VG16009

Adoption of precision systems technology in vegetable production

Literature Review

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VG16009: Adoption of precision system technologies in vegetable production

Literature review on the available and emerging precision agriculture technologies for the Australian vegetable industry.

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Executive summary

This literature review outlines progress in the application of precision agriculture (PA) technologies to vegetable production systems. Despite decades of development and application of PA technologies in other agricultural industries, PA in the Australian vegetable industry is primarily limited to the adoption of tractor based guidance systems (e.g. autosteer). International and Australian research highlights the breadth of relevant PA technologies and specifically the potential for precision approaches in vegetable production.

The precision approaches reviewed here encompass the following technologies:

- remote and proximal sensors and sensing platforms
- applications of crop sensing
- soil sensing
- variable rate technologies
- yield monitoring
- sampling and ground-truthing

A range of sensors and platforms are available for crop sensing in vegetable systems. These include satellite, aerial, unmanned aerial vehicle (UAV) or ground based platforms. These can be categorised as either remote (i.e. the sensor is a considerable distance from the target object or area e.g. satellite, aerial or UAV) or proximal (i.e.in close proximity to the target object or area e.g. ground based). These all differ in terms of the spatial resolution of their associated imagery, ground coverage and deployability. These factors can determine which sensor is the most appropriate for any given situation and purpose in vegetable production. For example, satellite imagery, available as large blocks of 100 square kilometres at a minimum, is unlikely to be used for imagery of a single 4 ha broccoli field. Also, satellite imagery availability can be compromised by factors such as cloud cover and revisit times of individual satellites. The ability to access historical satellite captures and low resolution, freely available imagery may reduce the impact of these issues. Aerial or UAV captured imagery may be an option for the vegetable industry where very high resolutions over a smaller production area are required. Importantly, the accuracy and repeatability of UAV derived sensing products are still yet to be fully tested in vegetable production systems.

Crop sensing is undertaken for two primary purposes:

- Determining in-field variability for remedial management actions that aim to reduce crop or field variability and maximise yield
- Estimation of crop yield (yield forecasting) in advance of harvest.

Crop sensing data are presented as vegetation indices (e.g. normalised difference vegetation index (NDVI)), calculated from plant reflectance data at different band-widths of the light spectrum (e.g. near-infrared (NIR), visible spectrum (VIS)), depending on the sensor used.

Research literature highlights the various functions of crop sensing data. These include:

- Nutritional status
- Physiological status
- Disease detection
- Yield forecasting

Despite limited research in horticultural industries, there is extensive published literature on the relationship between crop reflectance and crop nutrient status. Nitrogen (N) is the most extensively investigated nutrient, with accurate prediction of N status in a range of crops using remotely sensed crop spectral data. While phosphorus and potassium are also key crop nutrients, they have not received as much research attention as nitrogen. However, the available studies have demonstrated accurate assessment of phosphorous (P) and potassium (K) status from crop sensing data. The success in establishing good predictions of nutrient status from crop sensing data in a range of crops (e.g. cotton, grains) suggests similar relationships could be developed for horticultural crops. There is some evidence that assessment of nutrient status requires multispectral or hyperspectral (primarily a research tool) sensor data, to obtain data from a greater number of wavelengths.

In terms of physiological status, water stress is the most widely investigated in numerous agricultural crops, although with limited application in horticulture. Research has identified specific regions of the spectrum that, in conjunction with spectral changes in VIS and NIR, can be used for pre-visual assessment of water stress. Similarly, the use of crop sensing for disease detection has been mostly limited to forestry species rather than horticulture. Multispectral, hyperspectral and thermal imagery have been applied to various crops (peanuts, opium poppy and avocadoes) to successfully identify disease and to discriminate between levels of severity. Analysis of the significant wavelengths and the optimal vegetation indices is required to understand reflectance variability in vegetable crops, and relate these to specific causal factors, before these techniques will be commercially applicable.

With many vegetable crops still hand-harvested, there are limited commercial options for yield mapping using machinery-based technologies. However, the use of crop sensing imagery provides significant opportunities for yield forecasting in vegetable crops. In addition to mapping predicted yield and identifying spatial variability, yield forecasting (if achievable from early season crop imagery), could provide valuable data for marketing as well as logistics planning for harvest labour, grading and packing. Although remote sensing has been used successfully in various broad acre crops to estimate yield, research on its application to vegetable crops has been limited. The potential of crop sensing imagery for predicting yield in vegetable crops is highlighted by the good prediction accuracies obtained by work in citrus, onion, potatoes and cabbage.

Yield prediction in vegetables from remotely sensed crop imagery can be done by volume estimation from image analysis or direct plant counts of readily identifiable units such as lettuce, broccoli, cauliflower and cabbage. For other crops, if relationships between plant biomass or spectral data and yield can be determined, these factors can be measured as a surrogate for yield. Due to the complexity of factors that contribute to yield, spectral data must be collected over multiple wavelengths (i.e. multispectral sensors must be used).

The most commonly implemented soil sensor available in agriculture is the electromagnetic induction (EMI) sensor used for EM38 mapping. This technology has been available for decades, but has not been widely adopted in vegetable or indeed most horticultural systems. EM38 maps depict spatial variability in clay content (soil texture), soil salts and soil moisture as indicated by differences in apparent electrical conductivity. While EM38 mapping indicates differences in these characteristics, it does not identify which of these characteristics is causing the change in electrical conductivity, so subsequent in-field sampling is required. In addition to understanding inherent soil types differences, EM38 data can be used to develop variable rate irrigation prescription maps and can identify areas of high salt concentration that may require management intervention. Other sensors such as Veris® technologies for soil pH and electrical conductivity mapping are increasingly being used.

Variable rate technologies (VRT) can be added to irrigators, spreaders, sprayers and seeders. VR applications represent a shift from uniform crop management to aligning crop management with variation in the field. Due to its past history of spatial data collection, adoption of VRT is most progressed in the grains industry (although still not widespread). The application of VRT's to vegetable systems is still developing with VR irrigation and fertiliser or soil amendment (lime and gypsum) being the key practices adopted to date. Use of VR is reliant on access to appropriate equipment (i.e. VR controlled spreaders, seeders and irrigation systems) as well as an understanding of spatial variability. Collection of the required data layers in vegetable systems is only just commencing. The magnitude, type, cause and distribution of variability are all factors that determine whether VR applications are a feasible management option.

Georeferenced yield maps, generated from yield monitors are primarily used to identify yield variability and inform management decisions for future crops. Yield data can be converted into profit and loss maps as decision support tools for managing variability. Currently, yield monitoring in vegetables is limited to machine-harvested crops and the authors' are aware of only a handful of yield monitors on vegetable harvesting equipment nationally, primarily in carrots, potatoes and tomatoes (processing). These have been adapted from other industries such as grains, cotton and viticulture, which have a longer history with these technologies. There are a range of commercially available sensors (mass, volume or vision), that with optimisation, could be adapted for other vegetable harvesting equipment such as for green beans and sweet corn.

The precision agriculture technologies outlined in this review have the potential to provide valuable data for vegetable production management. However, associated field sampling is required to understand what the data means in terms of the crops or the soil resource. Sampling programs for spatial data differ from traditional 'bulking for representative' sampling. When ground-truthing spatial data, the goal is to find out how different areas of fields or crops differ from each other. Sampling protocols reflect this through either grid (sampling per unit area e.g. 1 ha grids) or zonal sampling (sampling from zones identified from crop or soil imagery). Whilst out of the scope of this review, the analysis costs (ca. $150.00 per sample) for soils in Australia is proving to be a major impediment to more precise understanding and management of soil or crop variability.

In addition to commercially available technologies, there are emerging technologies that have the potential to provide significant benefit for vegetable production systems. Global Navigation Satellite Systems (GNSS) currently allow field equipment positioning to accuracies of $\pm$2cm horizontally and $\pm$4cm vertically. This level of accuracy will be required by autonomous 'driverless' machinery for accurate and reliable positioning in the field. Field robotics is a highly competitive and rapidly developing area of research with technologies such as LettuceBot, RIPPA™ (Robot for Intelligent Perception and Precision Application), AgBot II and Swarm Farm platforms becoming commercially available or in advanced development. These are designed to undertake simple management tasks and operate as field-based platforms for crop sensing.

This review has highlighted the significant potential for precision agriculture technologies in vegetable production, although current adoption of these technologies across the industry is negligible. Barriers to adoption identified from a survey of Queensland vegetable growers include:

- lack of knowledge and awareness of PA technology
- perceived high cost of equipment
- time required to learn how to use the technology, process, understand and apply the data
- return on investment (ROI)
- limited equipment currently on farm – would require turnover of equipment or access to contract services
- complexity of the technology available
- level of support required to address and adapt the technology to vegetables
- perception of PA as not profitable for vegetables

This review concludes with key recommendations and considerations collated from the literature and recent Australian studies as to how the Australian vegetable industry can progress the adoption of precision technologies.

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1 Introduction to Precision agriculture (PA)

Precision agriculture (PA) is a farming system approach based on identifying, measuring and managing inter and intra-field crop variability. According to Roberson (2000), the potential outcomes from incorporating precision agriculture technologies and methodologies into modern agricultural systems can be summarised as:

- increased production efficiency
- improved product quality
- improved efficiency of crop inputs (chemicals, fertiliser and seeds)
- energy optimisation, and,
- improved environmental stewardship.

PA technologies have been developing since the launch of the US NAVSTAR navigation satellites in the 1970s and 80s. Developments have accelerated over the last 30 years to where PA now encompasses:

- high accuracy GNSS (Global Navigation Satellite System) guidance
- electromagnetic soil mapping tools
- sensing technologies (e.g. hyperspectral, multispectral, proximal, remote, active and passive)
- rapid sampling and measuring systems
- a multitude of data processing software options
- variable rate (VR) technologies and
- geo-referenced yield mapping to help determine the success of PA interventions.

Many of the technologies associated with PA have been commercially available to Australian agriculture since the early 1990s. However, widespread adoption of PA approaches in the horticultural sector have been limited with the exception of machine guidance. The precision agriculture technologies and methodologies encompassed by this literature review include:

- crop biomass sensing technologies, platforms and applications
- yield monitoring
- variable rate technologies (soil and irrigation applications)
- soil mapping (e.g. EM38) and strategic soil sampling programs

1.1 Vegetable industry context

1.1.1 Distribution

The Australian vegetable industry encompasses a wide diversity of crops, business enterprise sizes and values and spans almost every climatic region in the country. The Hort Innovation publication, 'Australian Horticulture Statistics Handbook – Vegetables 2014/15' reports on 32 separate categories of vegetables (from artichoke to zucchini) while the Ausveg website (https://ausveg.com.au/) provides data on 34 discrete categories. Each source also provides an additional 'other' category for minor vegetables (Ausveg, 2017; Horticulture Innovation Australia [HIA], , 2016).[1]

Production occurs from the wet and semi-arid tropics of north Queensland and the Northern Territory to the cool temperate regions of Tasmania and the coasts of Western Australia. Production areas tend to be concentrated in the coastal hinterlands, although there are exceptions of inland production in all eastern States. The coastal hinterland influence is also apparent in Western Australia, with a few discrete production regions spread from the south-west to the north of the State. **Figure 1** indicates areas of vegetable production in Australia.

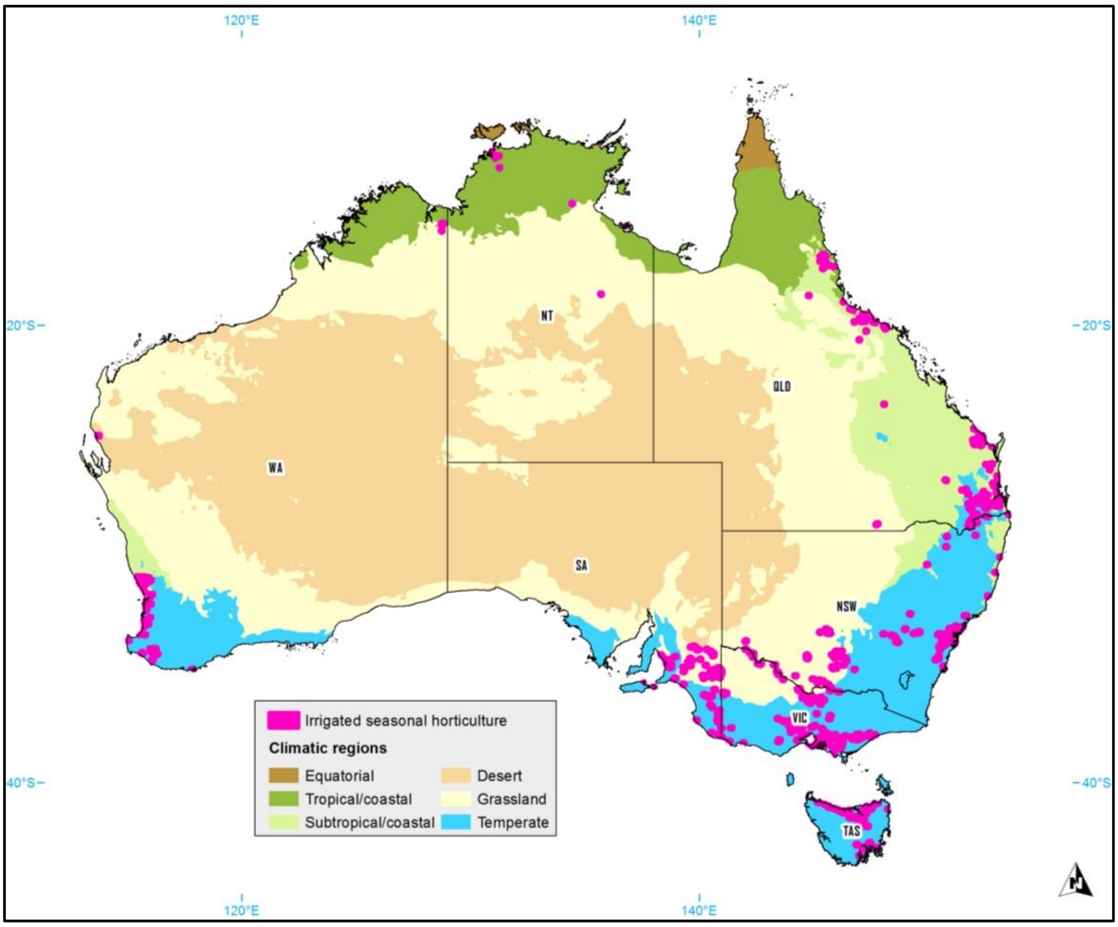

Figure 1. Vegetable production areas in Australia, showing their distribution with respect to climatic regions. *Source*: Australian Bureau of Agricultural and Resource Economics and Sciences (2010); Bureau of Meteorology (2017).

[1] In the Hort Innovation context, the vegetable industry is deemed to be comprised of those industries that pay into the Vegetable levy. This categorisation excludes five industries that sit outside the vegetable levy (potato, onion, tomato, mushroom and sweetpotato), four of which are nationally significant in terms of one or more of the following parameters – production, area and gross value. Except where stated otherwise, all industries have been included in industry overview data in order to set the national context, and to highlight the inevitable overlaps of precision agriculture technology and its applications across industries.

1.1.2 Key statistics

Economic value

In 2014-15, the Australian vegetable industry had a gross value of $3.35 billion, which was produced from over 114,000 ha by some 4,500 growers. **Table 1** shows data on those parameters for the period 2009-10 to 2014-15 (Ausveg, 2017). These data show that over the six years:

- the production area expanded slightly then contracted to finish 6% below 2009-10 figures
- gross value rose by 24% then declined to finish 11% below 2009-10 figures
- grower numbers dropped by 24% below 2009-10 figures.

Table 1. Overall vegetable industry statistics for the period 2009-10 to 2014-15.

Vegetables	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15
Area planted (ha)	121,686	124,615	126,411	125,677	126,092	114,158
Gross value ($m)	3,023	3,338	3,339	3,770	3,510	3,350
Number of growers	5,956	5,753	6,018	5,611	5,332	4,527

Source: (Ausveg, 2017).

As is the case for most agricultural industries, it is likely that grower numbers will continue to decline, area will remain reasonably stable, and gross value may gradually increase. These trends point to the need for increased productivity from individual enterprises, some of which will come from economies of scale, and some from the application of technologies such as those related to precision agriculture. **Table 2** shows the top ten ranking vegetable crops based on production (t), gross value ($m) and area of production (ha) for 2014-15.

Table 2. Top ten ranking vegetable crops for each of three key industry statistics [A, B].

RANK	PRODUCTION (t)		GROSS VALUE ($M)		AREA (ha)	
1	Potato	1,154,503	Potato	618.0	Potato	29,414
2	Tomato	570,000	Tomato	570.0	Tomato	7,700
3	Onion	314,934	Leafy salad	315.3	Head lettuce	6,906
4	Carrot	261,057	Onion	240.2	Broccoli	6,276
5	Head lettuce	139,531	Head lettuce	168.0	Pumpkin	6,257
6	Pumpkin	118,495	Carrot	144.7	Bean	6,210
7	Leafy salad	54,579	Bean	124.4	Onion	5,986
8	Broccoli	50,091	Capsicum	114.8	Carrot	4,623
9	Capsicum	43,732	Broccoli	97.0	Capsicum	1,950
10	Bean	34,045	Pumpkin	81.2	Cucumber	733

[A] *Mushroom data has been excluded from this table in order to focus only on field-based crops for the precision agriculture context.*
[B] *Tomato statistics are an estimate based on a range of industry sources as ABS data are known to be incorrect for this industry. Sources: Ausveg (2017); HIA (2016).*

Area

Vegetable farms tend to be small compared to other agricultural enterprises. The most recent data available (2009-10) shows that 64% of farms were smaller than 50 ha, 75% were smaller than 100 ha and 95% were smaller than 500 ha (Ausveg, 2017). The only category to show expansion was farms in the size range 2,500 – 25,000 ha, which probably reflects consolidation of farms through retraction in grower numbers.

Diversity

Despite the huge diversity of vegetable crops produced, very few growers produce more than a few products. The most recent available data (2008-09) shows that just over 50% of growers produce only one vegetable crop, 75% produce up to two and 95% produce five or fewer crops (Ausveg, 2017). Only 5% produce six or more crops, and less than 1% are in the highly diverse group that produce 10 or more crops. These data suggest specialisation amongst growers. Over the period 2005-06, the number of growers focusing on just one crop increased by 12%. All other categories up to and including eight crops fell in percentage terms. There was fluctuation in the number of growers producing nine or more crops, but in reality, the number of growers represented in this cohort is a small portion of the total.

Regardless of whether or not a vegetable grower produces one crop or is highly diversified, most enterprises would be classified as ‘mixed’. It is often the case that a single vegetable crop may be produced alongside other farming enterprises, such as grain cropping or livestock, or in the case of high crop diversification, a grower may produce only vegetables, but of many different types. The latter situation is most likely to occur in the market garden sector on relatively small farms close to major population centres.

State distribution

Data from 2005-06 to 2011-12 show that NSW and QLD have the highest number of enterprises, representing 50% of the national total (at 25% each), while Vic has just short of 20%. WA, SA and Tas are around 10% each. NT and ACT represent less than 1% of the national total number of enterprises (Ausveg, 2017).

1.1.3 Industry trends and implications for precision agriculture adoption

There is a gradual trend towards consolidation and specialisation in the vegetable industry. In broad terms, this means larger farms, economies of scale and a focus on fewer crops in any given enterprise. If industry size and critical mass of the potential market are indicators of where the precision agriculture focus should be in the vegetable sector, these trends would suggest that the potato, tomato and onion industries may be early targets. However, the vegetable industry is probably not that simple or predictable. What is more important is the capacity to show value from the data collected and techniques employed that is relevant to growers who are interested in investing in PA technologies. Further, while a little over half of growers produce more than one crop, there are many aspects of PA that can be applied to a range of crops – e.g. EM38, nutrient and drainage mapping, VR application of inputs etc. When it comes down to crop specific data and technologies, such as spectral imaging and yield mapping, it is likely that industry size, as measured by number of growers and/or area will be more important indicators of technology development and adoption focus.

1.2 Precision Agriculture in Australia – other industries

1.2.1 Grain industry

Australia's largest agricultural industry by area of production, is grains. This industry has experienced a long history of PA development and adoption with a range of technologies (e.g. crop sensing, yield monitoring, VR) developed locally and internationally, provided as standard components. Australia has contributed significantly to the development of PA technologies, being the origin of Beeline, the first GNSS guidance system for tractors. Research on the application of PA in the grains industry began in the 1990s (Bramley and Trengove, 2013) and has continued since then with investigation of many aspects including yield, protein, soil and weed mapping, VR nutrient application and data processing and management (Florin*, et al.*, 2011; McBratney*, et al.*, 2009; Rew*, et al.*, 2001; Rossel*, et al.*, 2007; Sun*, et al.*, 2013; Whelan*, et al.*, 2009).

The first technology commercially adopted was GNSS guidance and auto-steer, with recent data suggesting adoption rates of 80 - 90% (Bramley and Trengove, 2013; Llewellyn and Ouzman, 2014). While guidance and auto-steer does not make PA, it is a necessary first step to provide the precision and geo-referencing required by other PA technologies, and it provides a platform and technology familiarity on which users can build the expansion of their PA investments. GNSS guidance is also critical for the implementation of controlled traffic farming (CTF), which is an important element of high accuracy PA applications.

A survey of grain growers in the southern and western growing regions found significant regional differences in the uptake of PA technologies and practices, with the presence of supportive and interested agronomic advisors having a strong influence on the decision to adopt (Llewellyn and Ouzman, 2014). This same survey shows that while about 60% of growers have a yield monitor, less than half of them collect yield mapping data. Similarly, 35% have VR fertiliser application equipment, but only half of those use it. The use of soil mapping and crop imagery remains low (15%), although it is far more likely to be used by growers who are also using VR technology and yield mapping. This low level of adoption may be partially explained by the fact that most growers expect to achieve profit increases of only about 10% through the adoption of PA, particularly in the case of VRT (Llewellyn and Ouzman, 2014).

Case study analyses of a number of grain-growing farms across all regions found that the highest profit return of any PA technology or practice was attributed to the adoption of controlled traffic farming (CTF), which makes use of the precision provided by Real-Time Kinematic (RTK) GNSS guidance and auto-steer (GRDC). The economic advantages of CTF are well-established, and include improved yield, water and nitrogen use efficiency, reduced crop variability, time and energy use in field operations, and capital and operating cost of machinery. (Chamen, 2008; Dickson and Ritchie, 1993; McPhee*, et al.*, 1995a; McPhee*, et al.*, 1995b; Spoor*, et al.*, 1988; Tullberg, 2000; Wang*, et al.*, 2009). By comparison, many PA applications are single-focus (e.g. VR fertiliser application) and do not generally generate system-wide change.

1.2.2 Cane

PA interest in the cane industry began with attempts to develop a yield monitor in the late 1990s. However, it was the late 2000s before any significant activity occurred (Bramley and Trengove, 2013). While soil mapping (e.g. EM38, topography etc.) has become more widely used as a PA practice in the cane industry, there has been considerable focus on the issue of yield mapping. It has been considered by researchers as quite difficult to develop yield monitoring sensors that are reliable and provided meaningful results (Bramley and Jensen, 2014; Bramley*, et al.*, 2013; Bramley and Quabba, 2002; Jensen*, et al.*, 2013). Yield forecasting from satellite imagery however, has shown great promise at the regional level (Rahman and Robson, 2016; Robson, *et al.*, 2016a) and is now provided as annual tool to all Australian growing regions.

1.2.3 Cotton

Research into PA in Australian cotton production commenced in the late 1990s (Stewart, *et al.*, 2005). Cotton yield monitors first appeared in the industry in 1997 and have evolved since then. As irrigation is important in many cotton growing regions, PA efforts have been directed at addressing yield variability and irrigation scheduling and monitoring. Figures are not available for adoption of PA practices in the cotton industry, but it is suggested that they are similar to those observed in the grains industry.

1.3 Previous Australian work targeting PA in horticulture and specific veg systems work

The earliest research efforts in the application of precision technologies to non-broad acre crops were in the wine industry. This has encompassed:

- Remote sensing for grape yield and quality based on measurement of canopy descriptors such as grapevine shape, size and vigour (Hall, *et al.*, 2002)
- Assessment of spatial variability (Bramley, 2005; Bramley and Hamilton, 2004; Bramley, *et al.*, 2011a).
- Identification of zones for selective harvest through either direct or surrogate measures of grape quality (Bramley, *et al.*, 2011b),
- Yield monitoring (Bramley and Trengove, 2013)
- EM38 soil mapping for block design and planting segregation based on soil characteristics.

The bulk of Australian research related to PA techniques and technologies in horticulture has occurred in perennial horticulture, with a focus on data collection through imagery. The portfolio of work includes:

- collection of data to locate and identify individual trees for data validation and orchard inventory purposes (Bargoti, *et al.*, 2016; Robson, *et al.*, 2016b; Underwood, *et al.*, 2016)
- measurement of tree health and nitrogen status (O'Connell, *et al.*, 2016; Perry, *et al.*, 2016)
- yield and quality estimation to assist in planning, harvest, packing and marketing including vision systems for fruit identification and characterisation (Hung, *et al.*, 2016; Payne, *et al.*, 2016; Robson, *et al.*, 2017; Robson, *et al.*, 2016b)
- the automation of data collection and interpretation (Bargoti, *et al.*, 2016; Hung, *et al.*, 2016; Patten, *et al.*, 2016; Underwood, *et al.*, 2016)

There is limited reported evidence that PA technologies have been used to facilitate VR input management, although this is a possible pathway to management of within-orchard variation.

The uptake of PA in the national vegetable industry is still in its infancy with some initial scoping and research studies:

- scoping study gap analysis for the adoption of PA in vegetable production (Taylor, *et al.*, 2005) including the development and use of sensors to measure in-field crop variability and the development and use of yield mapping technologies for both quantity and quality.
- investigation of spatial variation in sweet corn highlighting the lack of yield monitoring technology as a limitation to the adoption of PA approaches (Taylor, *et al.*, 2008).
- a research study in Tasmania investigating the potential of soil sensor-based real-time VR irrigation to improve water use efficiency and reduce energy costs and environmental impact (Lambert, *et al.*, 2012). Sensor network issues were problematic in establishing successful real-time irrigator control.

- recommendations for a significant focus on robotics and automation arising from workshop series (Mulcahy, 2010). This has since been pursued through the development of prototype robots that are currently equipped largely for data capture but which could be adapted for differential management purposes (Anonymous, 2015).
- research study to understand the spatial variability in Tasmanian potato crops, with a view to improving yield and production efficiency (Whelan and Mulcahy, 2016) including zoned soil and elevation maps for VR management, yield monitoring of potato harvesters, aerial NDVI imagery correlation with soil variability early season, and with yield late season. Yield mapping identified that yield variability in potato crops can be over three-fold on uniformly managed paddocks. VR irrigation and precision drainage were identified as two of the more important PA technologies that would provide benefits in potato production.
- Queensland Department of Agriculture and Fisheries study focused on assisting vegetable growers to optimise and evaluate PA technologies and services, ranging from soil mapping and crop sensing imagery to VR applications and yield monitoring and mapping (Limpus*, et al.*, 2016). As a result of the project, a number of growers have continued with various aspects of PA, including imagery to guide crop management decisions, yield monitoring and VR fertiliser application and irrigation.
- A similar project in Tasmania worked with six growers over a range of growing environments and enterprises to identify key issues associated with PA implementation, clarification of benefits and raise general awareness of available PA technologies and practices.

2 Remote and proximal sensing

Sensing falls into two categories: remote and proximal, where the main difference is the distance between the sensor and the object.

- **Remote sensing** (RS) refers to the acquisition of information from a target without making physical contact. In the sense of precision agriculture, remotely sensed data includes that which is collected at a distance from a target i.e. satellite, airborne, UAV etc. The acquisition of remotely sensed data can be divided into 4 types of resolution as described in section 2.3. Globally, remote sensing, or Earth observation, has been evolving since the 1970's following the launch of satellites such as Landsat. RS is currently experiencing unprecedented growth in research and development due to its ability to provide reliable, detailed and timely information about the physical, chemical, biological and geometrical properties of the Earth. This growth has also coincided with a boom of new technologies such as very high resolution satellites, UAVs and micro-satellite constellations, as well as the development of simple to use, freely available, interactive information delivery platforms such as Google Earth. Agriculture has been very much at the forefront of the current remote sensing boom, partly due to the mining industry downturn and also due to the increased interest in the information and technologies that can improve on-farm production, reduce crop inputs, labor costs and off-site impacts (Homolová*, et al.*, 2013).

- **Proximal sensing** involves the sensing of an object at close proximity (i.e. up to few metres). As proximal data is generally a discrete data point collected over a small area, some interpolation is required to derive a continuous data layer and this is generally achieved by the simultaneous collection of a spatial reference from a high precision GPS system i.e. differential of GNSS. Interest in proximal sensing technologies has accelerated with the advent of PA. Examples of proximal sensing include the use of hyperspectral reflectance-based sensors for all kind of biochemical, physiological and biophysical analysis (Suarez*, et al.*, 2016), grid sampling of soils for nutrient analysis, and held or vehicle-mounted technologies such as EM38 soil mapping and crop imagery sensors, all of which are widely used commercially. Others include technologies that engage with the soil to measure soil characteristics (http://veristech.com). Yield mapping using load cells is strictly proximal sensing (i.e. weighing in physical contact), and non-contact micro-wave or light sensors are also considered to be proximal sensors.

For the purposes of this review

Remote sensing *is considered to involve a sensor situated a considerable distance from the sensed object – i.e. flying height of an unmanned aerial vehicle or more, while* ***Proximal sensing*** *is considered to be sensing that is in close proximity to the sensed object, with or without physical contact with the object (e.g. load cell yield mapping, ground-rig mounted crop imaging sensors and similar).*

2.1 Sensors

Spectral sensors can be further categorized based on the type of radiation required to illuminate a target (i.e. passive or active). This section provides a brief overview of each of these technologies as well as their advantages and potential limitations.

2.1.1 Passive sensors

A 'passive' sensor measures the amount of solar radiation a target reflects, absorbs or emits. Most satellite, aerial and UAV platforms rely on passive sensing (i.e. illumination provided by the sun) and therefore can only be used during daylight hours, and skies that are predominantly cloud free. More information about passive sensors is available in Section 3.

2.1.2 Active sensors

Active sensors are not reliant on solar radiation as they illuminate a target with their own light source. They therefore can be operated at night or under cloudy conditions, e.g. tractor mounted GreenSeeker NDVI sensors. Radar, LiDAR and many proximal sensors fall into this category.

The most commonly used active 'proximal' sensors for agricultural applications are the Holland Scientific Crop Circle™ 470 (Holland Scientific, Lincoln NE USA) (**Figure 2**A) and the Trimble Green Seeker Hand Held (GSHH) (NTech Industries, Ukiah, CA, USA) (**Figure 2**B). Refer to Appendix 11.1 for more details.

There are a number of additional active sensors available on the market such as:

- Yara N-Sensor™ ALS[2])
- OptRX[3])
- Trimble® WeedSeeker ®[4]
- Trimble® GreenSeeker®[5]

While the principles of these sensors are similar, there are differences in the technical setup of each such as the electromagnetic wavelengths measured (and subsequent vegetation indices), viewing angle and sensor to crop distances.

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2 http://www.yara.com.au/crop-nutrition/tools-and-services/n-sensor/
3 http://www.agleader.com/blog/what-is-optrx/
4 https://agriculture.trimble.com/precision-ag/products/weedseeker/
5 https://agriculture.trimble.com/precision-ag/products/greenseeker/

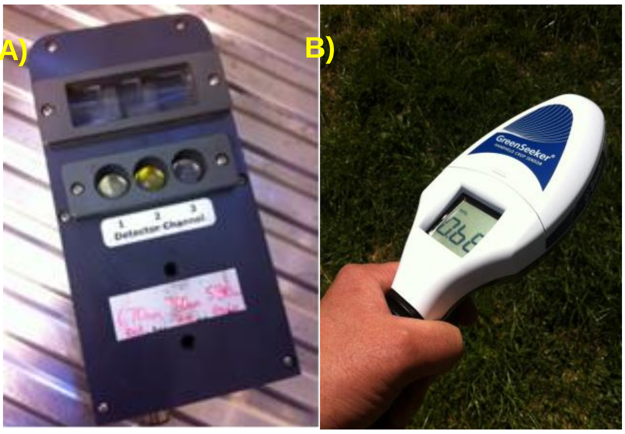

Figure 2. Examples of proximal and active systems[6]. A) CropCircleTM ACS-470; B) GreenSeeker Hand held (GSHH).

Limpus*, et al.* (2016) installed GreenSeekers in vegetable production systems and reported on their use in detecting spatial variability due to 'cut and fill' land levelling activities (**Figure 3**A) and the detection of Fusarium in tomatoes prior to plants appearing symptomatic (**Figure 3**B). The GreenSeeker is generally mounted on a tractor or spray rig allowing for multiple in-crop passes and real time viewing of variability in the cab (**Figure 4**). Similarly to the GSHH, NDVI is the only vegetation index that can be derived from the tractor mounted GreenSeeker and data requires manual downloading to be processed.

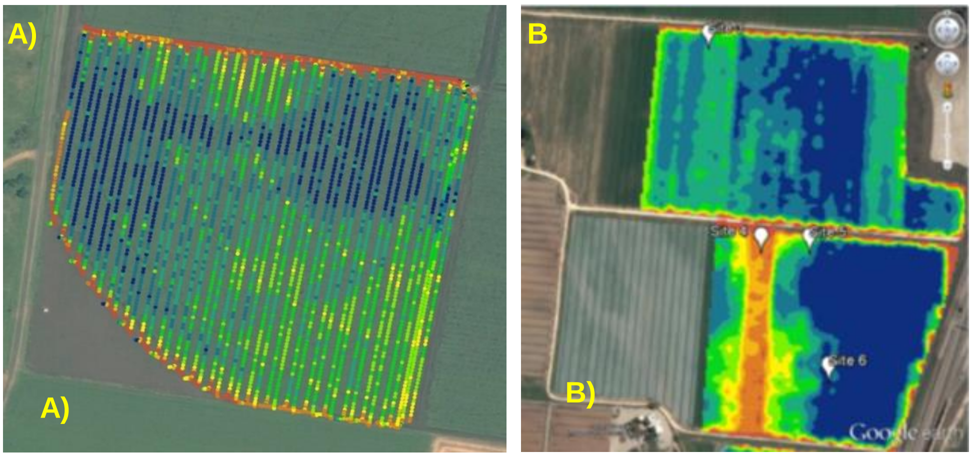

Figure 3. GreenSeeker® spatial mapping of A) carrot biomass variability where blue is higher biomass and green/yellow is lower biomass and B) Fusarium in tomatoes. *Source*: Limpus*, et al.* (2016)

[6] Photographs supplied by PARG-UNE

Figure 4. Greenseeker operation. A) tractor-mounted GreenSeeker® and B) real time display of crop sensing data.*Source*: Limpus*, et al.* (2016)

Spaceborne radar

Synthetic Aperture Radar (SAR) systems (i.e. radar) transmit energy towards the surface and record the variable strength and phase of the "backscattered" return signal. As radar is highly sensitive to texture and moisture, it offers an alternative technology for viewing crops, and estimating biomass and soil moisture (**Figure 5**).

LiDAR sensors

LiDAR (Light Detection and Ranging) is a laser-based technology that provides accurate structural information about a target by measuring the distance between the object and the instrument. The laser produces a point cloud that identifies the position of each point in terms of x, y, and z coordinates. As such, it is used to monitor changes in landscapes, topography, erosion, canopies etc. LiDAR measurements can be obtained from both on-ground (Terrestrial laser scanners (TLS)) and airborne sensors (Airborne laser scanners (ALS) (Tilly*, et al.*, 2014). ALS is more suited for the stratified imaging of the upper canopy, whilst TLS is more appropriate for measuring lower canopy without canopy stratification (Hilker*, et al.*, 2010) (**Figure 6**).

Although LiDAR technologies have the capacity to accurately measure the architectural parameters of a plant and potentially plant health (Friedli*, et al.*, 2016), more research and development is required to support their integration into agriculture. Currently, the technology is expensive, not practical for agricultural deployment, and produces large data sets that require specialist data interrogation and software.

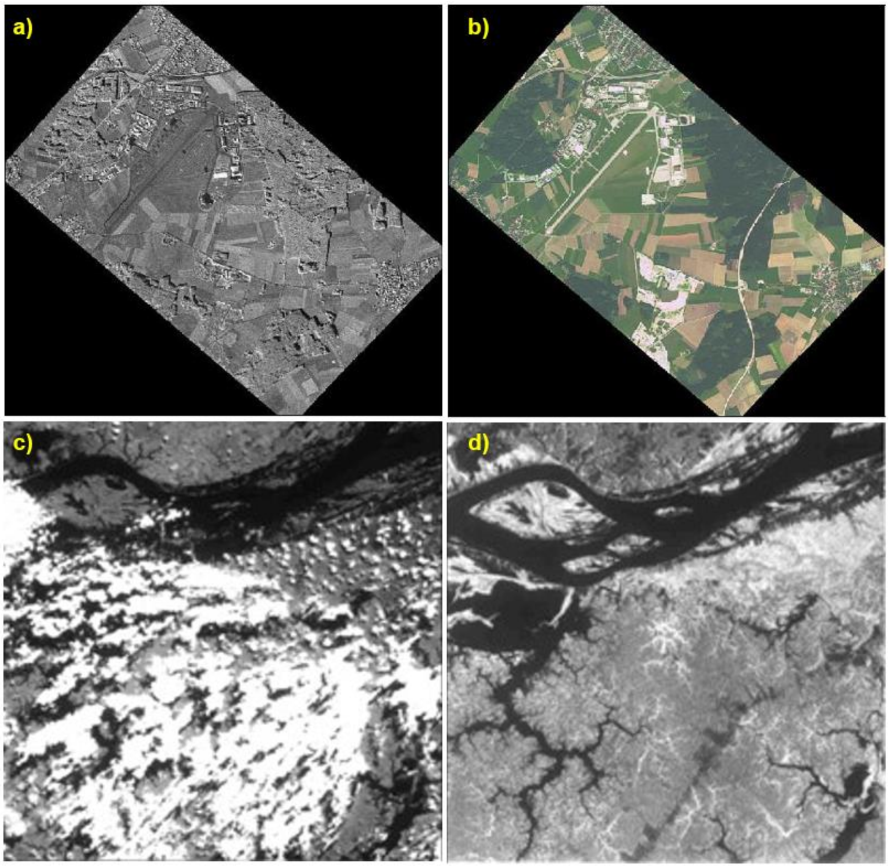

Figure 5. Satellite radar and multispectral image[7]. a) X-band SAR image (radar); b) RGB multispectral image; c) JERS-1 radar image; d) JERS-1 red band (optical band). Note the differences in texture of the radar image and the insensitivity to cloud cover.

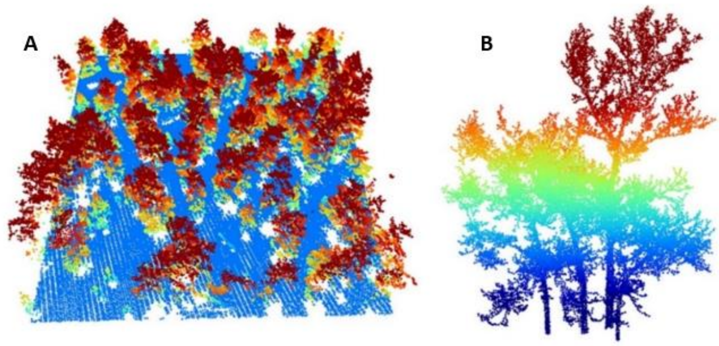

Figure 6. Comparison of TLS and ALS. A) ALS's point cloud and B) TLS's point cloud. Note the capabilities of ALS to provide location and height while TLS provides more detail information at a branch level (angle, size and length). *Source*: Tao*, et al.* (2015).

[7] https://directory.eoportal.org/web/eoportal/satellite-missions/i/iss-urthecast#CuAKL1282Herb
http://slideplayer.com/slide/6379936/

2.2 Sensing platforms

Sensors can be mounted on a range of platforms e.g. tractor, satellite, unmanned aerial vehicle (See Figure 7) and depending on whether it is a remote or proximal sensor, the characteristics of the platform play a major role on how efficiently and accurately the object can be observed (Toth and Jóźków, 2016). For more detail see 11.4 Appendix 4 which summarises typical platform characteristics. This includes highlighting differences in spatial resolution, ground coverage, deployability etc.

2.2.1 Satellite platforms

There are currently many commercial satellites that can provide imagery relevant to agricultural and horticultural applications. These satellites, as listed in Appendix 2, offer a range of spatial, spectral, radiometric and temporal resolutions.

Selection of the most appropriate satellite platform is dictated by the desired application. Worldview (WV)-2 and Worldview-3 satellites are optimal for the development of specific algorithms, particularly when calibrated against replicated field experiments. Both offer very high spatial resolution (up to 31 cm) as well as high spectral resolution (up to 16 bands). However, the cost of imagery is relatively high depending on the product required. The minimum purchase area for a WV image is 100km^2. For regional mapping, with the capacity to additionally provide derived products at the individual crop level, SPOT, RapidEye and Sentinel imagery are all suitable. SPOT6 and 7 offer 6m spatial resolution and 4 spectral bands at under $US1.50 per km^2, whilst RapidEye provides 5m imagery with inclusion of a red-edge band which is optimal for mapping foliar nitrogen (approx. $US1.30 per km^2). Sentinel offers slightly lower spatial resolution (10m for 4-band Blue, Green and Red and NIR) but is freely available to the public.

Sensing Platforms

Satellite

- *offers large coverage (10 km)*
- *Repeat rate in days*
- *Wide range of spatial resolution from 0.3-300 m*
- *Spatial accuracy of 1-3 m*

Airborne

- *Medium ground coverage (1 km)*
- *Repeat rate of hours*
- *Spatial resolution 5-25 cm*
- *Spatial accuracy 5-10 cm*

UAV

- *small ground coverage (50 m)*
- *Repeat rate in minutes*
- *Spatial resolution 1-5 cm*
- *Spatial accuracy 1-25 cm*
- *Easy to deploy*

Ground based

- *small ground coverage (10 m)*
- *Repeat in crop as desired*
- *Live to cab*
- *Spatial resolution 1-5 cm*
- *Spatial accuracy 3-50 cm*

The choice of platform depends on the application for which imagery is being acquired and subsequently the resolution, ground coverage, budget etc required.

More details on platform characteristics in Appendix 11.4.

2.2.2 Manned Airborne platforms

Airborne platforms e.g. light aircraft were the primary source of geospatial information until the introduction of commercial satellites. With new developments, increased spatial resolution and shorter revisit times of satellites, the difference between airborne and spaceborne platforms is decreasing significantly.

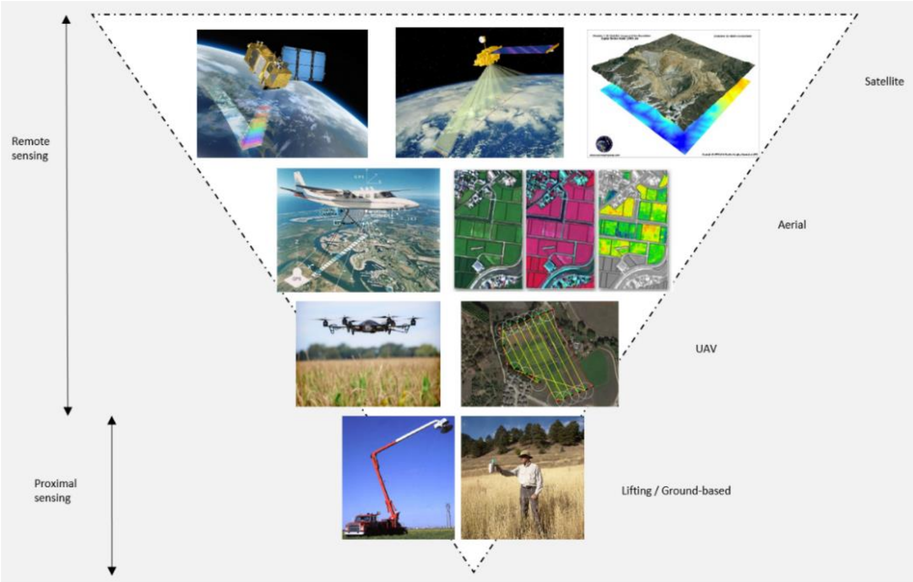

Figure 7. Crop sensing platforms.

2.2.3 Unmanned aerial vehicles platforms

Unmanned aerial vehicles or drones have gained rapid popularity in recent times due to their apparent simple operation, ability to capture extremely high resolution imagery (2 cm), ease of on-farm deployment, rapid turnaround from image capture to image viewing, general low cost and availability. UAVs are a significant advancement in the evolution of remote sensing platforms, as they have the capacity to carry high precision optical camera systems (including multispectral, NIR and LiDAR sensors). Miniature fixed-wing airplanes, quadcopters and other multi-bladed small helicopters are among the most commonly used UAV platforms costing anywhere between $US1,500 to over $US25,000 (after being fitted with sensors) (Nixon, 2014). Fixed winged UAVs generally have a longer flight time and include AgEagle RAPID[8], PrecisionHawk Lancaster[9] and SenseFly eBee SQ[10], whilst multi-rotor (quadcopters) drones such as Phantom 4 PRO and Matrice series platforms (DJI) are more suitable for scouting, spotting and detailed surveying tasks (**Figure 8**) .Quadcopters are better suited to capturing higher spatial resolution imagery as they can fly at a lower heights and slower speeds. These UAVs are commonly equipped with multispectral sensors that can derive NDVI.

UAVs have demonstrated their usefulness for identifying crop variability, weed detection, targeted spray applications[11], release of insect biocontrol agents and monitoring of livestock and water points. However, in most cases the commercialisation of UAV applications has come well before the

8 http://ageagle.com/
9 http://www.precisionhawk.com/lancaster
10 https://www.sensefly.com/drones/ebee-sq.html
11 http://onlinelibrary.wiley.com/doi/10.1111/j.1365-3180.2010.00829.x/full

appropriate scientific research has been undertaken. Much research is needed to develop specific crop parameter algorithms before UAV imagery is accepted as an accurate tool for agricultural monitoring. This would include a better understanding of optimal flying speed, height, direction (across or along planted rows), influence of solar elevation and shading, overlap of images, calibration and processing methods. Although commercial software is available for processing UAV imagery, many questions remain regarding the accuracy of the derived products (Planet stories, 2016).

Figure 8. AgEagle RAPID[12] flying over the field (left), Phantom 4 PRO11[12] (centre) and multir-otor UAV sensing sweet corn[13] (right).

Coinciding with concerns of the scientific integrity of UAV imagery is the uncertainty of legal regulations around the safe operation of UAVs in Australia. As it currently stands the Civil Aviation Safety Authority requires a "clear visual line of flight", which limits the flying distance of the UAV from the operator. Practically, this limits the use of UAVs over broad acre crops as well as over highly undulating tree crop environments. Due to power constraints, UAVs are also limited by flying time (generally around 30 minutes). Again, this questions the usefulness of UAVs over large areas, plus increases operational costs for multiple batteries and time delays in image acquisition (Planet stories, 2016).

Sensors for UAV platforms

Coinciding with the rapid evolution of UAVs is the development of suitable cameras and sensors for mounting under the platform. Some of the most popular cameras include Sony QX1[14] (high precision VIS image) and the multispectral sensors RedEdge[15] and Parrot Sequia[16] (both by MicaSense) (**Figure 9**). Low cost image processing software, such as Pix4D[17] and DroneDeploy[18], have been developed and adopted commercially to process UAV imagery.

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12 http://bestdroneforthejob.com/drone-buying-guides/agriculture-drone-buyers-guide/

13 O'Halloran, J. and Parker, N. (2016). *Potential applications of Unmanned Aerial Vehicle multispectral imagery in vegetables: Agri-Science Queensland Innovation Opportunity*. Retrieved from Queensland, Australia:

14 https://www.sony.co.uk/electronics/interchangeable-lens-cameras/ilce-qx1-body-kit

15 https://www.micasense.com/rededge/

16 https://www.micasense.com/parrotsequoia/

17 https://pix4d.com/

18 https://www.dronedeploy.com/

Figure 9. Visible and multispectral cameras [14,19]. From left to right: Sony QX1, RedEdge and Parrot Sequia.

2.2.4 Lifting/ground-based platforms

Lifting and ground based platforms encompasses handheld hyperspectral sensors, yield monitors and other sensing systems mounted in, for example, tractors, harvesters and sprayers. These type of platforms carry sensors that provide discrete information requiring GNSS data to geo-reference the recorded information.

2.3 Resolution

An important consideration of remote and proximal sensing is the resolution of the data obtained. Resolution can be segregated into four classes as shown in **Figure 10**.

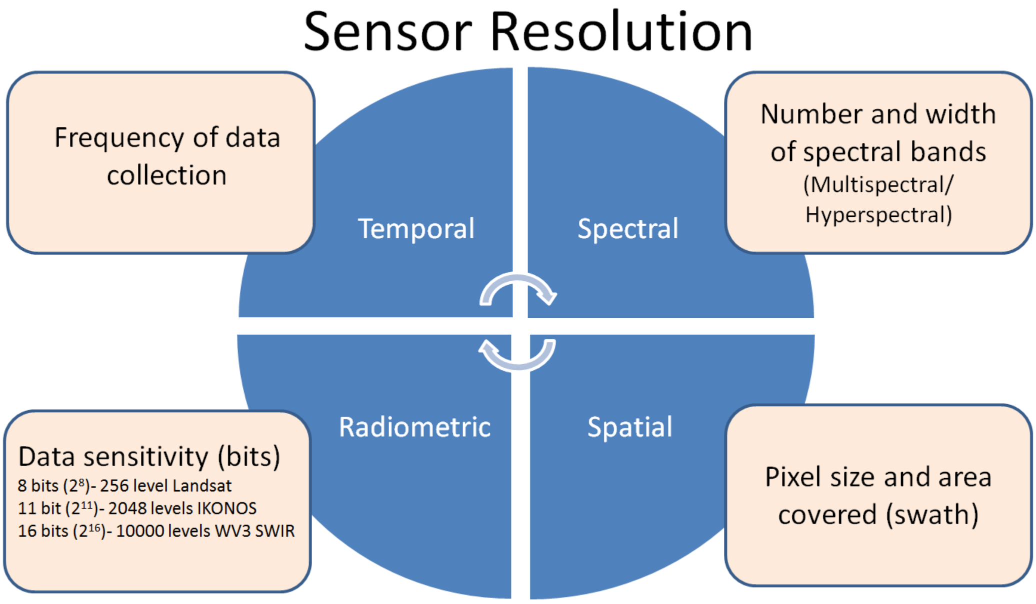

Figure 10. Four classes of sensor resolutions: spectral, spatial, temporal and radiometric.

It is essential to have some understanding of the four resolution parameters when developing remotely sensed applications for agriculture as the relative importance of each of these depends on the purpose and application of the imagery. For example, if a grower wanted to monitor daily crop

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[19] https://www.micasense.com

water stress at the individual field level (i.e. for irrigation management), they would require multispectral, high temporal resolution imagery with a low area of coverage (i.e. calibrated UAV imagery). Alternatively, if an industry body wanted to map annual industry-wide production then SPOT or Sentinel imagery would be appropriate (lower resolution, larger coverage area).

Table 3. Classes of resolution and characteristics.

Spectral	Spatial
• Refers to the number and width of wavelengths recorded by the sensor (**Figure** 11). • Multispectral sensors provide up to 20 spectral bands with wide bandwidths • Multispectral sensors commercially available • Hyperspectral sensors can measure thousands of bands of data in narrow bandwidths. • Hyperspectral sensors are still primarily a research tool	• Refers to the pixel size of the image, with smaller pixels producing higher spatial resolution. • Higher spatial resolution provides greater image clarity and capacity to undertake intensive image analysis (**Figure 12**). • Commercial satellites provide spatial resolutions that range from 250 m MODIS (Moderate-resolution Imaging Spectroradiometer) (bands 1 - 2) to 31 cm Worldview-3 (panchromatic band). • Aerial imagery acquired from an airplane or UAV can achieve far greater spatial resolution but the area covered is far less than that provided by satellite platforms. This can have an effect on cost per hectare (Planet stories, 2016; Xue and Su, 2017).
Temporal	**Radiometric**
• Refers to how often data is collected. • Temporal resolution is less of an issue for ground based sensors as data can be collected as often as required. • Satellite imagery is limited by their period of orbit and can only be acquired when the sensor is over the target region. • Temporal resolution of satellite varies based on the number of satellites in the constellation, height of orbit and demand on imagery products.	• Refers to the actual information provided in each pixel, i.e. the level of sensitivity provided by the data or how well the differences in brightness in an image can be perceived. • A sensor providing an 8 bits image would be considered as having a low radiometric resolution (a data range of 0-255 grey values), whilst a sensor that provides 14 bit data (e.g. Worldview-3 SWIR) would be considered as having a high radiometric resolution (a data range of 0-16,384) (SEOS Project, 2018). • Higher radiometric resolution provides better capabilities to measure small differences in reflected or emitted radiation and it provides a larger volume of measured data.

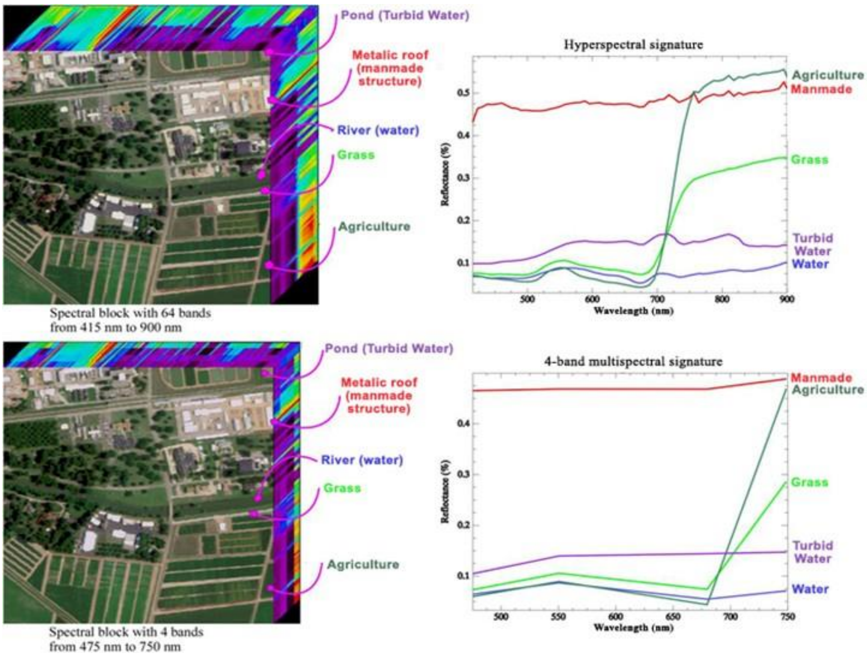

Figure 11. A comparison of spectral signatures measured from a range of land cover targets using hyperspectral (Top) and multispectral (Bottom) sensors[20].

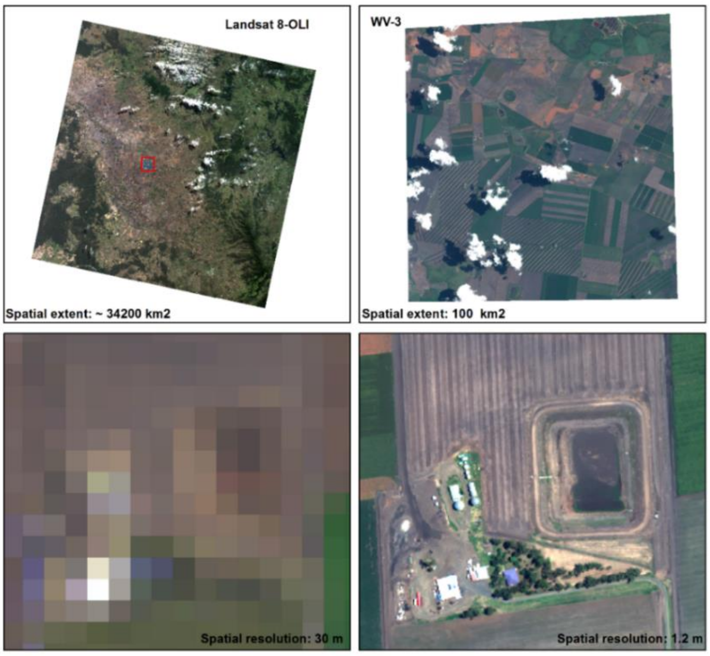

Figure 12. A comparison of different spatial resolutions provided by Landsat 8-OLI and Worldview-3 satellites. Note the differences in the spatial extent and the impact of pixel size. The solid red line determine the spatial extent of the WV-3 capture.

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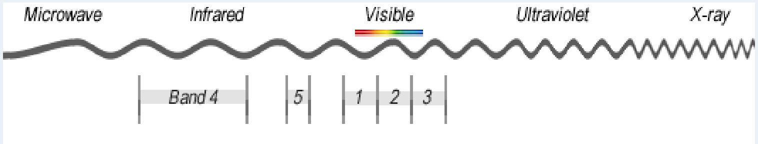
[20] Compiled image from http://slideplayer.com/slide/8984954/

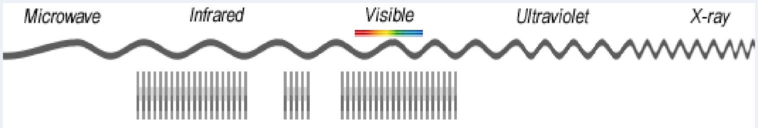
Multispectral versus Hyperspectral imaging

Initial crop sensors (VIS/NIR sensors) captured reflectance data from RGB (visible) and NIR wavelengths to assess crop growth. Crop sensing technologies have continued to progress with the development of multispectral and hyperspectral sensors. Multispectral sensors are now commonly used in crop sensing while hyperspectral remain predominantly a research tool.

Multispectral imagery – sensor comprises up to 20 wide bands



Hyperspectral imagery – comprises data from many narrow (10-20 nm) bands



The narrow bandwidth of hyperspectral sensors allows the user to obtain a greater degree of detail in the crop.

Where multispectral imaging can show limited information from the crop canopy (e.g. NDVI biomass, vigour), hyperspectral sensing can provide information on different factors affecting crop production:

3 Crop sensing

Crop sensing technologies measure how much light is absorbed or reflected by a crop canopy at specific electromagnetic wavelengths (**Figure 13** and **Figure 14**) (Craigie, 2013).The electromagnetic spectrum is a continuous range of wavelengths including those not visible to the human eye from very short wavelengths (gamma rays) to longer wavelengths (microwaves and radio waves). The spectral range visible (VIS) to the human eye is 400-700 nanometers (nm).

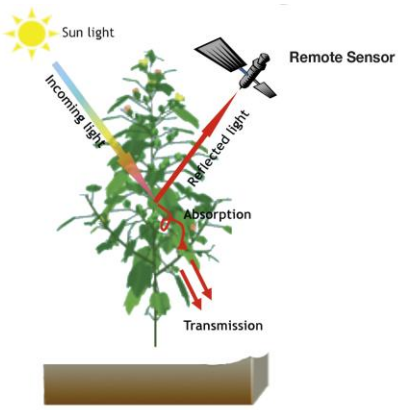


Figure 13. Remote sensors capture the energy emitted (reflected) by the object after the incoming light is absorbed by the object and posteriorly transmitted. *Source*: Ortiz, *et al.* (2011).

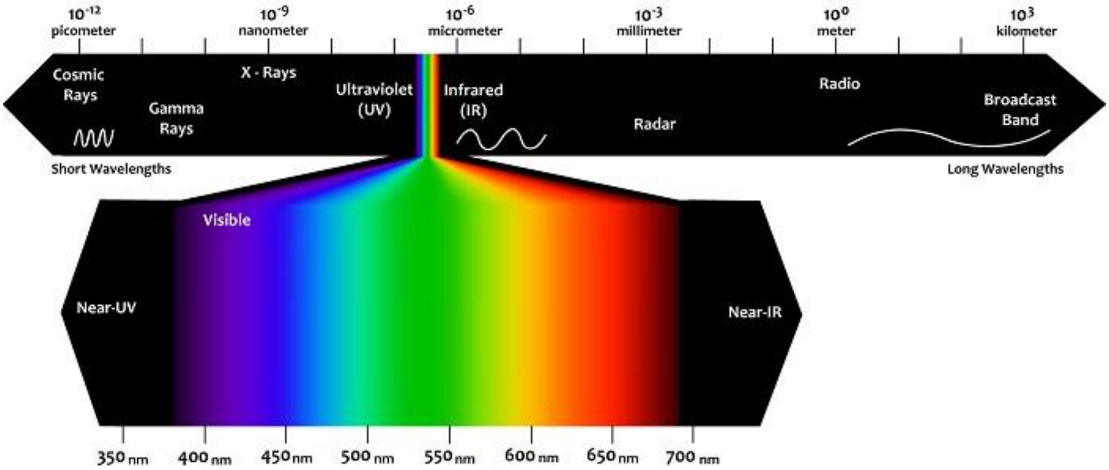


Figure 14. Electromagnetic (EM) spectrum with the visible region highlighted[21].

The characteristics of the spectral signature for vegetation differ between healthy and stressed vegetation with healthy vegetation absorbing more visible red light (and therefore reflecting less) than an unhealthy plant (Craigie, 2013). **Figure 15** illustrates an example of the reflectance characteristics of healthy and unhealthy vegetation. In healthy vegetation, the reflectance response curve is characterized by low reflectance in the VIS region, particularly around 450 nm (blue) and 680 nm (red), with a small peak around 550 nm (green peak) (Suarez, *et al.*, 2017). The small

21 https://www.chroma.com/knowledge-resources/about-fluorescence/introduction-to-fluorescence/working-in-wavelengths

reflectance peak exhibited within the green spectral region is why the human eye perceives healthy leaves as green.

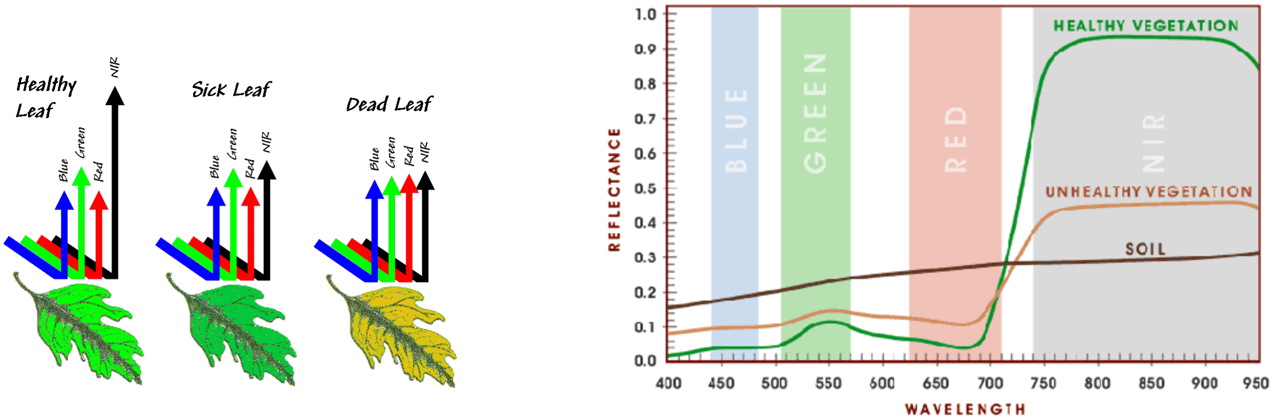


Figure 15. The spectral shape of healthy vegetation, unhealthy vegetation and bare soil[22].

Differences in the emitted light at different wavelengths, obtained from spectral measurements of a plant leaf or canopy, can help distinguish vegetation from soil, differentiate cultivars, detect stress, disease, weed infestation, nutrient status and predict yield under different crop conditions (Liu*, et al.*, 2015; Yu*, et al.*, 2015; Zarco-Tejada*, et al.*, 2005) (**Figure 16**).

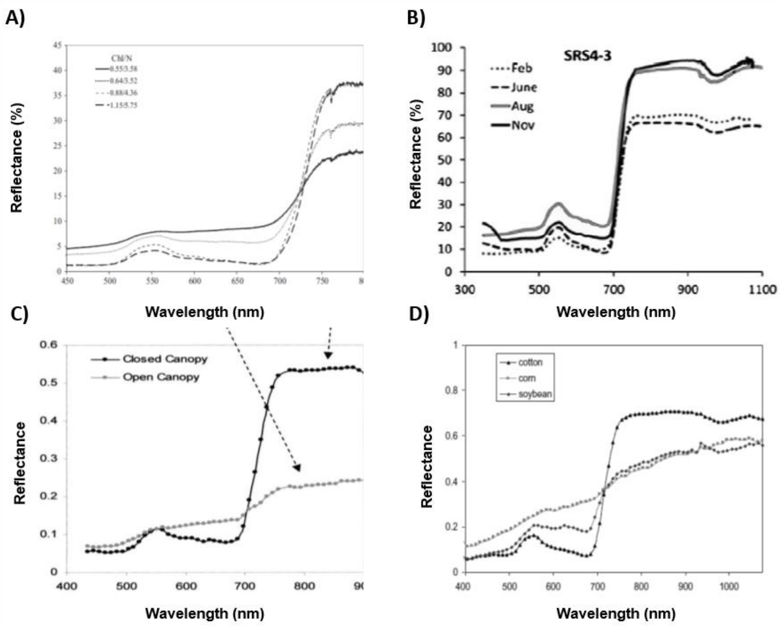


Figure 16. Spectral changes of crops under different conditions: A) variation in nitrogen and pigment concentrations in maize; B) maturity of red mangrove leaves; C) canopy structure of cotton crops and D) different crop types. *Source*: Suarez (2018)

22 http://www.innovativegis.com/basis/pfprimer/topic7/topic7.html
https://phenospex.com/blog/the-power-of-fusing-3d-with-multispec/

Crop sensing is a powerful tool because the information collected and quantified by the sensors is related to phenomics and internal cell structure rather than the visual appearance of the plants. Understanding how the spectral response at a specific wavelength relates to plant components and health is critical for applying spectral imagery to crop production. The spectral reflectance characteristics of the Red-Edge spectral region (~720 nm, non-visible range) have been well established as a strong indicator of foliar nitrogen concentration (Robson*, et al.*, 2016b; Zhai*, et al.*, 2013). As seen in **Figure 17**, healthy leaves reflect most solar energy in the Near Infrared (NIR) (700 nm -1200 nm) range, a spectral region associated with the spongy mesophyll tissue and internal cell structure of the leaves. This region is strongly associated with plant health or turgidity and therefore any constraint on plant health will reduce the amount of reflectance in this region. Beyond the NIR, the SWIR (shortwave infrared) spectral region is strongly influenced by the water status of the plant. Leaves that are not water stressed have higher absorption values in the SWIR (Rapaport*, et al.*, 2015).

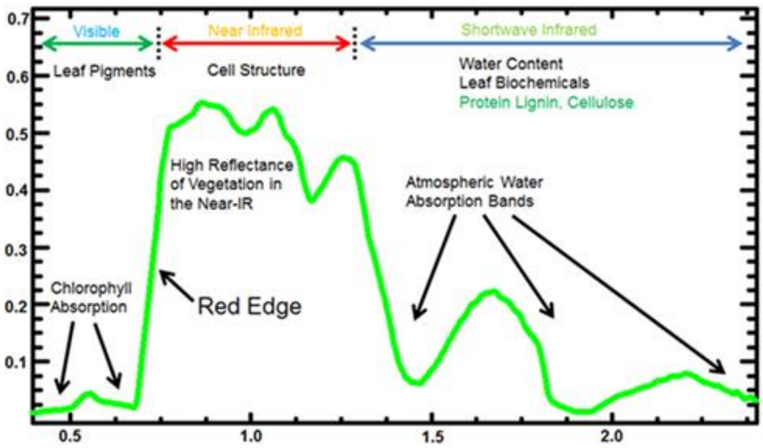


Figure 17. Electromagnetic spectrum and spectral shape of green vegetation[23].

[23] http://light-measurement.com/wavelength-range/

3.1 Vegetation indices

The previous section describes how the spectral response of a specific wavelength can provide useful information about the presence, absence or concentration of certain plant constituents and components. However, obtaining a measure at only one wavelength is not recommended for the diagnosis of specific plant constraints or the subsequent derivation of crop condition algorithms, due to a 'path radiance' influence. In simple terms, this influence relates to the distance between the sensor and the target, i.e. the greater the distance, the lower the amount of reflected light detected. To compensate for this influence, band ratios or Vegetation Indices (VIs) are employed. VIs are calculated as a ratio of reflectance between two spectral bands or ratios of differences and sums of spectral bands (Ortiz et al 2011). The simple ratio NIR/Red and the Normalised Difference Vegetation Index (NDVI) are among the most well-known of these indices and the most commonly applied to date in agriculture (Yang*, et al.*, 2009a).

Vegetation indices not only negate the sensor to target distance issue, but also help reduce other effects such as canopy and cloud shadow. Structural related indices are often strongly related to biomass and yield, while pigment indices are sensitive to the concentrations of chlorophyll, carotenoids and anthocyanins (Blackburn, 2007). The table in Appendix 3 summarises some of the most commonly used vegetation indices.

NDVI

NDVI is the most robust and widely applied vegetation index.

Commonly used vegetation indices, such as NDVI employs only two band widths i.e. red and near infrared (Rouse, et al., 1974).

$$NDVI \quad \frac{(NIR - Red)}{(NIR + Red)}$$

The universal nature of this index limits it applicability to crops at later stages of growth where canopy cover is at its highest Leaf Area Index (LAI). At these later stages of crop growth, the index provides little indication for any response to variability, such as N content (Zarco-Tejada, et al., 2005).

More than a hundred narrow and broadband vegetation indices have been developed.

VIs can be used as indicators of maturity, health and stress condition (**Figure 18**). For example, during the growing season, pigment-related indices can be used for scheduling harvest. At maturity, the photosynthetic capacity of plants is reduced and indices, especially pigment-related, show changes that can be used as indicators to schedule or target harvest to maximise yield quality and quantity (Bramley*, et al.*, 2011b; Zarco-Tejada*, et al.*, 2005).

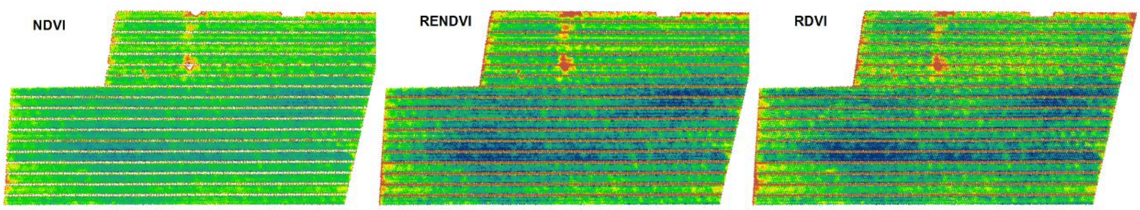


Figure 18. Broad vegetation indices showing within-field variability. Structural-related indices NDVI and RDVI and pigment-related index: RENDVI.

3.2 Applications of crop sensing technologies

Crop sensing technologies are used for two primary purposes:

- Determination of in-field variability for remedial management actions to reduce variability and maximise yield
- Estimation of crop yield (yield forecasting) in advance of harvest (see section on yield forecasting)

Remote and proximal sensing have been demonstrated as effective tools for detecting subtle differences in the spectral signature of vegetation and is therefore a tool for assessing spatial crop variability, crop growth and enabling management options that would not have been possible with traditional ground based crop scouting. In addition to agricultural applications this imagery can also provide spatio-temporal information on potential issues at the subregional and regional levels for applications such as environmental monitoring, land cover classification, climate and land use change detection and drought monitoring (Pinter*, et al.*, 2003; Rahman and Robson, 2016).

3.2.1 Crop sensing for nutrient conditions

Due to the high demand for nutrition, vegetable crops represent around 10% of production costs in the Australian vegetable industry, but reaching up to 45% in growing regions around the world (Aquino*, et al.*, 2015). The level of nutrition applied to a crop can have contrasting effects on yield and quality. Excess applications of fertiliser can result in a limited improvement in yield and quality up to a certain degree of uptake, before it becomes detrimental or ineffective. A study conducted by Veitch*, et al.* (2014) identified applications of nitrogen above 150 kg N ha^{-1} to carrots did not significantly improve yield or quality. An example of this principle is shown in

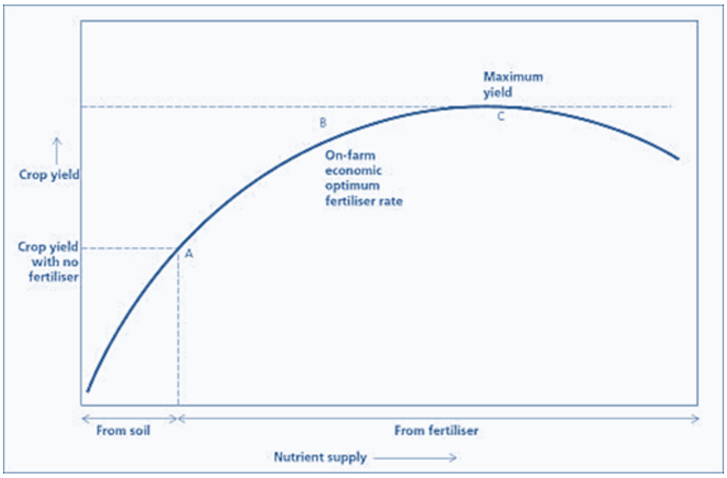


Figure 19. Excessive nutrient applications can also be detrimental to the surrounding environment through run-off and leaching, resulting in significant nutrient loading in waterways.

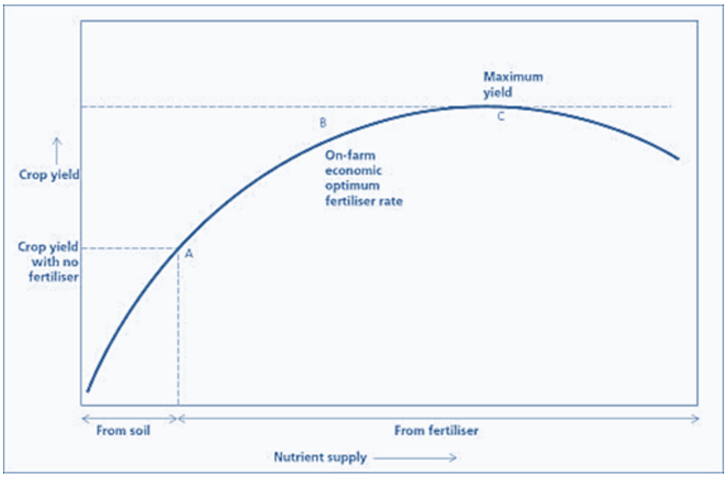


Figure 19. Schematic depicting the crop growth response to applications of nitrogen above the usual crop requirement[24].

Given the drivers to optimise agricultural production and pressure on landholders for maintaining environmental stewardship, there has been significant emphasis on monitoring of crop growth and nutrient status through the adoption of more efficient management practices (Mahajan, *et al.*, 2014) (Pimstein, *et al.*, 2011). The standard approach to evaluating the nutrient requirement of a crop involves soil and plant tissue sampling and analysis. Although this traditional approach of physical sampling for estimating nutrient content is accurate, it is not time and cost effective (Rapaport, *et al.*, 2015) and not widely adopted across all industries. Remote sensing can offer the horticultural industry opportunities for more efficient resource use and provide a tool to optimise nutrient management.

Extensive published research relating the spectral crop reflectance to observed nutrient status is available in cereal and cotton crops, while the information is significantly limited for horticultural crops (Lee, *et al.*, 2010). The newest developments in high spatial and spectral resolution satellite imagery allow for better estimation of soil characteristics and crop status (Khanna, *et al.*, 2007) and, combined with the success in cotton and grains, support the potential applicability of reflectance-based approaches for the estimation of nutrient content in the horticultural industry.

Nitrogen is one of the most investigated nutrients using remote sensing data and it has been accurately predicted as a limiting factor using simplified models (i.e. wavelengths or vegetation indices). Research shows that a spaceborne hyperspectral sensor (EO-1 Hyperion) can establish a reliable and stable relationship between spectral reflectance and two plant biochemical parameters, chlorophyll-N concentration and leaf N accumulation, at the pixel level across all possible wavelength ratios (Rama Rao, *et al.*, 2008). The result from this study highlights the capabilities of remote sensors for acquiring important information associated with leaf structure and components. Zhao, *et al.* (2013) demonstrated the usefulness of integrating narrow wavelengths for predicting N and chlorophyll content across two crop types: maize and maple. Blue (440 nm) and the NIR (720 nm and 750 nm) range were the most significant wavelengths for the prediction of chlorophyll while the

[24] http://adlib.everysite.co.uk/adlib/defra/content.aspx?id=2RRVTHNXTS.88UF41WXRQOZS

SWIR range (from 1700 nm to 2100 nm and at 2150 nm) were the most significant bands for the prediction of N with high prediction accuracies ($R^2 > 0.90$).

Other macronutrients like K and P are also important but have not been broadly investigated using remote sensing techniques (Pimstein*, et al.*, 2011). However, the limited available studies reported accurate P (Christensen*, et al.*, 2004) and K estimations (Pimstein*, et al.*, 2011) with R^2 equal to 0.74 and 0.87, respectively. The significant wavelengths were located at the VIS, NIR and SWIR for K and in the VIS and red edge (up to 750 nm) for Christensen*, et al.* (2004) accurately measured the foliar N and P content of spring barley (*Hordeum Vulgare L.*) using the visible and red edge spectral region (from 400 nm to 750 nm). Regardless of crop growth stage, N and P content predictions generated only 12.2% and 15.3 % error, respectively.

In some cases, accurate nutrient prediction requires additional information or wavelengths. Pimstein*, et al.* (2011) demonstrated that increasing the number of wavelengths in prediction models (resulting in multivariate models) for K and P in wheat performed better than the traditional VIs (i.e. NDVI, GNDVI, simple ratio SR, SAVI, OSAVI and red edge position RED). These multivariate models (i.e. many predictors or wavelengths) provided an R^2 of 0.68 and 0.87 for the prediction of P and K concentration, respectively, and up to 0.90 for prediction of relative content in both P and K.

Predicting nutrient and pigment content in plants across different species or conditions can be a complex task. Understanding this variability is key not only to an extensive range of scientific research but to environmental and agricultural management endeavours (Blackburn, 2007). The key features influencing the spectral response are: 1) the parameter that is going to be estimated; 2) the object, such as a crop, to be analysed and 3) external parameters affecting the reflectance response of the object (crop). As such, the optimal VI must be carefully considered and selected.

Reflectance-based methods have proven to be reliable and accurate for the prediction of nutrient content /concentration and as an indicator of physiological status

3.2.2 Detection of physiological status

The physical and biochemical characteristics of the crop highlight which VIs should be applied or avoided. For example, in vegetable crops, NDVI was strongly related to fractional canopy cover across 11 seasonal and annual crops. In contrast, NDVI did not provide useful information in red leaved vegetable crops, such as red lettuce, due to saturation in the red band (Trout*, et al.*, 2008). To overcome these limitations, mathematical approaches (i.e. VI formulae) can be designed to account for the particular condition or characteristic that is being investigated. Water stress in agricultural crops causes reflectance changes that are clearly manifested in the SWIR region of the spectrum which, when analysed in conjunction with spectral changes in the VIS and NIR, provides unique patterns for monitoring drought stressed crops. Rapaport*, et al.* (2015) tested 12 commonly used narrow-band indices. Examples of this include: NDVI, the photochemical reflectance index (PRI) and the red-edge inflexion point (REIP). Results were poor for the estimation of leaf water potential, stomatal conductance and non-photochemical (or light use efficiency) variables of grapevine (*Vitis vinefera L.*). However, based on the spectral characteristics of the stressed crop, the authors developed new VIs that fitted more effectively with the measured variables ($R^2 > 0.90$), allowing an accurate estimation of water-related variables under water-stressed conditions.

Despite the extensive application of remote sensing technologies to arable crops, very few studies have assessed the applicability to horticultural production systems. Stagakis*, et al.* (2012) utilised remote sensing capabilities in an orange orchard to evaluate vegetation indices for fruit quality and water stress measurements. It was demonstrated that the wavelengths located at 515 nm, 570 nm and 531 nm can be used as a pre-visual water stress indicator linked to fruit quality (i.e. total soluble solids (brix %) and titratable acidity), particularly in the form of a VI such as PRI. This study also determined the most sensitive period for water stress was the final stages of fruit maturity, highlighting this as an optimal timing for capturing remote sensing imagery.

3.2.3 Disease detection

According to reported literature, it appears that remote sensing to detect disease infestation has been more widely used in native tree and bush environments, timber plantations and perennial horticulture, than in annual horticultural crops. Examples include the detection of *Phytophthora cinnamomi* in native heathland (Hilla*, et al.*, 2009), *Phellinus weirii* (laminated root rot) in Douglas fir (Pseudotsuga Menziesii) (Leckie*, et al.*, 2004), *Mycosphaerella* leaf disease in a *Eucalyptus globulus* plantation (Pietrzykowski*, et al.*, 2007), *Verticillium* wilt in olives (*Olea europaea* L.) (Calderon*, et al.*, 2015), laurel wilt in avocado (*Persea americana*) (De Castro*, et al.*, 2015), and grapevine leaf roll disease in vines (Hou*, et al.*, 2016).

Multi-spectral and thermal imagery captured using a UAV was used by Calderon*, et al.* (2014) to detect downy mildew (*Peronospora arborescens*) in opium poppy (*Papaver somniferum* L.). Image-derived canopy temperature, normalised by air temperature (Tc-Ta), and the R_{550}/R_{670} index were related to physiological stress caused by downy mildew infection, showing that it was possible to detect infestations using remote sensing. Both hyperspectral and thermal data have been investigated as a means of identifying early (*Cercospora arachidicola S. Hori*) and late leaf spot (*Cercosporidium personatum*) in peanuts (*Arachis hypogaea*) (Omran, 2017; Robson, 2007). Thermal imagery showed a pre-symptomatic decrease in leaf temperature of about 1.3^{o}C. Furthermore, Robson (2007) successfully examined the different spectral technologies (i.e hyperspectral and multispectral satellite sensors) to determine yield and maturity and identify aflatoxin contamination in peanuts.

Salgadoe*, et al.* (2018) demonstrated the capabilities of Worldview-3 imagery for the mapping of phytophthora severity in avocado trees as an alternative method to the traditional (visual) assessment. A simplified ratio vegetation index (SR) was strongly correlated with disease severity, and it was possible to discriminate between four levels of severity (**Figure 20**).

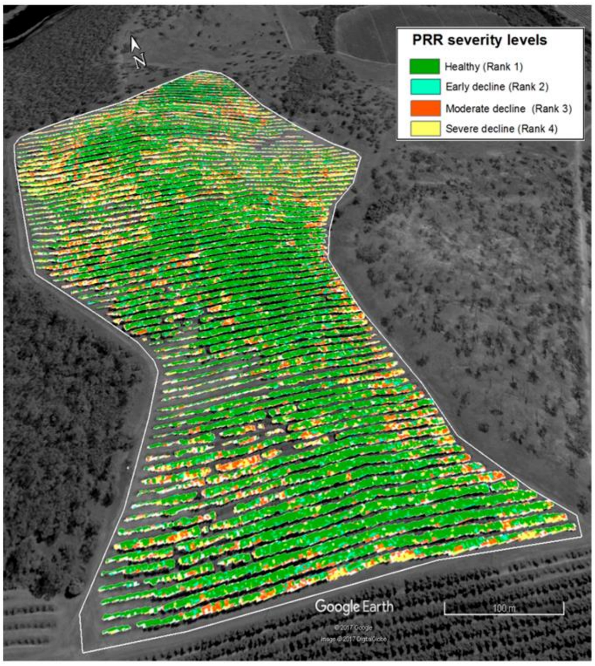


Figure 20. PRR severity distribution map derived from Worldview-3 *Source*: Salgadoe*, et al.* (2018)

Limpus*, et al.* (2016) reported a case study where GreenSeeker NDVI data detected *Fusarium* spp. in trellised tomatoes prior to symptoms becoming visible in the crop (**Figure 21**). The first capture using angled GreenSeeker sensors detected low biomass readings in July 2015, and in August 2015 during the second capture, discolouration of stems above the crown showed indications of *Fusarium oxysporum* f.s.p. *lycopersici* (**Figure 22**). Subsequent GreenSeeker captures revealed that the disease had spread from a highly susceptible variety to a resistant variety in a neighbouring area of the field. *F. oxysporum* f.s.p. *lycopersici* is a soil born disease that is a challenge to manage or control, due to its persistence in the soil, without investing in and growing resistant cultivars or applying conventional control methods. These findings offer vegetable growers another tool that is commercially available to assist in the monitoring and management of potential disease outbreaks in their crops.

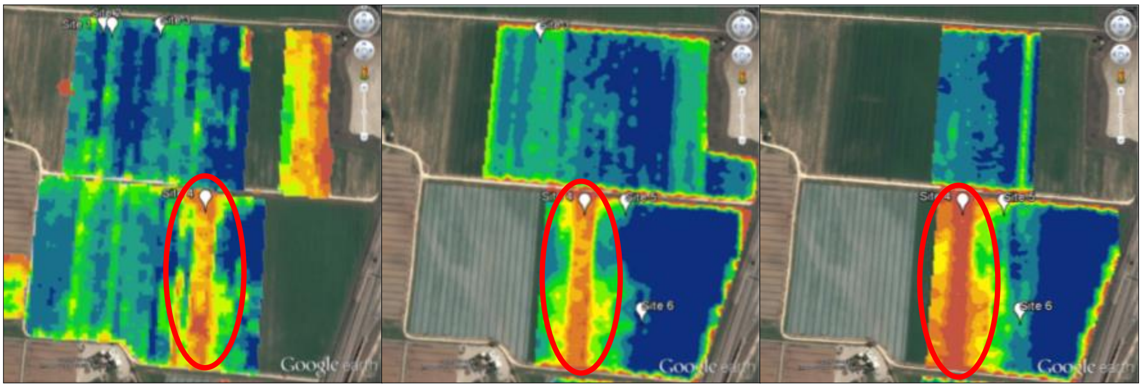


Figure 21. GreenSeeker imagery of tomatoes showing progression of Fusarium spp. symptoms. *Source*: Limpus*, et al.* (2016)

Figure 22. Visual symptoms of *Fusarium* in tomatoes. *Source*: Limpus*, et al.* (2016)

For the horticulture industry, a broad range of methodologies successfully tested in other crops, such as sugar, cotton, rice, can be used for evaluation and as a guide for the development of new strategies appropriate to horticulture. Analysis of the significant wavelengths and the optimal vegetation indices is required in order to understand the reflectance variability in vegetable crops, and evaluate the factors causing spatial and temporal variability.

3.2.4 Yield forecasting

Yield and quality are the ultimate measures of successful crop production. As remote and proximal sensing technologies increasingly enable the application of precision agriculture practices, spatial yield data to compare with other data layers is an important part of the overall system. Yield estimation and yield monitoring are different aspects of crop performance monitoring. Prior to harvest PA technologies can be used to estimate yield while yield monitoring is a quantitative measure of yield at harvest using various technologies e.g. visual systems, load cell. Yield monitoring will be covered in Section 6.

There are many benefits to accurate yield estimation prior to harvest, particularly in horticulture. These include:

- planning and targeting harvest labour,
- grading and packing logistics,
- more informed marketing of produce
- spatial information on crop performance.

A number of different methods may be employed for yield estimation and monitoring depending on the nature of the harvested part. If the product is able to be individually identified (e.g. lettuce, broccoli heads) it may be possible to estimate yield in advance of harvest by counting (**Figure 23**) or volume estimation via image analysis (Payne*, et al.*, 2016). Alternatively, if there is a relationship between plant volume or a spectral signature and yield (Robson*, et al.*, 2016b), an indirect measurement could be used as a surrogate. For some crops, spectral imagery can be used, while for others, shape recognition may be more appropriate. Research has demonstrated that where crop condition is closely related to spectral data or VIs, the latter can be used for yield prediction (Apan*, et al.*, 2004; Basnet*, et al.*, 2003; Broge and Leblanc, 2001; Clevers, 1999; Pinter*, et al.*, 2003).

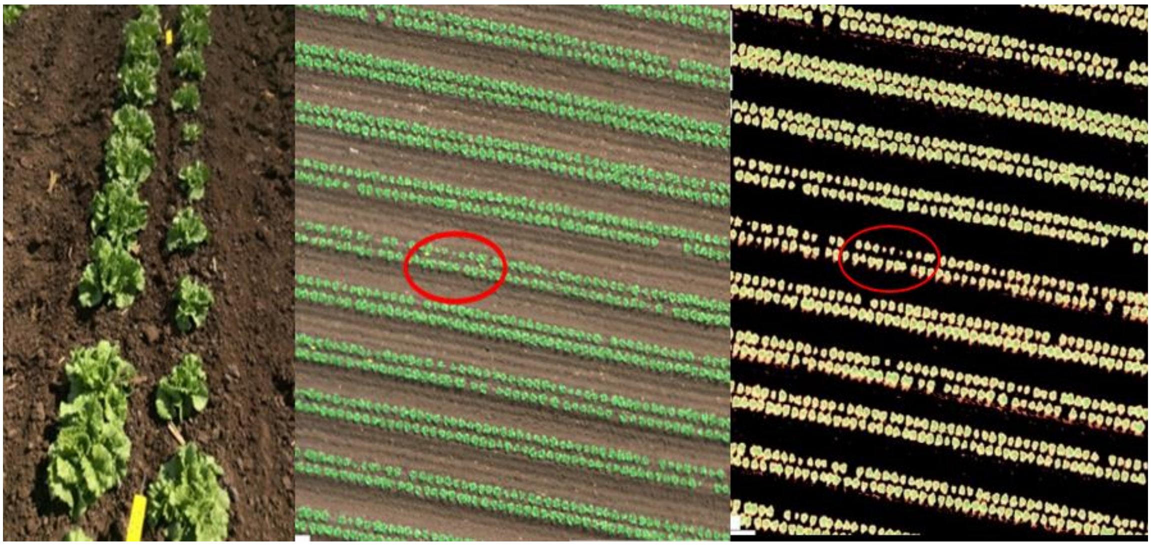


Figure 23. Comparison of on ground photo (left), high resolution digital image used for automated plant counts (centre) and NDVI imagery (right) of a lettuce field 4 weeks after transplant (the same 2 metres of row are highlighted in each image). *Source:* O'Halloran and Parker (2016).

The time of image collection is crop and sensor dependent. Information about the most significant wavelengths or spectral ranges for prediction of crop condition is as important as the development of appropriate predictive approaches, as this can simplify prediction models. The significance of the spectral bands varies according to the variable (crop) to be measured. For yield, wavelengths in the visible range (i.e. blue, green, red) and in the NIR range have been shown to be the most important. this has been demonstrated by the strong linear relationship between estimated and measured yield in cotton crops (R^2 up to 0.88) (Suarez*, et al.*, 2016), while for winter wheat, blue, red edge, NIR and SWIR wavelengths were better predictors of yield (R^2= 0.63) (Wang*, et al.*, 2017). As the SWIR range is susceptible to water content, this spectral range should also be considered as an input factor if the crop is under water stress (Rapaport*, et al.*, 2015).

Predictive modelling

Predictive modelling refers to the use of algorithms to estimate different crop characteristics.

Predictive modelling for yield, nutrient and physiological status is still in the R&D stage for most agricultural industries.

The estimation of yield using spectral imagery is a rigorous activity, as yield is a complex variable that depends on many different conditions within the field. Hence, the relationship between yield and reflectance becomes complex. Algorithms developed are commonly influenced by season, location, crop age and cultivar differences. It is particularly challenging when the crop is under stress caused by, for example, pest, disease, water status or exposure to biochemicals or pesticides. As yield estimations become more and more complex due to the resilence and recovery capabilities of the plant, manifested through the biophysical and physiological changes in the leaves (Henry*, et al.*, 2004; Suarez*, et al.*, 2016), managers and agronomists often struggle to accurately predict yield in stressed crops (Everitt and Keeling, 2009). As a result, the reflectance-based prediction models usually require more information (i.e. more wavelengths). Despite the above, remote sensing is proving to be a powerful approach for yield estimation whether using narrow VIs derived from hyperspectral data (Zarco-Tejada*, et al.*, 2005) or developing prediction models with individual wavelengths (Panda*, et al.*, 2010; Suarez*, et al.*, 2016; Wang*, et al.*, 2017; Yang*, et al.*, 2006).

Spectral satellite sensors also have potential to be a powerful technology used to predict yield at field and regional scales, especially with the relatively recent commercial availability of very high spatial resolution satellite sensors (Al-Gaadi*, et al.*, 2016; Xue and Su, 2017).

Comparisons between airborne sensor platforms, such as satellite imagery, have been shown to have a close relationship with yield monitor data at 2.8 m and 8.4 m resolutions in two separate fields of sorghum Yang*, et al.* (2006). When compared with the yield monitor data, the coarser resolution did not show the same detail as in the satellite imagery, but the prediction model still provided a high level of correlation, particularly when narrow bands were used instead of multispectral VIs (e.g. NDVI). Furthermore, they found that both fields yielded a different R^2 value, indicating that a different index was needed in the prediction model for different fields. Subsequent research by Yang*, et al.* (2009b) compared the yield prediction capabilities of SPOT-5 satellite multispectral imagery against records from yield monitor data collected in three grain-sorghum paddocks. That study showed that the prediction model could explain up to 83% and 84% of the yield variability across and within paddocks, respectively when using satellite imagery (**Figure 24**).

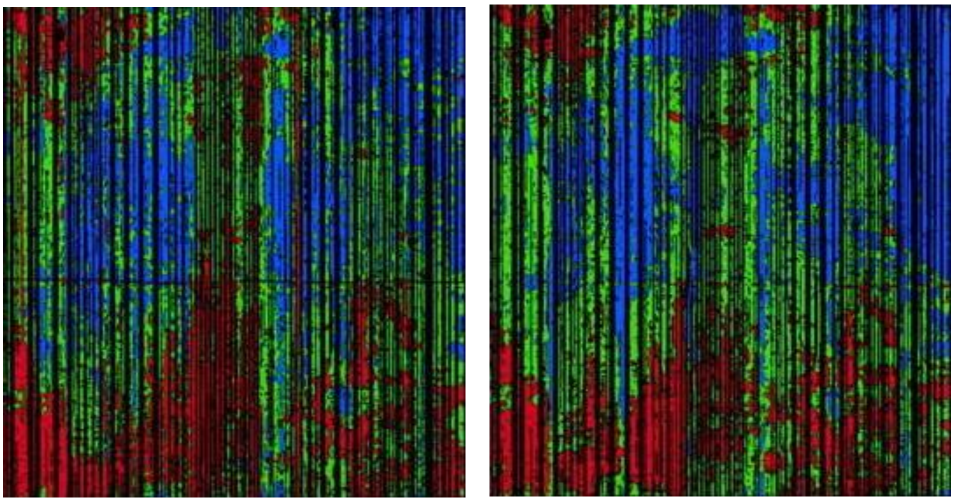


Figure 24. Comparison between yield classified maps derived from yield monitor (left) and OSAVI index (right) in a cotton field. Low (red), medium (green) and high (blue) yield classes. *Source:* Adapted by the authors (Zarco-Tejada*, et al.*, 2005)

Remote sensing can assist with crop monitoring by:

- *reducing times associated with traditional sampling methods, and*
- *allowing the assessment to be performed several times during the growing season.*

Conversely, Shanahan*, et al.* (2001) demonstrated that maize yield was strongly correlated to GNDVI (r > 0.80) under variable N conditions. GNDVI is a structural-related index useful for assessing green crop biomass (Gitelson*, et al.*, 1996) and ultimately yield estimation. In their study, GNDVI gave superior performance to NDVI or TSAVI. Similarly, extensive research on yield forecasting of Australian sugarcane from satellite imagery has identified GNDVI to be better correlated with yield and less likely to suffer saturation than NDVI (Robson*, et al.*, 2016a; Robson*, et al.*, 2014).

Understanding the optimal time for data capture allows enhanced scheduling and planning, and identifies potential issues in the crop that can be addressed with remedial action to maximise yield potential. Domenikiotis*, et al.* (2004) developed an approach based on NDVI minima and maxima values in a multi-temporal study for estimating yield at the field level. They tested the data throughout the growing season, with an overall accuracy of estimated yield higher than 80%. The multi-temporal study allowed them to determine the best time for data collection based on crop development, which indicated that spectral reflectance at early growth stages was better correlated with the measured yield ($0.52 \leq R^2 \leq 0.81$ and p-value < 0.05).

Although remote sensing has been used to estimate yield in various broad acre crops, limited research has been done on yield estimation for fruit and vegetables. Koller and Upadhyaya (2005) used aerial images and yield monitors to estimate tomato yield and found that it was not accurate to use the Leaf Area Index (LAI), derived from a modified NDVI, to predict and identify spatial yield variability within the field. On the other hand, Marino and Alvino (2015) tested 11 different narrower VIs derived from hyperspectral data and found significant prediction accuracies ($0.61 < R^2 \leq 0.67$) between eight of the VIs and onion (*Allium cepa* L.) yield. The transformed soil-adjusted vegetation index (TSAVI) was the best VI in predicting yield ($R^2 = 0.67$) at bulbing stage (i.e. 140 days after planting).

Satellite imagery has also been used in annual horticultural crops. Al-Gaadi*, et al.* (2016) tested a medium-coarse sensor (Landsat) and a high spatial resolution sensor (Sentinel-2) (both free-access) in three center pivot irrigated potato fields. NDVI and SAVI were derived from the multispectral bands and used to predict potato tuber yield. Although yield variability was high (mean yield per field was < 21 t/ha to > 40 t/ha), low prediction errors (< 10.5%) were achieved regardless of the sensor, highlighting the potential for yield prediction from crop sensing imagery for potatoes. These results show the benefit of using free satellite data to reduce the cost of operations.

Aerial photography has been used to estimate individual cabbage weight as a means of determing total yield in experimental plots. Yang*, et al.* (2008) used both aerial Colour Infrared (CIR) photography and field reflectance spectra to obtain plant growth and yield information (**Figure 25**). Deriving plant diameter from aerial photographs was the most accurate method for estimating head weight ($R^2 = 0.91$). A number of vegetation indices were investigated, with NDVI providing the best estimate of head weight ($R^2 = 0.66$). Using step-wise regression on the 60 spectral bands captured (400-1000 nm), an 8-band model was able to explain 71% of the variability in head weight.

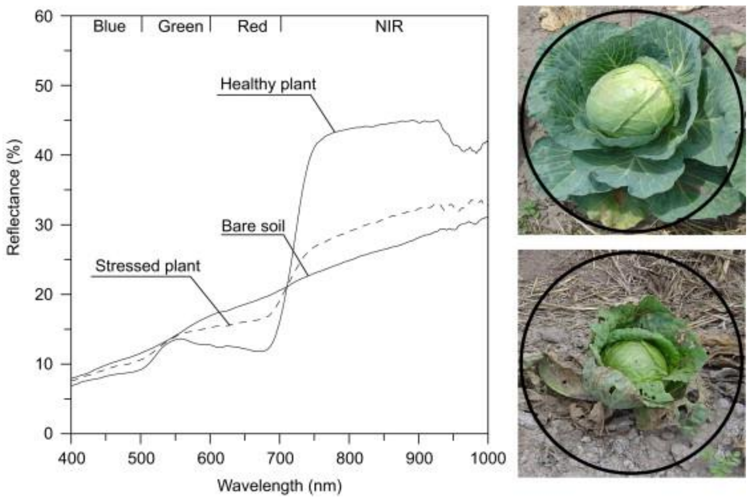


Figure 25. Measured reflectance spectra for cabbage plants. A healthy cabbage with a diameter of 45 cm (top plant), a stressed cabbage plant with a diameter of 25 cm (bottom plant), and bare soil in the visible (400–700 nm) to NIR (700–1000 nm) region of the spectrum. The spectroradiometer was held at 1 m above ground and had a field of view of 44 cm in diameter (dark circles over the plants). *Source:* Yang*, et al.* (2008).

Ye*, et al.* (2007) succesfully used robust models, in place of VIs, to accurately predict Satsuma mandarin yield. Airborne hyperspectral imagery was collected during three consecutive seasons (2003, 2004 and 2005) at different stages of growth. The predicted citrus yield was strongly and linearly related to the measured yield (R^2 up to 0.58) in an independent set of measurements which support the transferability of the models across seasons. More imporantly, the results indicated that it is possible to successfully forecast the yield several months, or even a season, ahead. This is a significant development for planning harvest schedules, general management practices and generating prescription maps to address with-in yield variability in specific trees (Ye*, et al.*, 2007).

Yield estimation may use spectral imagery or shape recognition algorithms applied to captured images to calculate the number and size of fruit. However this is most likely to involve autonomous intelligent systems or robotics as in Hung*, et al.* (2016) where autonomous intelligent systems were used to collect images that were subsequently analysed to estimate fruit counts in apple, mango, lychee and almond orchards. Validation of the estimates against harvest yield data showed a positive correlation (R^2 = 0.81). This type of yield estimation approach is generally performed when the fruit is close to maturity. Within the Australian vegetable industry, robotic technologies such those produced through the Australian Centre for Field Robotics (e.g. Ladybird, Shrimp, RIPPA^{TM}) are potential platforms for vision system technologies and shape recognition algorithms to estimate yield (see Section 8.2).

4 Soil sensing and mapping

Several sensors have been developed to measure the characteristics of soils. Matched to GNSS technology, these sensors can provide geospatial information about soil moisture, texture, salinity and nutrient availability. This information can identify areas in which variable crop performance is associated with soil characteristics, thus providing complementary information for PA crop management.

Soil sensors have been developed to provide alternatives to existing laboratory methods. Although laboratory methods are more precise, they also require more time for collecting and processing data, with associated higher costs.

Indirect measurements of soil conditions can be performed with different sensors such as:

- electromagnetic
- optical
- mechanical
- electrochemical
- airflow
- acoustic

EM-38 is an example of an electromagnetic induction (EMI) device that provides a rapid measure of soil electromagnetic conductivity (apparent electrical conductivity). Electromagnetic sensors measure the capacity of soil particles to conduct or accumulate electrical charge. This is mainly influenced by soil texture, salinity, organic matter and moisture content (Schneider, 2017). This sensor has two modes of operation (horizontal and vertical), each with its own characteristic depth of soil penetration (Precision Agriculture Research Group [PARG], 2017). The horizontal model is most responsive to soil characteristics at approximately 50 cm depth, while the vertical mode is most responsive to parameters at approximately 1.2 m depths. The vertical mode is the most commonly used as it is less influenced by variation in ground clearance during data collection (Geonics Limited,

EM38 soil mapping

EM38 soil mapping illustrates differences in soil characteristics such as clay content, soil salts and soil moisture. Soil sampling is required to ground truth the EM38 mapping and identify which factor is influencing differences in soil conductivity.

Soils higher in clay content or soil salts will have a higher electrical conductivity.

2013). **Figure 26** shows the difference in apparent conductivity in the two modes of the EM38.

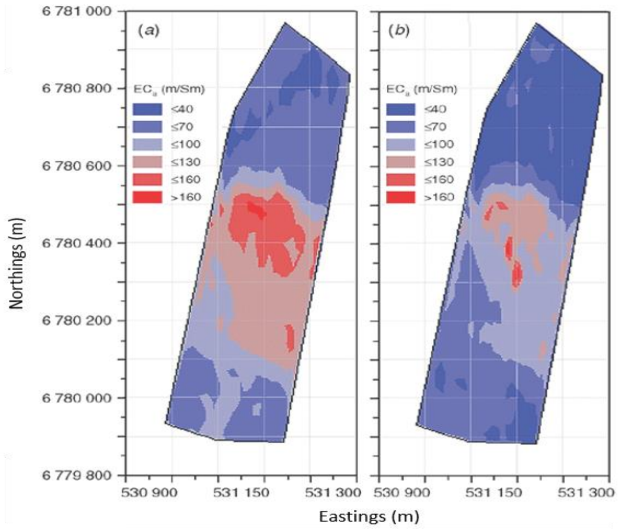


Figure 26. Apparent soil electrical conductivity collected with the EM-38 in a) horizontal mode and b) vertical mode. *Source*: Adapted by the authors (Huang*, et al.*, 2014).

EM38 soil mapping identifies spatial differences in soil water, salt and clay contents. However, subsequent in-field soil sampling and analysis is required to determine which of these characteristics are contributing to the observed differences in electrical conductivity. Soil analysis to ground-truth EM38 data includes soil texture and particle size analysis, electrical conductivity and soil moisture. The EM38 can be used as a handheld device, or mounted on a range of vehicles (**Figure 27**). EM38 mapping is done by driving over the paddock at pre-determined swath widths of 10-50 m with research suggesting that using wider transect widths results in the inability to properly characterise the variation presented in broadacre cropping situations (Stanley*, et al.*, 2014). Depending on travel speed (generally < 40 Km hr^{-1}) and swath width, data collection points are 3-4 m apart in the direction of travel, and 10-20 m apart across the swath, such that each data point represents 30-80 m^2 of soil. Interpolation procedures are used to 'fill in' the data to produce a smooth and continuous data layer.

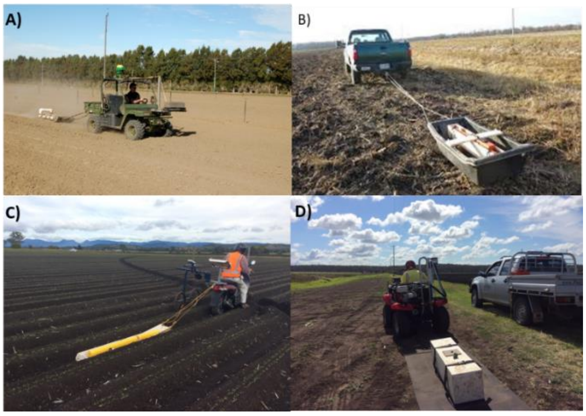


Figure 27. Different platforms for EM38 surveying. A) Gator[25]; B) SUV[26]; C) motorbike[25]; and D) four-wheel motorbike[25].

Optical sensors use light reflectance to characterize soil (i.e. predict PH and clay, organic matter, and moisture content). These sensors capture emitted energy from the visible (VIS), near-infrared (NIR) and mid-infrared (MID) light bands or polarized light reflectance. Vehicle-mounted, satellite or

[25] Queensland Department of Agriculture and Fisheries (2018)
[26] http://aben-saregrant-ndsu.blogspot.com.au/2015/03/agricultural-survey-measuring-soil.html

aerial platforms are available (Adamchuk*, et al.*, 2004). However, clouds and heavy plant residue cover can present major issues, limiting the use of optical sensors. On the other hand, close-range, subsurface and vehicle-based optical sensors have the potential to be used "on-the-go", similar to electromagnetic sensors, providing more information at one point since reflectance can be read in more than one part of the spectrum at a time (Adamchuk and Jasa, 2002). Some of these sensors are called as "bare soil images", "organic matter sensor or ground penetrating radar (GPR).

Mechanical sensors can be used to estimate soil physical properties of the soil (e.g. compaction) while electrochemical sensors represent the most promising future in soil monitoring with the potential to measure soil nutrient levels and pH. Airflow sensors have been tested to measure soil air permeability 'on the go' (Institute of Agriculture and Natural Resources, 2017). Results indicated the potential to distinguish between various soil types, moisture levels and soil structure (compaction). Acoustic sensors have also been tested to determine soil texture but low signal-to-noise ratio limited the further development of this technology (Adamchuk and Jasa, 2002). Although various research has been done exploring the capabilities of these technologies, only electromagnetic and optical sensors are commercially available for soil monitoring (Institute of Agriculture and Natural Resources, 2017).

5 Variable rate technologies

The most common application of precision agriculture technologies is for Site Specific Crop Management (SSCM). SSCM is based on accepting that fields are not uniform in nature, and therefore crops should not be managed uniformly. Rather, crop management should be aligned with variation in the field or crop. Soil mapping or crop biomass imagery provide the basis for variable input management at a spatial level. SSCM is essentially defined as providing the right input, at the right time, in the right amount, in the right place through the use of variable rate technologies (VRT).

Key factors need to be considered to determine if SSCM through the use of VRT is an appropriate approach. These include (Whelan and Taylor):

- Magnitude of variability – is the variability of a magnitude that is of economic concern?
- Type of variability – is the variation spatial and/or temporal i.e. is it spread across the field, does it change through the season or is it consistent across subsequent crops?
- Cause of the variability – is the variation caused by something that can actually be overcome through the application of VRT, such as nutrient deficiency or pH?
- Distribution – can the variability be clustered into zones of manageable size, or is it made up of many small areas within the paddock that are beyond the practical resolution capacity of VR technologies?

VRT combines the use of GNSS technology with variable input controllers on farm equipment to adjust crop inputs based on measured variability in a field or crop (Whelan and Taylor). The VR controller manages product output on the basis of a prescription map prepared in advance. Inputs can be any product used to enhance crop production, although most VR technologies have been developed for irrigation, fertiliser and pesticide inputs. In the case of fertiliser application, the VR controller adjusts the output of the machine by adjusting the flow of product to the distribution mechanism. For VR irrigation, output is generally adjusted by pulsing the delivery from the sprinkler pack to provide different ratios of on/off time depending on the output required. Pesticide application is controlled at the section or individual nozzle level of the spray boom, depending on the sophistication of the application technology.

In most cases, fields are split into 'management classes' or zones based on an analysis of available data layers (e.g. soil and nutrient maps) and prescription maps are developed to manage applications based on percentages above or below the normal uniformly applied rate. Technology is evolving to allow for continuous variable rate management (as distinct from the use of a limited number of management zones) based on real-time monitoring and adjustment.

While theoretically VRT can be used with any crop inputs, not all situations that may require VR management have available technology, and not all will be economically viable to treat. A management decision tree to help determine the suitability of SSCM is shown in **Figure 28** (Whelan, 2013).

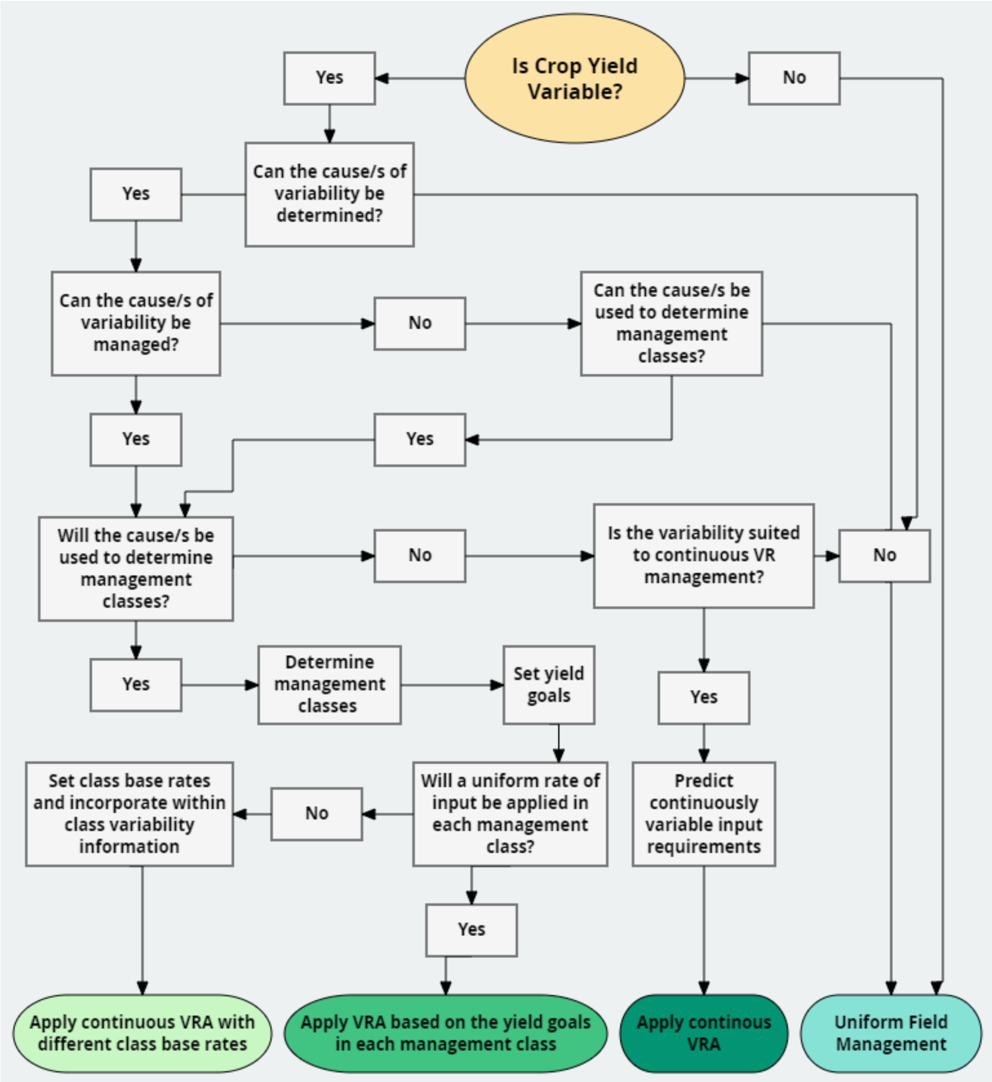


Figure 28. Management decision tree for SSCM based on the options of uniform, management class or continuous crop treatment. *Source*: (Whelan, 2013).

VRT provides the opportunity to manage inputs to alleviate variability such that the maturity of a crop, or subsequent crops, is as uniform as possible at harvest. However, it is important to understand the causes of variability, and the capacity to manage it before investing in VRT. For example, traffic and tillage management are two factors that impact the variability of soil conditions, and subsequently crop uniformity/variability. The management of these factors is best achieved with the application of controlled traffic and zero or reduced tillage techniques, neither of which require adoption of VRT (Chamen, 2009).

Another factor to consider is the achievable accuracy of input application compared to the mapping or imagery resolution used to produce VR application maps. Modern image capture techniques allow imagery resolution with pixel sizes measured in cm^2. In contrast, the application footprint of an irrigator sprinkler pack is likely to be in the order of 30-50 m^2. Similarly, a 24 m throw fertiliser spreader will cover 100 m^2sec^{-1} when operating at 15 kmh^{-1}. In these cases, the capacity to collect spatially precise imagery far outstrips the capacity to vary application at the same level of resolution.

Wider adoption of VRT in the grain industry than other sectors is partly due to the longer history of imagery collection and the development of relationships between spectral signatures and input requirements. There is also a perception that optimising inputs to match crop requirements is more cost effective across the extensive areas involved in grains production. However, even in the grain industry, uptake of VRT is low at approximately 17% of the grower base (Llewellyn and Ouzman, 2014).

At the simplest level, spatial control of irrigators, spreaders, sprayers and seeders can be used to avoid application of materials to non-crop or environmentally sensitive areas such as fence lines, riparian areas or roadways, and over-application in areas like headlands. This can be achieved by on-off control of individual sprinklers, nozzles or seeder units, section control of a bank of application devices, or adjustment of throw width in the case of spreaders (Velandia*, et al.*, 2013). All these modes of operation are controlled by spatial boundaries provided to the machine controller. In the context of SSCM, VR control provides gradation of variation governed by soil or crop needs, rather than just on-off control as required to prevent over application or treatment of non-target areas.

Given that field crop production is based on soils, and soils are generally spatially heterogeneous, variability in crop growth is almost inevitable. VRT allows the use of SSCM in the application of crop inputs to minimise crop variability with the objective of achieving uniform maturity and quality at the time of harvest. Current uses are well developed for VR application of fertiliser and irrigation, although there is still more development required to facilitate reliable real-time VR operations, particularly in irrigation. The use of VRT for applications such as disease and insect management is much less developed.

5.1 Fertiliser and soil amendments

VR fertiliser inputs are one of the most common applications of SSCM. Soil mapping of nutrient status can be used to develop a prescription map, which is then uploaded to the VR controller to vary the amount of fertiliser applied to different areas of the field. This technique has been widely applied in the grain industry (Llewellyn and Ouzman, 2014; Robertson*, et al.*, 2009; Robertson*, et al.*, 2012) and has been the subject of considerable research internationally (Basso*, et al.*, 2016; Boyer*, et al.*, 2011; Diacono*, et al.*, 2013; Mayfield and Trengove, 2009) in many different crops, including perennial horticulture (Colaco and Molin, 2017). VR application has also been investigated for the use of materials such as manure (Haneklaus*, et al.*, 2016) and other soil amendments.

The economics of using VR application depends on the crop, the level of variability and the season (Brennan*, et al.*, 2007; Koch*, et al.*, 2004; Murray and Yule, 2007). Limpus*, et al.* (2016) reported on numerous case studies of VR fertiliser and soil amendments in Queensland vegetables. These case studies included a range of outcomes of VR applications including up to 40% savings in applied lime and 25% fertiliser savings (**Figure 29**). In other cases, there was no reduction in total applied product, however, the grower co-operators were confident that products had been more effectively used in the areas of greatest need.

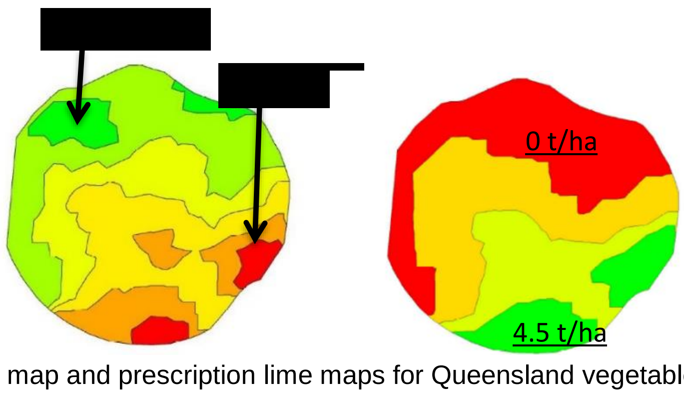


Figure 29. pH zonal map and prescription lime maps for Queensland vegetable fields. A) Zonal pH map based on pH grid sampling with pH increasing from 4.5 (red zone to 5.5-5.9 (bright green zone); B) Increasing lime rate from 0 t/ha (red zone), 1.5 t/ha (orange zone), 2.5 t/ha (yellow zone) to 4.5 t/ha (green zone). *Source*: Limpus*, et al.* (2016).

While soil maps prepared in advance can be used to inform prescription maps for VR fertiliser applications, considerable research and development effort has also been invested in estimating nutrient status based on real-time crop canopy monitoring to vary fertiliser application (Maleki*, et al.*, 2007; Samborski*, et al.*, 2016). Examples of commercially available technologies for achieving this capacity include GreenSeeker™[27], Crop Circle™[28], and CropSpec™[29].

VR fertiliser requirements can also be determined by analysis of previous yield maps, from which it is possible to calculate nutrient export, and hence determine nutrient replacement requirements. This technique is widely used in the grain industry where the most common data layers available tend to be a soil nutrient map and successive yield maps.

Irrigation

Water is a major input in vegetable cropping systems, and one which requires precise management in order to achieve efficient use and high crop productivity. While interest in VR irrigation (VRI) has been driven by soil variability, water availability, energy costs and crop variability (Evans and King, 2012), the first recorded instance of VRI use in the research literature was for frost control based on predicted fruit bud temperatures (Hamer, 1980). Similar to the now more common applications for crop growth, significant water savings were achieved while successfully controlling frost.

As with other VR technologies, the objective of VRI is to reduce inputs (water and pumping energy) and improved crop uniformity by matching the application rate to the water holding capacity of the soil (Vories*, et al.*, 2017). The ability of soil to store water for crop use is a function of soil texture and management. For this reason, EM38 mapping and in-field validation is often the starting point for creation of soil maps which then inform the development of VRI prescription maps (Fortes*, et al.*, 2015). Irrigators can be controlled to apply less water to soils with low water holding capacity or poor drainage, while applying more to soils with higher infiltration and storage capacity. However, there are more determinants than soil texture in designing a functional VRI map, as topography and crop growth factors during the season should also be considered. Successful VRI uses soil mapping as the basis for VRI prescription maps and adjusts the boundaries of the differential watering zones depending on crop requirements and the weather as the season progresses.

All major manufacturers of centre pivot and linear irrigation systems market VRI controllers that can either be supplied at installation or retro-fitted. The status of VRI technology purchases in Australia is not known, but as with other PA technologies, ownership levels appear to be significantly higher than levels of use, as it has been reported that only about 10% of VRI controllers are used with any regularity (*pers.comm*., A. McCarthy).

One of the long-pursued goals of precision irrigation is the capacity to vary irrigation applications based on real-time water demand data. This may be done either through real-time soil moisture sensing data relayed to the VRI controller (Lambert*, et al.*, 2012), or through real-time crop imagery capable of detecting plant water stress or demand, which in turn adjusts the information available to the VR controller (Evans*, et al.*, 2012; O'Shaughnessy*, et al.*, 2015; O'Shaughnessy*, et al.*, 2013;

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27 https://agriculture.trimble.com/precision-ag/products/greenseeker/
28 http://hollandscientific.com/portfolio/crop-circle-acs-430/
29 https://www.topconpositioning.com/agriculture/crop-sensing

Shin and Son, 2015). Current research in this area includes the use of real-time data capture, active weather monitoring and forecasts in crop models to predict and control water application rates (McCarthy, *et al.*, 2010; McCarthy, *et al.*, 2014).

5.3 Agricultural chemicals

VR spray technology is of great interest in agriculture. Blanket spraying of pesticides for spatially distributed targets is an inefficient use of resources, is costly and has the potential to cause environmental harm in the event of off-target spray drift. As for fertiliser application, the identification of areas requiring VR chemical application can be done prior to spray operations to create a VR map through the use of crop imagery (more appropriate for weed infestations) or in real-time using tractor mounted sensors which control product application via the on-off sequencing of spray nozzles.

5.4 Weeds

The earliest example of targeted pesticide application came with the use of sensing technology in 1984 by Warwick Felton, DPI Tamworth, NSW. The commercialisation of this technology ultimately led to WeedSeeker®[30]. This is an active near infra-red (NIR) sensor originally designed to detect green weeds against a background of soil or stubble for the purpose of weed control during the fallow phase of zero-till grain systems. While successful in that application, WeedSeeker® is limited by its inability to discriminate between crop plants and weeds. Other options include the use of chlorophyll fluorescence (Hilton, 2000; Mattila, *et al.*, 2013) and machine vision systems (Nieuwenhuizen, *et al.*, 2007). Significant work has also been done with remote sensing imagery to map weed infestations, with the processed images used to prepare a VR spray application map (Castaldi, *et al.*, 2017; Herrmann, *et al.*, 2013; Lopez-Granados, *et al.*, 2016; Wiles, 2009).

5.5 Diseases

Crop biomass has been proposed as an indicator to target preventative fungicides based on the premise that fungal disease outbreaks are more likely to be concentrated in areas of high biomass or in plants at different stages of growth (Jensen and Jorgensen, 2016; Jensen and Nielsen, 2015; Tackenberg, *et al.*, 2016). A similar approach has been used in vineyards, where variations in crop canopy width are used as the basis for VR control of spray volume (Gil, *et al.*, 2013). While crop biomass may be a useful predictor of fungal disease risk, use of VR application in these circumstances requires either a knowledge of the disease risk (for preventative sprays), or on-ground disease identification (for curative sprays), as there is currently no commercial sensor that can detect specific diseases or disease symptoms using remote sensing. A significant amount of research has focused on the identification of spectral signatures for particular diseases in specific crops (Bauer, *et al.*, 2011; Calderon, *et al.*, 2014; Devadas, *et al.*, 2015; Feng, *et al.*, 2016; Zhang, *et al.*, 2011). With such information, it would be possible to prepare VR application maps or eventually move to real-time control based on spectral data gathered from sprayer mounted sensors. In the meantime, it is possible that imagery such as NDVI, followed by on-ground inspection, could be used to detect early on-set of diseases, allowing VR treatment.

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[30] https://agriculture.trimble.com/precision-ag/products/weedseeker

5.6 Insects

Compared to weeds and diseases, the mobility of many pest insects may limit the use of advance detection methods for VR spray operations. Insects are also more difficult to detect using remote sensing and spectral imagery, and the use of VR spraying will rely on the detection of crop stress caused by insect attack, rather than the presence of the insects themselves (Luo*, et al.*, 2013; Mirik*, et al.*, 2012; Prabhakar*, et al.*, 2011). The application of precision agriculture techniques for VR insect control is a relatively new area of research, with very little reported literature. As is the case for diseases, crop biomass has also been used as a surrogate for insect infestation on the basis that areas of high biomass are more likely to harbour high populations of insects if an infestation is present. Using commercially available biomass sensing technology, such an approach used real-time sprayer control to apply insecticide in wheat, with a 13% saving in chemical use (Dammer and Adamek, 2012). Similar to disease detection, there are currently no commercially available insect sensors to enable real-time control, and other spectral imagery that indicates crop health is more likely to provide a surrogate measure for VR applications.

5.7 Growth regulators

Many crops are treated with growth regulators to either control plant height for ease of harvest or to alter the partitioning of plant resources to increase yield of the harvestable plant component. Uniform application of growth regulators to crops with variable spatial biomass will result in inefficient use of product as well as the over-regulation of those areas of the crop that are already below average in growth. Therefore, growth regulation is also an opportunity for the use of VR techniques (Grenzdorffer, 2003). Recent work in mapping the height of poppy crops (*Papaver somniferum*) opens the possibility of using 3D surface modelling as an approach to create VR maps for growth regulator application (*pers. comm*., A. Lucieer).

5.8 Seeding

Different soils have different capacities to support plant production, resulting in variable plant growth. Similar to VR fertiliser inputs to treat crop variability, VR seeding rates can be used to vary plant population to align with the productive capacity of the soil (Horbe*, et al.*, 2013; Lowenberg-DeBoer, 1999). VR seeding research dates back to the early 2000s (Maguire*, et al.*, 2003; Reining*, et al.*, 2003), and controllers, both factory-fitted and after-market, are available for many commercial seeders, particularly those used in the wheat, corn and soybean industries. Variable rate seeding of potatoes has been used in Tasmania for a number of years, particularly in situations of highly variable soil type within individual pivot circles (*pers. comm*., S. Creese).

5.9 Tillage operations

Tillage is not normally thought of as a target for the application of VR technology. However, there are at least two applications that are either in use or the subject of research investigation. Although the purpose of potato planting is to place seed pieces in the soil for crop establishment, the massive soil disturbance that occurs during furrow opening and ridge forming constitutes a tillage operation. Soil mapping and VR control technology have been used to equip potato planters with the capacity to form ridges in heavier soil types, and to lift the furrowing bodies out of the soil to enable flat planting on lighter, sandy soils in Tasmania (*pers. comm*., S Creese). The changed configuration assists with reduced wind blast and improved water management under irrigation.

While tillage is usually applied as an extensive operation across a field, there are circumstances in which it may be useful to vary the depth of tillage depending on soil type or some other factor, such as soil compaction. The control that is afforded by spatial mapping and automatic depth control mechanisms facilitates a process that is more commonly referred to as ‘strategic’ tillage rather than

VR tillage (Basso*, et al.*, 2003; Jia*, et al.*, 2016). A further application of this approach may involve the use of tillage to eradicate herbicide resistant weeds from zero-till systems. Using detection systems similar to Weedseeker®, research and development is currently in progress to control the lowering and lifting of individual tines on a cultivator to selectively remove identified weeds from a zero-till fallow (*pers. comm.*, P. Newman).

6 Yield monitoring

Yield monitoring refers to the gathering of spatially referenced data during the harvest process. Its purpose may be to validate yield estimates determined from earlier imagery, but in many cases, the primary purpose is to understand yield variability and to inform management decisions for future crops. Spatial yield data can be overlaid and compared to other data layers (e.g. soil mapping, drainage/wetness) to assist planning and decision making. Combined with cost of production data, yield mapping data can be converted to profit and loss maps, which are powerful motivators for implementation of management practices to reduce variability and improve paddock areas with poor performance.

Yield sensors

Many different types of yield monitoring technologies have been developed to cater for the many different physical properties and flow behaviours of produce that vary from small seeds (grain) to fibre (cotton), stalks (cane) and large objects (fruit, vegetables).

Important components of any yield monitoring system are: a) the capacity to measure either the mass or volume of the harvested crop, b) the operating speed of the system conveying the product, and c) the ground speed and location of the harvester at the time of data collection. This latter data is obtained from Global Navigation Satellite Systems (GNSS) technology which is the foundation for all spatially mapped data.

If the product flows as a mass during the harvest process, then either mass, volume or cumulative weighing will be most appropriate means of measuring yield (Ehsani and Karimi, 2010). This is the case for grain and cotton. Hand-picked products are better suited to cumulative weighing to measure yield, although that will depend on how the crop is handled in the field at harvest. For example, crops harvested onto a picking aid which conveys the product to a packing platform or a central bin (e.g. lettuce, broccoli) may also be suited to mass measurement on the feed conveyors. A lack of readily available yield monitoring technology for horticultural crops is a barrier to the collection of this important data set from a PA perspective. Different methods that may be used for yield estimation or measurement are shown in (**Figure 30**) (Ehsani and Karimi, 2010).

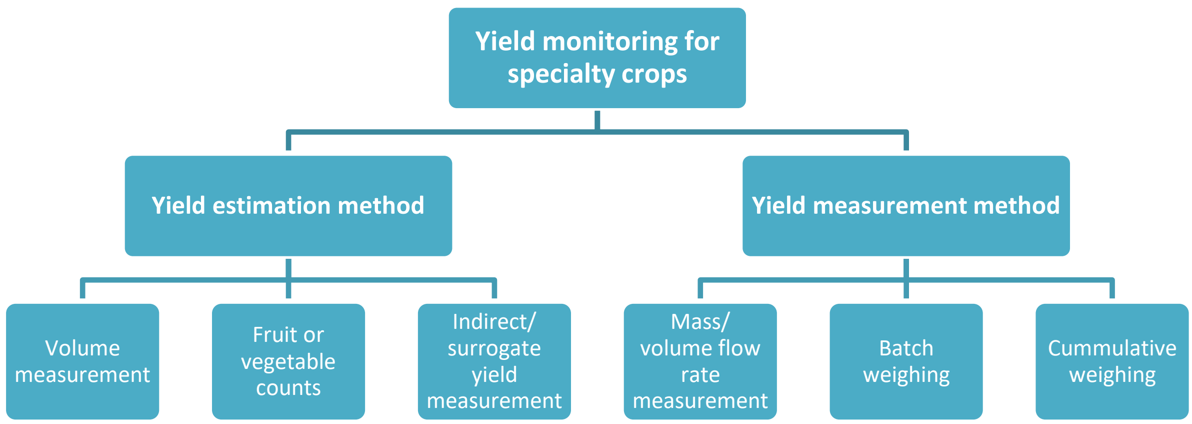


Figure 30. Different methods used for yield estimation and monitoring for specialty crops. *Source*: Ehsani and Karimi (2010)

Quality measurement sensors

Quality is often more important than gross yield in horticultural crops, although much more difficult to measure in real time during harvest. Quality takes many different forms, dependent on the demand of the market. It may be defined by the product fitting within a certain size range, meeting certain shape uniformity characteristics, colour, being blemish free or exhibiting certain biochemical characteristics, such as brix. One of the few examples of an attempt to measure quality at harvest is in the viticulture industry, wherein berry anthocyanins were measured with a hand held device on the harvester as a proof of concept, demonstrating the potential of being able to measure grape quality in real time during harvest (Bramley*, et al.*, 2011a).

The technologies for sorting products based on size, weight, colour or blemish are relatively well developed for the packing house environment. Their application on harvesters is rare, as it is not usually the location where quality sorting is done. In terms of being able to map quality in the same way that yield is mapped, the most promising technology is image analysis. It is questionable that it is necessary to monitor quality and be able to display it in real time on a tractor or harvester console, as it the case for gross yield. However, with post-processing technologies, it should not be difficult to adapt the image capture technologies used in pack houses to harvesting equipment to record geo-referenced images of, for example, potatoes on a harvester conveyor, for subsequent image analysis and map preparation. The field is clearly a more difficult operating environment than the pack house, and image analysis algorithms would potentially have to deal with issues such as surface dirt, which could make blemish detection more difficult. However, basic properties such as shape, size and colour should be relatively easily captured, and this has been achieved in some cases such as seed potatoes (*pers. comm*., J. Wilson).

Horticultural crops

While yield monitoring is highly developed in the grain and other field crops industries, commercially available systems for specialty crops have only started to become available in recent years (Lee*, et al.*, 2010). Very few yield monitors are fitted as standard equipment ex-factory. While Europe's largest potato harvester manufacturer (Grimme®) offers a yield monitoring system as an optional extra, most are retro-fitted as after-market extras by owners and operators. There has been little incentive for commercial manufacturers to invest in the development of yield monitoring systems for specialty crops, due to the large diversity in crop type and harvesting methods, and the small global market for specialist machines (Ehsani and Karimi, 2010). Despite the diversity of crop and machine types, the most successful sensors for yield monitoring in horticulture are load cell based systems, used either in-line to continuously measure the mass of product moving over a conveyor, or fitted under a bin to measure the incremental increase in load as the bin fills.

Grapes and tomatoes

Amongst the horticultural industries, viticulture has been an early adopter of yield monitoring (Bramley and Trengove, 2013; Bramley, 2005; Bramley and Hamilton, 2004). The first commercially available yield monitor was based on a volumetric sensor that used ultra-sonic sensors to measure the height of the load on a conveyor belt (Taylor*, et al.*, 2016). This then required the use of a density factor to calculate mass. This was not particularly successful, due to the need to constantly adjust the density coefficient between varieties and even at different times of the day. Yield monitoring technology subsequently moved to load cell based systems which continuously weigh the mass of product on the final discharge conveyor. The most commonly used system on grape harvesters is the ATV grape yield monitor produced by Advanced Technology Viticulture (Adelaide, South Australia) (Taylor*, et al.*, 2016). Development of a yield monitor for tomatoes was first reported in

1999 for a continuous mass flow system using load cells under a conveyor (Pelletier and Upadhyaya, 1999).

[redacted] Root and tuber crops

The use of yield monitors on potato harvesters in research dates back to at least 1999 (Davenport*, et al.*, 2002; DeHaan*, et al.*, 1999), although commercial availability has not occurred in any great measure until the past few years. The application of yield monitoring to root crop harvesters is fundamentally no different to the viticultural situation, and systems are based on load cells which monitor the mass of product on the conveying system just prior to loading into a bunker or trailer. There are two dominant systems in use, one being the ATV system originally developed for grape harvesters[31]. The other system in most common use is manufactured by Greentronics™[32]. Both of these systems have been used for yield monitoring on potato, sweet potato and carrot harvesters (**Figure 31**) (Layden and O'Halloran, 2016; Limpus*, et al.*, 2016). The ATV system has been used on potato harvesters in Tasmania (Whelan and Mulcahy, 2016).

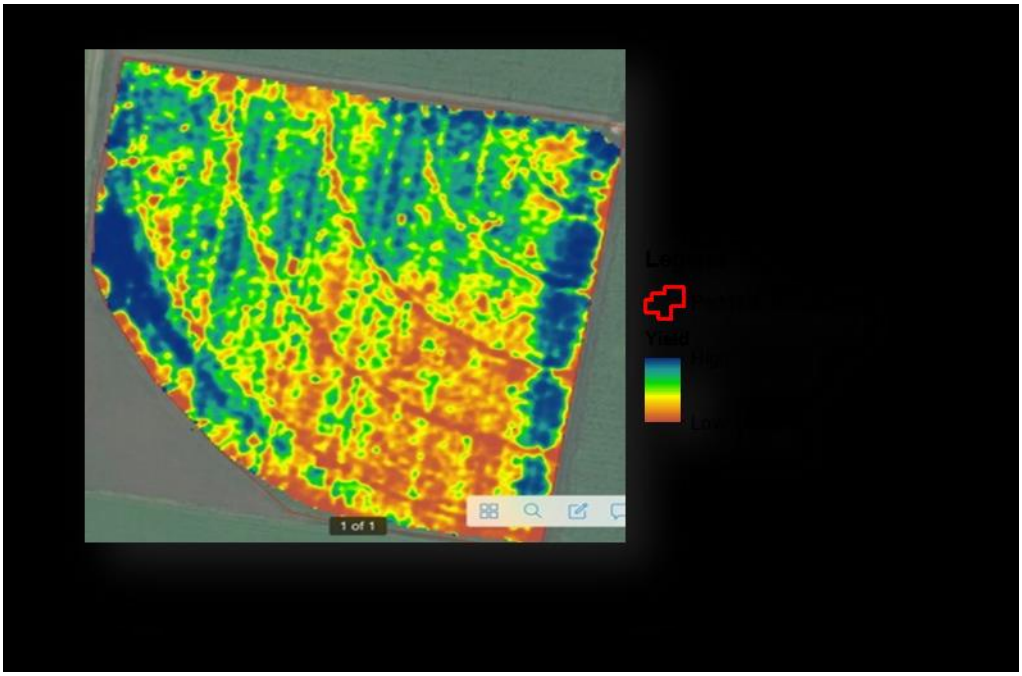


Figure 31. Yield map derived from yield monitor data in carrots. *Source:* Limpus*, et al.* (2016)

31 http://www.atv.net.au/
32 http://greentronics.com/products/yield-monitor/

[redacted] Other field crops

[redacted] Yield

Yield monitoring is undoubtedly most developed and wide spread in the grain industry. Yield monitors used in grain harvesters measure the flow of grain either by mass or volume, using a variety of sensor types such as mass-flow, radiation sensors, photoelectric sensors or volumetric flow sensors.

- Mass-flow sensing is the most common approach in grains, and is achieved by measuring the impact force of grain hitting a plate mounted at the top of the clean grain elevator. Load cells measure the deflection of the plate mounting members, and through calibration, the data are converted to a measure of yield.
- An alternative means of measuring mass-flow is to use radiation sensors mounted in an emitter-receiver arrangement. The presence of grain between the emitter and receiver reduces the radiation received by the sensors and is a function of the mass of grain flowing between the two components.
- Photoelectric sensors can be used to measure the volume of grain on each paddle of the clean grain elevator. Paired emitter-receiver light sensors are placed on either side of the clean grain elevator and the volumetric flow is correlated with the timing of the interruptions of the light circuit.
- Volumetric flow can also be measured using a paddle wheel sensor at the base of the bubble-up auger in the grain tank. Grain volume is determined by recording the number of paddle wheel revolutions.
- Microwave sensors are mainly used in cotton pickers. This sensor transmits a beam of microwave energy through the walls of a plastic conveying duct, into the stream of flowing cotton. A portion of the energy reflects off the moving cotton and returns to the sensor, where the reflected energy is detected. By calibration, this then measures the volume flow rate of the cotton (Andrade-Sanchez and Heun, 2013).

A number of attempts have been made to measure yield variation in sugar cane. Early systems were based on direct discrete mass measurement, while later efforts focused on predicting yield by a number of surrogate measures, such as chopper pressure, feed train roller displacement and elevator power demand (Jensen*, et al.*, 2013). Optical sensors have also been used to measure the amount of cane on the slats in the elevator (Price*, et al.*, 2007).

The initial development of a yield monitor for peanuts consisted to monitor the incremental mass of product in the holding bin (Durrence*, et al.*, 1999; Vellidis*, et al.*, 2001). This alternative method proved to be 97% accurate on an individual trailer load basis. Optical sensors, based on cotton yield monitors, have also been developed for peanuts (Thomasson*, et al.*, 2006).

[redacted] Quality

Grain quality, as measured by protein or oil content, is an important variable that can be managed through precision agriculture techniques. The release of commercial quality sensors for grain harvesters came about 10 years after the release of commercial yield sensors (Taylor and Whelan, 2007). Current quality sensing technologies rely on the measurement of transmission (rather than reflectance) data from a narrow range of spectra, clustered around the red-edge and low NIR wavelengths.

There are a number of factors that are important to consider in achieving reliable results from quality monitors on grain harvesters:

- environment – heat, dust, vibration

- possible non-grain contamination
- incorrect sensor calibration
- impact of production system and varietal differences on calibration

Limitations to yield mapping in horticulture

The long history of yield mapping in the grain industry has identified some useful qualifiers regarding the best way to use yield maps. For example, it is generally accepted that it takes yield maps from 3-5 crops of grain to gain a reasonably accurate and useful understanding of yield variability in a given paddock (*pers. comm.*, T. Neale). In many grain producing areas, particularly dry land wheat regions, this can be achieved in as many seasons. The situation in the vegetable industry is somewhat different, as crops are usually grown in rotations that may not see a return of the same crop type to the same paddock for 3-6 years. Therefore, it could conceivably take anything from 9-18 years to obtain three yield maps of the same crop type. This is problematic for building an archive of yield maps related to the one crop, although it also accepted that annual yield maps of different crops from the same paddock can still provide useful information for year to year management purposes.

The technologies for yield monitoring are generally well developed, particularly for those based on continuous measurement of mass flow via load cells. The application of yield monitoring in horticulture is increasing, but is still far from common practice. Although there are successful models available for after-market installation, there seems to be only slight interest on the part of manufacturers to offer yield monitoring as a standard feature, or even as an option, on many vegetable harvesters. The lack of ubiquitous yield monitoring on vegetable harvesters is seen as a major impediment to the more widespread uptake of precision agriculture practices. Understanding variability in crop yield, and its impact on profitability, is a powerful motivator for growers to investigate the underlying causes of variability and options to address it.

7 Sampling and ground truthing

As indicated in the review of sensing technologies, there are many options that can add benefit to the Australian vegetable industry in terms of improved crop monitoring. However, it is important to keep in mind that these technologies are all ‘tools’ that can assist with improved on-farm management, and not direct replacements for sound agronomic disciplines.

All of the sensors and technologies described in this review provide data which can be used to help inform management decisions to improve crop production. It is important to understand that data is all they provide. Understanding what the data means is a key, and often overlooked, element of the precision agriculture process. For example, an EM38 soil map will show the variation in apparent electrical conductivity (EC_a) in the soil. However, the data values are influenced by soil texture (sand, clay, and silt proportions), soil moisture content and salinity. It is essential to soil sample for analysis to understand exactly what the characteristics of the soil are in the different zones indicated by the map. Whether a high or low EC_a is desirable, or not, will depend entirely on which characteristic is most influential, and whether or not that characteristic is a benefit or a limitation to production.

Similarly, spectral images, of which NDVI is the most commonly derived product, could be providing information on all manner of aspects of the crop. A low NDVI reading indicates that something is limiting the vigour of the crop, but it could be nutrients, disease, pests, water stress (either too much or too little) or any number of other influences. Without going to the relevant parts of the field to understand what the data means, it is not possible to enact suitable remedial management practices on a differential basis. Sensing technologies provide a broad range of data, hence the sampling and ground-truthing protocols need to be chosen according to the variable to be measured. It is then important to always adapt the protocols to optimize the analysis and results.

The soil sampling protocol for ground-truthing spatial data differs from traditional sampling in that rather than bulking random samples across a field to get a ‘representative’ sample, sampling is focused on understanding how samples at specific points in the field differ. Samples are commonly taken from spatially distributed locations around the paddock, which may be determined on a regular grid pattern or based on zones of variability in individual data layers (**Figure 32**). The standard practice for grid sampling is 1 sample per hectare, although for some measures, such as soil texture and organic matter, larger grids may be acceptable depending on the degree of variability (**Figure 33**) (Nanni*, et al.*, 2011). It may also be possible to integrate point sampling with other cheaper techniques, such as NIR spectroscopy, to increase the density of data while reducing the cost of laboratory analyses (Wetterlind*, et al.*, 2010).

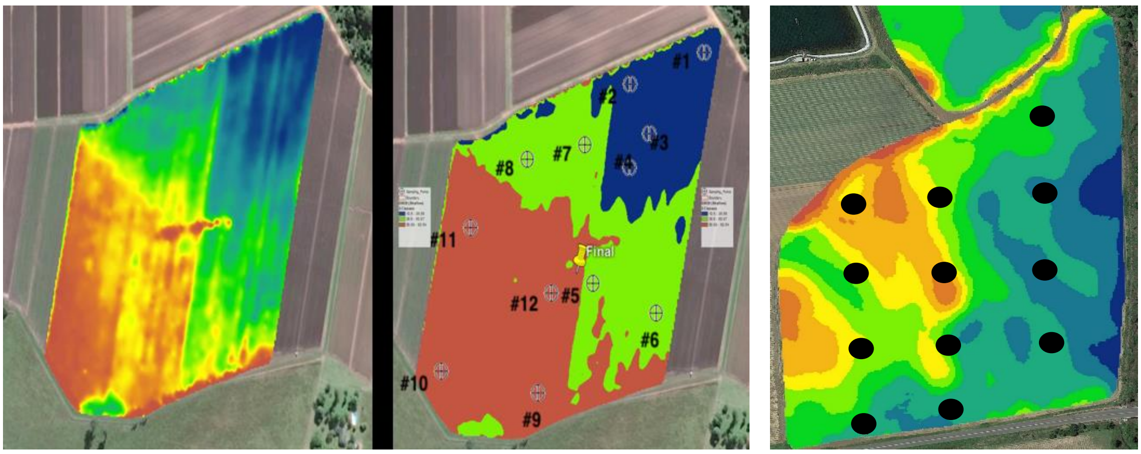
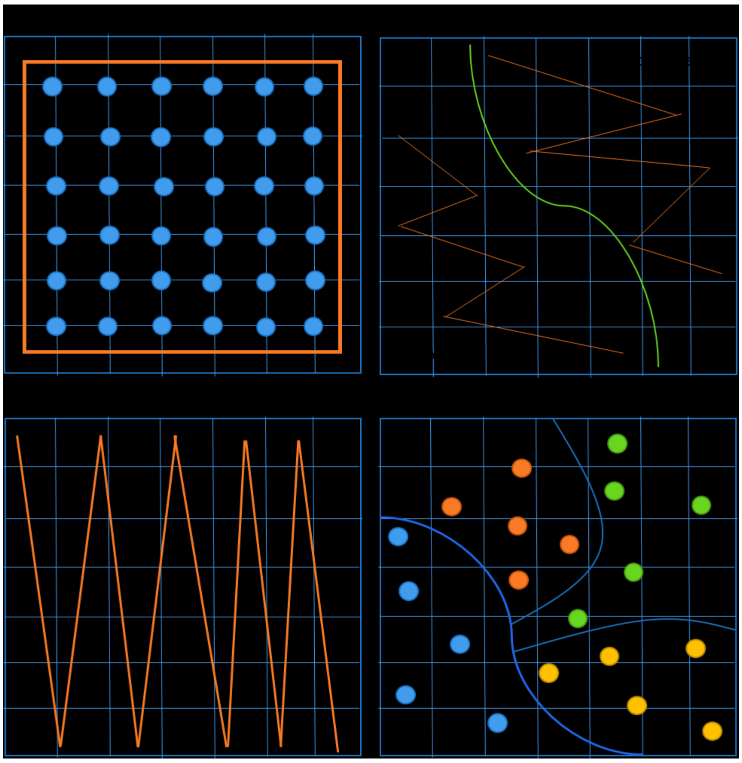


Figure 32. An EM map of a vegetable crop (left) and associated zonal sampling map (centre) where the management zones identified in the EM38 map have been allocated and sampling points plotted and grid sampling points across EM mapping. *Source:* Limpus*, et al.* (2016)



[redacted]

Zones of variability, developed from other mapping data, may also be used to inform the location of sampling points. Trimble Soil Information System™ (SIS) is one commercially available service that uses this approach[33] . In-built algorithms determine the locations for soil sampling based on a prior survey that obtains EM38, topographic and aspect data. The process collects soil cores for chemical analysis, as well as mechanical data such as soil resistance Regardless of whether sampling is based on a grid or zones of difference, soil samples are laboratory analysed and maps developed, which can then be used to prepare VR application maps. Sensors which measure and map pH on-the-go are available, which allows for more intense data collection without the laboratory cost.

Unlike spectral imagery, which provides data at a high pixel resolution that is considered to be continuous, there are large zones of interpolation present in nutrient maps prepared from grid or zone of difference sampling. This is a function of cost and practicality, and will remain the case until other more continuous methods are developed. Progress is being made in the area, with machines such as those produced by Veris Technologies®[34] which allow continuous mapping of soil organic matter and rapid pH sampling to provide a high density grid sample of one sample per 100 m^2.

The latter sampling protocol is also required prior to crop establishment to generate suitable prescription maps for nutrients such as P, K and lime for pH correction. These nutrient maps, in addition to prescription maps for nitrogen application that are usually developed from spectral imagery, are an important data layer for the adoption of VR fertiliser application, particularly with respect to pre-season applications.

33 https://agriculture.trimble.com/software/soil-information-system/
34 http://veristech.com

8 Accessible technologies, compatibility and opportunities for the Australian vegetable industry

Precision Agriculture uses a variety of technologies to provide information on the variability of soils and crop performance at different spatial and temporal scales. Such technologies include, but are not limited to, GNSS guidance of farm machinery that not only supports auto steer, controlled traffic and precision alignment of plant rows, but also provides a mobile platform to enable specialised sensors to measure in-field variability at high spatial accuracy and precision placement of crop inputs.

The following sections discuss some of the accessible and emerging technologies in precision agriculture.

[redacted] GNSS technologies for annual horticulture

Global Navigation Satellite Systems (GNSS), with signal correction provided by Real Time Kinematic (RTK) base stations, allow the positioning of equipment to an accuracy of ±2 cm horizontally, and approximately ±4 cm vertically. This high degree of positioning accuracy offers several benefits to agriculture including:

- lower fatigue levels of machine operators in-auto steer tractors
- capacity to use lower skilled personnel
- optimising field drainage to reduce waterlogging
- savings in pesticide and herbicide applications through targeted applications
- reduced soil compaction and erosion (e.g. such as controlled traffic farming (CTF))
- reduced nutrient runoff (Masters B*, et al.*, 2008) and loss (Vanderfield).

Most guidance systems use a standard single-baseline RTK system to achieve high vertical accuracy. However, this single-baseline system can suffer from an interrupted or inconsistent signal generally attributed to changes in atmospheric conditions (GPS World, 2016). An inconsistent signal leads to lengthy delays as the signal is being re-established, making the system unreliable for precision applications such as laser levelling for improved irrigation and drainage. Recently, North America and Australia have had access to VerticalPoint RTK (by Trimble), which addresses the limitations of the single-baseline, and offers 75%-95% productivity improvements. The new system integrates two rovers (i.e. GNSS receivers) for dynamic data collection that reduce atmospheric interference and therefore vertical accuracy inconsistencies (GPS World, 2016).

[redacted] Geostationary satellite systems

As a further evolution of GNSS accuracy and reliability, the Australian government is working towards improved on-farm telecommunications and supporting research into geostationary satellite systems. These include a satellite-based augmentation system (SBAS) and the Japanese Quasi-Zenith Satellite System (QZSS) system. Such systems remove the need for on-ground base stations and offer data that is not brand specific, thereby potentially overcoming compatibility issues between operation systems that have plagued the agricultural sector due to machinery manufacturers adopting in-house data standards. Ultimately, the optimal evolution of GNSS positional technology is to develop autonomous ‘driver-less’ machinery. To reach that point, accurate and reliable position signaling is needed.

[redacted] The potential of field robotics for horticulture.

The previous sections have discussed GNSS guidance and sensing technologies that can accurately measure crop health and performance. The following section brings these technologies together by providing some examples of machinery platforms that can potentially improve the on-farm management of horticultural crops. LettuceBot (Blue River Technology), developed in the USA and purchased by John Deere, integrates high precision guidance technologies with electronics, computers, cameras and sophisticated algorithms to assist farmers with autonomous thinning of individual lettuce plants based on optimal spacing and the most uniform size of available seedlings. LettuceBot has the capacity to operate at 5,000 plants per minute or 16 ha per day (**Figure 34**).

Figure 34. LettuceBot for precision lettuce thinning. Note the selection of the green leaves and the targeted-sprayed unwanted leaves (brown leaves). Source: (Blue River Technology)

As demonstrated, high positional accuracy on farm can not only increase on-farm efficiency and profitability but also support improved environmental stewardship by growers. As well as the commercially developed platforms, there has been significant development in on-farm robotics. Robotic platforms are generally accepted to be autonomous, i.e. reliant on GNSS antennae, provide guidance and crop sensing (multispectral or 3D cameras) and on-board image analysis to perform the tasks. Currently, these plaforms are within the research and development stage but are demonstrating their capabilities for autonomous driving, data collection, mechanical weeding, real-time variable rate fluid dispersion, and soil mapping and sampling (Calleija, 2016).

Robotic platforms recently developed in Australia include the RIPPA^{TM}, Ladybird and Shrimp developed by the Australian Centre for Field Robotics (ACFR, Sydney University), the AgBot II, developed by the Queensland University of Technology (QUT) and the Swarm Farm platforms (**Figure 35**). The Ladybird has been developed as a scientific research tool to test a range of functionalities, including an array of sensors that can repeatedly scan the field to measure crop phenotypes. Underwood (2015) reported that in testing on a commercial horticultural farm, the RIPPA^{TM} robot reduced herbicide use to 0.01% of the blanket spraying application rate. This is due to the ability to identify and spot spray individual weeds. The AgBot II prototype has achieved an overall success rate in weed detection and classification above 90% across different crops, and has demonstrated its capabilities of spot-spraying and mechanical removal of selected weed species (Queensland University of Technology).

Figure 35. Robotics in the field. From left to right: AGBot II by QUT, RIPPA™ and Ladybird by ACFR[35].

9 Increasing the adoption of PA systems in Australia vegetable production

Undoubtedly, the greatest rates of PA adoption in Australian agriculture have been in the grains, rice and viticulture industries (Whelan, 2007) with vehicle navigation systems, yield mapping and soil electrical conductivity mapping as the tools most adopted. While modest adoption has been evident in some agricultural sectors, uptake of PA technologies in the Australian vegetable industry has been negligible.

A study by Best (2016) analysed the perceptions of growers and consultants towards the application of precision agriculture methods in vegetable production systems. While participants recognised the potential benefits of PA and variable rate technologies for the vegetable industry, survey and interview results show that the barriers to adoption included lack of knowledge and awareness of new PA technology, perceived high cost of equipment, time consumption, return on investment (ROI) and limited equipment (in relation to what the grower already owns compared to what is available to the vegetable industry). Other limitations were identified as the complexity of the technology available and the level of support provided that is required to address and adapt the technology to the vegetable growing industry. Results of the surveys identified lack of knowledge as the most relevant barrier to the use of precision methods, as well as lack of awareness of technologies, perception of PA as not profitable for vegetables, high costs and lack of appropriate equipment. Jochinke*, et al.* (2007) highlighted that the lack of understanding of technologies, compatibilities and interpretation could lead to the purchase of inappropriate equipment. Interestingly, in the study by Best (2016) 'not profitable' was the least relevant barrier and there was a significant difference in the ratings of costs, with growers rating this higher as a barrier to adoption than consultants.

While there are instances of rapid uptake, generally, technology adoption in agriculture is an intrinsically complex process. Rogers (1995) clearly defined the adopters of new technologies into five categories of innovativeness (the relative degree to which individuals are likely to adopt technology earlier relative to others): innovators, early adopters, early majority, late majority and laggards (**Figure 36**). Each of these groups tend to vary in their personal characteristics and how they interact and there is a tipping point beyond which the rate of adoption rapidly increases to become widespread (Rogers, 1995). Lamb*, et al.* (2008) highlighted that while the breadth of PA

[35] http://www.queenslandcountrylife.com.au/story/4336205/robot-weeder-on-show-at-bowenville-today/

activities has increased significantly, this has not been reflected in higher rates of adoption. In reality, PA adoption in Australian agriculture has not progressed beyond early adopters.

Figure 36. Adoption of innovations can be described in five categories of the above bell curve.
Source: Lamb*, et al.* (2008)

Innovators are generally more proactive, seeking information from multiple sources, not risk averse and tend to be involved with the development of technologies. Early adopters are generally more highly educated with regional leadership roles while later adopters tend to rely on the experiences of early adopters when making adoption decisions. Each category of adopter exhibits inherent differences in how the obtain and act upon information. Where product developers would work closely with farmers during the development stage, it is easy for the focus to shift towards the early adopter farmers. This causes the mainstream segment of the market, the early and late adopters and the laggards the potential to adopt the new innovation at a slower rate, or not at all. Lamb*, et al.* (2008) suggests that engaging the broader cross-section of potential users of the process or product during development or evaluation stages may alleviate the impediment of uptake by the majority.

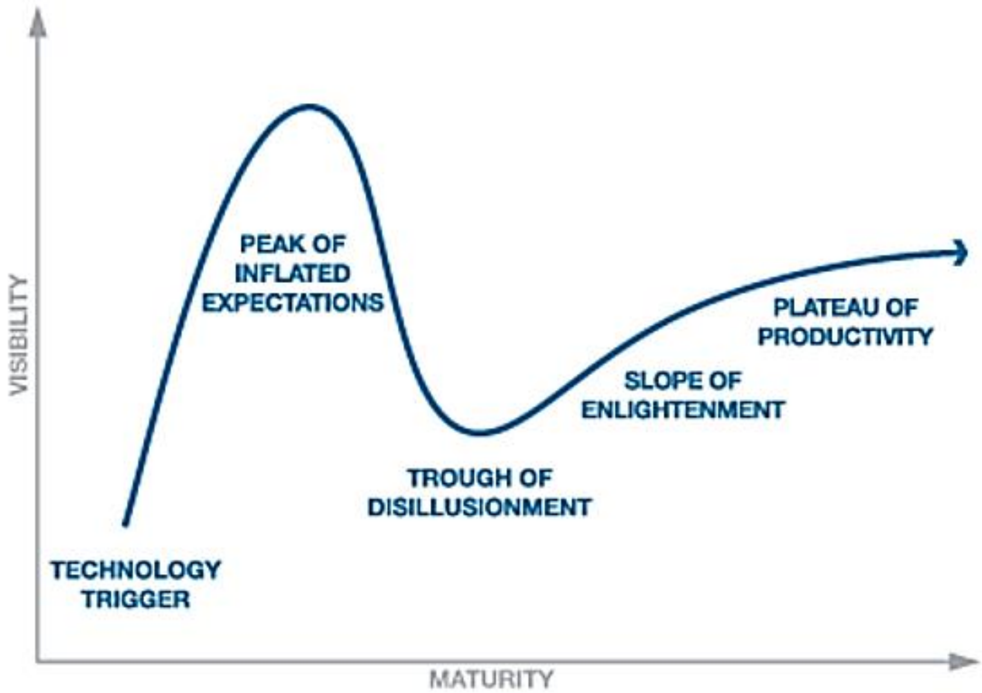


Figure 37. An example of the Gartner Hype cycle, which is relevant to the adoption of PA technologies over time[36].

The Gartner Hype Cycle is an alternative model of technology adoption that uses product utilisation within a market to illustrate the adoption of emerging technologies over time (**Figure 37**). The initial release of a technology (Technology Trigger) is generally associated with media and industry hype, which builds unrealistic expectations of what it can achieve (Peak of Inflated Expectations). Practical implementation and realistic applications is generally associated with some disillusionment (Trough of Disillusionment) followed by a Plateau of Productivity as the methodologies and processes to ease and assist with implementation become more readily available. According to Lamb*, et al.* (2008), very few PA technologies have reached the end of the Hype Cycle as they are still very much in the uptake phase.

Numerous studies, such as Kuehne*, et al.* (2017) and Pierpaoli*, et al.* (2013) have been categorised based on the aspects that contribute to the rate and extent of PA adoption (Kuehne*, et al.*, 2017; Pierpaoli*, et al.*, 2013; Robert, 2002; Tey and Brindal, 2012). This data has been collated and is presented in Table 4.

36 *Source*: https://www.linkedin.com/pulse/big-data-welcome-slope-enlightenment-maybe-brady-leavitt/

Table 3. Categories of the types of barriers faced by growers adopting PA technology

CATEGORY	BARRIERS	REFERENCES
SOCIOECONOMIC	Age Previous experience Formal education, knowledge of PA technology Risk Cost	Pierpaoli, *et al.* (2013) Kuehne, *et al.* (2017) Adrian, *et al.* (2005) Robertson, *et al.* (2008) Daberkow and McBride (2003)
AGRO-ECOLOGICAL	Farm size Land tenure Soil quality	Robertson, *et al.* (2012) Pierpaoli, *et al.* (2013)
INSTITUTIONAL	Farm location and associated resources Access to telecommunications	Best (2016)
INFORMATIONAL	Use of agricultural advisor/consultants Skill level of agricultural advisors/consultants Appropriate sampling protocols Use of PA advisor/consultants Access to extension services Time consuming ground-truthing Difficult to measure impact	Robertson, *et al.* (2012) Robert (2002) Limpus, *et al.* (2016)
FARMER PERCEPTION	Perceived relative benefit Perceived profitability Perceived cost Perceived ease of use	Adrian, *et al.* (2005) Robertson, *et al.* (2008)
BEHAVIOURAL/ ATTITUDINAL	Willingness to adopt Intentionality Confidence	Adrian, *et al.* (2005)
TECHNOLOGICAL	Technology incompatibilities Computer literacy Software Complexity of use Trialability Ability to access large volumes of data	Robertson, *et al.* (2008) Daberkow, *et al.* (2003) Robert (2002) Robinson (2009) Jochinke, *et al.* (2007) Limpus, *et al.* (2016)

* Barriers identified specifically for horticulture

The numerous barriers identified through studies of the pathways to PA adoption highlights the complexity associated with PA technology implementation. Understanding the mechanisms of adoption is critical to determining the most appropriate methods for promoting adoption (Orr, 2003). In particular, comprehending producer perceptions and attitudes can assist in the developments of products and processes to address producer concerns (Adrian et al 2005). The Australian vegetable industry has an opportunity to consider previous work on adoption of PA technologies in other agricultural sectors and incorporate strategies to address key barriers into appropriately designed adoption programs.

From the literature reviewed here and specific vegetable production work by Best (2016) and Limpus, *et al.* (2016), key recommendations and considerations for adoption pathways for precision agriculture technologies in the Australian vegetable industry can be summarised as:

- Technical PA support, which is currently widespread and available to the grains and broad acre industries, is lacking in the greater part of the vegetable industry, particularly in the more regional areas. Greater collaboration between PA technical providers and the vegetable production industry is required to ensure the necessary support is provided.
- Need to address questions regarding cost and timing for vegetable industry and demonstration of economics and cost benefit analysis is critical.
- Consideration of needs of all adopters in the development and implementation of technologies and how they access information and make decisions.
- Better understanding and information on technology compatibilities and software integration.
- Need to assess yield data, to assess any pre and post on-field changes.
- Implementation of processes that include clear steps for timing of data and technology, support for data collection and interpretation through more engagement with consultants, and pre/post assessment data in order to create whole-farming systems with integrated approaches. Consultants also generally have little knowledge of PA indicating that consultants may need to be engaged from the very start of future projects to make sure outcomes are relevant and the support exists.

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11 Appendix

11.1 Appendix 1. Active proximal sensors

HOLLAND SCIENTIFIC CROP CIRCLE™ 470	The Crop Circle™ 470 sensor head (Figure 2A) is fitted with three polychromatic (white) light emitting diodes (LEDs) which illuminate the target area with spectra up to 670 nm. The returned spectral radiance is measured through three exchangeable narrow waveband (±10 nm) filters between 532 nm and 760 nm. The Crop Circle™ 470 can be used for point source or transect mapping of crops and pastures when coupled with a Holland Scientific GeoSCOUT™ GLS-420 data-logger (Holland et al. 2004). The Crop Circle™ 470 sensing system currently retails above $A12,000.
TRIMBLE GREEN SEEKER HAND HELD	The Trimble Green Seeker Hand Held (GSHH) illuminates a target with three LEDs, two of which are within the red spectral region (660 nm) and one in the Near infrared (770 nm). Three photo-detectors (PD) mounted behind a Fresnel lens receive target radiance information and calculated NDVI is displayed on the output screen (Figure 2(B)). Limitations of the GSHH is that it does not offer logging capabilities, so can only provide an average NDVI value over a transect. The inability to obtain reflectance measures for the individual Red and NIR bands means NDVI is the only vegetation index that can be derived. The GSHH currently retails at ~$A600.
SPACEBORNE RADAR	Synthetic Aperture Radar (SAR) systems are generally operated from satellite and include the Space borne Imaging Radar-C/X-Band, Synthetic Aperture Radar (SIR-C/X-SAR), European Remote Sensing (ERS-1 and -2), Advanced Synthetic Aperture Radar (ASAR), Japanese Earth Resources Satellite (JERS-1), RADARSAT-1 and -2, and Advanced Land Observation Satellite (ALOS-1). These systems offer data at either medium (15 m < pixel size < 100 m) or very high spatial resolution (pixel size < 4 m) (Joshi, *et al.*, 2016). However, more research is required to provide more adaptable tools to the agriculture sector.

11.2 Appendix 2 Comparison of available commercial satellites

SPECTRAL SPECIFICATION	WV-3*	SENTINEL-2*	GEO-EYE -1*	RAPIDEYE*	SPOT 6-7*	LANDSAT 8-OLI*
Revisit time	5 days	5 days	3-jan	1-6 days		16 days
Panchromatic			450-800 nm (41 cm)		450-745 nm (1.5 m)	550 – 680 nm (15 m)
Coastal	400-450 nm (1.24 m)	433-453 nm (60 m)				430 – 450 nm (30 m)
	405-420 nm (30 m)					
Blue	450-510 nm (1.24 m)	457-522 nm (10 m)	450-510 nm (2 m)	440-510 nm (6.5 m)	450-520 nm (6 m)	450 – 510 nm (30 m)
	459-509 nm (30 m)					
Green	510-580 nm (1.24 m)	542-577 nm (10 m)	510-580 nm (2 m)	520-590 nm (6.5 m)	530-590 nm (6 m)	530 - 590 nm (30 m)
	525-585 nm (30 m)					
Yellow	585-625 nm (1.24 m)			630-685 nm (6.5 m)		
Red	630-690 nm (1.24 m)	650-680 nm (10 m)	655-690 nm (2 m)	690-730 nm (6.5 m)	625-695 nm (6 m)	640 - 670 nm (30 m)
	635-685 nm (30 m)					
Red edge	705-745 nm (1.24 m)	697-712 nm (20 m)				
		732-747 nm (20 m)				
		773-793 nm (20 m)				
NIR	770-895 nm (1.24 m)	784-899 nm (10 m)	780-920 nm (2 m)	760-850 nm (6.5 m)	760-890 nm (6 m)	850-880 nm (30 m)
	845-885 nm (30 m)					
	897-927 nm (30 m)					
	860-1040 nm (1.24 m)	855-875 nm (20 m)				
	930-965 nm (30 m)	935-955 nm (60 m)				
SWIR	1195-1225 nm (3.7 m)					
	1220-1252 nm (30 m)					

	1365-1405 nm (30 m)	1360-1390 nm (60 m)				
	1550-1590 nm (3.7 m)	1565-1655 nm (20 m)				1570 - 1650 nm (30 m)
	1620-1680 nm (30 m)					
	1640-1680 nm (3.7 m)					
	1710-1750 nm (3.7 m)					
	2105-2245 nm (30 m)					
	2145-2185 nm (3.7 m)	2100-2280 nm (20 m)				2110 - 2290 nm (30 m)
	2185-2225 nm (3.7 m)					
	2235-2285 nm (3.7 m)					
	2295-2365 nm (3.7 m)					

Note: Spatial resolution (pixel size) is presented in parentheses.

*Source**: WV-3: https://www.geoimage.com.au/satellite/worldview-3
Sentinel-2: https://earth.esa.int/web/sentinel/user-guides/sentinel-2-msi/resolutions/spatial
Geo-Eye: https://www.geoimage.com.au/satellite/geoeye-1
Rapieye: https://www.geoimage.com.au/satellite/rapideye
Spot 6-7: https://www.geoimage.com.au/satellite/spot-6
Landsat 8-OLI: https://www.geoimage.com.au/satellite/landsat-8

11.3 Appendix 3. Narrow and broadband vegetation indices.

VEGETATION INDEX (VI)	ABBREV.	EQUATION	DESCRIPTION	REFERENCE
ANTHOCYANIN REFLECTANCE INDEX	ARI	$(1/R_{550}) - (1/R_{700})$	Sensitive to accumulation of anthocyanin in intact senescing and stressed leaves	Gitelson, *et al.* (2001)
CHLOROPHYLL VEGETATION INDEX	CVI	(NIR*R) / (G^ 2)	Sensitive to chlorophyll at Canopy scale	Vincini and Frazzi (2011)
DIFFERENCE VEGETATION INDEX	DVI	NIR - R	Sensitive to the amount of photosynthetically active vegetation (Biomass)	Tucker (1979)
ENHANCE VEGETATION INDEX	EVI	2.5*[(NIR-R) / (NIR+(6*R)-(7.5*B)+1)]		Huete, *et al.* (2002); Huete, *et al.* (1997)
ENHANCE VEGETATION INDEX 2	EVI2	2.5*[(NIR-R) / (NIR+(2.4*R)+1)]		Jiang, *et al.* (2008)
EXCESS GREEN INDEX	ExG	[2.0*(G/∑)] - (R/∑) – (B/∑); Where ∑ = R+G+B	Best separation of plants from the background.	Woebbecke, *et al.* (1993)
GLOBAL ENVIRONMENTAL MONITORING INDEX	GEMI	eta * (1 – 0.25 * n) – [(R – 0.125) / (1 – R)]; where eta = [(2 * (NIR^ 2 – R^ 2) + 1.5 * NIR+ 0.5 * Red)] / (NIR + R+ 0.5)	To compare observations under varying atmospheric and illumination conditions	Pinty and Verstraete (1992)
GREEN ATMOSPHERICALLY RESILIENT INDEX	GARI	NIR – [(G – l*(B –R)) / NIR+ (G – l *(B – R))]; Where l is a parameter that controls the atmospheric correction (better > 1.7)	Sensitive to Chl-a concentration	Gitelson, *et al.* (1996)
GREEN CHLOROPHYLL INDEX	GCI	(NIR / G) – 1	Sensitive to Chl content at canopy and leaf level	Gitelson, *et al.* (2003)
GREEN LEAF INDEX	GLI	[(2*G) − R − B)] / [(2*G) + R + B)	Separation of green vegetation and soil	Louhaichi, *et al.* (2001)

GREEN NORMALISED DIFFERENCE VEGETATION INDEX	GNDVI	(NIR – G) / (NIR + G)	Sensitive to Chl content	Gitelson*, et al.* (1996)
GREEN RATIO VEGETATION INDEX	GRVI	NIR / G; (R_{750}/R_{555})	Leaf Chl	Gitelson and Merzlyak (1994)
MODIFIED CHLOROPHYLL ABSORPTION REFLECTANCE INDEX	MCARI	[(R700 −R670) − 0.2*(R700 − R550)] * (R700 / R670)	Sensitive to leaf Chl concentration	Daughtry*, et al.* (2000)
MODIFIED SOIL ADJUSTED VEGETATION SPECTRAL INDEX	MSAVI2	$\frac{(2*\mathrm{NIR})+1-\sqrt{(2*\mathrm{NIR}+1)^2-(8*\mathrm{NIR}*\mathrm{R})}}{2}$	Improved vegetation sensitivity	Qi*, et al.* (1994)
NORMALISED DIFFERENCE RED EDGE INDEX	NDREI	(NIR – RE) / (NIR + RE); (R_{750} – R_{705}) / (R_{750} + R_{705})	Close relationship between chl-a (when high chl is present)	Gitelson and Merzlyak (1994)
NORMALISED DIFFERENCE VEGETATION INDEX	NDVI	(NIR – R) / (NIR + R)	Sensitive to biomass, photosynthetically active radiation (PAR) and vegetation fraction	Rouse*, et al.* (1974)
NORMALISED DIFFERENCE INDEX (RED)	NGRD	(G – R) / (G + R)	To discriminate between green veg and soil/residue.	Woebbecke*, et al.* (1993)
OPTIMISED SOIL ADJUSTED VEGETATION INDEX	OSAVI	(NIR – R)/(NIR + R + X); X = 0.16	To minimise the soil background	Rondeaux*, et al.* (1996)
RATIO TCARI/OSAVI		TCARI/OSAVI	Crop Chl content	Haboudane*, et al.* (2002)
RATIO VEGETATION INDEX	RVI	NIR / R		Jordan (1969)
RED-EDGE CHLOROPHYLL INDEX (RED EDGE MODEL)	CIre	(NIR / RE) – 1	Sensitive to leaf and canopy Chl content	Gitelson*, et al.* (2003)
RED-EDGE NORMALISED DIFFERENCE VEGETATION INDEX	ReNDVI	(NIR – RE) / (NIR + RE)	Sensitive to pigment and photosynthetic status	Barnes*, et al.* (2000)

RENORMALISED DIFFERENCE VEGETATION INDEX (RDVI)	RDVI	$(\mathrm{NIR} - \mathrm{R})/\sqrt{(\mathrm{NIR} + \mathrm{R})}$		Roujean and Breon (1995)
SIMPLE RATIO	SR	NIR / R		(Jordan, 1969)
SOIL ADJUSTED VEGETATION INDEX	SAVI	(1+L) * [(NIR - R) / (NIR + R+ L)]		Huete (1988)
TRANSFORMED CHLOROPHYLL ABSORPTION REFLECTANCE INDEX	TCARI	3*[(R700 − R670) − 0.2*(R700 − R550) * (R700/R670)]	Sensitive to Chl content	Kim*, et al.* (1994)
TRIANGULAR VEGETATION INDEX	TVI	0.5 * [120 * (NIR – G) – 200 * (R - G)]	Green LAI and canopy Chl density	Broge and Leblanc (2001)
VISIBLE ATMOSPHERICALLY RESISTANT GREEN INDEX	VARI	(G – R) / (G + R – B)	Vegetation fraction	Gitelson*, et al.* (2002)
VEGETATION INDEX GREEN	VIgreen	(G – R) / (G + R)		Tucker (1979)
NORMALISED WATER BALANCE INDEX - 1	WABI-1	$(R_{1490} - R_{531}) / (R_{1490} + R_{531})$	Sensitive to water status	Rapaport*, et al.* (2015)
NORMALISED WATER BALANCE INDEX - 2	WABI-2	$(R_{1500} - R_{538}) / (R_{1500} + R_{538})$	Sensitive to water status	Rapaport*, et al.* (2015)
NORMALISED WATER BALANCE INDEX - 3	WABI-3	$(R_{1485} - R_{550}) / (R_{1485} + R_{550})$	Sensitive to water status	Rapaport*, et al.* (2015)

Note: B: Blue; R: Red; RE: Red Edge; NIR: Near infrared; R_{xxx}: Reflectance at specific wavelength

11.4 Appendix 4 Typical sensor and platform configurations with main operational parameters*.

	DATA ACQUISITION PLATFORMS				
Applicability and operation aspects	**Satellite (spaceborne)**	**Airborne**	**UAV**	**Mobile/static (ground)**	**Crowdsensed (use of multiple mobile devices by individuals)**
Maneuverability	No/limited	Moderate	High	Limited	High
Observation space	Worldwide	Regional	Local	Local	Local
Sensor diversity	MS/HSI/SAR	MS/HSI/LiDAR/SAR	MS (LiDAR/HSI)	MS/LiDAR (HSI)	MS/video
Environment	Outdoors	Outdoors	Outdoors/indoors	Outdoors/indoors	Outdoors/indoors
Scale (inverse sensor range)	Small/medium/large	Small/medium	Medium/large	Medium/large	Medium/large
Ground coverage	Large (10 km)	Medium (1 km)	Small (100 m)	Small (50 m)	Small (10 m)
FOV	Narrow	Wide	Wide/super wide	Wide/super wide	Wide/super wide
Repeat rate	Day	Hours	Minutes	Minutes	Minutes/seconds
Spatial resolution (gsd)	0.30–300 m	5–25 cm	1–5 cm	1–5 cm	1–5 cm
Spatial accuracy	1–3 m	5–10 cm	1–25 cm	3–50 cm	1–2 m
Deployability	Difficult	Complex	Easy	Moderate	Simple
Observability	Vertical/oblique	Vertical/oblique	Vertical/oblique/360°	Oblique/360°	Oblique
Operational risk	Moderate	High	Low	Moderate	No

MS: Multispectral, HSI: Hyperspectral Image, LiDAR: Light Detection And Ranging, SAR: Synthetic Aperture Radar, FOV: Field-of-view
**Edited by the authors. Source: (Toth and Jóźków, 2016).*