my early research career naivety, I believed in a philosophy of 'if you build it, they will come' [or rather 'if you publish it, they will read and adopt it']. Protocols, no matter how good they are, rarely work without good engagement with end-users, as I now know.



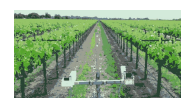


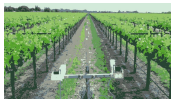
Following my PhD, I undertook a 4 year post-doctoral position working directly with growers to support the adoption of PA in the Australian grains industry. Unlike my PhD, this project was strongly embedded within grower groups, although primarily with growers who would be considered early innovators and adopters of technology. From this project came a second protocol paper on how to properly map common spatial agricultural data sets (soil sensor data, yield monitor data and canopy sensor data) and compress them using a statistical approach (**Taylor et al., 2007a**). This protocol originated within an academic group but was refined within workshops held with early innovators in the industry. The workshops help to understand how it could be, and would be, used 'on-farm'. It was grounded in shareware and freeware applications, unlike the earlier PTF protocol that provided no software guidance or support. It was also published within a more applied, agronomy journal and supported with publication in an industry magazine (CSA news⁴). The protocol has wide acceptance and provides a clear approach for PA practitioners to process raw data into management units.

Unfortunately, this wider acceptance is still primarily within academic circles. Early adopters and innovators tend to operate at a similar level to academics, thus we arrived at a good academic protocol. It is still used by some practitioners, but not adopted by general precision agricultural service suppliers. It is a protocol that relies on good access to data. This works within research domains and for growers who control their own data within a farm management information system (FMIS). However, until recently it was poorly suited to third party FMIS service suppliers due to issues with connectivity and interoperability. It is only within the last few years that serious solutions to these issues, including effective mobile data transfer, have become available. When the protocol was developed, it was done with desktop operations, not cloud-based applications in mind. The protocol suited end-user needs but did not meet the requirements of potential service providers (who were not part of the co-design process). The ability now to automate the integration of data into extensible databases has renewed interest in service providers to extend this protocol (and is the subject of a current Knowledge Transfer Partnership, Innovate UK, UK). This is exciting, however, the approaches in the protocol, while still effective, are perhaps a little outdated now.

More recently, I was involved in research designed to transfer proximal (vehicle-mounted) canopy sensing technology (widely used in arable systems) into single, high-wire 'sprawl' vineyards, and specifically into Concord (*Vitis labrusca* cv Bailey) juice grape vineyard systems (**Taylor et al., 2017**). This work was performed using expertise from Cornell Viticulture and Enology, Cornell Cooperative Extension (CCE) and working directly with innovating growers. The inclusion of the CCE agents provided a more balanced view to protocol development for all users. It also provided a clear route to engagement and service provision and consideration was given to how the protocol would be delivered in the long-term. The viticulture expertise, via innovative growers and from academic expertise at Cornell University, provided important input into how the vines are expected to behave. It enabled the formation of clear hypotheses for testing sensor operations within vineyards. The process evolved from a clear, multi-step, multi-disciplinary approach to understand a) how to properly deploy sensors in the vineyard to collect relevant information and b) how to translate the sensor information into a relevant (usable) viticulture metric that growers and viticulturists can understand and respond to. This was done by;

⁴ <https://dl.sciencesocieties.org/publications/csa-news>

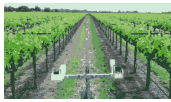




- Using viticultural knowledge to understand how vines grow to answer the key question of when relevant information can be gathered using proximal sensors. Alternative sensing approaches were tested and used to verify the best way to generate a vine vigour image (**Taylor et al., 2013b**) and to confirm previous work with either remote or proximal sensors (Drissi et al., 2009; Stamatiadis et al., 2010). It also tested how early in the season a stable vine vigour image could be generated, such that the mid-season image reflects the late season (final vigour), given that spatial growth rates in grapes are known to be variable (Hall et al., 2011).
- When a preferred timing was identified from the viticultural studies, the extension service and a mixture of growers were used to test alternative methods of mounting the sensors onto various vineyard machinery (tractors, self-propelled units, all-terrain vehicles). These were deployed for various vineyard operations during the preferred time window, e.g. late-season canopy spraying, under-vine weed management or inter-row operations, such as cover crop establishment or mowing.
- Growers, extension agents and viticulturists also clearly indicated that the sensor output was not directly relevant or interpretable. It showed relative vigour patterns but did not give absolute, viticulture information on which decisions could be made. The protocol was therefore extended to include a calibration step to transform the sensor output (a vegetative index) into a viticulture parameter (pruning mass). This calibration used existing data to properly interrogate how variable pruning mass was at a vine-to-vine scale and the implications that this would have on collecting local calibration data (**Taylor and Bates 2012**) (see also Fig 4.1(3)). A smart sampling design was proposed, and embedded into vineyard operations, that optimised sample size and reduced the sampling effort needed to properly estimate the mean pruning mass.
- The previous steps led to the development of a scientific robust and commercially applicable method for mapping pruning mass using canopy sensors. It did not however provide tools to achieve this, just a road map to develop tools. To further support this approach, financial support has been obtained from the USDA with the intent to develop an open platform that the industry can use to develop a 'vine size' mapping service (see www.efficientvineyard.com for details).

This last process is still on-going and the final result is still unknown. I am hopefully that this provides a more effective translation, but only time will tell. It maybe that another innovation trumps this approach in the very near or the more distance future. However, my understanding of how the 'valley of death' in Fig. 3.1 could and should be bridged has evolved and continues to evolve. A good idea is not enough. It is only the start. Scientists need to provide clear pathways for adoption that industry can easily adopt. This must include user-friendly methods as very few people in agriculture currently have a good understanding of spatial data. Having been through these processes, there is no doubt that I would drastically change earlier attempts at protocol development to ensure that a more responsible research and innovation approach (Von Schomberg, 2013) was used.





3.2 What we want vs. what we have – the availability and uncertainty associated with observations and ancillary data

Making spatial management decisions is reliant on having good information, which derives from good data. In agriculture, however, it is rare to be able to directly measure the production attribute of interest at the correct time. In some cases, direct measurements are possible, but not at the time when the information is most valuable. Yield sensors are an example of this, particularly in perennial crops where mid-season knowledge of yield (fruit load) is desirable for crop management. Good yield information is obtained at harvest, but is (was) unavailable for within season management. Alternatives to direct measurement are needed for yield estimation. One possibility is to use image analysis to count fruit/berries, but such sensors need to be calibrated to account for occluded (hidden) fruit (Mirbod and Nuske, 2016; Aquino et al., 2017).

In other situations, direct measurements of the attribute of interest are never possible and estimation is reliant on the availability of relevant ancillary data and transfer functions or calibrations between the desired attribute and the ancillary data. The determination of Leaf Area Index (LAI), which dictates radiation interception and dry matter accumulation in crop models is an obvious example. LAI cannot be directly measured using current on-the-go sensing technologies. However, the vigour or greenness of a crop can be inferred as a relative value using vegetative indices based on visible and near-infrared spectroscopy. This in turn can be related to LAI i.e. a relative measure of vigour is transformed into a preferred attribute.

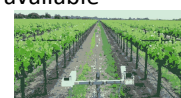
With direct observations, the quality of the data (and the subsequent information and decisions) is determined by both the accuracy of the sensor and the operation of the sensor (and associated machinery). Good sensing systems can be undone by poor operation and conversely, good operation does not always fix issues with a sub-optimal sensing system. Grape yield monitoring is a good example of both of these, where data quality within any given day is associated with good sensor and harvester and harvest operations. However, the grape yield sensor⁵ tends to experience drift (or shifts in calibration) when restarted, so that data integrity between days is directly affected by the quality of the sensor (Taylor et al., 2016) and requires daily correction to known harvested mass.

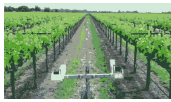
For sensors that directly measure a crop attribute, the potential sources of error are generally well understood and multiple approaches have been proposed to;

- a) correctly preprocess the data before analysis and
- b) to correctly interpolate or analyse the data,

with the overall intent to minimise the effect of such errors on the final map or decision process. Pre-processing has tended to be focussed on filtering algorithms that remove outliers in the data, typically using classical statistical processes applied to the raw data (Blackmore and Moore, 1999; Sudduth et al., 2007). Newer algorithms also tend to address and remove 'inliers' (local outliers) based on geostatistical analyses (Lyle et al., 2014; Leroux et al., 2018a). More advanced pre-processing, using data harmonization techniques to correct multi-operator errors or temporal sensor drift are also in

⁵ Advanced Technology Viticulture Grape Yield Monitor (ATV GYM) (Adelaide, SA, Australia), which is the only current retro-fitted commercial grape yield monitor commercially available





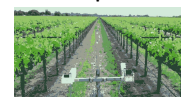
development (e.g. Sams et al., 2017). The result is that incrementally the quality of agriculture data being delivered to mapping and decision processes is improving, although filtering cannot remove all errors, particularly stochastic and short-range errors.

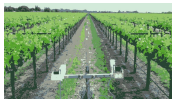
Once filtered, the choice of interpolation can also have a significant effect on the quality of the final map – both in the way it is visualised (and therefore interpreted by the human eye) and the quality of the interpolated data for future decision-making (Whelan et al., 1996). The need for correctly matching an interpolation method to the type and nature of the data collected (precise or imprecise observations, high or low spatial resolution) has long been identified in Precision Agriculture, although poorly translated in commercial practice. Commercial services tend to use the simplest processes, rather than more complex, optimised approaches. However, more advanced approaches, such as block-kriging and area-to-point kriging (Kerry et al., 2012), are gaining more acceptance and use in Precision Agriculture research. More traction and translation is certainly needed to extend these improved interpolation approaches into commercial services.

For information layers that are derived from ancillary data using a calibration or transfer function, the situation is further complicated by errors induced from the calibration process. In addition to potential sensor and operator effects (as above), potential errors in the collection of validation data and from the quality of the calibration/transfer function will add further uncertainty to any derived information layers. To further complicate matters, these errors may potentially propagate when individual information layers are merged (via data fusion) in an analytic or decision process. Figure 3.2 (adapted from **Taylor et al., 2018b**) illustrates this using a vineyard yield map (a primary information layer obtained directly from a sensor) and vine size map (a secondary information layer derived from calibration to a canopy vigour map) to generate a Crop Load map (a tertiary information layer derived from the yield and vine size map). The Crop Load map is used as a basis for many vineyard management processes, particularly fruit and canopy thinning operations that directly impact grape quantity and quality (and therefore profit).

Figure 3.2 also shows an ‘uncertainty’ map for Crop Load prediction based on known interpolation and calibration errors in the production of both the yield and vine size map. It is not a definitive error map, but a simple example to illustrate that the potential error in Crop Load prediction is also spatially variable. This is a very rare example in the precision agriculture literature of an uncertainty (error) map being presented with an agricultural attribute map, particularly a derived attribute map. Maps and information layers are the basis on which agronomic decisions are made, but it is very rare that site-specific information on the quality of the original data and derived information layers is recorded and then used to assist in decision-making. One example is the simple use of the interpolation error to determine confidence intervals for determining if yield and soil attributes are significantly different between management zones (**Taylor et al., 2007a**). More advanced approaches for assessing map quality (Bishop et al., 2001; Heuvelink et al., 2016) have been proposed in other domains, but are yet to be exploited in PA.

The uncertainty associated with precision agriculture data and information is a major issue for the industry but one that is poorly elucidated and poorly researched. With the advent of ‘Digital Agriculture’ and increasing access to data of increasingly diverse quality, this issue is only likely to increase. Fundamentally, in an uncertain, biological production environment, how can effective agronomic and management decisions be made if the uncertainty in the data is not known? At present





precision agriculture data are assumed to be true or to be the best guess available. If a measure of confidence in the information/decision can be supplied alongside the information/decision, then the industry will be much better placed to interpret and act on the decision. The PA community is a long way from obtaining this goal.

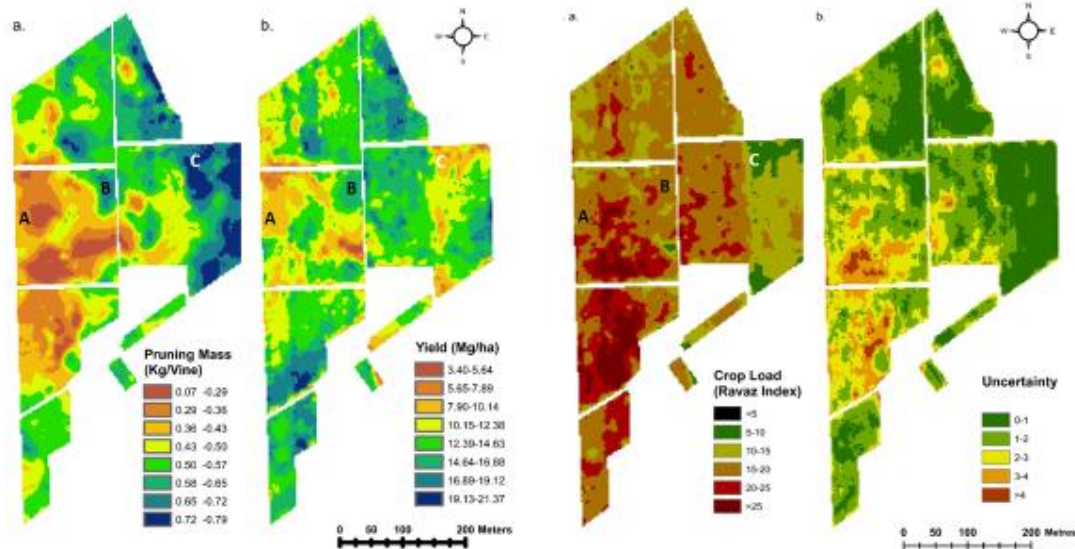
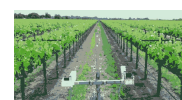


Figure 3.2 An example of mapping both a desired attribute (Crop Load or Fruit:Leaf ratio) in vineyards and the potential uncertainty in the derived layer. The Crop Load map derives from a yield map and a calibrated canopy vigour map and contains potential errors associated with sensing, calibration and interpolation (adapted from Taylor et al., 2018b).





4 - Discoveries to date:

4.1 Quantifying the amount of crop variation and the nature of this variation

There are two key ideas when seeking to understand spatial variability in a crop (or any other) system;

- if you cannot measure it, you cannot (properly) manage it, and
- how we manage an attribute is dependent on the (spatial) variability of that attribute

In the former case, generations of growers have been responding to known variability in their production system, without actually quantifying the variance. All good growers can identify the higher and lower yielding areas of their fields, but without sensing technology they cannot give definitive answers to the amount of variability and the exact spatial pattern to the variability, nor can they determine an optimal response. Until the advent of precision agriculture, growers were restricted to a marginal management response i.e. a little more here and a little less there. Developments in sensor technology, in conjunction with directed efforts to manually collect high-resolution crop and soil information, has provided the opportunity to actually quantify observed variance in crop attributes, particularly yield although not exclusively. In some systems, efforts have been made to quantify the spatial variability in crop quality attributes as well.

Classical statistical and sampling theory dictates that the number of samples needed to describe the mean of a population is a function of the variance observed in the population and the precision (error) in mean estimation needed. For spatial studies, an estimation of the mean is not usually the intent of an analysis, but it is sometimes desirable and the theory holds. Any spatial sampling approach should still consider the attribute variance and the precision needed. The difference is that the variance considered is now a spatial variance, often expressed using variogram or correlogram structures. This information can be used to determine correct sample sizes for mean estimation and for mapping to a defined prediction quality. **Taylor et al. (2007b)** presented an example of how the variogram parameters can be analysed for multiple attributes to determine the best average sampling grid size that generates the best quality maps.

Spatial variance is also normally spatially autocorrelated, i.e., neighbouring points are more strongly related than points that are further away. This violates the assumption of error independence that is the basis for many classical statistical methods. If the errors are not independent, then the total number of data available does not represent the number of independent data points available (n) (Clifford et al., 1989; Dutilleul, 1993). Estimations of significance, e.g. p-values and f-tests, which use n , will therefore be incorrectly calculated. It is particularly problematic in PA research, as the majority of correlation studies published ignore this autocorrelation (**Taylor and Bates, 2013a**).

As noted above, my research interests have been varied in terms of both location and crop type. However all cropping systems have the same intent – can production be improved by improved spatial (and/or temporal) management? This generates the first important question – How much spatial variation is there in production? It is surprising that even after 20+ years of precision agriculture there is very little information on the expected variation in cropping systems. In fact there is no real consensus on the method for reporting within-field and spatial variability in agriculture (Leroux and





Tisseyre 2019). In part, this is because spatial variability is often reported for differing reasons and it has not been clearly defined for the (non-spatial) agricultural community.

In contrast, in the soil science community, where the application of geo-statistics is strong within the pedometrics and digital soil mapping domains, the reporting of spatial variances (particularly variograms) is common. Meta-analyses and metrics associated with soil spatial variance have been performed since the 1990s (e.g. Cambardella et al., 1994; McBratney and Pringle 1999). One of my key research focuses over the past decade has been in the collation and publication of spatial crop information in a variety of crops. These include viticulture (**Taylor et al., 2005 and 2018b; Taylor and Bates 2013b**), potatoes (**Taylor et al., 2018a**), kiwifruit (**Taylor et al., 2007b**), grains (**Whelan et al., 2009**), sweetcorn (**Taylor et al., 2010b**) and multi-crops (**McBratney and Taylor, 2000; McBratney et al., 2000; Pringle et al., 2003**). All of the previous publications contain direct information in the form of variogram plots or published tables of variogram parameters that related to individual or average field responses for crop yield, crop quality or crop canopy attributes. It provided empirical evidence of the expected average spatial variance and the ranges of observed variation to provide *a priori* information for any future spatial work.

This body of work has also recognised the importance of understanding the spatial variance in crop quality attributes, not just yield. Variogram analysis has shown that quality attributes may be less, equally or more variable than yield components depending on the system and on the year (**Taylor et al., 2007; Whelan et al., 2009; Taylor et al., 2018a and 2018b**). A clear pattern was not expected as quality is known to be temporally variable. What has been revealed is that there is typically as much variance to manage in quality as there is in yield. However, crop quality sensing systems are less advanced than crop yield sensing systems. In cropping systems, there will be a trade-off between yield and quality. Altering the yield potential will influence partitioning within the plant and the quality of the resulting crop. A limitation to my work to date has been a lack of interrogation of interactions and cross-variances between yield and quality attributes. While many publications present multiple attributes, the analysis itself has tended towards a univariate approach in understanding how individual attributes behave spatially, rather than how attributes interact spatially. There is an opportunity to revisit these data and interrogate spatial interactions.

In some cases the presentation of spatial crop variance has been predominantly descriptive and done to provide general information (e.g. **Taylor et al., 2010a, 2010b, 2018a and 2018b**), rather than for a specific objective e.g. improved sampling. This was deemed relevant to provide a library of spatial crop structures for future work. In particular, the development of predictive spatial models needs information on the expected and likely range of spatial crop variance. While the library of variograms published was not exhaustive, it is still one of the few published starting points for any future spatial crop modelling exercise. Earlier publications (pre 2013) focussed on sampling implications, while the more recent work has considered how these fundamental observations feed into more detailed spatial models and applications (**Chen et al., 2017**). As an example, detailed vine water status measurements were used to determine the amount of spatial variance in vineyards from scales that ranged from neighbouring vines to the whole vineyard (**Taylor et al., 2010a**). Ancillary information on soil conditions and vine canopy vegetation were then used to explain the scalar information and the resulting knowledge used to propose and validate a spatial prediction model for vine water status (**Acevedo-Opazo et al., 2013**)



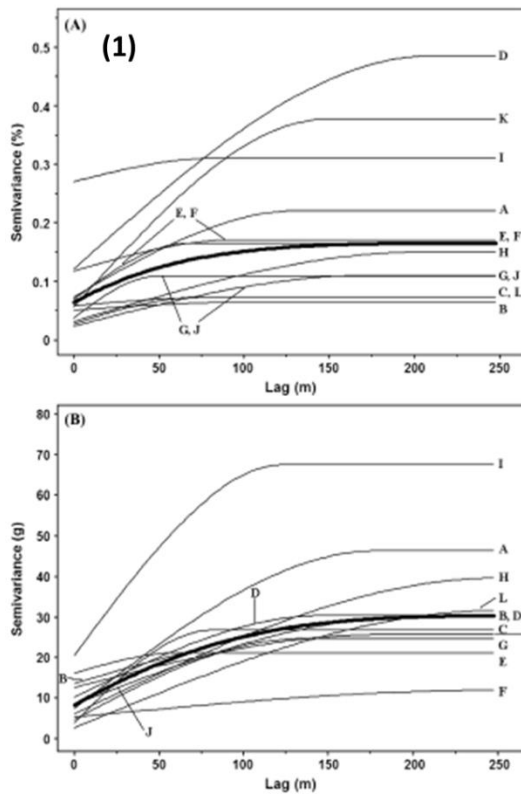


Fig. 2. (A, B) Individual orchard and average variograms for dry matter (A) and fruit weight (B; measured in grams). Average variograms are in bold; individual orchards are labeled with their alpha indicator (Table 1).

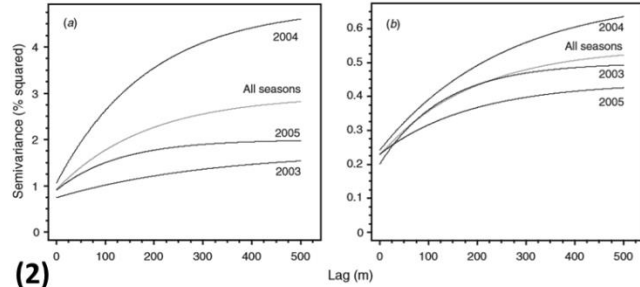


Fig. 6. Average semivariogram models for (a) GPC and (b) GY calculated using all fields for the three seasons under study. The 'all seasons' model reflects the average of the three seasons at each lag.

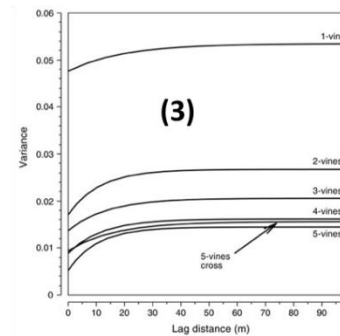


Figure 2 Average variograms for pruning weight under different sampling schemes derived from data collected over three years (2009–2011).

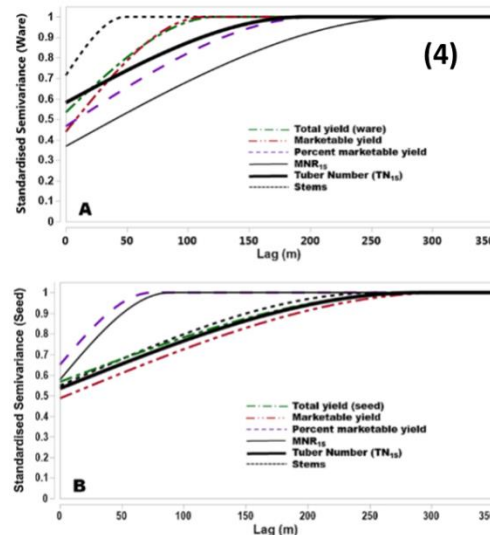


Fig. 2. Standardised 'average' variograms of quantity metrics (Total yield, Marketable yield and Percent marketable yield), quality metrics (ratio of mass to number of tubers (MNR₁₅)) and a crop growth metric (Stems counts) in both ware (A) and seed (B) potato production systems. Units as listed in Tables 1–4.

Table 4 Best fitting theoretical semivariogram models and associated parameters for the yield trend-surface residuals of each field

Field	Year	Best theoretical model	Semivariogram parameters						J_s (ha)
			C_0 (Mg/ha) ²	C_1 (Mg/ha) ²	a_1 (m)	r_1 (m)	C_2 (Mg/ha) ²	a_2 (m)	
B4	1995	Double spherical	0.043	0.164	11.74	—	0.158	44.92	0.019
East Creek	1997	Double spherical	0.813	0.451	40.39	—	0.580	103.96	0.076
Maidens	1995	Exponential	0.046	0.323	—	20.77	—	—	0.074
West Creek	1996	Exponential	0.164	0.171	—	27.20	—	—	0.074
West Creek	1997	Spherical	0.300	0.328	169.42	—	—	—	0.300
West Creek	1998	Exponential	0.554	0.159	—	28.32	—	—	0.035
Home 1	1998	Exponential	0.029	0.119	—	37.35	—	—	0.220
Home 5	1998	Spherical	0.018	0.041	91.88	—	—	—	0.118
Rowlands 1	1995	Exponential	0.011	0.179	—	24.10	—	—	0.108
Shire 4	1997	Exponential	0.008	0.032	—	17.83	—	—	0.050
Shire 4	1999	Spherical	0.084	0.052	110.62	—	—	—	0.094
C3-8	1999	Exponential	27.430	8.707	—	28.30	—	—	0.038
C9-11	1999	Spherical	19.746	3.611	10.21	—	—	—	<0.001
D3-4	1999	Exponential	18.652	11.950	—	6.22	—	—	0.003
Norwood 28	1998	Spherical	0.249	0.091	89.72	—	—	—	0.043
Telleraga 10	1998	Spherical	0.071	0.037	127.03	—	—	—	0.112
Blackies 6	1998	Exponential	0.026	0.039	—	50.49	—	—	0.301
Home 8	1997	Spherical	0.007	0.013	64.36	—	—	—	0.054
East Creek	1996	Double spherical	0.533	0.232	46.12	—	0.104	271.10	0.187
W80	1997	Exponential	0.172	0.348	—	13.93	—	—	0.026

(—) denotes that the parameter is not applicable for the particular model. Values of J_s are also shown.

Figure 4.1 Selected examples of published variograms [(1) – (4)] and variogram parameter tables (5). (1) Kiwifruit dry matter and fruit size variograms from NZ that were used to determine sampling grids for optimal map production (Taylor et al., 2007b); (2) Average annual variograms for grain yield and grain protein in Australia, illustrating similar variogram structures for the two variables (Whelan et al., 2009); (3) Changes in variogram structures for pruning mass as the sampling size (number of vines) changed, which helped inform new sampling designs for vine size estimation (Taylor and Bates, 2012); (4) Standardised 'average' variograms of potato yield and tuber size parameters in both ware and seed systems that were used to identify management effects on spatial variance (Taylor et al., 2018a); and (5) variogram parameters and trend residuals for the determination of spatial structure in yield data sets from cereal, cotton and vineyard systems (Pringle et al., 2003).





In all cases, these publications were either the first or the most detailed publications that explicitly presented information on spatial crop variance. In some cases the data were derived from sensors, and had a high spatial resolution (100s or 1000s points.ha⁻¹) while others were derived from manual samples at a much lower spatial resolution (1-10s points.ha⁻¹). Different types of data provided different types of information but all provided clear (if not always complete) implications for how the field could be managed, and potentially how management influenced the observed variance. For example, the observed short-range nested variogram structures in a study of high spatial resolution potato yield sensor data indicated a management effect in the yield data, which has implications for how these data should be mapped and interpreted at short spatial scales (**Taylor et al., 2018a**). Manual (low resolution) data in the same study showed a similar long range yield trend to the yield sensor data, but did not show this short-range nested management effect. In an earlier study in vineyards (**Taylor et al., 2005a**), variogram parameters (and derivatives) were similarly able to identify differences in spatial yield response between ‘old world’ (France) and ‘new world’ (Australia) viticulture systems. The structure of spatial variation was very different, which resulted from irrigation practices and the scale of production. This had strong Implications for how site-specific management could be deployed into the different systems.

Understanding the nature of the spatial variation in production attributes also has clear implications for future spatial sampling design. Sampling can be performed for a variety of reasons – generating a map, calibrating and validating of a model of crop/soil attributes or simply to achieve a good estimation of the field mean or a good variogram model (e.g. **Taylor et al., 2007b; Taylor and Bates, 2012**). The number of samples needed for different uses will differ, for example map generation tends to require more data than field mean estimation, but all can be optimised by using knowledge of the intrinsic spatial variability (**de Gruijter et al., 2010; Brus 2014**). The case presented in **Taylor and Bates (2012)** illustrated this and, furthermore, also included the effect of the spatial ‘footprint’ of sample size on spatial variance. In this study, each individual vine in a 1 ha vineyard was measured for pruning mass (canopy size) over multiple years. These data clearly quantified for the first time the amount of stochastic vine-to-vine variability in the field, which was up to 80% of the total variability in the system. Individual vine data also allowed data aggregation into multi-vine ‘footprints’ to observed the effect of sampling area on spatial variance (Fig. 4.1(3)). As expected, increasing the area sampled (the footprint), decreased the total variance, but had little effect on the shape of the variogram. This resulted in a trade-off between the size of a sample taken and the number of samples needed in a vineyard block for estimating the average field pruning mass, which could be optimised to minimise the effort needed by growers to obtain good spatial data. In other cases above (and most other reported studies), the spatial ‘footprint’ cannot be interrogated as it was predetermined by the sampling routine.

4.1.1 Concept of opportunity indices and diagnostics based on observed data

Providing a baseline geostatistical description of crop attributes is a first step, and an important one, for future research and development. However, variograms and derived statistics are not directly relevant for a comparison of spatial variance between different production systems. Neither is it feasible or sensible to expect non-geostatisticians in agriculture (i.e. the majority of agricultural researchers and the industry) to be able to correctly understand and interpret variograms and





variogram parameters. End-users tend to respond and react better to indices that are based on a simple scale. The derivation of an index may be complex (so long as it is automated) but the output needs to be simple to interpret. The index also needs to support a clear question.

From my very first publication (**McBratney and Taylor, 2000**), the concept of how observed spatial variation in crop can be transformed into an opportunity for site-specific crop management has flowed through my research (**McBratney et al., 2000; Pringle et al., 2003; de Oliveira et al., 2007, Taylor et al., 2018a**). This has prompted the development of other opportunity indices (e.g. Tisseyre and McBratney, 2008; Roudier et al., 2011) as well as applications to other data sets, e.g. canopy data by Monsó et al. (2013). The idea for an opportunity index is simple – if, as a grower, I have multiple fields with crop data (normally yield data), then in which of the fields am I more likely to successfully apply site-specific crop management? In commercial situations, a return on investment, and PA is an investment, is paramount for economic sustainability. An opportunity index should therefore help a grower rank their fields in order of potential opportunity and also permit benchmarking against other farms/growers where PA has been successfully (or unsuccessfully) implemented. Opportunity indices are intended to be used as a decision tool.

The opportunity to apply PA to a field in simple terms (after **Pringle et al., 2003**) should be a function of

- a) the amount (magnitude) of variation in a crop attribute of interest (often yield)
- b) the spatial structure of this variation.

Theoretically it should also include an aspect of environmental and economic benefits as well (**McBratney and Taylor, 2000; McBratney et al., 2000**). However this is generally omitted. Methods for quantifying environmental benefits are poorly developed, thus not applicable. For the economic benefits, these can be considered as a constant when ranking fields within an enterprise. When benchmarking fields across enterprises, such data were usually difficult to obtain and to standardise.

Therefore, among comparable fields, a system with a larger magnitude of variation and a more ordered spatial structure to this variation should present a) clear management decisions and b) simpler patterns (units) to manage. This general idea is shown in Fig. 4.2. If there is a large magnitude in variation but it is completely random (Fig. 4.2a) then field equipment is unable to respond fast enough to the rapid changes in spatial variation (Note: it is likely that the high level of stochastic variation in this field is error-induced (sensor or operator error) and not real data). If there are trends and spatial patterns in the data then machinery (and decisions) can adapt to changes (Fig. 4.2b-d) and the opportunity then changes depending on the magnitude of variation (Fig. 4.2b vs. Fig. 4.2c) and the strength of the patterning (Fig. 4.2d). If the yield within a field has a small magnitude of variance, e.g. a total range from 4 - 5 t.ha⁻¹, then it is likely that an 'average' application of inputs for a yield target of 4.5 t.ha⁻¹ will be relatively effective. The value of managing more precisely to a narrow yield potential may not cover the cost of investment in PA infrastructure, even with good spatial patterns. However, another field, with hypothetically the same spatial patterns, but with yield potentials ranging from 2 - 7 t.ha⁻¹ (with an average of 4.5 t.ha⁻¹) will have greater inefficiencies if managed to the 'average' and more opportunity to apply variable-rates of inputs.





Opportunity defined in this manner is self-evident. Metrics to assess this are not. Classically, the coefficient of variation (CV) statistic is used for describing variation in non-spatial contexts. However, it is not suitable for broad applications with spatial data. In the first instance, it ignores spatial structure, thus Fig. 4.2 a, c and d would all have a similar CV, but visually they present clear differences in ‘opportunity’ for PA. The CV does not differentiate between auto-correlated variance that is likely to be manageable, and stochastic variation (which is highly likely to be unmanageable as in Fig. 4.2a). A metric that assesses the spatial structure (patterning) of the variance in the crop attribute is needed, and this needs to be based on geo-statistical analyses. The CV has another problem. It is aspatial. There is no consideration of the size of the field production system. Should the magnitude of variance within a 5 ha field be directly compared with a 100 ha field? Proponents of Opportunity Indices for PA argue that any metric for assessing the magnitude of spatial crop variation should only consider the auto-correlated component of the variance and should be standardised to a nominal area (**Pringle et al., 2003**). Equations for calculating an areal CV (CV_a) that achieves these two aims have been proposed (**Pringle et al., 2003; de Oliveira et al., 2007**). These can be automated and are relevant for any type and size of production system.

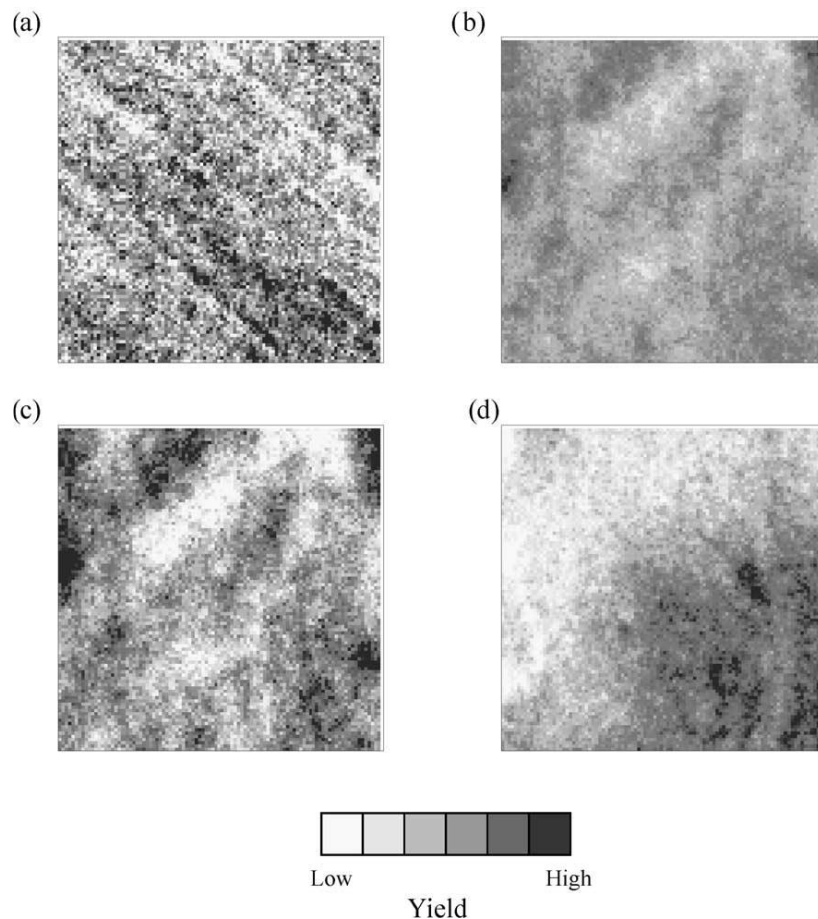


Figure 4.2 Yield maps of four hypothetical fields of equal area and differing characteristics in yield variation. Field (a): relatively large magnitude, relatively poor spatial structure; Field (b): relatively small magnitude, relatively moderate spatial structure; Field (c): relatively large magnitude, relatively moderate spatial structure; Field (d): relatively large magnitude, relatively strong spatial structure. It is hypothesised that the opportunity for SSCM will increase with Fields (a)–(d) with Field (d) having the greatest opportunity because its yield map displays both a large magnitude of variation and a strong spatial structure (from **Pringle et al., 2003**)





Assessing spatial structure (patterns) directly from crop (yield) data is even more complex. It is related to the distance over which auto-correlated variance occurs – referred to as the ‘range’ in a variogram. The generation of a stable statistic to assess spatial structure is complicated by the presence of non-stationarity in the data and the potential for the spatial variance to be unbounded, i.e. the spatial structure of the crop variance could be greater than the field (area) measured. A framework for processing yield has been proposed (Sun et al., 2013), but these approaches have not been incorporated into commercial yield data processing platforms yet.

Alternative and derivative opportunity indices have been proposed and developed based on this initial work. These considered different dimensions to PA, such as an assessment of the technical (operational) constraints associated with PA and the opportunity (or limitations) imposed (Tisseyre and McBratney 2008) or the opportunity associated with zone-specific management in a field (McBratney et al., 2000, Taylor 2004 p198; Roudier et al., 2011).

These opportunity indices have been used as diagnostics to determine if a field is suitable for site-specific management. However, as well as understanding the potential opportunity for site-specific management, end-users also need an indication of whether the spatial variation in the data is likely to be associated with (spatial) differences in management, or if it is driven by environmental factors. If variation in a field is caused by management effects, then the first step is to correct basic field management before considering further opportunities for site-specific management (Whelan and Taylor 2013, p8).

Understanding the potential sources of variation is particularly important in ordered, perennial cropping systems, with vineyards being an example. In such systems, management is very focused on activities along a row. There exists the potential for adjacent rows to receive different levels of management. A very practical example of this is in the level of pruning (bud numbers left) by different individuals working along adjacent rows. This can impact yield and canopy development (Bates, 2008). Other possibilities include incorrect machinery set-up or equipment operations on one row of a multi-row machine, such as a sprayer. Such management effects could leave a systematic pattern of crop response in a vineyard, orchard or field. If this is the case, then differences in anisotropic, or directional, analysis of crop data should provide an indication of an effect of management on production. Figure 4.3 illustrates this potential problem using vineyard yield monitor data. Area A had an irregular yield pattern that is likely to be following an environmental effect – and likely to be soil variation, while area B had a yield pattern that was aligned with the rows, indicative of different management in different sections of the vineyard blocks. There will of course be intermediate situations where there are some management effects overlying a spatial environmental effect.

To provide growers with rapid relevant information on the likely cause, management or environmental, of spatial variation in a cropping system, a diagnostic has been proposed (Taylor et al., 2018). It considered how crop production, in this case yield, varied along and across trellised vineyard systems. The hypothesis was that environmental variation tends to be isotropic in nature, so similar spatial variance structures should be observed along and across rows. In contrast, management effects, if present, will be oriented along rows resulting in different spatial variance structures parallel and perpendicular to the rows.





When applied to actual and simulated vineyard yield monitor data, the new index could identify fields where management effects were likely. It fills a gap for a diagnostic tool to identify data sets that may be compromised and need validation before being used in data analytics and decision systems. It is proposed to be used with, not instead of, existing diagnostic statistics and ‘opportunity’ indices in precision agriculture.

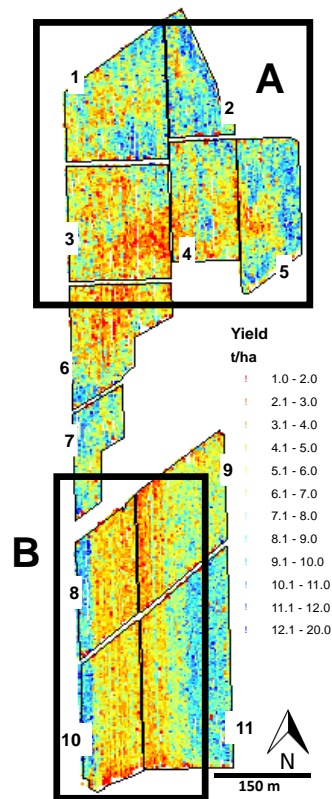


Figure 4.3 A 2014 grape yield map from a Concord (*Vitis Labrusca* cv Bailey) vineyard in the Lake Erie Region of NY State. Boxes A and B show regions where yield relates to environmental variations (A) and where yield shows strong linear effects associated with management (B). The numbers on the graph are block identifiers (1 – 11) (from Taylor et al., 2018c)

4.2 Zonage and its role in defining production management units and interpreting data. A data-fusion step

Site-specific crop management is contingent on being able to move from making ‘average’ decisions at the field-scale to ‘sub-field’ scale decisions and operations. This potential change is dependent on the scale at which data/information is available and on the ability of farm machinery to implement decisions. Figure 4.4 shows that this is an evolution. As sensing, decision-making and operational capabilities improve, the industry will shift ever closer to real site-specific (i.e. plant or even leaf-specific) management. In the interim, however, it is widely recognised that some intermediate resolution of management is needed. This is generally referred to as management zone or management class level operations. Although similar and often used interchangeably, classes and





zones are not exactly the same (Pedroso et al., 2010), so the term management unit (MU)⁶ will be used as a generic term for both management classes and zones.

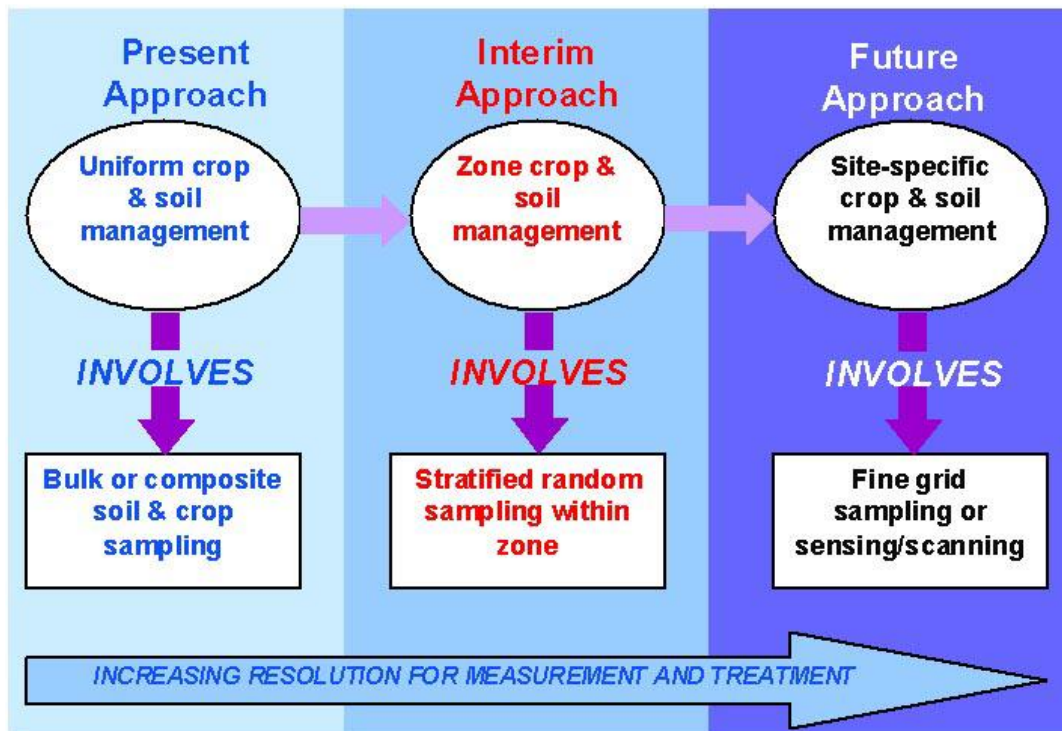


Figure 4.4 Schematic illustrating the shift from a conventional uniform field management strategy to a true site by site-specific management strategy by using zone (management unit) management as an intermediate. The required increase in data with the shifts are also indicated. (Image courtesy of the Precision Agriculture Laboratory, The University of Sydney).

MU's were advocated very early on in the application of PA as a means of interpreting observed crop and soil variation (Lark and Stafford, 1997). The derivation of MUs tends to use some form of expert knowledge system or multivariate analysis to identify areas of a field where crop and soil responses are similar. It effectively makes a virtual 'fenceless' sub-field within a field. This 'sub-field' or MU is then managed as a single entity. It recognises that there is still some level of variability within each MU. However, each MU in a field has a different production potential (or different production-limiting factor) that can be managed differentially to greater effect.

How MUs are derived and how effectively they partition the within-field crop and soil variation will ultimately determine how useful they are for PA. There will always be some trade-off between the number of MUs, the production differences between MUs and the size and shape of each individual

⁶Although Lark and Stafford (1997) originally proposed the term 'management units', the term 'management zones' is generally used. This can be somewhat ambiguous because the majority of statistical methods for management unit delineation, including the original *k*-means approach by Lark and Stafford (1997), are based on classification algorithms. These approaches produce 'management classes'. The difference is important. A *management zone* (MZ) is a spatially contiguous area to which a particular treatment may be applied. A *management class* (MC) is the area over which a particular treatment may be applied. This may constitute more than one zone. A *management unit* (MU) is a generic term that relates to both MCs and MZs





unit. Too few MUs and the variance in production is not adequately described. Too many MUs will generate small and irregularly shaped units, which are operationally difficult to manage, and small production differences between MUs that may or may not be real or manageable (see for example Fig. 4.7 later).

Management units are a derived information layer. In the simplest form they are based on a single layer, usually a soil map and commercial examples are available (Li et al., 2019). However, in the majority of cases, they integrate multiple data and information layers to simplify disparate spatial data sets into a single, more interpretable map. The quality (uncertainty) in the data/information used for zoning has a potentially large impact on MU delineation. It was evident from conference presentations in the late 1990s and early 2000s that many researchers were incorrectly generating MUs, either through poor choices in data pre-processing (filtering), interpolation or multi-variate data-fusion. To correct this, a protocol was published that clearly outlined a method and a reasoning to arrive at agronomically valid MUs using a *k*-means classification method (Fig. 4.5) (Taylor et al., 2007a) (Described in more detail in Section 3.1).

The *k*-means algorithm has been widely used for MUs (Fridgen et al., 2004; Frogbrook and Oliver 2007; Castrignano et al., 2009), however, it does have limitations. It requires data to be co-located. Data collected on different days and/or with different sensors are unlikely to be collected at the same location and therefore need to be interpolated onto common points for analysis. This requires an interpolation step, and correct interpolation, to be effective. Interpolation is usually needed for mapping and correct visual interpretation of the data. However, it is not directly necessary for MU derivation and, ideally, it would be preferable to not have to do this. The *k*-means algorithm generates classes, not discrete zones. The data are considered to be independent and not spatially constrained. It is usual to have small unmanageable 'zones' generated in the process that then require filtering. Having more coherent shaped (spatially constrained) MUs is desirable to facilitate machine operations (Tisseyre and McBratney, 2008) and therefore there is some interest in the use of alternative algorithms for pattern recognition in MU delineation.

One recent proposed method has applied pattern analysis using image processing techniques to multi-year crop data sets (Blasch and Taylor, 2018; Blasch et al., *submitted*) (Fig. 4.6). This was based on principal component analysis (PCA), with the objective to generate more discrete MUs than the 'traditional' *k*-means approach. An application to multi-year yield data showed benefits over the *k*-means approach in a single field in Australia (Blasch and Taylor, 2018) and in several fields in the UK and Australia (Blasch et al., *submitted*). In all fields, the MUs derived from the new yield pattern analysis explained more yield variability and were more spatially coherent. However, while an improvement, this approach still retained some limitations - it required an image (regular pixels) that required interpolation of raw data, and the PCA was not explicitly spatially constrained. However, post-interpolation, the process was robust, repeatable and easily implemented.

An alternative approach is to use a segmentation algorithm. Segmentation algorithms also derive from image processing and perform analyses on neighbouring pixels. In this way, they will always generate discrete, spatially constrained zones via neighbourhood region-merging or region-splitting approaches. These segmentation algorithms were developed for use on regular gridded (image) data, and therefore direct translation into PA would again be reliant on interpolation processes. However, an adapted segmentation algorithm was proposed in 2010 that permitted the algorithm to be applied



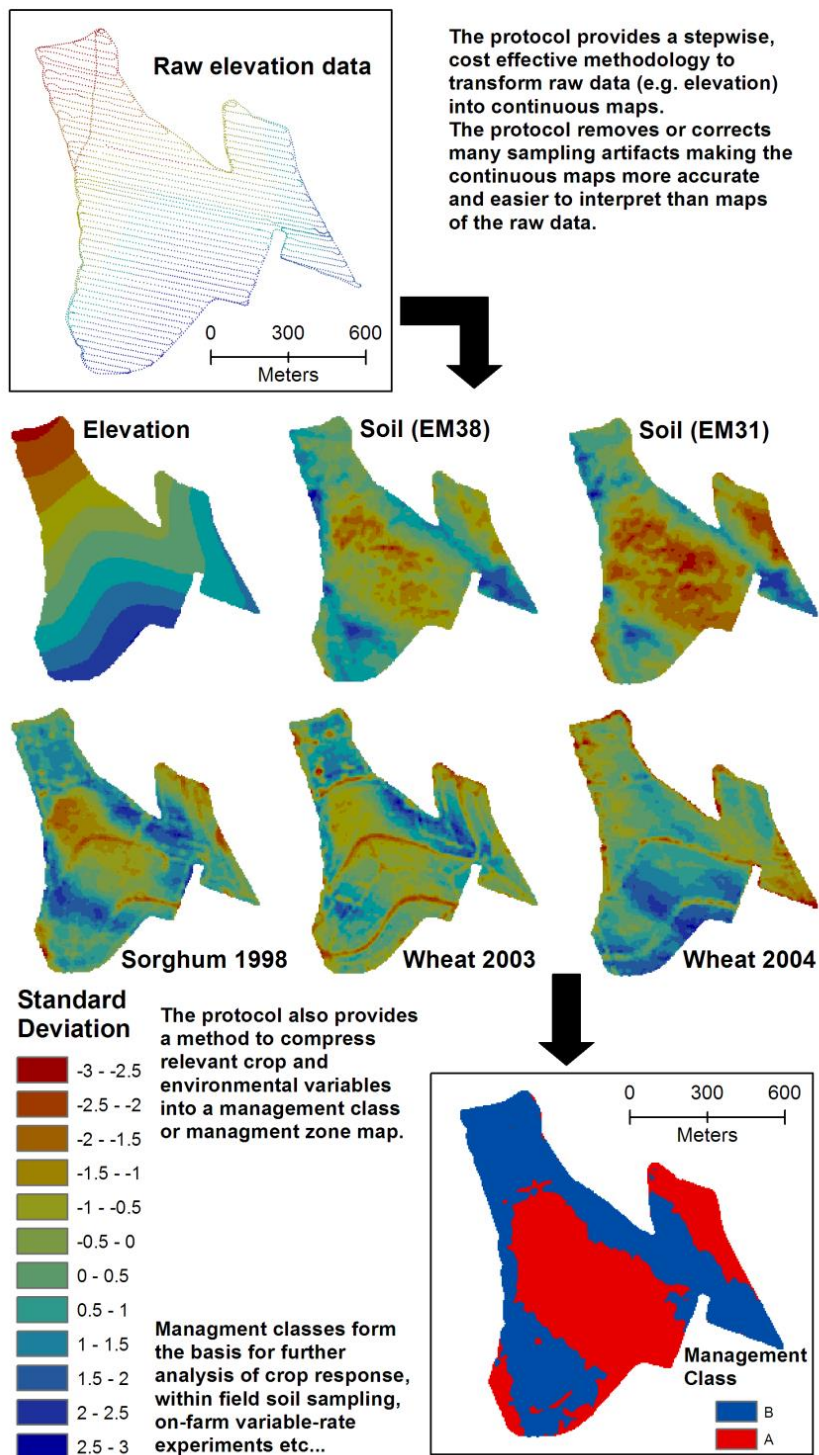


Figure 4.5 A visual illustration of the protocol outlined in **Taylor et al. (2007a)** to transform raw irregular crop and environmental data into flat single layer maps and the fusion of these layers into a potential 2-management unit map (using *k*-means classification). The image was first published in CSA News, which is an industry magazine that supports research published within ASA, CSSA and SSSA journals.





to univariate, irregularly spaced data (**Pedroso et al., 2010**) (Fig. 4.7). This was a significant advance as it permitted a quantitative MU delineation to be made directly from raw data, without the need to interpolate. The initial limitation was that it was only univariate. Multivariate analysis could be performed via the intersection of 2 or more univariate outputs (**Taylor et al., 2013a**), but this is a convoluted step and required the introduction of more advanced image processing and filtering approaches to generate a final MU map. A true multivariate segmentation solution has been proposed (**Leroux et al., 2018b**) that is based on a multivariate Euclidean distance between pixel vectors. In this case, pixels of aggregated mean values over a given area are used, which is easier, faster, and more robust to automate than interpolation methods used for map generation. The next step will be to translate this gridded multivariate approach to irregular data sets, particularly with data of varying spatial densities and types (soil, biomass, yield, etc...).

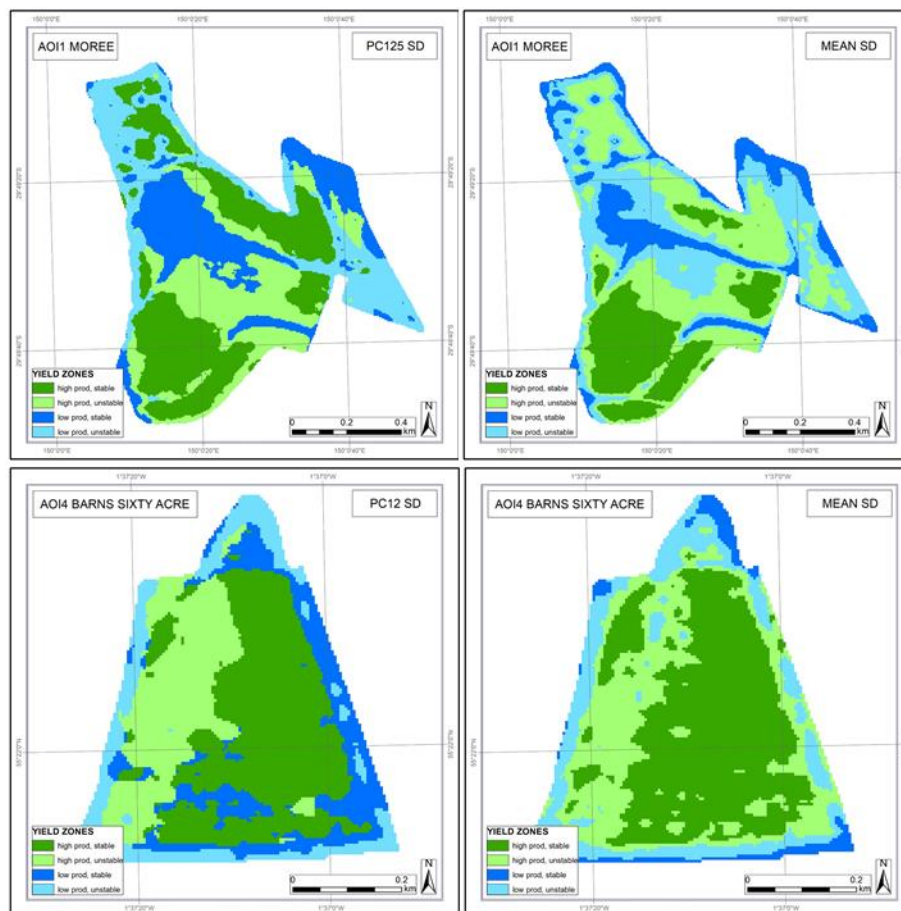


Figure 4.6 A comparison of yield stability zones derived for two fields using Principal Component Analysis applied to interpolated yield map mages (Left images) and the same maps classified into yield stability classes using k-means classification. The top field is from North-west NSW Australia (and the same field used in Figs 2.1 and 4.5). The bottom field is from Northumberland in North-east England. The PCA-based method (left images) show clearer patterns with less fragmentation than the k-means approach. (Images reproduced from **Blasch et al., submitted**)





The difference in MU output between classification and segmentation is clear In Figure 4.7. Within each approach, the difference between a 2, 4, 6 and 10 unit solution is also clear. But which output is best for management? Selecting the right number of classes/zones/units is a key decision in making MU maps. For the k -means classification approach, a value of $k < 5$ is usually optimum (Whelan and McBratney 2003; **Pedroso et al., 2010**), although this generates many more discrete zones. For example, the 4-class solution in Fig. 4.7 has 30 zones of a manageable size (**Pedroso et al., 2010**). The optimum number of MUs is an optimisation function that needs to consider the size and shape of MUs, the difference in production levels between units, the machinery available and a producer's intent.

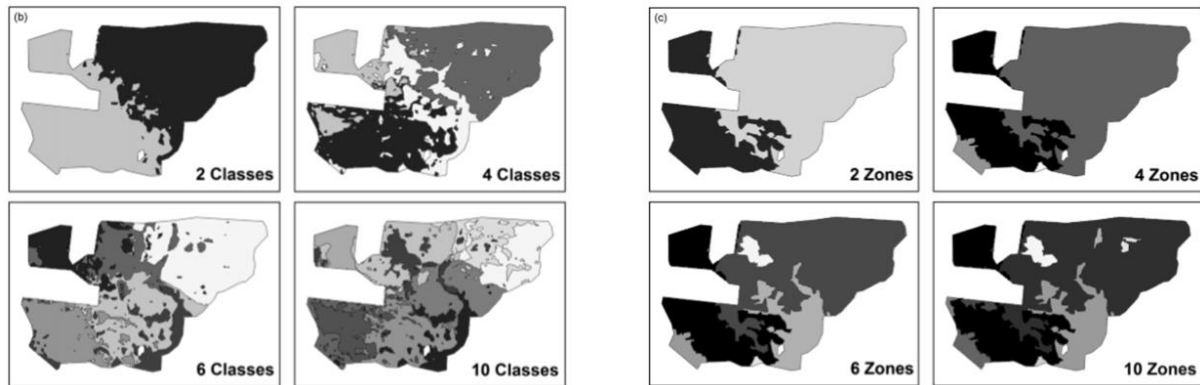


Figure 4.7 A comparison of the application of a spatially constrained classification (left) (Frogbrook and Oliver, 2007) and a segmentation (right) algorithm to canopy vigour data in a vineyard in Spain. For both approaches a 2, 4, 6 and 10 'class' solution was found. For classification, this generates k classes, while the segmentation generates k (discrete) 'zones'. The 4-class solution explains a similar level of variance as the 10-zone map but has three times as many discrete 'zones'. (Image and details from **Pedroso et al., 2010**).

Size and shape can be assessed visually and small, unmanageable areas filtered automatically (Betzek et al., 2018). A determination of the difference in response between MUs is usually done statistically, often by means comparison, e.g. mean yield of each MU. However, the direct calculation of a statistical difference is not valid, because of the autocorrelation in the data. **Taylor et al (2007a)** proposed an alternative confidence interval based on the median error of prediction in the maps that were used for the MU delineation. This provided growers with information on the difference in means and a likely error and provided the opportunity for them to make their own assessment of the agronomic significant differences between MUs. A statistical difference does not necessarily equate to an agronomic difference (and vice versa).

An alternative to direct means comparison is to use statistics associated with the partitioning process. It is for this reason that the fuzzy variant of k -means clustering is often advocated (McBratney and Boydell, 2002; Gavioli et al., 2016). It generates partitioning and entropy indices, based on likely memberships, which can be used to identify the most 'stable' solution. This, however, is only statistical. There is no direct consideration of the agronomic difference and if it is worth managing differentially.





Using the right data fusion method is important in making MUs. Selecting the right layers to use in the process is also important, but less researched. In general, the selection of layers for input is left to the discretion of the user, i.e. it is an expert choice. Historically this has not been a major problem as the number of data layers has been small. However, every year the amount of available layers is increasing, making correct selection more difficult. To assist in selecting the right ancillary data to derive MUs, **Taylor and Whelan (2011)** proposed the use of MANOVA with an information criterion, which identified canopy data, and preferably multi-temporal canopy data, as being better than soil information for the derivation of yield MUs in irrigated sweetcorn in Australia. This provided a clear methodology for layer selection but also clear advice to growers to direct their investment into canopy sensing systems.

With more data generated, and more fields connected and analysed, data-mining techniques to select preferred layers will be necessary. Figure 2.1 presented a series of yield maps, some of which had unusual effects caused by management (e.g. the 1997 yield map). Maps with strange effects should not be used for MU delineation (unless the strange effect is permanent and intended to be managed), so tools to identify if a map is 'strange' are needed for automated processes. **Blasch and Taylor (2018)** have proposed an iterative approach of filtering whole layers using Principal Components Analysis (PCA) to plot outlying data layers in the attribute space. This was useful in identifying layers to remove, but also for identifying layers to keep (i.e. layers selected for removal by an expert that were suitable for use in the statistical process). In this study, and in a similar approach with remotely-sensed imagery (Georgi et al., 2018), the use of PCA was effective. However, other data-mining approaches are also likely to be applicable. Alternative approaches may be better suited for selecting preferred layers across heterogeneous sets, e.g. simultaneously selecting preferred yield, canopy and soil data layers for the MU process.

Management units play a key role in getting producers involved in PA. When done correctly, the producers can see how the various layers are compressed into a single usable map, which is usually easily interpretable with their existing local knowledge of crop and soil response. Management units can be treated as fields and decisions made as before, but applied on a smaller scale. This achieves a higher level of spatial management while maintaining the producer in a familiar decision space. Of course, if poorly constructed, MUs will be uninterpretable, the producer will be disillusioned with PA, and the default uniform field management will be used. As a result, a large part of my research has been, and continues to be, directed at issues around MUs. Firstly it was to ensure that there was a clear state of the art protocol and since then, how to improve the process. Research into using irregular data points, the selection of correct ancillary data and the correct number of MUs and alternative data fusion approaches has added to the collective knowledge around MU delineation. Ultimately, this and other research will need to reach a next step 'black box' model that is able to select, fuse and delineate agronomically practical MUs. This needs to be robust and with minimal (or no) skill requirement from the operator, and only requires their local knowledge as an input.

4.3 Advanced applications of management units to inform decision systems

Management units are very useful for translating normal agronomic decisions into a sub-field region. This does not fundamental change the agronomy. The MUs are used to set different yield potentials





in different parts of the field. This is most commonly a change in fertiliser applications between MUs. Decisions are being made at a higher spatial resolution, but the fundamental decision process is not changed. The same approach is used in each MU, just tailored to a different yield potential. Generic, regional response functions are nearly always used to drive decisions, even though it is unlikely that any particular field or any particular MU has that exact response function.

The generation of MUs typically requires detailed yield, soil and/or biomass maps that form a strong historical background and platform from which to start further analysis. Therefore, once MUs have been defined, historic responses and/or on-farm experimentation can be used to better understand crop productivity within each MU. This generates MU-specific information to assist in the decision process.

On-farm experimentation (OFE) is an area that is of particular interest for PA. Precision agriculture technologies should be capable of automatically setting out experiments (via variable rate application (VRA) maps) and assessing the treatment response (via biomass/canopy sensors or yield/quality sensors). However, despite its potential, OFE has not been widely used as it tends to be invasive or poorly designed to properly define MU-specific data. With this in mind, a new approach to OFE based on sub-plots within MUs was proposed (Whelan et al., 2005; Taylor et al., 2006; Whelan et al., 2009). This new design recognised that the treatment areas has to be as small as possible, but still able to give a desired quality of information, i.e. the producer wants to maximise the information gained from a minimal area so that the preferred (default) field management was not disrupted. MUs have a key role to play in this. They allow production units to be well defined and for treatment plots to be spatially targeted based on this production variance (Fig. 4.8)

The proposed OFE design also recognised that treatments needed to be invasive. To understand crop responses properly then treatments with very high and low rates (i.e. theoretically unprofitable treatments) needed to be part of the design. Less information is gained when treatment rates are only changed by a small amount (10 – 20 %). Treatment rates are a key concern for producers. The more invasive a treatment, the more likely there is to be a production/profit loss. Consequently, with many OFE approaches there is a lack of range in the ‘treatment’ (e.g. N fertiliser rates) due to growers being risk averse in treatment design. By using VRA, small areas are targeted that minimise the potential financial risk to the producer of applying extreme treatment rates (even zero rates). This approach was successfully applied to understand MU-specific fertiliser and seed rate responses (example presented in Fig. 4.8) in Australia (Whelan et al., 2005; Taylor et al., 2006; Whelan et al., 2009). It was possible to clearly show differences in yield response to fertiliser and seed between MUs in the same field, with a very small change in production costs. The value of the information, however, permitted very detailed MU-specific fertiliser wastage (lost revenue) to be calculated. The value of these ‘waste functions’ far outweighed the cost of the experiment (Whelan et al., 2009). With real, locally derived empirical response functions, decisions on required fertiliser and rates are much closer aligned to the actual production conditions.

Although developed and first published a decade ago, this OFE approach is not widely adopted (for many of the reasons outlined previously). While the field/MU experimental design is well described, tools to automatically establish and analyse the treatments are not well developed. These are not classical, replicated experiments, which are the backbone of traditional white-peg agronomy trials and analysis. This is a new method of experimentation and still needs the development of methods for





statistical and agronomical interpretation of these data to gain acceptance. This ‘missing link’ is acknowledged (Marchant et al., 2018) and it is expected that recent advances and continuing evolution in sensing technology and in digital agriculture, particularly machine-learning applications, will be able to fill this void in the near future.

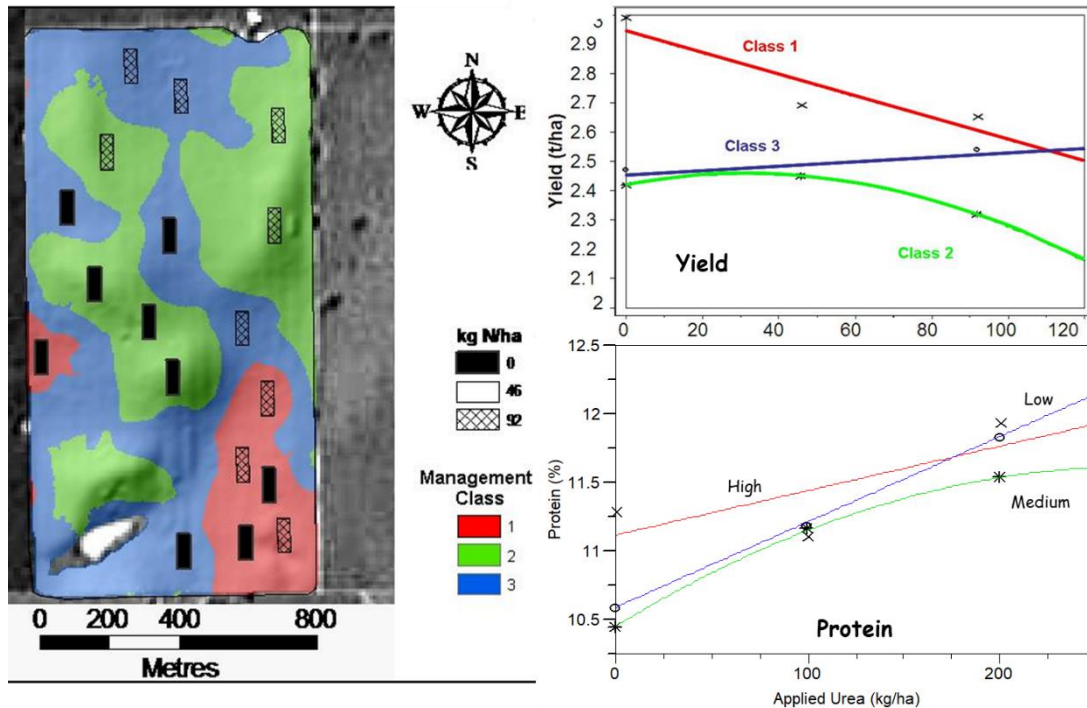


Figure 4.8 Left: An illustration of how management units (MUs) could be used to establish treatment ‘sub-plots’ to investigate input (nitrogen) response. No fertiliser, average (default) or double rates were applied in each MU. A yield monitor and a ProSpectra grain protein sensor were used on-combine to obtain yield and protein values for the treatments in each MU. MU 1 (red) had high pre-season soil N and additional fertiliser actually decreased yield. MUs 2 and 3 exhibited different responses, which were easily explained by agronomic practices. N response and optimum N differed between MUs (from Whelan et al., 2005).

Even without embedding experiments into MUs, the response within and between MUs can be interrogated. In the simplest manner, average yield, soil fertility and crop attributes for each MU can be compared within and between years to improve agronomic understanding (e.g. Taylor et al., 2007a). There does, however, exist opportunities to move beyond ‘mean comparisons’ and to translate advanced agronomic concepts, such as yield gap analysis, to a field and MU-level. A first step in this direction has been formulated (Leroux et al., 2019) that proposed the use of (site-specific) multi-year historical yield data to compute site-specific production potentials and production gaps (Fig. 4.9), i.e. the differences between actual observed yield and the observed production potentials. This is based on arbitrary aggregated yield areas and illustrates the possible maximum production possible at a site as well as the stability of that production target (or the potential gap based on varying seasonal factors) (Fig. 4.8). The yield area (20 m²) was done in consideration of the smallest possible manageable unit in the field. Equally, this could incorporate larger-sale MU effects as well and this is





a target for future work. The true value of this approach will only be realised when the economics of production and the use of OFE are incorporated into the process to enhance the quality of annual information collected. MUs will be needed to achieve this.

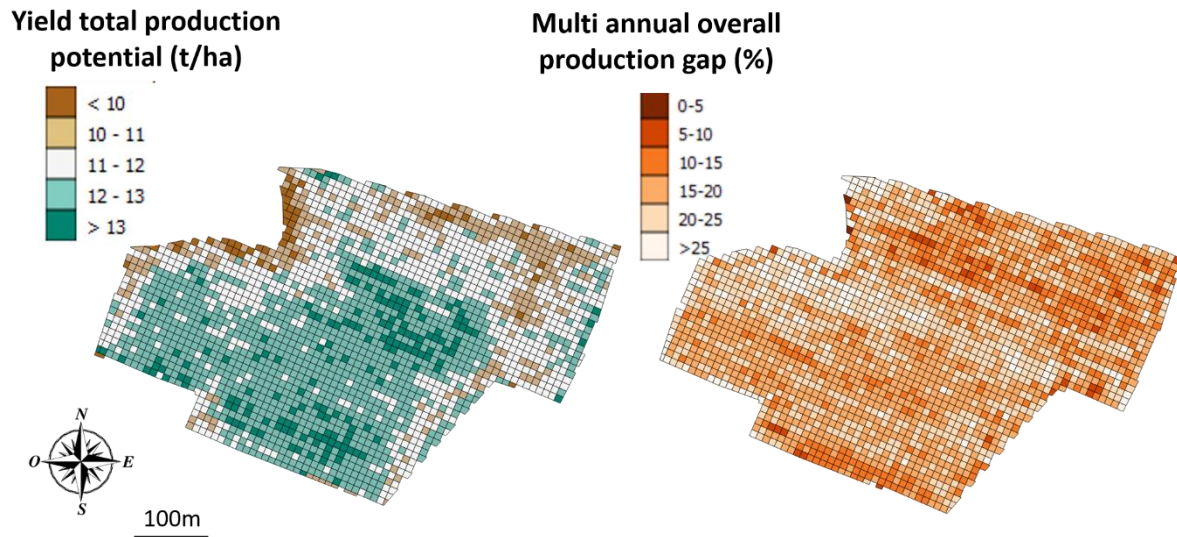


Figure 4.9 Local maximum yield production potential map (left) based on yield data collected from 2003-2015, and the corresponding multi-annual local production gap (right) (average % difference between the highest observed value and the annual values in each pixel). This has been computed on aggregated pixels but could be applied to MUs. (from **Leroux et al., 2019**)

4.4 Translational PV/PA – protocol publication, prototype testing and industry-led projects.

The role of protocol production within my scientific work has already been outlined in Section 3.1. This described a personal learning curve, more so than an advancement of scientific knowledge in protocol development. Advancements in scientific knowledge in my translational work has come from prototype sensor testing and the evaluation of the analytic systems that have been embedded either indirectly or directly into the protocols.

Precision Agriculture often uses new and emerging technologies to improve decision-making. Some sensing systems are developed in academic environments, which tends to support detailed theoretical development but may not produce robust commercial products. Alternatively, some sensors are developed by private industry, who often guard the intellectual property, and the operation of the sensors may not always be rigorously tested (or made publicly available) before commercialisation. In both cases, there is a need for independent evaluation of the performance of commercially available sensors in commercial situations and much of my research has been involved in this testing.

My PhD studies effectively began with the first HarvestMaster HM570 grape yield sensor (HarvestMaster, Utah, USA) in Australia and the simple question – does it work in Australian vineyards? The HM570 was an ultrasonic sensor mounted over the discharge conveyor to measure the volume (not mass) of grapes being harvested. Over four vintages (1999-2002), the sensor was





evaluated and found to have flaws that made commercial use very difficult (Taylor, 2004). Variations in grape density and the amount of juice being harvested caused issues with the correct calibration of a volumetric sensor. This work, together with complementary work at CSIRO led by Dr Rob Bramley, ultimately led to the sensor not being adopted in Australia. A direct mass measurement was identified as being preferable and trials with another PA electronics company lead to the release of a load cell-based grape yield monitor in the mid 2000s (Farmscan, WA, Australia). In 2012, I was involved in the adoption of this yield sensor (Fig. 4.10) into the US viticulture industry. In the Eastern US, the sensor was directly evaluated for accuracy in the vineyard, while in California, training and protocols to correctly process the data were given to industry partners (Sams et al., 2017). The on-harvester assessment of the yield sensor in both research and commercial vineyards in New York State clearly showed that the sensor was accurate (Fig. 4.10), provided that the correct daily maintenance and sensor operation protocols were followed (Taylor et al., 2016). The work also illustrated for the first time that the sensor was also suitable for measuring and mapping mechanical crop thinning operations, although a different calibration factor was required for mid-season operations (compared to harvest) (Taylor et al., 2016).

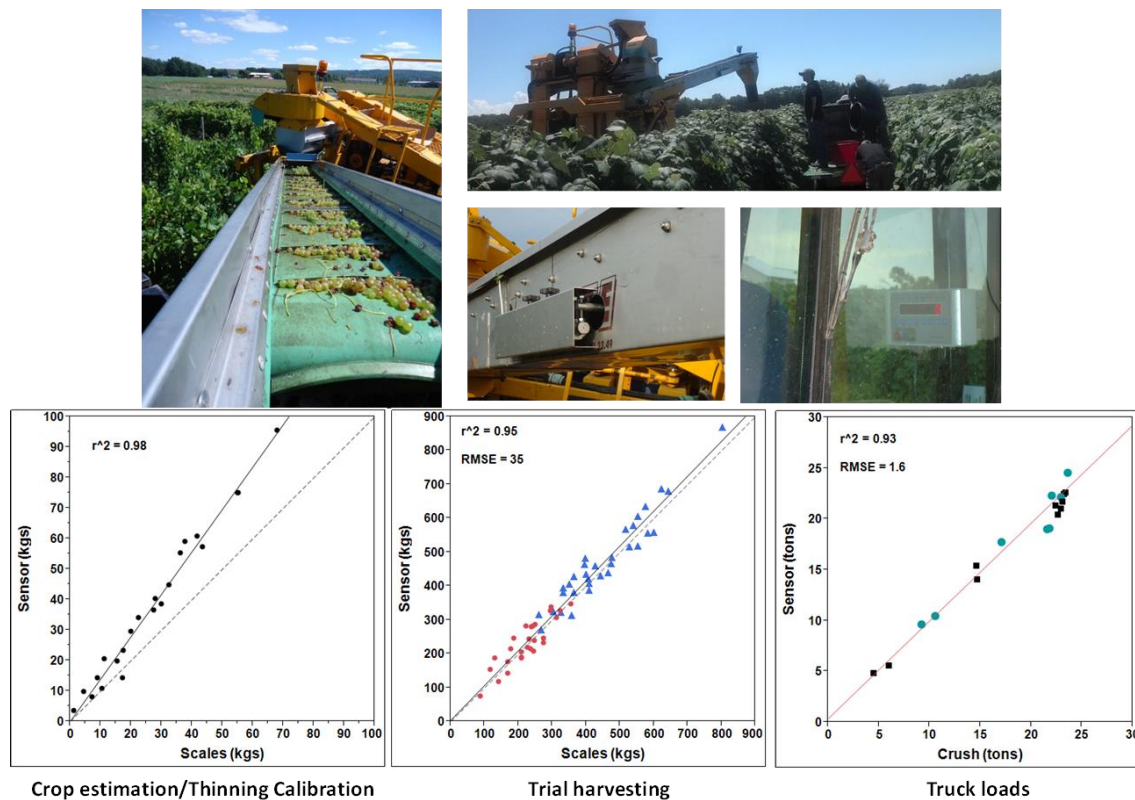


Figure 4.10 Top - images showing grapes on a grape harvester discharge conveyor, a harvesting operation, the load cells mounted on the side of the discharge conveyer and the display within the tractor cab. Bottom - Three validation plots to compare the calibrated yield sensor against different scales of measured mass; From left to right these were i) mid-season buckets for crop estimation (~30 kg), at-harvest trial plots (~400 kg) and truck loads delivered to the crush (~20 ton). The at-harvest calibration is stable even for small masses. There is a midseason bias in sensor operation that needs recalibrating but the relationship remains strong and linear (images from Taylor et al., 2016).





As a direct result of this work, grape yield monitors in the US increased from 0 in 2011 to > 100 monitors in 2015. The current grape yield monitor does have limitations, particularly in data visualisation in the cab and in data management. The success of this yield monitoring system in the US has resulted in other companies actively developing alternative yield monitors for grapes. This competition will be beneficial for grapegrowers in the USA (and elsewhere) who are looking for improved yield monitoring and mapping services.

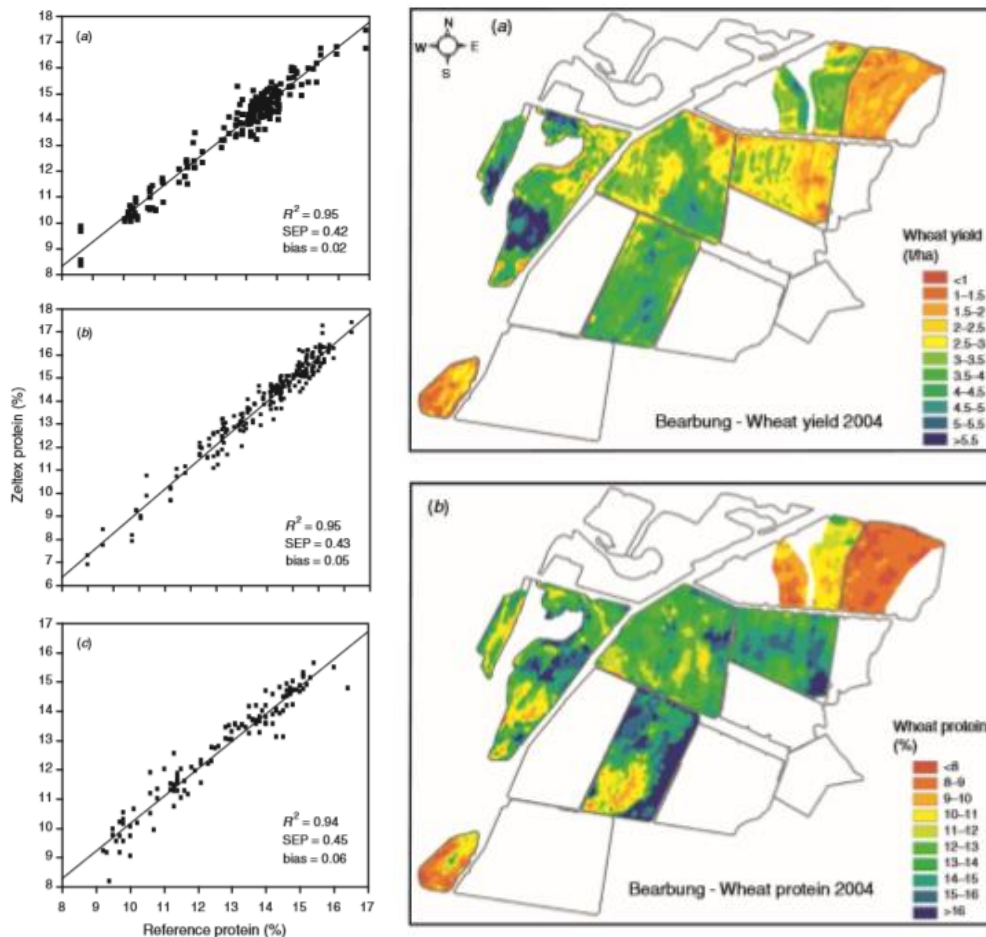


Figure 4.11 Example of assessment of a prototype commercial on-combine grain protein sensor (AccuHarvest, Zeltex Inc.). The sensor was supported by academic staff over three seasons and sampling performed to compare the on-combine protein sensor with a reference bench-top laboratory system at the grain silo. Calibration fits for each year (2003-05) are shown on the left and farm level maps of yield and protein in 2004 to illustrate the spatial patterning of both variables (right) (from Whelan et al., 2009).

During my post-doctoral position at the University of Sydney (2004-8), I was also involved in the assessment of prototype on-harvester grain protein sensors (Taylor et al., 2005b; Taylor and Whelan, 2007; Whelan et al., 2009). Two systems were assessed, the AccuHarvest On-Combine Grain Analyzer (Zeltex Inc. Hagerstown, MD, USA) that was mounted on the clean grain elevator and the ProSpectra sensor (Textron Systems, Wilmington, MA) that was mounted in the clean grain bin auger. The





AccuHarvest system was more robust and effective, although it had lower spectral specifications than the ProSpectra. Both were able to produce good relationships between on-harvester measurements and reference (at-silo) measurements in Australian conditions. This corroborated similar studies in the USA (Long et al., 2008) using the same sensors and has had a direct influence on the adoption of grain protein sensors in Australia. The current supported system in Australia is manufactured by NIR Technology Systems (Condell Park, NSW, Australia). It uses a full spectrum approach (similar to the ProSpectra) with the mounting system based on the AccuHarvest system, i.e. the best of the two original systems identified from research-led technology assessment.

Industry-led project work

In addition to testing prototypes and engaging with growers, since 2015 I have been involved with three industry-led projects in the UK. Two of these have been Knowledge Transfer Partnership (KTP) projects with Small-Medium Enterprises (SMEs) and the third a collaborative project under the Agri-Tech Catalyst (ATC) that involved large multinationals and a SME. The KTP and ATC programs are designed to allow academic knowledge to become embedded in commercial enterprises. They are a funding mechanism supported by the UK government to try to bridge the TRL 4-6 gap identified in Fig. 3.1. This is done by allowing industry partners to lead the project and determine the best route for innovation.

There was no requirement for the research within the project to be new, however the commercial services (or goods) must be. One KTP focussed on delivering a commercial service based on an updated version of the yield mapping and MU protocol (Taylor et al., 2007; Fig. 4.5). The second KTP was originally aimed at commercialising predictive crop model simulation outputs. As the project developed, it became clear that these services were highly reliant on good, local weather information. The project, under the industry partner's direction, became more focussed on supplying virtual weather services for agricultural applications. It was proven that there was no difference in crop model behaviour when using short-range weather predictions or observed on-farm measurements (Launspach et al., 2017). The first can be obtained for free with no hardware costs/maintenance, while the latter requires capital investment and communication maintenance. The company now offers virtual weather stations as a basis for all the advice being offered to producers.

In all three cases, the projects generated agricultural innovations. The need to deliver spatial agronomy services that growers have confidence in, makes PA well suited to these industry-led funding streams. Service providers need help in developing effective services and academics need help in getting their ideas put into practice. From my perspective, the ability to work closely with industry and to mentor employees has been very beneficial. It has broadened my understanding of the practical limitations and needs associated with PA services. It has forced me to reconsider the detail within some of the research, and whether the level of detail is needed to make more effective on-farm decisions. Very small incremental improvements may require a lot of (unprofitable) effort. This is not to say that research should be simplified, but rather that outcomes from research may need simplification, while maintaining integrity, to be considered for commercialisation. The engagement with industry has also highlighted the lack of knowledge and skills in PA in the workforce. The biggest problem across all three projects was finding suitable candidates to be employed onto the projects. It was clear that in the UK at least, education structures are not delivering people capable of working in precision and digital agriculture.





4.5 Barriers to and Drivers of PA adoption – a social science perspective.

Within my research trajectory, I have become much more aware of the need for wide consultation when developing agricultural solutions (Sections 3.1 and 4.4). The development of PA technologies, methodologies and services needs input from all industry actors, particularly end-users and potential future service providers. The role and need for good social science in PA has become more evident to me overtime and in the past 3 years I have begun to collaborate more closely with social scientists to better understand the adoption and translation of PA technologies. This has mainly been driven by funded research into UK agri-technology translation into Chinese production systems. However, it has broad applications to all agricultural systems and particularly global small-holder agriculture.

There has been some research that describes adoption trends in PA, mainly in well-developed agricultural systems with large production systems (Daberkow and McBride, 2003, Adrian et al., 2005; Paustian and Theuvsen, 2017), however the barriers and the drivers of these adoption trends are still not well understood. As described previously (Section 2.4), adoption is often associated with differences between embedded knowledge and information intensive technologies (Miller et al., 2018). However there are other factors at play that need to be collectively considered. To do this a framework for assessing and understanding the benefits of new agricultural innovations (and specifically PA services) is needed. It must be an integrated framework for technology assessment that balances traditional measures of agronomic success (farm profitability) with the socio-economic welfare of rural populations and national and international policies and goals for food and environment security. Alignment of a new innovation with societal values, needs and expectations is critical for ensuring that the newly introduced technologies address socially sensitive issues (Asveld et al., 2015). Such a framework has been recently published (Clark et al., 2018) and its intended benefits are schematically shown in Fig. 4.12 with reference to the Gartner Hype Cycle (www.gartner.com). It illustrates how a well-structured technology development strategy with early engagement and co-design among all stakeholders will ensure that expectations are not over-inflated and adoption is enhanced by addressing both socio-economic and technical barriers in product development and enacting timely policies and off-farm support for the technology.

The framework itself (Clark et al., 2018) is based on the concept of responsible research and innovation (RRI) for agriculture (Coles et al., 2012), which has previously been advocated for PA (Lamb et al., 2008) but not enacted. An application of the proposed framework to PA adoption by ‘family-farms’ in China, typically 8-20 ha commercial production systems, has generated clear indicators of technology needs and technical and socio-economic concerns over adoption (Kendall et al., 2017; Clark et al., 2018). Among PA experts in China there was a consensus that current PA technologies only hold relevance for larger farms. This mirrors conventional thinking in developed agricultural economies (Daberkow & McBride, 2003; Adrian et al., 2005), although it has been challenged by others who believe that PA is applicable to small-holder agriculture (Cook et al., 2003; Zheleva et al., 2017). The experts (mainly academics) also pointed to issues with technology transfer between systems with different field sizes and levels of mechanisation, prohibitive cost structures for investment, an aging farm population and the need for younger, computer literate farmers with better education level to operate the new technologies. All these barriers have previously been identified within developed (larger-scale) agricultural systems as well (e.g. Daberkow and McBride, 2003; Kutter et al., 2009). Preliminary interviews with growers reflected limited knowledge and understanding of PA on-farm in





China (Kendall et al., 2017), despite a large investment in PA research and extension in China over the past decade (Zhang et al., 2016).

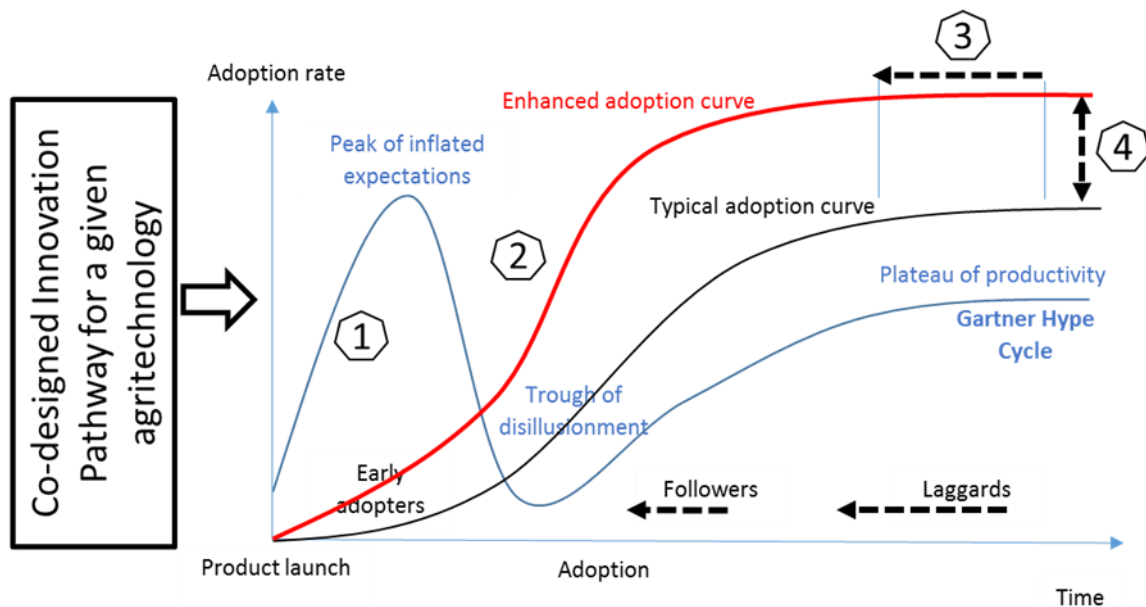


Figure 4.12 How effective co-design is predicted to accelerate technology adoption by bringing forward adoption by “followers” and “laggards” and thereby boosting the adoption curve. This is achieved by 1) Co-design with end-users in the technology development phase to generate reasonable expectations and to reduce the possibility of a new technology being overhyped; 2) Consideration of the socio-economic and technical barriers and appropriate extension service type mechanisms; 3) Twinning the technology with correct policy, regulation and service support to reduce the time to ‘full’ market penetration; and 4) Increasing penetration of the technology and generating higher rates of adoption by considering ‘laggard’ barriers that are likely to be underpinned by socio-economic rather than technical issues. (reproduced from Clark et al., 2018)

The proposed framework (Clark et al., 2018) and initial interviews (Kendall et al., 2017) were used to develop a comprehensive quantitative model of PA adoption in China. A more comprehensive, targeted review of PA drivers and barriers to agri-technology adoption in China (Fig. 4.13) (Li et al.a, *submitted*) informed a new hybrid model to assess agri-technology adoption in China (Li et al.b, *submitted*). This hybrid model linked an existing Need to Fit (NTF) model with an Adapted Unified Theory of Acceptance and Usage of Technology (AUTAUT) to directly interrogate hypotheses concerning technical and socio-economic effects on PA adoption (Fig. 4.14).



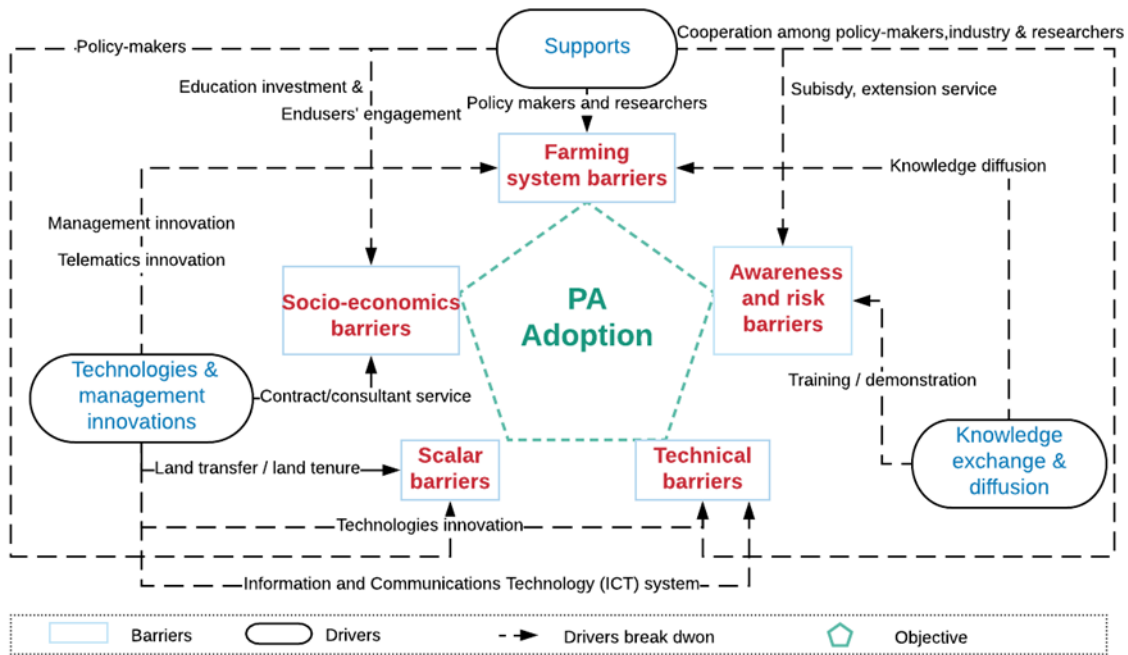


Figure 4.13 Conceptual model of barriers to and drivers of adoption of PA technologies by end-users and interactions between drivers and barriers. The schematic was populated from a literature review on PA adoption and discussions with a variety of growers, industry service providers and academics (from Li et al.a, *submitted*)

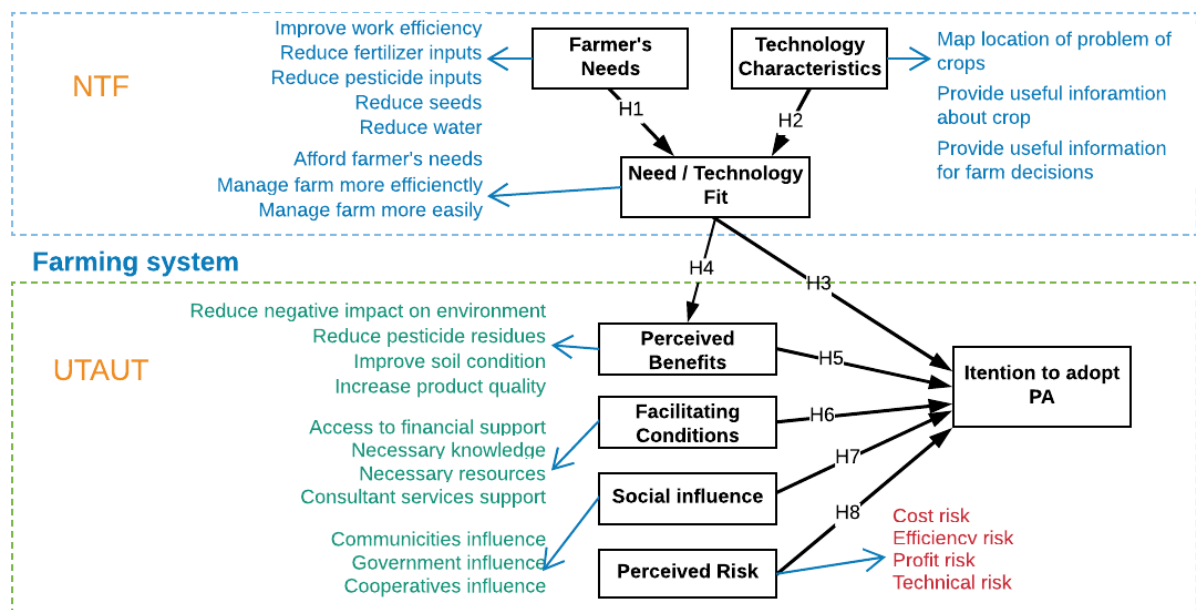
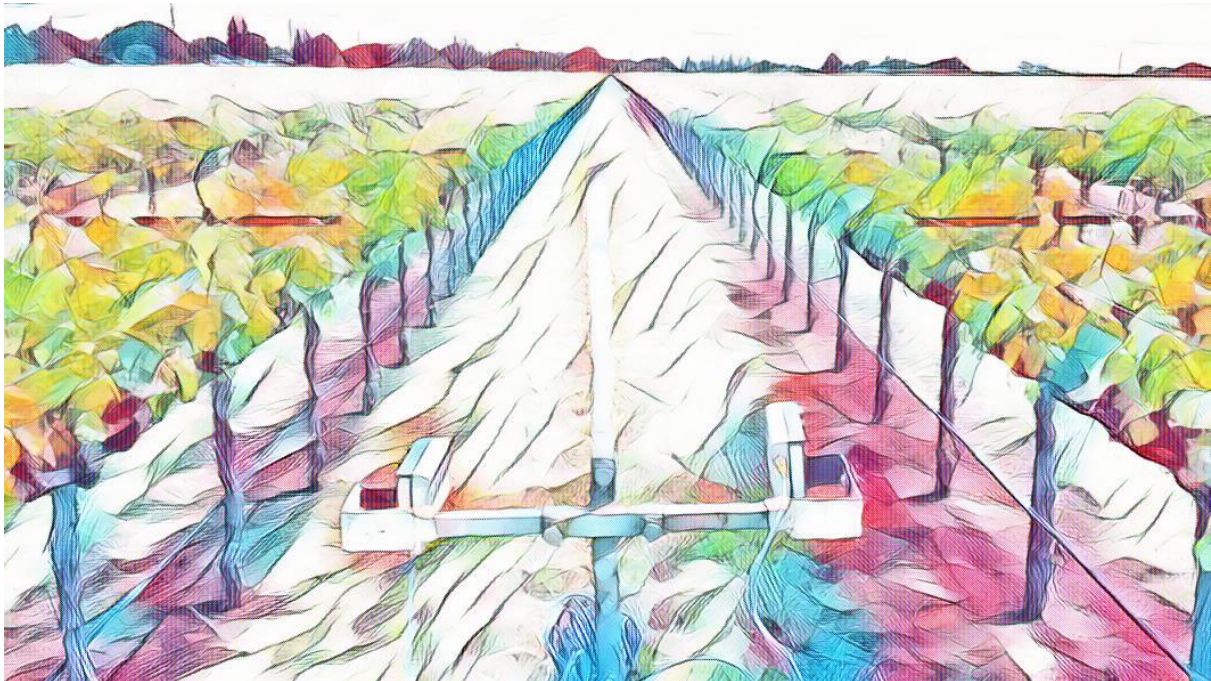


Figure 4.14 A theoretical model of intention for PA adoption that links a need technology fit (NTF) model with an adapted unified theory of acceptance and use of technology (AUTAUT) model. Multiple hypotheses (denoted Hx) are proposed to understand and model farmer behaviour. A blue arrow links the latent variable with the observational variables in a measurement model and black arrows indicate the hypotheses proposed in this study (from Li et al., b, *submitted*).





The proposed hybrid model connects a producer's needs for a technology with their intention to adopt a technology. It was populated via a survey of 450 producers, with questions specifically targeted to address the hypotheses. The modelling showed quantitatively for the first time that PA adoption is dependent on both the farmers' perception of benefit vs. effort of the PA technology as well as the technology characteristics and the match between the grower's need and the technology. This provides clear evidence for the co-design process advocated by Lamb et al. (2008) and formalised in **Clark et al. (2018)**. The modelling also revealed that improving farmer knowledge and the availability of resources to promote and use PA technologies was the most important factor that needs Improving to facilitate adoption. The fit between technology capabilities and grower's need was identified as the second most important priority. The only hypothesis not supported was that of Social Influence (H7 in Fig. 4.14). This is often cited as a dominant effect in the early stages of adoption of new innovations (Choi et al., 2014; Swinerd and McNaught 2015), but does not seem relevant in Chinese agricultural systems. There was no apparent peer pressure effect on adoption trends.





5 - Conclusions and Future plans:

5.1 (Re-)Evolutionary 'PA' – from 'Precision Agriculture' to 'Personalised Agriculture'

Precision Agriculture (PA), especially when considered from the perspective of site-specific crop management, is often described as doing the 4 R's; 'the right thing, in the right place, at the right time, in the right way' (after Pierce and Nowak, 1999). These address the goals around improved production management but do not address the final intent of the management. Who is the management for? A 5th R could therefore be added to this list - 'for the right person'.

This 5th R transforms site-specific crop management into a personalised crop decision system by formally identifying a target end-person (or process). But who is this 'person'? If 'Personalised Agriculture' is used in the same context as 'Personalised Medicine' (Jameson and Longo, 2015; Collins and Varmus, 2015), then the target person will be the consumer. 'Personalised' agricultural products would be produced to meet the specific needs of a specific consumer. In reality, the value of the product and the economies of scale within large commercial cropping systems would preclude targeted production for specific individuals. However, targeted production for specific cohorts in the population are possible. In such situations, the target 'person' may actually be an entity within the supply chain that is tasked with delivering a specific product to a market/population segment (rather than the actual consumers). Production must therefore meet the processing or supply chain actor's demands as well as the end consumers.

A potential example of altering production to generate a new product that is able to correct for broad nutritional deficiencies in target populations are 'Sunshine eggs' (Hill and Kyriazakis, 2018). These are eggs that are enriched with Vitamin D to overcome population deficiencies during winter (low sun exposure) months. Enhancing the nutritional or medicinal benefits of commercial crops may similarly be possible using precise and targeted management that corrects limiting management or environmental effects on the target compound. For example, UK soils are known to be low in selenium, which leads to low selenium content in the grain crops produced, low selenium content in bread sold and is considered a contributing factor to selenium deficiency within the general UK population (Stoffaneller and Morse, 2015). Site-specific fertiliser and soil management could be used to ensure soil selenium availability was improved. This would be a direct precision agriculture application to an existing cropping systems. More likely, bioengineering will be used to develop future crops with an enhanced ability to deliver a nutritional or medicinal benefit. These in turn may require precise and site-specific management to cultivate the crop and to deliver an effective product into the supply chain and ultimately to the target consumer.

For true personalised crop demands, i.e. a crop that delivers specific individual requirements, it is likely that bioengineering coupled with at-home or intensive greenhouse cultivation will be used, rather than large-scale commercial cropping systems. This mirrors the personalised medicine approach. However, instead of producing a tailored synthetic medicine for an individual's requirement, the plant genome would be bioengineered to produce the target compound, which is delivered via consumption of the plant rather than through synthetic medication. This is not science fiction, but a current potential reality of molecular biology. However, fiscal and social restraints for genetically modified organisms make it an unlikely scenario in many markets in the near future (Frewer et al., 2013).





There is an alternative consideration of the ‘right person’. If the direction of intent in the supply chain was aimed upstream, rather than downstream, then the ‘right person’ could equally be the producer, rather than the consumer. **i.e. Agriculture production could equally be personalised to meet the ‘personal’ needs of the producer.**

Currently the majority of applications of precision agriculture into commercial systems are ‘site-specific’ in that they use site-specific information within a non-site-specific decision system. For example, an optical crop sensor can determine the greenness of a crop and the operator can specify target nitrogen rates for target yield potentials. However, the yield-nitrogen response curve used to vary N rates IS NOT a local (site-specific) response function. In most cases, it is a generic ‘average’ response function derived from experimental or monitoring farms, often using small plot trials rather than data derived from a commercially cropped and managed system. Do we expect the yield-nitrogen response function to a) be the same at a research plot and at a grower’s field (with a different cropping history), and b) even be uniform across a grower’s field? No, and it is clear that nitrogen responses, to both yield and protein vary both between and within fields (**Whelan et al., 2009**; Mong et al., 2016). A ‘Personalised Agriculture’ solution must evolve to meet the needs and conditions inherent in the local production system.

This is the grand challenge for precision agriculture going forward and with the digital agriculture revolution. How do we transform precision agriculture into a ‘personalised precision agriculture’ management system? How can this be achieved with the new and evolving connected data and information structures in agriculture? Every field and management operation has the potential to become some form of experiment – nominally as a uniformity trial in the general sense, but also with embedded smart experimental designs that allow growers and agronomist to determine local agronomic response functions that inform truly local site-specific decision support systems. To achieve this ‘precision’ agriculture and precision agriculture research needs some reimagining.

5.1.1 Key areas for enabling the next PA evolution

The following points focus on areas where I would like to see my research interest and experience evolve into over the next decade. It is not intended to represent all the areas of development that are needed to support a more systematic integration of precision agriculture into current and future agricultural systems around the world.

i) Dynamic management units

The delineation of management units (MUs) using classification methods was a big step forward in multi-layer data fusion (Lark and Stafford, 1997). There is no doubt that MUs have been effective for moving towards truly site-specific management (Fig. 4.4). However, the current use of management units tends towards static patterns and they are applied as a ‘one size fits all’ approach. Multi-layers of information are compressed to generate fixed zones and with fixed boundaries. This is the intent of the **Taylor et al. (2007)** protocol. These zones are then used for all potential variable rate applications – for example seeding, herbicide management, fertiliser and harvest in arable crops.

This is (was) sensible when only limited information layers were available. As more information, particular temporal information, becomes available for multiple crop and soil attributes, the opportunity to tailor and develop management units for specific operations and for specific times in





the season becomes possible. i.e. MUs should be dynamic in space and time, not static. The within-field drivers for variable plant establishment (and the climate in which it occurs) may differ from the within-field drivers of variable crop development. If this is the case, then management units for variable rate seeding and variable rate fertiliser should be different. Similarly, since production potentials for yield and quality attributes are known to be spatially different within fields, fields should equally have different production units for different production goals. This was hypothesised within my PhD thesis with the concept of digital terroirs and sub-digital terroirs (Taylor 2004, p2), however it is only in the past 5 years that data and information availability and connectivity has improved to a level to start to make this a potential reality (Scuderio et al., 2018).

The increased availability of ancillary crop and soil information, and the proposed development of dynamic MUs, generates a new set of questions and challenges. How do we choose the right data for these dynamic MUs and which method of data fusion should be used to generate the MUs? Currently, with fixed, static MUs, the delineation is performed by an expert in consultation with the producer. It helps ensure a rigorous selection of input data and a standardised method of delineation. A shift to dynamic MUs will make this approach economically unsustainable. Service suppliers will not be able to provide a level of personal contact to be constantly altering MUs within evolving seasonal conditions and for disparate management operations. It will therefore be the producer or an automated system that will generate these dynamic MUs in the future. The current (and future) expert knowledge, of both the agronomist and producer, in selecting the relevant data for specific operations, and the method of MU delineation needs to be captured within a 'black box' model. This is necessary to permit producers themselves to derive MUs with confidence.

This is not an easy objective. There is essentially a need to shift MU delineation from an *information intensive* system to an *embedded knowledge* system (Miller et al., 2018). More robust and repeatable data fusion methods are needed to replace the current use of *k*-means classification (and its derivatives). Ideally, as proposed in Leroux et al. (2018b), these multivariate data fusion techniques should operate directly on the raw data and include filtering and pre-processing steps. Machine-learning techniques, particularly techniques that enable soft-computing solutions, are likely to be at the forefront of this approach to MU delineation.

ii) *A new concept of on-farm experimentation.*

Each grower is unique in setting the goals for their production system and in the manner in which the production system (and the production risks) are managed. Therefore, the only way to characterise a producer's system properly is to directly interrogate that particular production system. This can be done by passively observing management and productivity. Every crop cycle is effectively an experiment, a uniformity trial, whether the producer realises this or not. However, to understand the system performance properly, and to model potential changes, treatments or shocks into the production system need to be introduced and quantified. Every field should be an active experiment! Every producer should be performing on-farm experiments, whether they are conscious or not of doing it. Modern technologies permit the possibility for on-farm experiments to be embedded into general management operations.

Within PA there has already been a shift away from controlled random-block designs and Fisher's statistics, but this is far from optimised and automated. To realise the potential of OFE, producers need clear support systems that are able to interrogate the underlying production variation and impose effective treatments that a) will generate relevant information and b) will fit within the acceptable risk to production of the individual producer. The same system also needs to be able to





process the data and provide relevant statistical and agronomical outcomes. All growers exhibit different levels of risk, it is therefore not appropriate to quote standard statistical parameters, such as levels of significance. Growers need clear information on production trends and differences on which they can impose their own knowledge, preferences and decisions.

The deployment and analysis of on-farm experiments should be highly automated. There is no technical reason why well-posed experimental designs cannot be automatically placed within a crop production system using variable-rate technology. Similarly, the treatment response can be automatically captured through crop or soil sensors within-season or at harvest. The treatment effect can then be automatically determined. However, the method of analysis must be compatible with the type of data (i.e. classical statistics are rarely relevant to spatial applications) and the complexity of the treatment design. The latter needs to consider historical management effects as well as current management. If the assumptions in the experimental design are inappropriate then the inferences gained from the experiment are likely to be unreliable (Marchant et al., 2018). The use of dynamic MUs (as proposed above) are likely to support experimental design but to confound the final analysis if the (dynamic) MU effects are not properly accounted for in the analysis.

Machine-learning and advanced data analytics are reliant on lots of data; so called 'Big Data'. While agriculture does not necessarily fall into the big data category, embedded OFE offers the potential for much greater levels of data and information to be collected at a site or within a MU. This should help to improve the quality of future decision-making, either in computer- or human-based decision systems, if managed correctly. Certainly if the decision system is to be personalised to each field/producer, then this data will be essential in the long-term.

The small strip approach that has been previously advocated (Whelan et al., 2005 and 2012), is only as a first step towards a new era of OFE. It is my belief that agriculture, particularly precision and digital agriculture, needs the same type of fundamental step change in biometry and experimentation that Fisher's work produced nearly a century ago (Fisher 1925 and 1935). While 'white peg' agronomy and ANOVA may not be dead, a new family of (spatial) agricultural statistics are needed for modern data sets. Some of this work has already been done e.g. Dutilleul (1993), but it needs considerably more collective development within the PA community to support potential commercial applications. The creation of a new international group, the Consortium for On-Farm Experimentation (COFE) (*pers. comm.* Prof Simon Cook, Curtin University, Australia, 2018), will hopefully provide a focal point for collaborative efforts.

iii) Predictive Spatial Crop Modelling

Many crop models exist (Basso et al., 2013). These are typically mechanistic or semi-mechanistic models of plant physiology, which are derived from our general knowledge of plant behaviour and refined with empirical experimental data. These models are primarily developed for simulating crop response under varying production conditions, with projected climate change scenarios being the classic example at the moment. As such, they are designed to work with 'average' field/farm/regional input values. The output is considered to be of strategic value to assist with future planning and expectations.

However, enhanced modern agriculture management will need short-term 'tactical' predictions as well as longer-term strategic predictions. i.e. not just which crop will be best suited to my production system in 2050 but also what type and rate of fertilizer should I apply in 2 weeks time? Improved





short-term predictive capabilities will generate improved production practices. Prophylactic measures are more effective and less costly than treatment after crops are affected by either abiotic or biotic stresses. Tactical applications are now a potential reality because of a) the increasing amount of high-resolution agri-environmental data available to growers (from both on- and off-farm sources) and b) constantly improving connectivity and communications technologies for agriculture (Wolfert et al., 2017).

However, most traditional crop models were not designed for tactical, short-term uses. Nor were they designed to operate with these large amounts of spatio-temporal agronomic, climatic and environmental data (e.g. weekly crop biomass maps). However, if the inherent physiological knowledge within the models can be interfaced with these new high-resolution data, then a real possibility exists to transform these crop models and to use them for predictive tactical management. The alternative is that the crop model needs to be completely rebuilt to incorporate these new data and be applied at higher spatio-temporal resolutions. This latter approach would require enormous effort, thus exploring the options for transforming existing models (rather than rebuilding) is preferable.

Accepting the need to 'spatialise' crop models generates a challenge of how to use new data streams in current mechanistic models to achieve this spatialisation (Faivre et al., 2004). There are many ways to begin to answer this. In a perfect world, with a perfect model, and perfect sensor information, then the new data could be directly incorporated and the crop model applied at smaller spatial resolutions to obtain 'site-specific' predictions. However, crop models are rarely, if ever, perfect. They are constructed to the best of known knowledge. When used in a strategic context there is always an understanding that the outcome has uncertainty and is one (of many) potential realities. There is no 'future' data for the model to be compared against, thus it cannot be 'wrong'. If a crop model is adapted to predict crop development within a season, immediate direct observations are available to 'validate' the model accuracy. It could be 'wrong', which may be due to the model (and require future improvements) or due to poor input data. If a model is deviating from reality, then there is a potential to update or recalibrate or reinitialize the model locally to improve the prediction to date and (hopefully) to improve predictions for the remainder of the season.

Within the context of Digital Agriculture, improved methods to promote better predictive capabilities, particularly crop model-based predictions, are necessary to make the best use of the increasing amounts of digital data available in agriculture. As predictive modelling becomes more important to good and best practice agricultural management, it will be important that the models are adaptive and flexible enough to be used locally with site-specific data inputs.

Moving from static (typically field, farm or regional scale) point models to spatialized or spatial sub-field crop models presents a myriad of research questions that need to be addressed. For example, at what scale should the model be run for optimal performance and how are variable input scales reconciled with the desired output scale? How are these new data incorporated into the model? What is the effect of (and solution to) the noise induced in the model by higher levels of stochastic variation in these new high-resolution spatial data? How do we determine the preferred parameter or sub-model to modify to achieve a stable crop output? And, how do we assess spatial crop model performance (relative to the point model)?





There is also a philosophical next step question as well. In an increasingly data-rich agricultural environment, is there a future need for mechanistic crop models? If OFE and high-resolution spatio-temporal monitoring becomes the norm in agriculture, will it be sufficient to use empirically derived local crop response functions to predict productivity within a season? The rise (and rise) of statistical modelling in agriculture is likely to provide a challenge to conventional mechanistic crop modelling approaches in the future.

iv) Incorporation of local knowledge into experimental design and ultimately into spatio-temporal Decision Support Systems

The discussion in points i-iii above have primarily focussed on how crop and environmental data/information feeds into and informs management units, OFE and predictive modelling processes. However, there is another inherent information source, namely the historical knowledge and intuition of the grower and/or the agronomist. In many cases there is a wealth of knowledge stored inside the grower's/agronomist's head, which could and should be used to inform decision-making. Equally though, there will be situations where there is little or no 'grower' knowledge, such as when new land or a new farm is managed for the first time.

This local 'expert' knowledge has two key potential uses. Firstly, it could help to better inform the processes above (MU delineation, OFE, crop modelling) so they are better attuned to local conditions. Secondly, and perhaps more importantly, this local knowledge should be used in the development of decisions based on the outcomes from the MU/OFE/modelling.

In either case there is a key barrier to use, namely that the knowledge tends to be qualitative in nature and of course encapsulated in the grower/agronomist's head. How can such subjective and local information be interfaced with the quantitative data being generated by crop and environmental sensing and modelling systems? A simple solution would be to completely discount this local knowledge information and to place absolute faith in deep-learning and machine-learning algorithms based on the observed crop/environmental/management data. This may be sensible (or not), but it is unlikely to be acceptable to most growers. Such an approach transfers control from the grower to a computer system. It is also likely to require significantly more data than is currently collected, and will particularly need OFE-derived data to work effectively. The alternative is to incorporate soft-computing techniques into the decision process that allow for this local knowledge to be considered in the decision process. Such systems have been proposed (**Guillaume et al., 2013**), but are poorly developed. Agriculturists tend to think in more quantitative than qualitative terms, and it is to be expected that the data analytics associated with digital agriculture will tend toward hard-computing solutions in the first instance. For translation and adoption, this is unlikely to be sufficient and growers must have some ownership and input into the decision system for it to be successful. How soft-computing approaches are adapted or even developed for agricultural conditions will form a key part of the future adoption matrix.

v) Temporal variance in crop production

Section 4 described my work in characterising the spatial variation in crop production. My efforts to quantify local temporal variance (including spatio-temporal variance) have been less effective, although this is not unusual within the precision agriculture community. Some work has looked at how sensor signals evolve within a season (e.g. **Taylor et al., 2013b; Rodriguez et al., 2018**) or how time-series can be compressed and transformed (**Leroux et al., 2018b, Blasch and Taylor 2018**). However,





detailed analyses and detailed methods for analysis of temporal (and spatio-temporal) variance in agricultural systems is an area that needs considerable attention. Without this information it is difficult to model and account for the effect of temporal variation on decision systems. The environment, particularly climatic conditions, for farming is likely to become more variable, potentially creating greater temporal variance in the future.

vi) PA for socio-environment outcomes and enabling metrics

The success of PA in cropping systems is almost always determined via gains in productivity and profitability. Producers only count dollars, or euros or pounds etc. This is despite the fact that PA should also provide improved environmental and social benefits to crop management. The assessment of PA should consider all 'net benefits'. The reality, however, is that social and environmental benefits are much more difficult to quantify. PA may or may not provide an ecosystem service and a one-size-fits all approach is not relevant. Therefore, while metrics to assess ecosystem services have been proposed, e.g. McElwee (2017), their usefulness for assessing site-specific value in crop systems is very limited. Conceptual models of how the economics could be derived from production and environmental aspects have been proposed (Ancev et al., 2004, Griffin et al., 2004) and some efforts made to calculate the joint value (e.g. Rogers et al., 2016). However, metrics to give value to the socio-environmental benefits of PA are very much still in the research and development phase and a long way from being used commercially to support decisions on-farm or, crucially, to drive governmental interventions. Without such support, producers cannot properly assess the environment benefit and the socio-environmental value of this benefit. Consequently, the recuperation of costs associated with this benefit cannot be passed to the supply chain/consumer, nor can it be compensated for via government payments/policies.

In regards to the social benefits of PA, these are not captured at all in any spatial economic analysis. For producers, the final decision on adoption of PA services is driven by financial questions. However, social and particularly environmental concerns do play a major role in a producers intention to adopt a new technology (Li et al., *submitted, b*). Providing correct indicators of non-production benefits, even simple indicators, will be a big step forward. The PA community is relatively weak in (spatial) agricultural economics and needs to broaden engagement to provide the right economic tools for growers.

vii) Socio-innovation understanding of 'Personalised Agriculture'

The shift from Precision to Personalised Agriculture proposed above is only possible with improvements in digital technologies and the increasing availability of 'connected' sensing systems. It will be data driven. The increase in data, and its potential conversion into information and knowledge, raises serious socio-innovation questions for the agriculture community.

Firstly, who owns the data and who has access to the data? As the saying goes, "scientia potentia est", or "knowledge is power". Traditionally, on-farm data were stored and managed in isolated, desk-top software in the farm office. Nowadays, new farm-information systems are web-based, which increases flexibility, but diminishes data security from the grower's perspective. There is no doubt that the web-base services add enormous (potential) functionality for growers (Fountas et al., 2015; **Shahar et al., 2017**), but attitudes to this 'connectivity' among producers is largely ignored. Among large agricultural companies there is an effort to accumulate data and to start to act as data warehouses. For machinery companies in particular, the warehousing and sharing of data from embedded on-machine sensors is





increasing. Farm management software companies are also uniquely placed to exploit new data analytics to value-add to 'other peoples' data, potentially at the expense of these 'other people' (producers). From personal contact with growers, this centralisation of data is a major concern and perceived to be a potential barrier to technology adoption.

Secondly, producer attitudes to increased automation and how new technologies fit into differing production systems is largely overlooked. The projected rise of robotics and the possible removal of a farm manager from the farm to a central control point is one potential example. How innovations are perceived by producers and how they are educated about them needs to be better understood. The development of frameworks, protocols, surveys and data analytics is needed to allow researchers and commercial entities to understand perceived benefits and risks from the end-users perspective. This knowledge must also be incorporated into the design of new innovations and services.

viii) Integration with other Agri-Innovations

Points *v* and *vi* have highlighted a future need for precision agriculturists to engage with economists and social scientist to properly address the social and environmental value (or cost) of PA. Increasing connections within the natural sciences and computer sciences is equally important. Sensing technologies in agriculture have largely relied on physical principles to date, often associated with mass measurements or the response of the crop or soil to some part of the electro-magnetic spectrum. Biosensing is not widely used to date. This often because of cost issues. The rapid increase in biomarker identification and the decreasing cost of the technology is making biosensing a reality. The development of rapid, molecular-based agri-diagnostic tools has the potential to change the quality and timeliness of information supplied to the grower (Gressel and Edwards, 2018). These molecular tools can provide very specific detail on the condition of the target plant, for example the level of multi-site herbicide resistance within a weed population or the type and level of micro-nutrient deficiency in a crop. However they are less effective at identifying where the weeds or the crop deficiency occurs in a field. To optimise their deployment, these agri-diagnostics need linking with field/farm-scale PA technologies. PA technologies are able to collect information over large areas and allow pattern detection in spatial crop production, however they tend to produce non-specific plant responses (e.g. weaker or stronger growth patterns, but not the reason why). Therefore linking agri-diagnostics with PA technologies will be mutually benefit to the application of both technologies. Figure 5.1 illustrates these potential interactions as well as the role that computer science/data analytics will play and the need for the information and knowledge gained to be used at multiple-scales of decision, e.g. for direct site-specific management decision on-farm, to farm level decisions on risk management and to regional and national scales to inform policy related to the productivity and protection of agri-ecosystems.

5.2 A brief comment on the role of 'Digital Agriculture' (or 'Smart Agriculture') in the evolution of Precision Agriculture

In Section 5.1 the increasingly level of 'connectivity' on farms and the need for on-going, and likely increased, interactions with the computer sciences was alluded to. The digital revolution is affecting all aspects of our daily lives, and agriculture is no exception. Digital Agriculture will precipitate some very disruptive changes in the food production and supply chains in the near future. It is a challenge





for PA researchers, and users of PA, to understand and to utilise Digital Agriculture innovations to improve spatio-temporal crop (and animal) management.

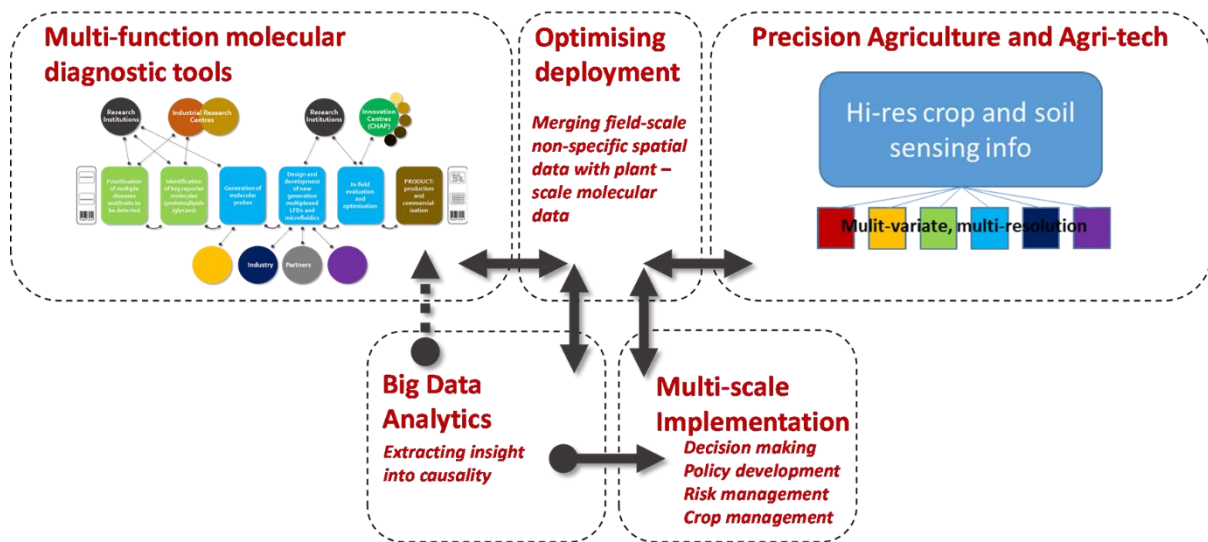


Figure 5.1 A conceptual illustration of how Precision Agriculture will intersect with molecular diagnostic tools, research science and social science domains to enable producers to make better decisions across all aspects of production, particularly in areas of crop health and quality.

Precision and Digital Agriculture are connected, and often Digital Agriculture is described in a similar way to PA; However these are slightly different concepts. As discussed in Section 2, PA is about better (higher resolution) decision-making. Digital Agriculture is still new, but it relates firstly to the collection and the connectivity of digital data structures. It should implicitly feed data and information into PA systems to improve them. However, on its own, Digital Agriculture is not a holistic decision support system. It is not concerned, for example, with non-digital data that could influence farm management. Its decision support derives directly from ICT applications. Digital Agriculture also has a much larger scope than PA. Digital Agriculture is equally concerned with non-spatial and non-temporal data structures. This is exemplified by the fact that PA is farm and production-centric while Digital Agriculture is concerned with ICT applications from farm to fork. Digital technologies in the supply chain will be a large part of the Digital Agriculture revolution, but may not necessarily be relevant to on-farm production management.

Interfacing the digital world with ‘real-world’ agriculture is a big challenge. Rural areas often lack the digital connectivity, via fixed and/or mobile networks (Mark et al., 2016), that is essential for Digital Agriculture (and preferable, though not critical for PA). The technical, as well as social aspects of building cyber-physical systems for agriculture remains a challenge. Unique cyber-physical solutions will be needed for agricultural enterprises (Caramihai and Dumitrache, 2015; Dumitrache et al., 2017). Inherent in this is the need for connectivity not just between a sensor and a database (or decision) but the need to form coherent ‘systems of agri-systems’ (Brewster et al., 2017; Moisescu et al., 2018). It will not be sufficient in the future to only provide a single PA service to a producer e.g. a precision nitrogen management service. Services will need to be interconnected i.e. how does my N plan





interact with variable crop protection control and with autonomous machinery? Demonstration and exemplar platforms, such as Le Mas Numerique in Montpellier (<https://lemasnumerique.agrotic.org/>), will play a key role in enabling these “systems of systems” to be developed via supported academic-industry partnerships. This is a major challenge for the agriculture industry globally.

5.3 Concluding remarks

Precision Agriculture is constantly evolving and will likely continue to do so at an even faster rate with the current digital revolution. It is however ultimately about making better decision and being able to justify those decisions. This must all come from a solid base of understanding the amount of spatial and temporal variation that occurs within production systems. It also requires pathways to simplify the available information to permit correct decisions to be made with confidence. Over the past 2 decades, I have researched and continue to conduct research in both of these areas to ensure that there is suitable knowledge available to promote further applications, particularly spatial applications. Advances in digital technologies and sensing systems are changing the way that data are collected and processed, but it does not change the underlying spatial structure and the fundamental knowledge. As data and information evolves, so too will the tools used to describe and analyse the data, but the underlying processes will be similar. It is important to note that the protocols and methods advocated here are not an end-point, just an intermediate point.

The methods developed have focussed on potential commercial applications. The main disappointment from this work is not a lack of recognition in the PA community, but rather a lack of translation into commercial services. A protocol to translate raw data into management units, which was first published in 2007, has only recently been actively incorporated into a PA service engine (miFarm[®], Precision Decisions, York, UK), despite the wide acknowledgement of the need for such a service. This is an indication of the disconnect between innovative research and commercial services in PA (as in Fig. 3.1). Governmental policies are trying to bridge this divide via funded research and development, with different countries employing different strategies. However, the socio-technical challenges of PA innovations, and not just the technical challenges, need to be addressed. PA innovations and services need co-design with researchers, service providers and end-users to be effectively commercialised. Ensuring that collaborations continue between the natural and social sciences in PA is a key objective for my future work.

The journey so far has been diverse, engaging, interesting and most of all enjoyable. The need for new approaches for better decisions will always exist in agriculture. It is not an exact science. However, the better that we can understand the variable environment in which crops grow, and the more effectively that we can respond to variability in a timely and spatial manner, the more sustainable our cropping systems will be. I hope to be able to contribute to this evolution in both academic and commercial circles in the future.





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