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Review

Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps☆

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Precision agriculture dates back to the middle of the 1980's. Remote sensing applications in precision agriculture began with sensors for soil organic matter, and have quickly diversified to include satellite, aerial, and hand held or tractor mounted sensors. Wavelengths of electromagnetic radiation initially focused on a few key visible or near infrared bands. Today, electromagnetic wavelengths in use range from the ultraviolet to microwave portions of the spectrum, enabling advanced applications such as light detection and ranging (LiDAR), fluorescence spectroscopy, and thermal spectroscopy, along with more traditional applications in the visible and near infrared portions of the spectrum. Spectral bandwidth has decreased dramatically with the advent of hyperspectral remote sensing, allowing improved analysis of specific compounds, molecular interactions, crop stress, and crop biophysical or biochemical characteristics. A variety of spectral indices now exist for various precision agriculture applications, rather than a focus on only normalised difference vegetation indices. Spatial resolution of aerial and satellite remote sensing imagery has improved from 100's of m to sub-metre accuracy, allowing evaluation of soil and crop properties at fine spatial resolution at the expense of increased data storage and processing requirements. Temporal frequency of remote sensing imagery has also improved dramatically. At present there is considerable interest in collecting remote sensing data at multiple times in order to conduct near real time soil, crop and pest management.

1. Introduction

Precision agriculture is one of the top ten revolutions in agriculture (Crookston, 2006), although it has only been practiced commercially since the 1990's. Over one-third of US Midwestern farmers already practice some form of precision agriculture. Precision agriculture generally involves better management of farm inputs such as fertilisers, herbicides, seed, fuel (used during tillage, planting, spraying, etc.) by doing the right management practice at the right place and the right time. Whereas large farm fields under conventional management receive uniform applications of fertilisers, irrigation, seed, etc., with precision agriculture, these fields can be divided into management zones that each receives customised management inputs based on varying soil types, landscape position, and management history. Precision

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Nomenclature

ALI	advanced land imager
AVIRIS	airborne visible/infrared imaging spectrometer
B	blue
DVI	difference vegetation index
EO 1	earth observing 1
EROS	earth resources observation and science
EVI	enhanced vegetation index
G	green
GDVI	green difference vegetation index
GNDVI	green normalised difference vegetation index
GOSAVI	green optimised soil adjusted vegetation index
GPS	global positioning system
GRVI	green red vegetation index
GSAVI	green soil adjusted vegetation index
HyspIRI	hyperspectral infrared imager
INSEY	in season estimated yield
IRS	Indian remote sensing
LAI	leaf area index
LED	light emitting diode
LiDAR	light detection and ranging
MCARI	modified chlorophyll absorption in reflectance index
MSAVI	modified soil adjusted vegetation index
MSS	multispectral scanning system
N	nitrogen
NASA	National Aeronautics and Space Administration
NDI	normalised difference index
NDVI	normalised difference vegetation index
NG	normalised green
NGNDVI	normalised green normalized difference vegetation index
NIR	near infrared
NR	normalised red
NSI	nitrogen sufficiency index
OMNBR	optimal multiple narrow band reflectance
OSAVI	optimised soil adjusted vegetation index
PNSI	plant nitrogen spectral index
PSSR	pigment specific simple ratio
R	red
RI	response index
RVI	ratio vegetation index
SPAD	soil plant analysis development
SPOT	système pour l'observation de la terre
SR8	simple ratio 8
TCARI	transformed chlorophyll absorption in reflectance index
TM	thematic mapper

agriculture offers to improve crop productivity and farm profitability through improved management of farm inputs (Larson & Robert, 1991; Zhang, Wang, & Wang, 2002), leading to better environmental quality (Mulla, 1993; Mulla et al., 2002; Mulla, Perillo, & Cogger, 1996; Tian, 2002). Other benefits perceived by farmers include more precise hybrid selection, rental agreements that are better aligned with actual soil productivity, better matching of fertiliser applications to crop yield potential, lower chemical bills and fuel costs, and reduced compaction. Benefits to society include creation of high technology jobs (computer hardware, computer software, machinery guidance, soil and crop sensors, information management, decision support systems), and mitigation of environmental pollution arising from over-application of nitrogen and phosphorus fertiliser.

Precision agriculture uses intensive data and information collection and processing in time and space to make more efficient use of farm inputs, leading to improved crop production and environmental quality (Harmon et al., 2005). Precision agriculture is beginning to emphasise spatial-temporal data analysis and management rather than spatial data analysis and management alone (Mamo, Malzer, Mulla, Huggins, & Strock, 2003; Miao, Mulla, Randall, Vetsch, & Vintila, 2009; Varvel, Wilhelm, Shanahan, & Schepers, 2007). Crop yield and response to N fertiliser varies significantly across years in response to changes in climate (Bakhsh, Jaynes, Colvin, & Kanwar, 2000), just as it varies significantly across the landscape in response to variations in soil type and landscape features.

Precision agriculture involves both data collection/analysis and information management, as well as technological advances in computer processing, field positioning, yield monitoring, remote sensing, and sensor design (Mulla & Schepers, 1997). More than 30% of the growth in US agribusiness (jobs, sales, exports, etc.) in the future is expected to come from further adoption of precision agriculture by farmers (Whipker & Akridge, 2006), including growth in demand for both information management services and technological advances such as global positioning system (GPS) autosteer guidance (e.g. Real Time Kinetic technology), variable rate irrigation, fertiliser and sprayer controllers, robotics, and real time decision making based on sensor networks and remote sensing. Adoption rates are also significant in Australia, Japan, Canada and Europe, specifically in Germany, Sweden, France, Spain, Denmark and the UK. Globally, there is little documented information about rates of adoption for precision agriculture in the developing world. Mondal and Basu (2009) state that countries such as Argentina, Brazil, China, India and Malaysia have begun to adopt precision agriculture. Precision agriculture is also widely used in the vineyards of Chile.

The farms of the future are likely to be managed with much greater spatial and temporal resolution than they are with present approaches to precision agriculture. In Chilean vineyards, each grape vine receives an individually customised fertiliser prescription that varies with soil type, landscape position and hybrid. It is not unrealistic to expect that crops on modern US farms of the future will be managed plant-by-plant, a huge advance over farming by soil approaches of the past. This approach will require massive data collection and analysis on a scale not considered feasible today, involving stationary or mobile sensors that can measure characteristics of individual plants in real time. Sensors of the future could be based on satellites (Bausch & Khosla, 2010), airplanes (Goel et al., 2003; Haboudane, Miller, Pattey, Zarco-Tejada, & Strachan, 2004; Haboudane, Miller, Tremblay, Zarco-Tejada, & Dextraze, 2002; Miao, Mulla, Randall, Vetsch, & Vintila, 2007), unmanned aerial vehicles (Berni, Zarco-Tejada, Suárez, & Fereres, 2009; Herwitz et al., 2004), tractors (Adamchuk, Hummel, Morgan, & Upadhyaya, 2004; Long, Engel, & Siemens, 2008), or attached to mobile robots (Astrand & Baerveldt, 2002) to record weed densities, crop height, leaf reflectance, moisture status and other properties important for decisions about fertilizer and pest management. These sensors must be robust, run on renewable energy sources, and be able to relay information using wireless networks (O'Shaughnessy and Evett, 2010; Wang, Zhang, & Wang, 2006) to computers that can perform data mining procedures and make complex management recommendations. These recommendations can be transmitted to computers and controllers in the field that are capable of varying the rates of irrigation, fertilisers, and herbicides at fine spatial resolution, if not plant-by-plant.

2. Remote sensing applications in agriculture

Remote sensing applications in agriculture are based on the interaction of electromagnetic radiation with soil or plant material. Typically, remote sensing involves the measurement of reflected radiation, rather than transmitted or absorbed radiation. Remote sensing refers to non-contact measurements of radiation reflected or emitted from agricultural fields. The platforms for making these measurements include satellites, aircraft, tractors and hand-held sensors. Measurements made with tractors and hand-held sensors are also known as proximal sensing, especially if they do not involve measurements of reflected radiation. In addition to reflectance, transmittance and absorption, plant leaves can emit energy by fluorescence (Apostol et al., 2003) or thermal emission (Cohen, Alchanatis, Meron, Saranga, & Tsipris, 2005). Thermal remote sensing for water stress in crops is based on emission of radiation in response to temperature of the leaf and canopy, which varies with air temperature and the rate of evapotranspiration.

The amount of radiation reflected from plants is inversely related to radiation absorbed by plant pigments, and varies with the wavelength of incident radiation. Plant pigments such as chlorophyll absorb radiation strongly in the visible spectrum from 400 to 700 nm (Pinter et al., 2003), particularly at wavelengths such as 430 (blue or B) and 660 (red or R) nm for chlorophyll *a* and 450 (B) and 650 (R) nm for chlorophyll *b*. Other plant pigments such as anthocyanins and carotenoids are also important (Blackburn, 2007).

In contrast, plant reflectance is high in the near infrared (NIR 700–1300 nm) region as a result of leaf density and canopy structure effects. This sharp contrast in reflectance behaviour between the red and NIR portions of the spectrum is the motivation for development of spectral indices that are based on ratios of reflectance values in the visible and NIR regions (Sripada, Heiniger, White, & Weisz, 2006). These spectral indices are often used to assess various attributes of plant canopies, such as leaf area index (LAI), biomass, chlorophyll content or N content.

The amount of radiation reflected by bare soils is affected primarily by soil moisture and organic matter content, but also by clay minerals and calcium carbonate or iron oxides (Thomasson, Sui, Cox, & Al–Rajehy, 2001; Viscarra Rossel, Walvoort, McBratney, Janik, & Skjemstad, 2006). Each soil constituent has a specific spectral region where reflectance is strongest (Ben-Dor, 2010), and a specific spectral signature. Bare soil and crop canopies are often both present in a remotely sensed image, and the mixture of two spectral signatures often confounds the interpretation of reflectance data (Fig. 1). Spectral unmixing algorithms (Huete & Escadafal, 1991), derivative spectra (Demetriades-Shah, Steven, & Clark, 1990) or spectral indices that adjust for soil effects (Haboudane et al., 2002, 2004) are often used to isolate information about plant characteristics when the reflectance is affected by both sources.

Remote sensing applications in agriculture are typically classified according to the type of platform for the sensor, including satellite, aerial, and ground based platforms. These platforms and their associated imaging systems can be differentiated based on the altitude of the platform, the spatial resolution of the image, and the minimum return frequency for sequential imaging. Spatial resolution affects the area of the smallest pixel that can be identified. As spatial resolution improves, the area of the smallest pixel decreases, and the homogeneity of soil or crop characteristics within that pixel increases. Poor spatial resolution implies large pixels with increased heterogeneity in soil or plant characteristics. Return frequency is important for assessment of temporal patterns in soil or plant characteristics. The availability of remote sensing images from satellite and aerial platforms is often severely limited by cloud cover (Moran, Inoue, & Barnes, 1997), whereas ground based remote sensing is less affected by this limitation.

Remote sensing applications in agriculture have focused on a wide range of endeavours (Adamchuk et al., 2004; Moran et al., 1997; Pinter et al., 2003). These include crop yield and biomass (Shanahan et al., 2001; Yang, Everitt, Bradford, & Escobar, 2000), crop nutrient and water stress (Bastiaanssen,

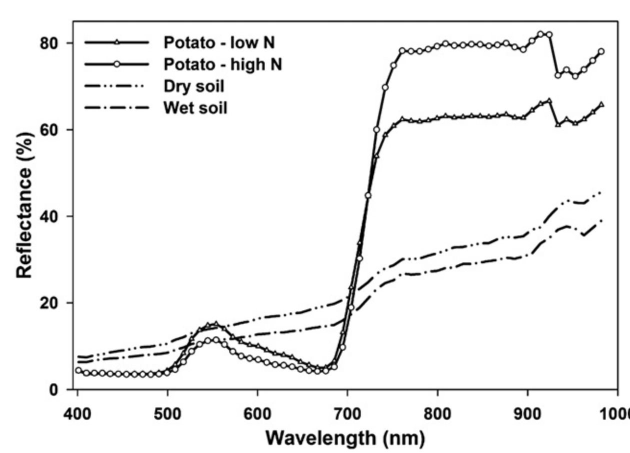

Fig. 1 – Reflectance signatures of dry or wet soil in comparison to reflectance signatures of a Russet Burbank potato canopy with low or high rates of N fertiliser application.

Molden, & Makin, 2000; Clay, Kim, Chang, Clay, & Dalsted, 2006; Cohen et al., 2005; Moller et al., 2007; Tilling et al., 2007), infestations of weeds (Lamb & Brown, 2001; Thorp & Tian, 2004), insects and plant diseases (Seelan, Laguette, Casady, & Seielstad, 2003), and soil properties such as organic matter, moisture and clay content, and pH (Christy, 2008), or salinity (Corwin & Lesch, 2003).

2.1. *Soil sensing in precision agriculture*

Precision agriculture started during the mid 1980's with two contrasting philosophies. The first was exemplified by the "farming by soil" school (Larson & Robert, 1991). This school promoted the use of soil sampling and customised management of farm inputs by soil mapping unit. The second was exemplified by the "Soil Sampling Management Zone" school (Mulla, 1991, 1993; Mulla & Bhatti, 1997; Mulla, Bhatti, Hammond, & Benson, 1992), which later became known as "site-specific crop management". Management zones are relatively homogeneous sub-units of farm fields that can each be managed with a different, but uniform customised management practice. This school became very popular when field comparisons of uniform versus variable fertiliser applications showed that there was considerable variability at scales finer than soil mapping units (Mulla et al., 1992). Bhatti, Mulla, and Frazier (1991) were the first to demonstrate that Landsat remote sensing had significant capabilities for estimating spatial patterns in soil organic matter, soil phosphorus and crop yield potential for use in precision agriculture applications.

A third approach to precision agriculture began to emerge in the early 1990's (Hummel, Gaultney, & Sudduth, 1996), known as proximal soil sensing. This approach was based on continuous real-time sensing of spatial variations in soil properties using sensors mounted on tractors. The first application of this approach was for soil organic matter sensing (Shonk, Gaultney, Schulze, & Van Scoyoc, 1991) based on reflectance from multiple light emitting diode (LED) sensors emitting radiation at 660 nm. The sensor was very accurate if calibrated for individual soil catenas, but was affected by variations in soil moisture. Sudduth and Hummel (1993) developed a portable NIR sensor which could simultaneously be used to estimate soil organic matter content and soil moisture content. Other related technology was developed by Christy (2008), allowing simultaneous measurements of soil organic matter content, soil moisture, soil pH, soil carbon and soil phosphorus, potassium, and calcium.

A major breakthrough in precision agriculture occurred when Carter, Rhoades, and Chesson (1993) introduced continuous real-time, non-contact proximal sensing of soil apparent electrical conductivity using non-invasive electromagnetic induction with the Geonics EM-38 (Geonics Ltd., Mississauga, Ontario, Canada). Soil electrical conductivity measurements with the EM-38 have been used to map spatial patterns in soil salinity (Corwin & Lesch, 2003), soil clay content (Doolittle, Sudduth, Kitchen, & lndorante, 1994) and soil moisture content (Sudduth et al., 2005). These patterns are often used to define management zones.

2.2. *Satellite remote sensing*

Satellites have been used for remote sensing imagery in agriculture (Table 1) since the early 1970's (Bauer & Cipra, 1973; Doraiswamy, Moulin, Cook, & Stern, 2003; Jewel, 1989) when Landsat 1 (originally known as Earth Resources Technology Satellite 1) was launched in 1972. Multispectral Scanner System (MSS) sensors on Landsat 1 collected imagery in the green, red and two infrared bands at a spatial resolution of 80 m and a return frequency of 18 days. Landsat 1 was initially used by Bauer and Cipra (1973) to classify Midwestern US agricultural landscapes into maize or soybean fields with an overall accuracy of 83%. Landsat 5 was launched in 1984

Table 1 – Satellite remote sensing platforms and their spectral or spatial resolution, return frequency, and suitability for precision agriculture (PA). P refers to purple, B to blue, G to green, R to red, IR to infrared, NIR to near infrared, MIR to mid infrared, TIR to thermal infrared. Suitability class L refers to low, M to medium and H to high.

Satellite (year)	Spectral bands (spatial resolution)	Return frequency (*d*)	Suitability for PA
Landsat 1 (1972)	G, R, two IR (56 × 79 m)	18	L
AVHRR (1978)	R, NIR, two TIR (1090 m)	1	L
Landsat 5 TM (1984)	B, G, R, two NIR, MIR, TIR (30 m)	16	M
SPOT 1 (1986)	G, R, NIR (20 m)	2–6	M
IRS 1A (1988)	B, G, R, NIR (72 m)	22	M
ERS-1 (1991)	Ku band altimeter, IR (20 m)	35	L
JERS-1 (1992)	L band radar (18 m)	44	L
LiDAR (1995)	VIS (vertical RMSE 10 cm)	N/A	H
RadarSAT (1995)	C-band radar (30 m)	1–6	M
IKONOS (1999)	Panchromatic, B, G, R, NIR (1–4 m)	3	H
SRTM (2000)	X-band radar (30 m)	N/A	M
Terra EOS ASTER (2000)	G, R, NIR and 6 MIR, 5 TIR bands (15–90 m)	16	M
EO-1 Hyperion (2000)	400–2500 nm, 10 nm bandwidth (30 m)	16	H
QuickBird (2001)	Panchromatic, B, G, R, NIR (0.61–2.4 m)	1–4	H
EOS MODIS (2002)	36 bands in VIS-IR (250–1000 m)	1–2	L
RapidEye (2008)	B, G, R, red edge, NIR (6.5 m)	5.5	H
GeoEye-1 (2008)	Panchromatic, B, G, R, NIR1, NIR2 (1.6 m)	2–8	H
WorldView-2 (2009)	P, B, G, Y, R, red edge, NIR (0.5 m)	1.1	H

and collected Thematic Mapper (TM) imagery at a spatial resolution of 30 m in the blue, green, red, near infrared, and three infrared (including thermal) bands. France launched a comparable satellite (système pour l'observation de la terre (SPOT) 1) in 1986, which collected 20 m imagery with a return frequency of up to six days in the green, red and near infrared frequencies. Jewel (1989) used four images collected between February and September in East Anglia, UK to distinguish cereal crops, field crops, grassland and forest land with an accuracy of 88%. India launched the Indian Remote Sensing (IRS-1A) satellite in 1988, with coverage in the blue, green, red and NIR bands at a spatial resolution of 72 m. Panigrahy and Sharma (1997) used reflectance in the red and NIR bands collected on four dates between October and March to classify agricultural landscapes in India into rice or rice–potato cropping systems with 95% accuracy.

These applications of remote sensing in conventional agriculture soon led to applications in precision agriculture. The first application of remote sensing in precision agriculture occurred when Bhatti et al. (1991) used Landsat imagery of bare soil to estimate spatial patterns in soil organic matter content, which were then used as auxiliary data along with ground based measurements to estimate spatial patterns in soil phosphorus and wheat grain yield (Mulla, 1997). The spatial resolution of Landsat, SPOT and IRS satellites is fairly coarse (20–30 m) for current applications in precision agriculture.

Efforts were subsequently started to design satellite imaging systems that had the higher spatial resolution and quicker revisit cycles required for precision agriculture (Table 1). IKONOS was launched in 1999 by Satellite Imaging Corp, Magnolia, TX, USA in partnership with Lockheed Martin, Bethesda, MD, USA. IKONOS collected 4 m resolution imagery in the blue, green, red and near infrared bands at a return frequency of up to 5 days. Seelan et al. (2003) used IKONOS images to identify N deficiencies in sugarbeet, fungicide performance efficiency in wheat and field sites that had inadequate artificial drainage in wheat. In 2001, DigitalGlobe, Longmont, CO, USA launched a satellite named QuickBird with capabilities similar to IKONOS. QuickBird had a revisit frequency of 1–3 days and collected imagery in the blue, green, red and near infrared at a spatial resolution of 0.6–2.4 m. Bausch and Khosla (2010) showed that QuickBird estimates of normalised green normalised difference vegetation index (NGNDVI) were strongly correlated with spatial patterns in nitrogen sufficiency in irrigated maize. García Torres, Peña-Barragán, López-Granados, Jurado-Expósito, and Fernández-Escobar (2008) showed that QuickBird images of olive orchards in Spain could be used to estimate areas of olive plantations, numbers of trees, and spatial patterns in projected area of tree canopies, and olive yields. These two satellites have steadily gained a substantial base of commercial subscribers interested in precision agriculture applications, in stark contrast to older satellite technology such as Landsat or SPOT.

The next major breakthrough in satellite remote sensing for precision agriculture was the five-satellite constellation developed by the RapidEye, Brandenburg_an_der_Havel, Germany in 2008 (Table 1). RapidEye satellites provide daily coverage for any location on the globe, and collect data with a 6.5 m spatial resolution. RapidEye is the first satellite to provide imagery in the chlorophyll sensitive red-edge region of the spectrum (690–730 nm), along with the more traditional blue, green, red and near infrared reflectance. In 2008, GeoEye, Herndon, VA, USA launched a commercial satellite designed to provide services similar to RapidEye. The GeoEye 1 satellite has a return visit frequency of less than three days, and collects data at from 40 to 60 cm spatial resolution in the blue, green, red and near infrared bands. One of the main uses for GeoEye 1 imagery is providing Google Earth maps that are available through the Internet. This has revolutionised the ability to visualise land use patterns around the world. DigitalGlobe launched the WorldView 2 satellite in 2009, which collects imagery at 50 cm resolution with a 1 day revisit cycle. WorldView 2 is significantly more advanced than DigitalGlobe's QuickBird satellite, as WorldView 2 collects imagery in the standard blue, green, red, and near infrared bands, as well as bands in the purple (450–480 nm), yellow, red-edge and a second near infrared frequency range.

Several trends are apparent in satellite based remote sensing (Table 1). Firstly, the spatial resolution of imaging systems has improved from 80 m with Landsat to sub-metre resolution with GeoEye and WorldView. Secondly, the return visit frequency has improved from 18 days with Landsat to 1 day with WorldView. Thirdly, the number of spectral bands available for analysis has improved from four bands (bandwidths greater than 60 nm) with Landsat to eight or more bands (bandwidths greater than 40 nm) with WorldView. Hyperspectral imaging systems such as Hyperion on the National Aeronautics and Space Administration (NASA) earth observing 1 (EO 1) satellite provided even greater spectral resolution, with imaging from 400 to 2500 nm in 10 nm increments.

As the spatial and spectral resolution of satellite imagery has improved, the suitability of using reflectance data from these platforms for precision agriculture applications has increased (Table 1). The most appropriate spatial and spectral resolution for precision agriculture applications depends on factors such as crop management objectives, capacity of farm equipment to vary farm inputs, and farm unit area. Estimation of spatial patterns in crop biomass or yield requires better spatial and spectral resolution (1–3 m) than variable rate application of fertiliser (5–10 m). Accuracy of variable rate application of fertiliser is often limited by fertiliser spreader delay times (Chan, Schueller, Miller, Whitney, & Cornell, 2004). Variable rate spraying of herbicides for spot weed control requires better spatial and spectral resolution (0.5–1 m) than variable rate irrigation (5–10 m). Larger commercial farms can often afford to pay for remote sensing data with higher spatial and spectral resolution than smaller farms in developing countries.

Satellite and/or aerial imagery is frequently used to estimate spatial patterns in crop biomass (Yang et al., 2000) and potential crop yield (Doraiswamy et al., 2003) using the Normalised Difference Vegetation Index (NDVI). NDVI is calculated using reflectance ratios in the NIR and red portion of the spectrum (Rouse, Hass, Schell, & Deering, 1973):

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{Red})/(\mathrm{NIR} + \mathrm{Red}) \quad (1)$$

NDVI has several limitations, however, including potential interference from soil reflectance at low canopy densities and insensitivity to changes in leaf chlorophyll content in mature canopies with leaf area index values that exceed 2 or 3 (Thenkabail, Smith, & De Pauw, 2000). The advent of crop combines equipped with yield monitors was a major advance in precision agriculture (Schueller & Bae, 1987; Stafford, Ambler, Lark, & Catt, 1996). Yield monitors provided fine scale resolution yield measurements across large spatial areas that could be used to improve the capacity of remote sensing to predict crop structural characteristics such as LAI, biomass, and yield.

Many broadband spectral indices (Table 2) other than NDVI are available for use in precision agriculture (Miao et al., 2009; Sripada et al., 2006; Sripada, Schmidt, Dellinger, & Beegle, 2008). These indices reflect two historical trends in remote sensing for crop characteristics; namely, the prediction of ratios of reflectance in the red (R) and NIR bands versus ratios in the green (G) and NIR bands. The normalised red (NR) index focuses on the portion of the spectrum where chlorophyll strongly absorbs radiation. In contrast, the normalised green (NG) index focuses on the portion of the spectrum where pigments other than chlorophyll (carotenoids, anthocyanins, xanthophylls) absorb radiation. Similarly, there are two forms of the ratio vegetation index (RVI), one that consists of the ratio of NIR to R reflectance, the other green red vegetation index (GRVI) that consists of the ratio of NIR to G reflectance. Two forms of the NDVI exist, one that involves NIR and R reflectance, the other green normalized difference vegetation index (GNDVI) involves NIR and G reflectance. The difference vegetative index (DVI) was developed using the difference between reflectance in the NIR and R bands to compensate for effects of soil reflectance (Tucker, 1979). Sripada et al. (2006) found that economically optimum N rate in corn was better correlated with green difference vegetation index (GDVI) (NIR − G) than DVI (NIR − R), and these indices that compensated for soil effects performed better than NIR and R ratio indices such as NDVI and RVI that did not compensate for soil effects. A wide range of other indices have been developed to compensate for soil effects, including soil adjusted vegetation index (SAVI), green soil adjusted vegetation index (GSAVI), optimised soil adjusted vegetation index (OSAVI), green optimised soil adjusted vegetation index (GOSAVI) and modified soil adjusted vegetation index (MSAVI). A comparison of NDVI and simple ratio (SR8) vegetation indices for an irrigated commercial Minnesota potato (*Solanum tuberosum* L.) farm is shown in Fig. 2. Spatial patterns in N stress are identified more accurately with the SR8 index than the NDVI index.

Moran et al. (1997) and Yao et al. (2010) summarised the major challenges for using satellite remote sensing for precision agriculture. Satellite imagery in the visible and NIR bands are limited to cloud free days, and are most usable when irradiance is relatively consistent across time. Only radar imagery collected using satellites or airplanes is unaffected by cloud cover. Other challenges include calibrating raw digital numbers to true surface reflectance, correcting imagery for atmospheric interferences and/or off-nadir view angles, and geo-rectifying pixels using GPS-based ground control locations.

2.3. *Proximal remote sensing of crops for precision agriculture*

Given the limitations of satellite remote sensing for precision agriculture, there has been significant interest in proximal remote sensing techniques to assess crop growth and crop stress (Table 3). Proximal remote sensing involves sensors mounted on tractors, spreaders, sprayers or irrigation booms. Proximal sensing allows real time site specific management of fertiliser, pesticides or irrigation. The foundation for a transition from remote sensing to proximal sensing based assessment of crop status was established by Schepers, Francis, Vigil, and Below (1992), who used a Minolta soil plant analysis development (SPAD) meter to measure leaf greenness (chlorophyll) in maize crops at the silking stage under a range of applied N fertiliser rates. SPAD meter readings of leaf reflectance at 650 and 940 nm were found to be correlated with applied rate of N fertiliser as well as independent measurements of leaf N concentration. Schepers et al. (1992) suggested that proximal chlorophyll readings could be used to estimate N stress in maize by referencing the SPAD readings for stressed crops with the readings in a reference strip that received adequate rates of N fertiliser. Chlorophyll content of

Table 2 – Multi-spectral broad-band vegetation indices available for use in precision agriculture. G refers to green reflectance, NIR to near infrared, and R to red reflectance.

Index	Definition	Reference
NG	G/(NIR + R + G)	Sripada et al., 2006
NR	R/(NIR + R + G)	Sripada et al., 2006
RVI	NIR/R	Jordan, 1969
GRVI	NIR/G	Sripada et al., 2006
DVI	NIR − R	Tucker, 1979
GDVI	NIR − G	Tucker, 1979
NDVI	(NIR − R)/(NIR + R)	Rouse et al., 1973
GNDVI	(NIR − G)/(NIR + G)	Gitelson et al., 1996
SAVI	1.5*[(NIR − R)/(NIR + R + 0.5)]	Huete, 1988
GSAVI	1.5*[(NIR − G)/(NIR + G + 0.5)]	Sripada et al., 2006
OSAVI	(NIR − R)/(NIR + R + 0.16)	Rondeaux, Steven, & Baret, 1996
GOSAVI	(NIR − G)/(NIR + G + 0.16)	Sripada et al., 2006
MSAVI2	$0.5*[2*(NIR + 1) - SQRT((2*NIR + 1)^2 - 8*(NIR - R))]$	Qi, Chehbouni, Huete, Keer, & Sorooshian, 1994

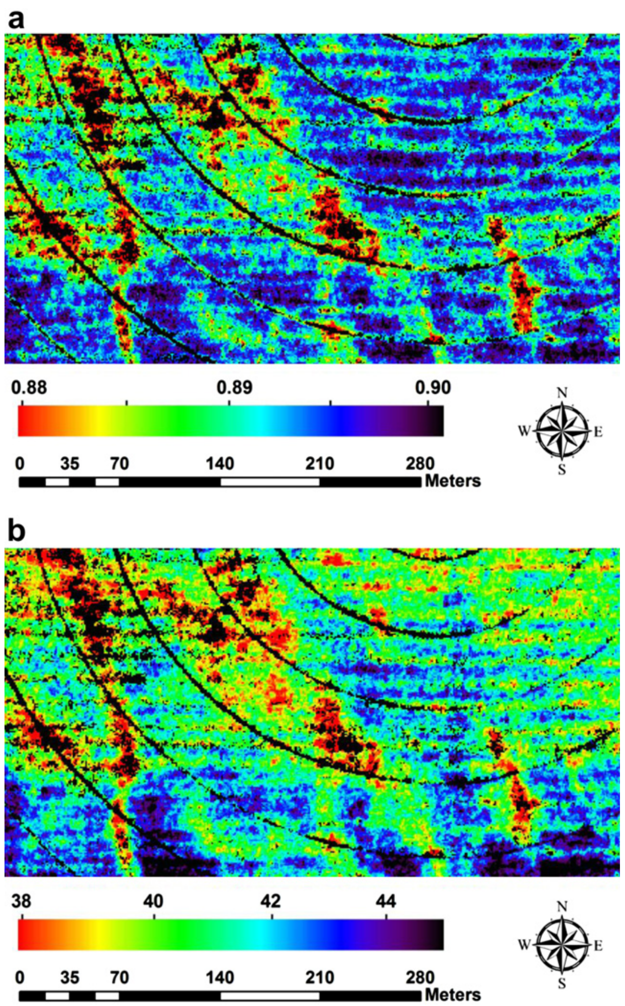

Fig. 2 – Comparison between a) NDVI and b) SR8 spectral indices in a commercial Russet Burbank potato field.

crop leaves is strongly affected by crop N status, but can also be affected to a lesser degree by other factors, such as crop variety and growth stage, pest infestations, water stress, and nutrient deficiencies other than N.

Blackmer and Schepers (1995) introduced the concept of a nitrogen sufficiency index (NSI) to assess the degree of N stress in maize. The NSI was defined as the ratio of SPAD meter greenness readings for crops in a given field location relative to SPAD readings for the same crop in a well-fertilised reference strip with no N deficiencies. NSI values less than 0.95 were used to indicate areas with N stress that required additional N fertiliser. Varvel, Schepers, and Francis (1997) showed that SPAD meters and NSI values could be used for in-season correction of N deficiency in maize. Bausch and Duke (1996) showed that the SPAD meter could be replaced with a boom-mounted radiometer to estimate spatial patterns in NIR/G ratio and NSI across an irrigated maize field based on comparisons with a well-fertilised reference strip. They observed that this approach could detect N deficiencies in the V6 growth stage (Ritchie, Hanway, & Benson, 1993, p. 21), but results were confounded by interference with reflectance patterns from bare soil.

Stone et al. (1996) measured spectral radiance in the red (671 nm) and NIR (780 nm) bands in wheat with a sensor mounted on a mobile lawn tractor. They used these data to estimate a spectral index known as the plant nitrogen spectral index (PNSI), which was the absolute value of the inverse of NDVI. Results showed that PNSI was strongly correlated with crop N uptake. Sensor readings were used to vary N fertiliser rates using an algorithm that increased exponentially with PNSI values (Solie, Raun, Whitney, Stone, & Ringer, 1996). This was the beginning of technology to variably apply N fertiliser "on-the-go" in response to proximal crop sensing, and was the basis for commercial development of the GreenSeeker NDVI active sensor marketed by NTech Industries, Ukiah, CA, USA in 2001. Raun et al. (2002) subsequently developed a seven step response index (RI)-based algorithm to estimate crop N fertiliser needs for maize and wheat based on in-season sensing of crop reflectance relative to check plots with no added fertiliser and reference plots with sufficient fertiliser. This algorithm accounted for both season-to-season temporal variability in crop growth using the concept of in-season estimated yield (INSEY) as well as within-field spatial variability in N supply. Algorithms for estimating potential crop yield and N uptake are available for many crops and locations around the world (Shanahan, Kitchen, Raun, & Schepers, 2008). The RI is estimated as the ratio of NDVI values in the crop relative to those in a reference strip with sufficient fertiliser.

Link, Panitzki, and Reusch (2002) and Reusch, Link, and Lammel (2002) developed a tractor based passive sensor to determine crop N status based on NDVI. This was originally

Table 3 – Innovations in remote and proximal leaf sensing in precision agriculture.

Year	Innovation	Citation
1992	SPAD meter (650, 940 nm) used to detect N deficiency in corn	Schepers et al., 1992
1995	Nitrogen sufficiency indices	Blackmer & Schepers, 1995
1996	Optical sensor (671, 780 nm) used for on-the-go detection of variability in plant nitrogen stress	Stone et al., 1996
2002	Yara N sensor	Link et al., 2002, TopCon industries
2002	GreenSeeker (650, 770 nm)	Raun et al., 2002, NTech industries
2004	Crop Circle (590, 880 nm or 670, 730, 780 nm)	Holland et al., 2004, Holland scientific
2002	CASI hyperspectral sensor based index measurements of chlorophyll	Haboudane et al., 2002, 2004
2002	MSS remote sensing of ag fields with UAV	Herwitz et al., 2004
2003	Fluorescence sensing for N deficiencies	Apostol et al., 2003

known as the Hydro-N sensor, but has since become known as the Yara-N sensor (Yara, Olso, Norway) (Table 3). A version of the Yara-N sensor is also available that uses active sensors (Link & Reusch, 2006), which reduces the errors caused by varying cloud cover, and allows the tractor operator to work at night.

Holland, Schepers, Shanahan, and Horst (2004) developed an active crop sensor known as Crop Circle (Table 3). This sensor initially used reflectance in the green and NIR bands to estimate crop N deficiencies. The rationale behind using green rather than red reflectance with Crop Circle was that as crop LAI increases beyond 2.0, the green NDVI is more sensitive to changes in chlorophyll concentration and potential crop yield than NDVI (Gitelson, Kaufmann, & Merzlyak, 1996; Shanahan et al., 2001; Sripada et al., 2006, 2008). This overcomes the limitation of using the GreenSeeker sensor at advanced crop growth stages. Solari, Shanahan, Ferguson, Schepers, and Gitelson (2008) used the Crop Circle sensor to show that N deficiencies could be better predicted using a green chlorophyll index defined as $(NIR_{880}/VIS_{590}) - 1$ in comparison with the green NDVI. Sripada et al. (2008) showed that the performance of spectral indices could be improved using ratios with the corresponding index values in reference strips receiving sufficient N fertiliser. Kitchen et al. (2010) and Scharf et al. (2011) showed that producers using the Crop Circle sensor could reduce N fertiliser applications by making in-season correction, while increasing crop yield and farm profitability.

One limitation of the chlorophyll meter, GreenSeeker, Yara N and Crop Circle sensors, however, is that they cannot directly estimate the amount of N fertiliser needed to overcome crop N stress (Samborski, Tremblay, & Fallon, 2009). To overcome this, scientists have conducted comparisons of sensor readings with readings in reference strips receiving sufficient N fertiliser (Blackmer & Schepers, 1995; Kitchen et al., 2010; Raun et al., 2002; Sripada et al., 2008). They have used these data to develop N fertiliser response functions that relate sensor readings to the amount of N fertiliser needed to overcome crop N stress (Scharf et al., 2011). Even with this approach, reference strips with adequate fertiliser have to be strategically placed in representative soils and landscapes because yield response to N fertiliser exhibits significant spatial variability across production fields (Mamo et al., 2003). Also, reference strips have limitations for other crops like wheat (subject to lodging) and potato (subject to excessive vine growth at the expense of tuber growth).

2.4. *Hyperspectral remote sensing in precision agriculture*

Hyperspectral remote sensing collects reflectance data over a wide spectral range at small spectral increments (typically 10 nm). It provides the ability to investigate spectral response of soils and vegetated surfaces in narrow spectral bands (10 nm wide) across a wide spectral range. This is not possible with multispectral imaging that traditionally collects reflectance data in broadbands (greater than 40 nm wide) centred in the B, G, R and NIR regions of the spectrum. When collected across large spatial extents at fine spatial resolution, hyperspectral imaging provides powerful insight into the spatial and spectral variability in reflectance for a bare or vegetated surface. This information is traditionally visualised using a three-dimensional hyperspectral data cube, with two spatial dimensions (x,y) and one spectral dimension (wavelength). An example of a hyperspectral data cube is shown in Fig. 3 for a commercial potato field in Minnesota, USA. The field shows significant spatial and spectral variability in reflectance.

The first hyperspectral sensor was the airborne visible/infrared imaging spectrometer (AVIRIS), launched in 1987. This sensor provides continuous imagery from 380 to 2500 nm in bands that have a spectral resolution of 10 nm and a spatial resolution of 20 m. The satellite based Hyperion sensor, launched aboard EO-1 by NASA in 2000, has hyperspectral imaging capabilities similar to AVIRIS. Hyperspectral imagery collected by EO-1 Hyperion via the advanced land imager (ALI) sensor continues to be collected and is available for public use through the US Geological Survey, Center for Earth Resources Observation and Science (EROS). Datt, Jupp, McVicar, and Van Niel (2003) showed that ALI hyperspectral data could be used to more accurately predict spatial patterns in rice yield grown in Australia with derivative indices and red edge position in comparison with predictions based on NDVI. Miglani, Ray, Pandey, and Parihar (2008) showed that 20 hyperspectral bands from ALI were necessary for agricultural remote sensing studies in the Meerut district of India. Wu, Wang, Niu, Gao, and Wu (2010) showed that vegetative indices based on red edge reflectance from hyperspectral ALI data could be used to accurately estimate canopy chlorophyll content and leaf area index for a broad range of agricultural crops in China. An aerial hyperspectral imaging system, the compact airborne spectrographic imager (CASI), has also been widely used (Haboudane et al., 2002, 2004). There are also hand-held or boom-mounted hyperspectral and multispectral imaging systems, including the CropScan (CropScan Inc, Rochester, MN, USA) sensor.

Hyperspectral imaging differs from multispectral imaging in the continuity, range and spectral resolution of bands. In theory, it offers the capability of sensing a wide variety of soil and crop characteristics simultaneously, including moisture status, organic matter, nutrients, chlorophyll, carotenoids, cellulose, leaf area index and crop biomass (Goel et al., 2003; Haboudane et al., 2002; Zarco-Tejada et al., 2005). Specific

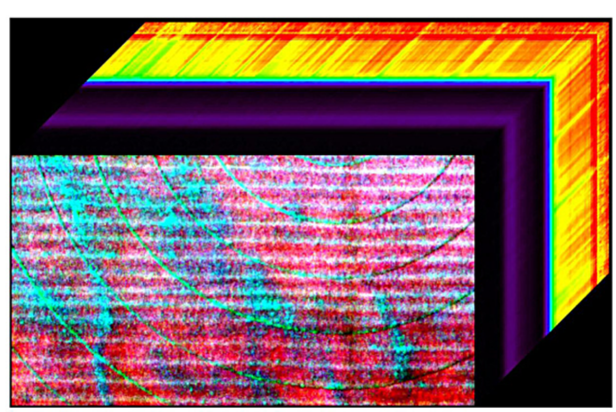

Fig. 3 – Hyperspectral data cube for a commercial Russet Burbank potato field in Minnesota. The face of the cube is a red–green–blue image of the same area shown in Fig. 2.

wavelengths are most sensitive to each type of soil or crop characteristic. A red band centred at 687 nm is sensitive to crop leaf area index and biomass, while a near infrared band centred at 970 nm is sensitive to crop moisture status (Thenkabail, Lyon, & Huete, 2010). Further examples of linking specific soil and crop characteristics with reflectance are given for 33 hyperspectral bands by Thenkabail et al. (2010). In contrast, multispectral imaging is often limited to analysis of single broadband combinations such as NDVI, which become insensitive to chlorophyll and other plant characteristics at LAI values exceeding 3.0 (Thenkabail et al., 2000), and are strongly interfered with by bare soil reflectance at low LAI values.

Thenkabail et al. (2000) showed that hyperspectral data can be used to construct three general categories of predictive spectral indices, including 1) optimal multiple narrow band reflectance indices (OMNBR), 2) narrow band NDVI, and 3) SAVI. Only two to four narrow bands were needed to describe plant characteristics with OMNBR. The greatest information about plant characteristics in OMNBR includes the longer red wavelengths (650–700 nm), shorter green wavelengths (500–550 nm), red-edge (720 nm), and two NIR (900–940 nm and 982 nm) spectral bands. The information in these bands is only available in narrow increments of 10–20 nm, and is easily obscured in broad multispectral bands that are available with older satellite imaging systems. The best combination of two narrow bands in NDVI-like indices was centred in the red (682 nm) and NIR (920 nm) wavelengths, but varied depending on the type of crop (corn, soybean, cotton or potato) as well as the plant characteristic of interest (LAI, biomass, etc.).

Advanced statistical methods for chemometric analysis of reflectance spectra have been used to interpret hyperspectral remote sensing data, including partial least squares (Lindgren, Geladi, & Wold, 1994; Viscarra Rossel et al., 2006), principal components analysis (Geladi, 2003), and pattern classification and recognition techniques (Stuckens, Coppin, & Bauer, 2000), including object oriented (Frohn, Reif, Lane, & Autrey, 2009) and decision tree (Wright & Gallant, 2007) classification techniques. Partial least squares (PLS) regression is perhaps more powerful than principal components analysis (PCA) in that PLS (like PCA) not only identifies factors that describe spectral variance, but also eliminates spectral bands that contain redundant information (Alchanatis & Cohen, 2010).

Jain, Ray, Singh, and Panigrahy (2007) explored hyperspectral remote sensing for identification of N stress in potatoes grown in India. They used three techniques to identify bands that were optimal for detection of N stress, namely; 1) lambda–lambda plots, 2) principal component analysis, and 3) discriminant analysis. Lambda–lambda plots involve calculating, for example, the coefficient of determination (r^2) for leaf N content at all hyperspectral reflectance bands. A graph of r^2 for all possible combinations of band 1 on the x-axis and band 2 on the y-axis results in a lambda–lambda plot. The lambda–lambda plot is useful for identifying which combinations of two bands contain redundant information about N stress. Spectral bands or narrow band indices should be selected with low r^2 to eliminate redundancy and maximise information about crop characteristics (such as N stress).

Principal component analysis was used by Jain et al. (2007) to identify which combinations of bands account for a majority of the variance in crop reflectance characteristics. This technique is used to eliminate hyperspectral bands that do not contain useful information about the crop characteristics of interest. Stepwise discriminant analysis uses a ratio of treatment sums of squares to total sums of squares to find spectral regions with distinctly different mean values of reflectance.

A variety of narrow band hyperspectral indices (Table 4) are available for use in precision agriculture (Haboudane et al., 2002, 2004; Li et al., 2010; Miao et al., 2007, 2009). Many of these have the same form as broadband spectral indices (Table 1), but differ in that the reflectance bands for hyperspectral indices are narrow (10–20 nm wide) bands centred around a single specific wavelength. These indices variously respond to canopy or leaf scale effects of leaf area index, chlorophyll, specific pigments, or nitrogen stress. Simple ratios (SR) 1 through 7 and normalized difference indices (NDI) 1 through 3 typically respond to leaf level changes in chlorophyll. In contrast, NDVI responds to canopy scale changes in leaf area index and chlorophyll. GNDVI, modified chlorophyll absorption in reflectance index (MCARI), transformed chlorophyll absorption in reflectance index (TCARI), MCARI2, OSAVI, and MSAVI respond to canopy scale changes in chlorophyll, with the latter two indices being designed to compensate for soil reflectance effects. PSSRa and PSSRb were designed specifically to respond to changes in chlorophyll *a* and chlorophyll *b*, respectively. New hyperspectral indices are continuously being tested and developed (Li et al., 2010) using techniques involving lambda–lambda plots where reflectance signatures are compared for all possible combinations of two reflectance bands.

Potential applications of hyperspectral remote sensing in precision agriculture have recently been reviewed by Yao et al. (2010). These applications include 1) bare soil imaging for management zone delineation, 2) weed mapping, 3) crop N stress detection, 4) crop yield mapping, and 5) pest and disease detection. Perhaps of greatest interest for precision agriculture is using hyperspectral remote sensing for variable rate, in-season management of nitrogen fertiliser based on spatial patterns in chlorophyll content. Wu, Han, Niu, and Dong (2010) used hyperspectral data from the Hyperion EO-1 satellite to study chlorophyll content in a variety of agricultural canopy types in China, including flax, chestnuts, corn, bamboo, potato, pine, saccharose and tea. Chlorophyll content of leaves were estimated using a variety of vegetation indices derived from red edge reflectance bands located at 705 and 750 nm. The MCARI/OSAVI$_{705}$ index performed better than all other vegetation indices evaluated, with an r^2 value of 0.71. Wu, Wang et al. (2010) estimated chlorophyll content of maize in China using Hyperion hyperspectral reflectance data. The Enhanced Vegetation Index (EVI) was more accurate ($r^2 = 0.81$) at predicting maize chlorophyll contents than MSAVI or NDVI.

3. Knowledge gaps for remote sensing in precision agriculture

Rapid advances in remote sensing for precision agriculture have occurred over the last twenty five years. Satellite imagery

Table 4 – Hyperspectral narrow-band vegetation indices available for use in precision agriculture. R refers to reflectance at the wavelength (nm) in subscript. NIR refers to near infrared reflectance.

Index	Definition	Reference
Greenness index (G)	R_{554}/R_{677}	Smith, Adams, Stephens, & Hick, 1995
SR1	NIR/red = R_{801}/R_{670}	Daughtry, Walthall, Kim, de Colstoun, & McMurtrey, 2000
SR2	NIR/green = R_{800}/R_{550}	Buschman & Nagel, 1993
SR3	R_{700}/R_{670}	McMurtrey, Chappelle, Kim, Meisinger, & Corp, 1994
SR4	R_{740}/R_{720}	Vogelmann, Rock, & Moss, 1993
SR5	$R_{675}/(R_{700}*R_{650})$	Chappelle at al., 1992
SR6	$R_{672}/(R_{550}*R_{708})$	Datt, 1998
SR7	$R_{860}/(R_{550}*R_{708})$	Datt, 1998
DI1	$R_{800} - R_{550}$	Buschman & Nagel, 1993
NDVI	$(R_{800} - R_{680})/(R_{800} + R_{680})$	Lichtenthaler, Lang, Sowinska, Heisel, & Mieh, 1996
Green NDVI (GNDVI)	$(R_{801} - R_{550})/(R_{800} + R_{550})$	Daughtry et al., 2000
PSSRa	R_{800}/R_{680}	Blackburn, 1998
PSSRb	R_{800}/R_{635}	Blackburn, 1998
NDI1	$(R_{780} - R_{710})/(R_{780} - R_{680})$	Datt, 1999
NDI2	$(R_{850} - R_{710})/(R_{850} - R_{680})$	Datt, 1999
NDI3	$(R_{734} - R_{747})/(R_{715} + R_{726})$	Vogelmann et al., 1993
MCARI	$[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})](R_{700}/R_{670})$	Daughtry et al., 2000
TCARI	$3*[(R_{700} - R_{670}) - 0.2*(R_{700} - R_{550})(R_{700}/R_{670})]$	Haboudane et al., 2002
OSAVI	$(1 + 0.16)(R_{800} - R_{670})/(R_{800} + R_{670} + 0.16)$	Rondeaux et al., 1996
TCARI/OSAVI		Haboudane et al., 2002
TVI	$0.5*[120*(R_{750} - R_{550}) - 200*(R_{670} - R_{550})]$	Broge & Leblanc, 2000
MCARI/OSAVI		Zarco-Tejada, Miller, Morales, Berjón, & Agüera, 2004
RDVI	$(R_{800} - R_{670})/SQRT(R_{800} + R_{670})$	Rougean & Breon, 1995
MSR	$(R_{800}/R_{670} - 1)/SQRT(R_{800}/R_{670} + 1)$	Chen, 1996
MSAVI	$0.5[2R_{800} + 1 - SQRT((2R_{800} + 1)^2 - 8(R_{800} - R_{670}))]$	Qi et al., 1994
MTVI	$1.2*[1.2*(R_{800} - R_{550}) - 2.5*(R_{670} - R_{550})]$	Haboudane et al., 2004
MCARI2	$\dfrac{1.5[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]}{\sqrt{(2R_{800} + 1)^2 - (6R_{800} - 5\sqrt{R_{670}}) - 0.5}}$	Haboudane et al., 2004

has improved in spatial resolution, return visit frequency and spectral resolution. Aerial hyperspectral imagery has revolutionised the ability to distinguish multiple crop characteristics, including nutrients, water, pests, diseases, weeds, biomass and canopy structure. Ground-based sensors have been developed for on-the-go monitoring of crop and soil characteristics such as N stress, water stress, soil organic matter and moisture content.

Precision farming has progressed through many stages. It began with farming by soil and progressed to site-specific crop management based on grid sampling and management zones. More recently there has been increasing emphasis on real-time on-the-go monitoring with ground based sensors. The challenge for the future is to develop precision farming approaches that can provide customized management of farm inputs for individual plants.

There is a significant potential in precision agriculture for combining archived remote sensing data with real-time data for improved agricultural management (Thenkabail, 2003). Historical archives of satellite remote sensing data are available at many locations for Landsat, SPOT, IRS, IKONOS, and QuickBird. These data typically include reflectance in the B, G, R and NIR bands, at spatial resolutions of from 0.6 to 30 m spatial resolution. Images at a fixed location could be analysed across multiple crop growth stages, seasons and years in order to identify relatively homogeneous sub-regions of fields that differ from one another in leaf area index, NDVI, and potential yield. Auxiliary data at these same sites, including crop yield maps, digital elevation models and soil series maps could be combined with historical remote sensing data to identify potential management zones where precision agricultural input operations can be implemented. Real time remote sensing with high spatial and spectral resolution satellites such as EO-1 Hyperion or the upcoming (2016) NASA Hyperspectral Infrared Imager (HyspIRI) satellite (or comparable data collected with aerial platforms) could then be used for real time precision agricultural decision making and to refine the location of management zones identified using historical imaging and auxiliary data.

With this in mind, there are several needs for future research in precision farming. These include the following:

- More emphasis is needed on chemometric or spectral decomposition/derivative methods of analysis since spatial and spectral resolution of hyperspectral sensing systems are now adequate for most precision agriculture applications
- Sensors are needed for direct estimation of nutrient deficiencies without the use of reference strips
- Spectral indices should continue to be developed that simultaneously allow assessment of multiple crop characteristics (e.g. LAI, biomass, etc.) and stresses (e.g. water and N; weeds and insects, etc.)
- Historical archives of satellite remote sensing data at moderate to high spatial resolution and traditional spectral resolution should be integrated with real-time remote sensing data at high spatial and spectral resolution for improved decision making in precision agriculture.

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