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# Remote Sensing in Crop Production: Applications and Value

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NUFFIELD CANADA

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3. Achieve personal development through travel and study
4. Deliver long-term benefits to Canadian farmers and growers, and to the industry as a whole

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# SCHOLAR PROFILE

I currently work as an independent agronomist in Alberta with clients in Sturgeon County and the Peace Country region. I have operated my company, Axiom Agronomy Ltd., since 2014 providing crop consulting, soil sampling, prescription nutrient mapping and assisting customers in acquiring, processing, and analyzing aerial imagery data.

My prior experience in the agriculture industry came from working six years in agronomy, research, grain marketing and sales. I spent two years with BASF Canada as a Technical Specialist covering southern Saskatchewan and four years with Viterra as Manager of Agronomic Services in northern Alberta/BC and a Regional Account manager in the Edmonton/Camrose area. I completed a Bachelor of Secondary Education, Bachelor of Science in Agriculture and Master of Science in plant science from the University of Alberta. I am currently a Professional Agrologist (P. Ag) in Alberta and a Certified Crop Advisor (CCA).

In 2017 I applied for a Nuffield Farming Scholarship to study and identify ways to adopt remotely sensed imagery as an application in crop production for precision agriculture. I was interested in learning how other countries were putting application to aerial imagery data in crop production. As my travels endured, not only was the application of imagery data important but the value this data had for agronomists, farmers and other stakeholders.

Personally, the Nuffield Farming Scholarship has been a life changing experience. I been able to expand my network of contacts in the agriculture business and lean on experiences and knowledge gained during the scholarship to assist in current work projects and expand my business.

## ACKNOWLEDGEMENTS

I am thankful to the Nuffield Canada program for granting me the opportunity to travel and learn in 8 different countries over the last 3 years. With the birth of my daughter Amelia during the middle of the program, I am thankful for the extension and understanding of juggling travels with family and running a business.

I am thankful to have had the support of the Alberta Wheat Commission whose mission is to invest in grower focused research.  This work would not have been possible without the financial support of the Alberta Wheat Commission. A special thank you to Tom Steve and Brian Kennedy who have been supportive of my Nuffield Scholarship and the Nuffield Canada Scholarship program.

I am thankful to the farmers whom shared their experiences during my Nuffield travels, but also to my clients at home whom I work with that endured my crazy travel program.

I have met many new people throughout this experience, whom have inspired me to think differently and challenge my viewpoints. Your generosity of time and wisdom are greatly appreciated and are the inspiration in my report.

I am indebted to the Nuffield community of scholars from across the globe whom not only shared their homes and businesses, but their passion for agriculture.

Thank you to the 2017 GFP Brazil global focus group: Ryan, Dan, Roland, Brendan, Cam, Georgie and Glenn. We have all grown from our Nuffield Farming Scholarship experience and I am thankful to have had a great group to travel with.

Nobody has been more important in the Nuffield Scholarship program than my family. I would like to thank my mom, whose incredible support and childcare assistance allowed me the time to travel.  Most importantly, I wish to thank my Australian Nuffield Farming Scholar and

husband Glenn Wormald and my sweet daughter Amelia Wormald, for keeping me inspired and smiling during the journey.

# EXECUTIVE SUMMARY

Remote sensing is the science of detecting and monitoring information about the Earth's surface through measuring reflected or emitted energy at a distance. The advancement in sensor technology to measure spectral emittance and reflectance has not only improved our understanding of agronomic factors but also improved its application in crop management.

This report reviewed different examples of applications of remote sensing in crop production, through global travel. Under various cropping systems remote sensing data has been utilized across many crops to monitor plant growth and detect plant stresses as they relate to water, nutrient and pest management. In addition, progress continues in developing remote sensing tools for monitoring crop development, screening new crop varieties and yield modelling.

The report further examined the value remote sensing data has for farmers and agronomists. Remote sensing can provide important information for crop management decisions but can also assist in determining management zones for variable rate technologies. One obstacle for remote sensing imagery adoption is the direct economic value it provides as many of the benefits are realized through a combination of other precision agriculture technologies.

Many aerial imagery data applications require additional analysis and interpretation to become actionable and usable which can translate to additional costs and outside expertise for usable applications. Similarly, further value of the remote sensing imagery comes when it is combined with additional data pertaining to agronomic practices, weather and climate, soil and plant development and rolled into a comprehensive, functional tool.  In Canada, more focus is needed to develop and expand these tools through present crop modelling initiatives and international collaboration.

Current adoption of precision agriculture technologies such as the utilization of remote sensing data remains slow, despite a long, embedded history in crop production. Progress to move forward our adoption of these technologies will require more investment of money and time into precision agriculture workshops, technology transfer programs, precision agriculture university degree programs and high-level precision agriculture research pertinent to Canada.

# DISCLAIMER

This report has been prepared in good faith but is not intended to be a scientific study or an academic paper. It is a collection of my current thoughts and findings on discussions, research and visits undertaken during my Nuffield Farming Scholarship.

It illustrates my thought process and my quest for improvements to my knowledge base. It is not a manual with step-by-step instructions to implement procedures.

Neither the Nuffield Farming Scholarships Trust, nor my sponsor, nor any other sponsoring body guarantees or warrants the accuracy, reliability, completeness or currency of the information in this publication nor its usefulness in achieving any purpose.

Readers are responsible for assessing the relevance and accuracy of the content of this publication.



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# 1.0 INTRODUCTION

Within the last 50 years precision agriculture (PA) has ranked as one of the top 10 innovations (Crookston 2006). The purpose of PA is to use technology to optimize the use of farm inputs while improving farm profitability and environmental stewardship. The number of PA technology tools being introduced continues to steadily rise in the marketplace. Specifically, data collection technologies which include yield mapping/monitoring, remote sensing, precision soil sampling/mapping and field scouting. A report published by Goldman Sachs (2016) estimated that new PA technologies will garner an additional 70% yield on existing agricultural land, translating into nearly $200 billion of the total addressable market by 2050 (Figure 1).

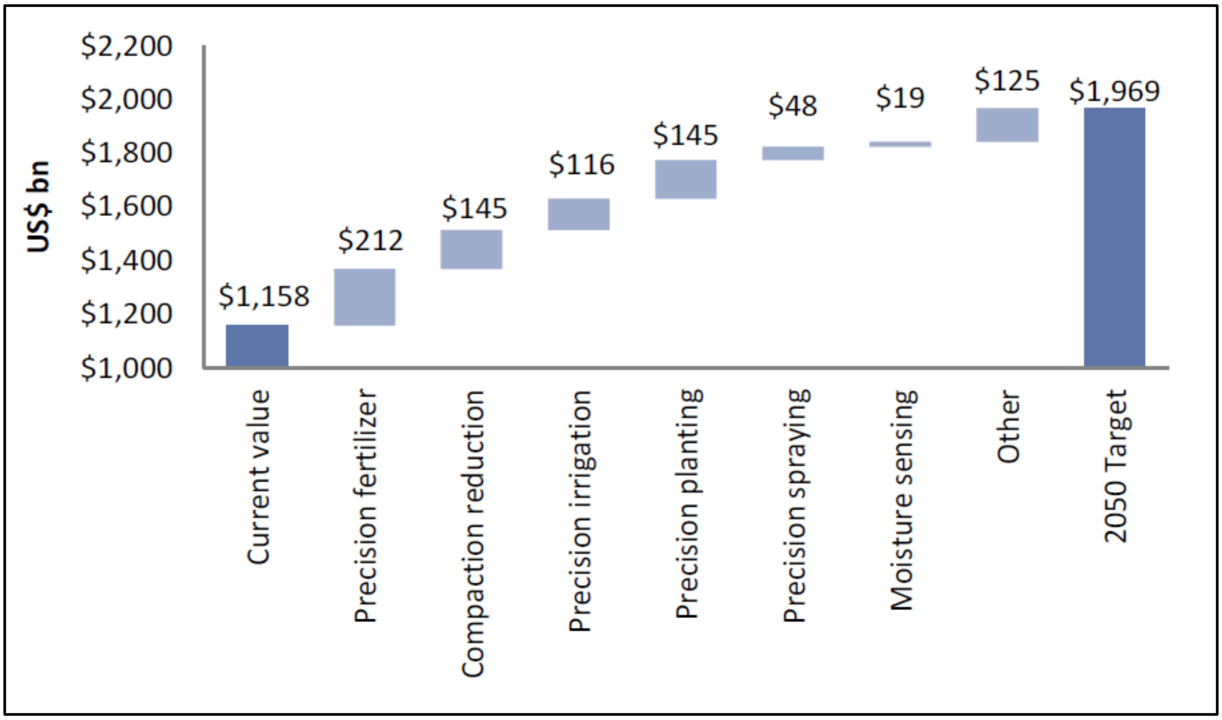



**Figure 1.** Technologies that will influence the global crop value in the USA. Global crop value in US$ billions (bn) (Source: Goldman Sachs Global Investment Research, Company Data, 2016).

The adoption of PA is driven by the need to manage variability on fields both spatially and temporally. Variability can be seen across many aspects of crop production such as soil fertility, soil characteristics, yield, moisture and pest populations. Consequently, a large focus of PA technologies is collecting samples and/or information about the factors that contribute to variability. The development of management zones for precision farming have most often been founded on soil properties such as soil texture and organic matter and sensing technologies, including electrical conductivity and remote sensing (Mulla and Khosla 2016).

Remote sensing has been used in PA to monitor and analyse soil and crops. The term "remote sensing" was first coined in the 1960s (Pruitt 1979) but researchers in many parts of the world, including USA and Canada were using panchromatic aerial images 30 to 40 years prior to complete soil and crop surveys (Goodman 1959). Canada has been actively involved in the digital processing of satellite data since the 1970s, which has included determining land use changes, measuring crop vigour and acreage of crops, mapping snow and ice distribution, and wetland habitat and forestry activities (Darragh et al. 2016). Despite a large depth of knowledge in Canada, the application of remote sensing into PA programs in Canada is still scarce. For example, in an analysis of PA adoption in western Canada, Steele (2017) reported, 59% of farmers in western Canada did not look at in-season satellite imagery or utilized remotely sensed imagery of their crops and fields. However, one may expect that with the rise of low-cost satellite imagery being offered in the current marketplace, the adoption and interest in remote sensing will rise.

The first objective of this report is to provide an overview of information on applications for remote sensing data within crop production. The second objective is to identify the value remote sensing data has for farmers and agronomists in Canada. The objectives of this report are founded on the importance of learning how technologies are being implemented and used in other parts of the world; principally, gathering the value they bring to implementing PA programs and improving crop production practices. An understanding of the applications and value of remote sensing data is also important in ensuring that the technology is being properly interpreted and utilized.

The objectives of this report were achieved through a combination of group travel during a 6-week Global Focus Program and 6 weeks of individual travel. The 6-week Global Focus Program, which included eight Nuffield scholars travelling to 6 countries (Brazil, Mexico, USA, Ireland, France and New Zealand), examined a diverse range of agri-businesses. Following the Global Focus Program, six additional weeks of individual travel to the USA, United Kingdom, Australian and Canada, provided more focused interviews with researchers, agronomists, farmers and agri-business managers.

## 2.0 WHAT IS REMOTE SENSING?

Remote sensing is the science of obtaining information about the Earth's surface from a distance through sensors that record reflected or emitted electromagnetic radiation. More commonly, the use of remote sensing in PA has been used to measure the sun's reflectance of visible and near-infrared light from crops or soils through cameras on satellites, manned aircraft or unmanned aerial vehicles (Mulla and Khosla 2016). For example, in Figure 2, the remote sensing process is illustrated with a satellite as applied to crop monitoring. The sun (A) emits electromagnetic energy (B) to plants (C). The sensors on the satellite measures the reflected energy/light (D). The data is then transmitted to the ground station (E), where it can be analyzed (F) and applied to maps that are displayed in equipment/monitors (G) (Nowatzki et al 2011).

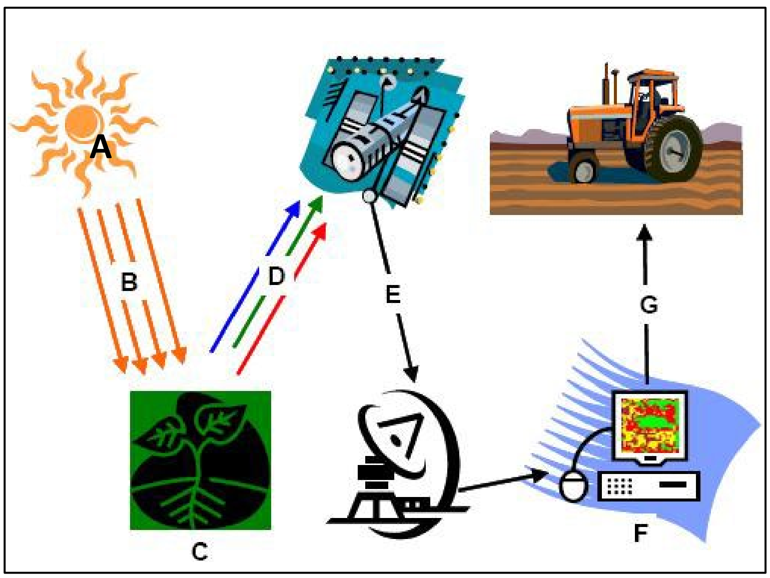



**Figure 2**. Remote sensing schematic (Source: Adapted from Nowatzki et al., 2011).

Proximal remote sensing varies from traditional remote sensing, as sensors are placed within 2m of the target (Viscarra Rossel et al 2011), and typically are placed on ground vehicles, such as farm implements, all-terrain vehicles and vehicles. Figure 3 and Figure 4 are examples of platforms with proximal sensors used in phenotyping wheat.

**Figure 3.** Research cart for carrying thermal, fluorescent and multispectral sensors at Embrapa Cerrados, Brazil (Source: Author).

A) B)

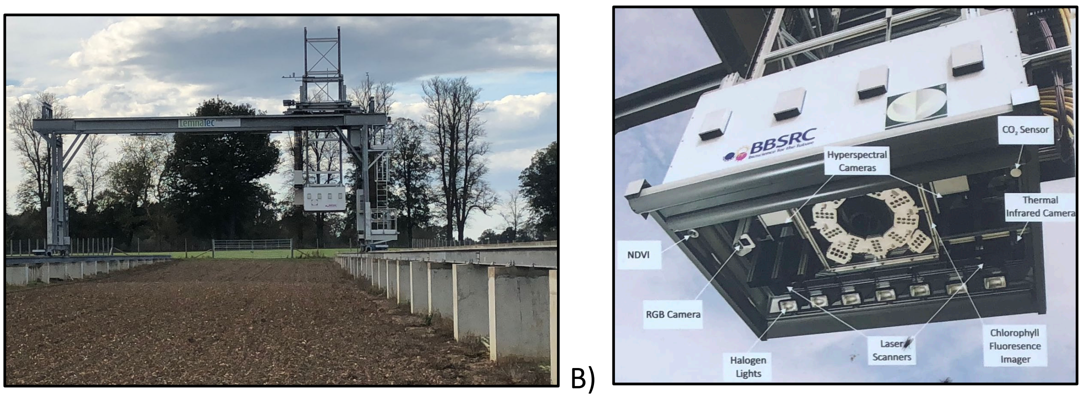



**Figure 4.** A) Field Scanalyzer at Rothamsted Research Farm, United Kingdom (UK) contains numerous proximal sensors that can be positioned over crops within a 10m x 120m area (Source: Author, 2018). B) The Field Scanalyzer is comprised of a chlorophyll fluorescence sensor, NDVI sensors, two hyperspectral imagers, twin scanning lasers for 3D visualization, carbon dioxide sensor, thermal infrared camera and red-green-blue (RGB) camera. The platform of sensors allows for automated 24 hour monitoring of crops throughout the season to observe crop architecture, crop health and crop development (Source: Author, 2018).

## 2.1 Principles of Electromagnetic Radiation

An understanding of the electromagnetic spectrum and how it interacts with the Earth's surface and the atmosphere are key to interpreting remotely sensed imagery. The electromagnetic spectrum contains a range of short and long wavelengths (Figure 5).

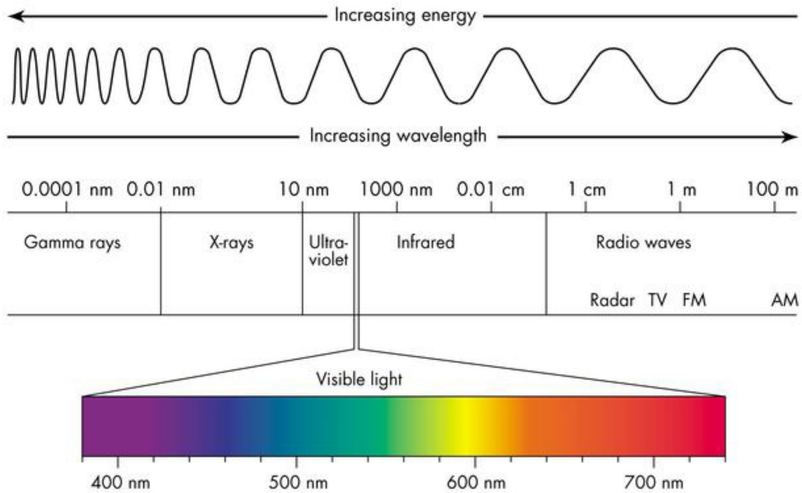



**Figure 5.** The electromagnetic spectrum (Source: UC Davis ChemWiki, 2019).

Within the electromagnetic spectrum are several regions that are valuable for remote sensing, including the visible light (380–780 nm), infrared (780 nm–0.1 mm), and microwave (0.1 mm–1 m) ranges (Zhu et al. 2018). In the visible light spectrum, remote sensing applications include the blue (450–495 nm), green (495–570 nm), and red (620–750 nm) spectral bands (Zhu et al. 2018). Although some differences exist in how infrared is divided, typically it is classified into near infrared (0.75–1.4 µm), shortwave infrared (1.4–3 µm), mid- infrared (3–8 µm), longwave infrared (8–15 µm) and far infrared (15–1000 µm) (Zhu et al. 2018).

Light can interact with objects in three ways: transmission, reflection (scatter) and absorption. The amount of transmitted, absorbed and reflected light depends on the interaction of different wavelengths with an object. For example, visible and near infrared light interacts with green plant tissue and will absorb, reflect and transmit depending on wavelength and plant tissue characteristics. Figure 6 shows examples of reflectance for dry bare soil, green vegetation, and water. The dry bare soil reflectance increases as wavelength increases from 0.4 to 1.8 µm.

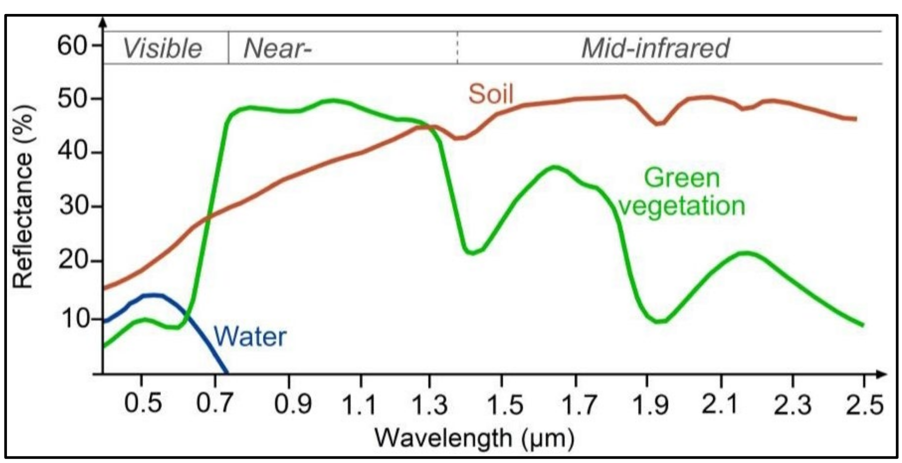



**Figure 6.** Reflectance of vegetation at different wavelength and comparison with soil and water (Source: SEOS, 2019).

Conversely, green vegetation shows high reflectance in the red (0.6 to 0.7 µm) and near-infrared (0.7 to 1.3 µm) regions. As a result, the reflectance of different wavelengths can be used to differentiate vegetation from other physical objects.

Wavelengths and frequency are inversely proportional to each other. Shorter wavelengths are higher frequency and possess more energy than longer wavelengths which possess lower frequency and less energy. The implication for this difference is that more surface area is needed to obtain a signal for longer wavelengths (Ferguson and Rundquist 2018). In addition, the Earth's atmosphere poses a significant obstacle in receiving signals, i.e. absorbing electromagnetic energy, especially for satellite remote sensing. The atmosphere contains elements such as water, particulates and ozone that can scatter or absorb energy, which impact the quality of remote sensing data. This is particularly evident with some wavelengths, such as within the thermal infrared, which has an atmospheric window that allows sensors to only detect energy from wavelengths between 3000 nm and 5000 nm as well as 8000 nm and 14000 nm (Ferguson and Rundquist 2018).

## 2.2 Remote Sensing Platforms

Remote sensing has a long history of use in monitoring and analyzing crop production using manned aircraft and satellites (Nellis et al. 2009). In the early part of this decade unmanned aerial vehicles (UAVs) started to become increasingly important tools in the collection of remotely sensed data. One of the benefits offered by UAVs is having more flexible flight scheduling, allowing for more timely data collections; alternatively, satellites and in some instances manned aircraft, may require several days in between when data is collected and processed (Ferguson and Rundquist, 2018). The advantage of satellites and manned aircraft over UAV platforms, however, has been the ability to capture imagery over a large expanse of area.

Cloud cover is a significant issue for imagery, especially in satellite imagery, even despite vast improvements in the frequency of returns over the same area by satellites. Clouds that are captured in imagery while a satellite is moving over a field of interest can interfere with the processing of imagery and may result in poor interpretation of field conditions. As a result, UAV and manned aircraft platforms can be scheduled to fly during more optimal conditions where cloud coverage is eliminated or reduced, ensuring quality imagery is accessed.

## 2.3 Remote Sensors

Sensors are generally classified as active or passive, depending on how they interact with the Earth's surface. Passive sensors utilize energy, such as solar radiation or heat, that exists naturally in the environment. Conventional cameras are an example of passive sensors, as they process red, green and blue wavelengths from the visible light spectrum to produce color photographs. Alternatively, active sensors provide their own source of energy to illuminate objects and measure observations. Radar, such as Synthetic Aperture Radar (SAR), uses microwaves to illuminate a target and measures the wavelengths that are deflected and returned from the target (Zhu et al. 2018).

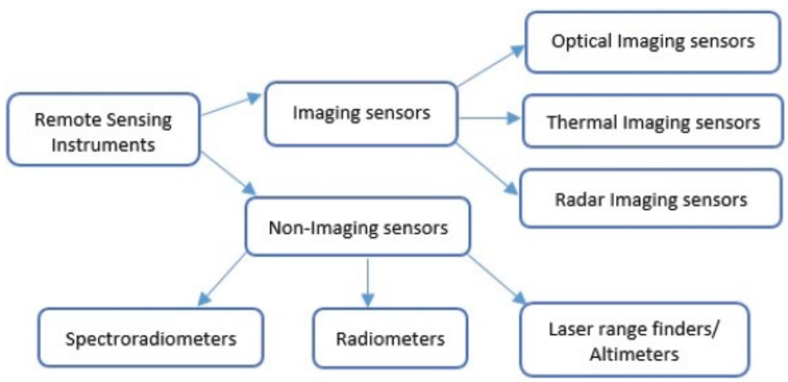



**Figure 7.** Remote sensors divided into imaging and non-imaging sensors (Source: Zhu et al., 2018).

Sensors can be further classified as either imaging or non-imaging (Figure 7). Imaging sensors typically use optical imaging systems, thermal imaging systems and radar imaging sensors (Zhu et al 2018). Panchromatic, multispectral, and hyperspectral images are examples of optical imagery systems which capture visible, near-infrared, and shortwave infrared wavelengths. Thermal images capture mid to longwave infrared wavelengths. Non-imaging sensors can include LIDAR (Light Detection and Ranging), microwave altimeters, and radiometers, laser rangefinders and altimeters, spectroradiometers and magnetic sensors (Zhu et al 2018).

In crop production, optical imaging sensors that produce panchromatic, multispectral, and hyperspectral images have been the most commonly used (Figure 8). Panchromatic systems produce black and white or grayscale images, as the sensor detects one spectral band within a broad wavelength range. Multispectral sensors contain multiple bands (i.e. 5-12) that detect radiation within a narrow wavelength band. As a result, the multispectral systems produce images that contain both the spectral information but also brightness. Hyperspectral sensors gather and process radiation from numerous narrow spectral bands, which can range from 100s to 1000s of bands. As a result, each spectral band creates a set of images that can separate and identify different objects or components within objects.

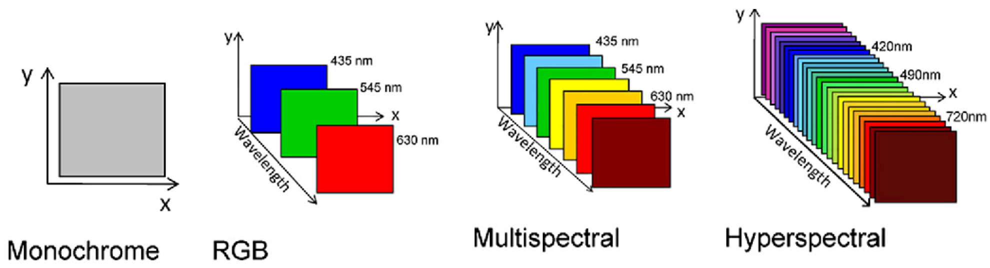



**Figure 8.** Schematic showing the wavelength features of monochrome, red-green-blue (RGB), multispectral, and hyperspectral imagery (Source: Adapted from Mehta et al., 2018).

In addition to the types of sensors, the resolution of sensors plays a significant part in the application of remote sensing. There are four resolutions that impact the quality and fit of remote sensing imagery which include spatial resolution, spectral resolution, radiometric resolution and temporal resolution.

The spatial resolution of an image is a function of the size of pixels (i.e. smallest area unit in a digital image) captured by a sensor. A higher degree of resolution translates to a finer grid, resulting in more detail being captured in an image (Figure 9). The resolutions of today's sensor systems vary from a centimetre to kilometres.

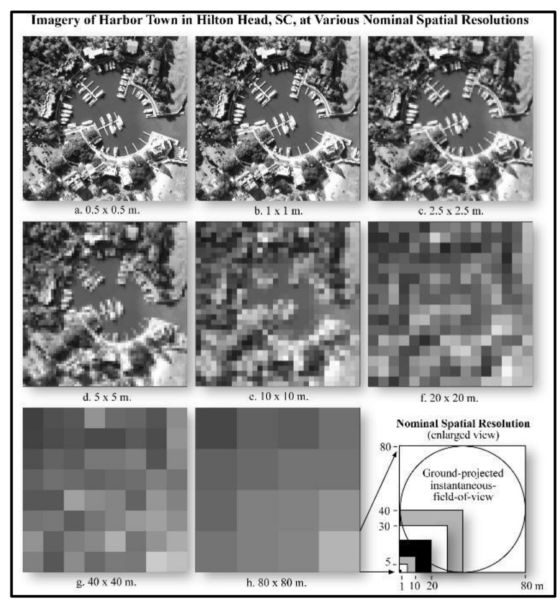
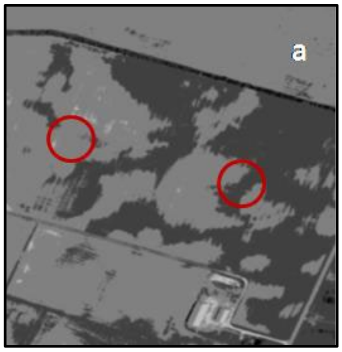



**Figure 9.** Illustrative example of different spatial resolution (Source: Jensen, 2007).

Spectral resolution is characterised as the number of spectral bands and their width in which a sensor detects and records. This type of resolution allows differences in the reflections of different surfaces to be characterized. For example, sensors with higher spectral resolutions, such as hyperspectral sensors, can have thousands of narrow bands that allow for objects to be perceived at more detail.

Radiometric resolution indicates the differences in brightness which is measured through the number of the grey value levels (Figure 10). Bits (binary numbers) are used to capture the maximum number of values. For instance, sensors with 8 bits per pixel has 256 grey values; that is, each pixel in an image will have a range of brightness from 0-255. In general, a higher radiometric resolution results in finer differences in reflected or emitted energy being measured. New cameras to the market, such as the Canon 6D, can have radiometric resolution of 14 bits (16,384 intensities).

A) 

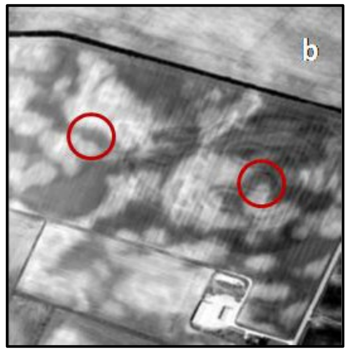
B) 


**Figure 10.** Red band in visual image at A) 2- and B) 16-bit radiometric resolutions representing the differences in the level of detail (Source: Khanal et al., 2017).

Lastly, temporal resolution is the ability to repeatedly capture an image over the same area. Some satellites such as Landsat 8 have a 16 day revisit time; whereas RapidEye can provide daily coverage. Temporal resolution of satellites can be largely affected by cloud cover since sensors that measure visible or infrared light do not penetrate through cloud. Utilizing images over different times (days, months, years) can provide a temporal analysis that identify changes in terrain, land use, city growth and seasonal changes in vegetation. For example, Figure 11 shows the growth of Las Vegas, Nevada over 40 years.

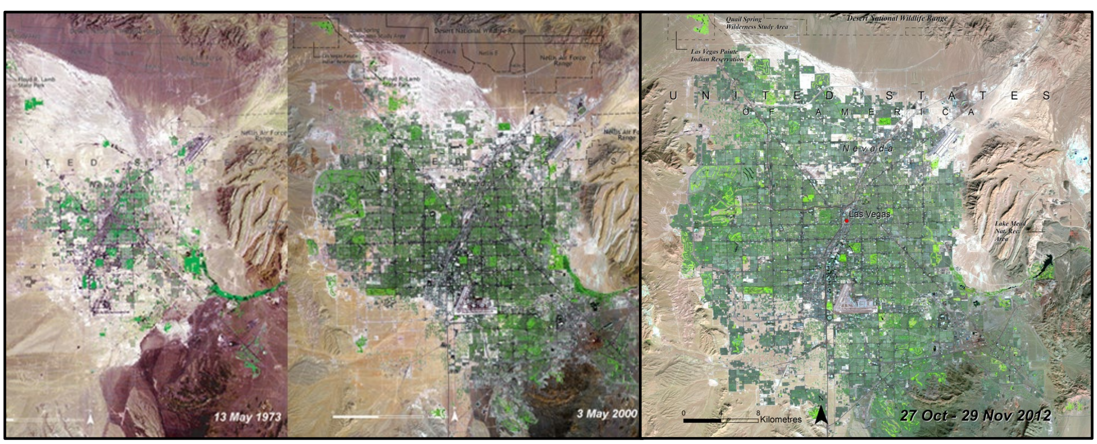



**Figure 11.** Las Vegas, Nevada city growth over time in 1973, 2000 and 2012 (Source: UNEP, 2019).

## 2.4 Spectral Properties of Plants

Since the early 1970s, dozens of vegetation indices have been developed, which relate reflectance from crop canopies or leaves with different light wavelengths and canopy parameters. Many vegetation indices have been developed to emphasize the differences between the ways in which visible light and near-infrared light interact with chlorophyll and leaf arrangements. As a result, sensors, such as red-green-blue digital, multispectral and hyperspectral cameras, have been developed to capture the differences in reflected energy from plants and crop canopies. The most important regions of the electromagnetic spectrum for crop production are the visible (400-700 nm), near-infrared (NIR) (700-1300 nm), middle-infrared (1300-2500 nm) and to a minor degree, the thermal-infrared (8000-14000 nm) (Ferguson and Rundquist, 2018).

Leaves contain chloroplasts with chlorophyll pigments, Chl a and Chl b, which absorb blue and red light for photosynthesis; in addition, pigments such as anthocyanins and carotenoids absorb strongly at different wavelengths (Figure 12) (Xiong, Li and Yue, 2013). For that reason, the greater the plant chlorophyll density, the less blue and red light is reflected (Gates et al, 1964). In contrast, plants do not absorb NIR light; instead most NIR light is reflected from plant leaves, with a portion transmitted through plant leaves (Knipling 1970). As the NIR light travels through the crop canopy, the process continues as some of the transmitted NIR light is reflected from leaves at lower levels of the canopy, while a portion is transmitted through those leaves. The net result is that the greater the plant biomass or leaf area or layers of leaves, the greater the reflectance of NIR light from an area (Knipling 1970). As green photosynthetically active plant biomass or leaf area increases, the less visible light is reflected and the more NIR light is reflected (Knipling 1970). As a result, the more plant biomass or leaf area, the greater the difference between the visible and NIR spectral values (Knipling 1970). Thus, large differences in reflectance properties of the visible and NIR are leveraged in the computation of vegetation indices, making those indices meaningful tools for analyzing plant health and vigor (Knipling 1970).

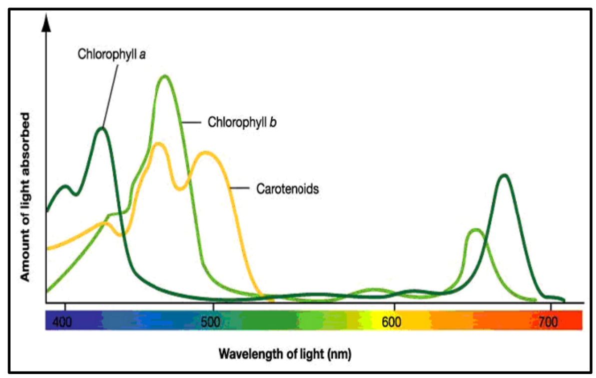



**Figure 12.** Chlorophyll a, b and carotenoids absorbance spectra (Source: Xiong, Li and Yue, 2013).

## 2.5 Soil and Vegetation Indices

The most widely used vegetation index was first introduced in the 1970s and is called the Normalized Difference Vegetation Index (NDVI). NDVI gained acceptance due to its ease of use, using only two wavelengths as well as its relationship of the ratio to plant characteristics, such as nitrogen status, chlorophyll content, green leaf biomass, and grain yield (Shanahan et al. 2003; Ma et al. 1996; Solari et al. 2008; Shanahan et al. 2001). Variations of NDVI have been developed using different specific wavelengths, such as green NDVI or blue NDVI. The NDVI calculated with the red band is generally considered the most widely used and recognized. To normalize index values, the difference between the NIR and visible red light is divided by the product of the NIR and visible light. The standard equation for red NDVI is as follows: (NIR – Red)/ (NIR + Red). The equation reveals that this method for calculating a vegetation index combines spectral information from the two regions of the spectrum that are among the areas where green vegetation is highly responsive to electromagnetic energy, the visible and NIR regions.

While there are several vegetation indices that can be computed, generally, the most notable difference among the indices is whether they factor out soil background and the effects of atmospheric scatter and absorption. For example, Qi et al. (1994a) developed the modified soil-adjusted vegetation index, MSAVI, and later the MSAVI2 (Qi et al. 1994b) to more reliably calculate a soil brightness correction factor when addressing areas with a high degree of exposed soil surface. Further advances have been made in developing and advancing vegetation indices through the development and improvement of narrow-band hyperspectral vegetation indices (Hatfield et al 2008).

## 2.6 Using Remote Sensing for Plant Growth and Development

Remote sensing data has had an integral role in crop classification, crop health, and yield assessments. The main advantage of remotely sensed data in crop production has been the ability to collect repeated measurements of a crop canopy through a non-destructive approach. However, the most common applications for remote sensing in crop production has been the use of remote sensing technologies to identify irregular areas in a field and diagnose the cause of the irregularity through field scouting and sampling (Ferguson and Rundquist, 2018).

The spectral properties of a plant or crop canopy can change due to many factors including growth stage (Zhang et al. 2012), architecture (Ollinger 2011), topography (Hantson and Chuvieco 2011), weather events (Pinter 1986) and biophysical measures, such as soil fertility (Masoni et al 1996). Assessing crop stress or damage can be determined through vegetation indices, such as NDVI. The leaves of stressed and damaged crops have less chlorophyll and more changes to the internal structure of the leaf. As a result, reflectance of green wavelengths is decreased due to reduced chlorophyll content and the changes to the internal structure of leaves also reduces the NIR reflectance. Crop stress and damage can be detected through these reductions in green and NIR reflectance. When examined through a NDVI, healthy plants have high values because of high reflectance of NIR, and rather low reflectance of red light

Assessing crop growth and plant responses to environmental stress with remote sensing can be a significant challenge. Separating spectral signatures originating from a plants response to a stress compared to signals related to normal plant biomass or background noise from external non-plant factors can be difficult (Pinter et al. 2003). The relationship between vegetation indices, like NDVI, yield and environmental conditions can also be highly variable (Turvey and Mclaurin 2012); as a result, it becomes difficult to identify the primary cause of the stress, when a multitude of factors (i.e. environmental, biophysical, biotic factors) are creating the damage. Therefore, the role of field scouting to verify the causes of the stress are important in validating these differences. Nevertheless, remote sensing has emerged as a useful tool for dealing with spatial variability and has complemented more traditional tactics such as field trials or simulation models (Lobell 2013).

## 2.7 Image Interpretation and Analysis

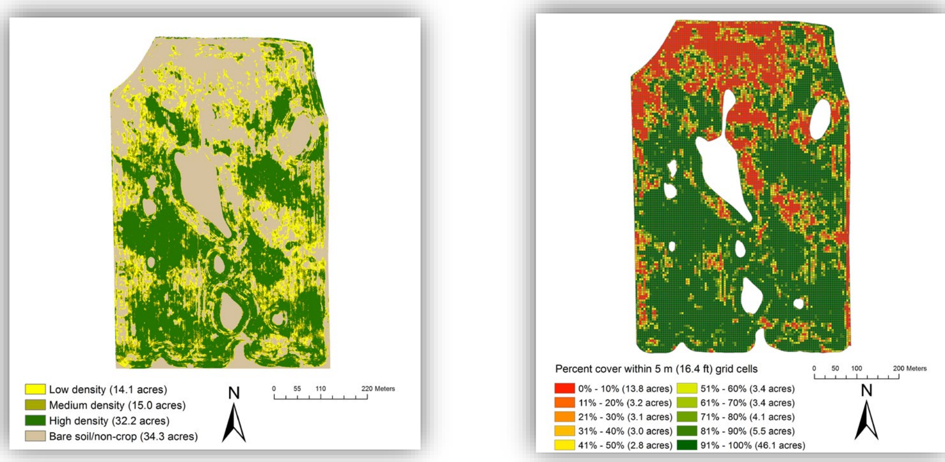
One of the most important steps in remote sensing is converting remote sensing data into usable and meaningful data. Most often remote sensing data processing and analysis involves a form of digital processing to format or correct data, digitally augment data to improve the visual interpretation and automate the classification of objects (Dodge and Congalton, 2013). The adoption of a specific technique or algorithm to process and analyze remotely sensed images, is largely dependent on the type of data and the use of the data.

Typically, there are five procedures that are employed in analyzing and interpreting remote sensing images: Pre-processing, image enhancement, image transformation, image classification and analysis and accuracy assessment (Dodge and Congalton, 2013). Pre-processing is the initial processing of raw data carried out to identify distortions due to features of the imaging system or imaging conditions. Correction procedures include radiometric corrections, atmospheric corrections and geometric corrections. Radiometric and atmospheric corrections are performed to remove variations caused by atmospheric conditions. Geometric corrections are done to adjust for distortions in how the imagery coincides with other images, spatial layers or the Earth's surface.

Image enhancement can also be used to improve the visual appearance of objects in the image which supports visual interpretation and analysis. Several enhancement procedures exist, such as grey level stretching to increase the contrast and spatial filtering, and spatial filtering to optimize spatial patterns in an image (Dodge and Congalton, 2013). Furthermore, image transformations, which are similar to image enhancements, combine processing of data from multiple spectral bands. For example, Principal Components Analysis, is a type of enhancement that can be applied to multi-band imagery. Using mathematical procedures, such as Principal Components Analysis can identify specific sets of bands that display the greatest spectral variations. NDVI, is another example of a common image transformation as image data is transformed into numerical indices to highlight vigorous vegetation with bright tones and dark tones for non-vegetated areas.

Image classification and analysis assign the pixels in each image to a class, using pixel brightness values. Two general methods often used are supervised and unsupervised classification (Dodge and Congalton, 2013). In supervised classification, areas of known surface cover types are identified from the image based off their spectral features and turned into training areas. Image processing software can then classify every pixel in an image that belongs to a specific training class. The more complex and heterogenous the image, the more training areas that are needed to classify. Alternatively, in unsupervised classification, a computer program applies a statistical clustering algorithm to automatically group pixels in an image into classes, based on their spectral features, and allow for clusters to be assigned a land cover or land use type Figure 13).

Lastly, accuracy assessments are performed on completed images to ensure the positional accuracy and thematic accuracy of maps. Positional accuracy ensures that the distance between images on the map are the same as on the ground. Thematic accuracy measures the accuracy of the classifications identified on the map. The level of accuracy can vary greatly depending on the type of data application; additionally, attaining extremely accurate data can be difficult or costly to assemble and produce.




A) B)

**Figure 13.** High-resolution color-infrared imagery used to develop classification models that identify the A) relative density of canola and B) percent cover of canola stand (Source: Author, 2015).

High quality image processing, analysis and interpretation are essential to achieving superior imagery data. Notably, as all imagery data collected is not the same and the requirements for each imagery project varies, the processing requirements will also vary. As a result, there is no standardization when processing or analyzing data. In many cases, there are proprietary techniques that are being developed to process, analyze and interpret the data. Building computationally intensive data platforms that can automate processing, improve the time and accuracy of data analysis and extract more data are some the essential features that are still needed to further develop remote sensing data processing and analysis (Huang et al. 2018).

# 3.0 APPLICATIONS OF REMOTE SENSING IN CROP PRODUCTION

Remote sensing has been used in PA for a variety of functions and continues to evolve as a tool that imparts additional information on managing soil and crop conditions. The goal of this section is to highlight some key examples of remote sensing applications that have been observed during my Nuffield Farming Scholarship travels or reported at scientific conferences and meetings with agronomists and researchers. Importantly, many remote sensing applications in crop production have been previously researched and are reported in scientific literature. The field of research around remote sensing and its applications in crop production continues to develop as the technology in sensors and remote sensing platforms constantly improves.

## 3.1 Water Management

Poor irrigation application timings and improper application amounts are key factors influencing crop growth in regions reliant on irrigation. Remote sensing technology has been historically used to improve irrigation scheduling based on monitoring the water status of the plant. Non-invasive thermal indices, such as Crop Water Stress Index (CWSI), have been commonly utilized for measuring the water status in many different crop types (Figure 14). CWSI captures the difference between the crop's surface temperature and ambient temperature. The premise behind CWSI is that as a crop transpires, the evaporated water will cool the leaves below that of the ambient air temperature. Thermal infrared is more sensitive to acute water stresses in crops than reflectance from visible, NIR or short-wave infrared (SWIR) wavelengths; however, the vegetation indices that measure reflectance from visible, NIR or SWIR can be useful as plants respond to water stress by changes in canopy architecture or reductions in green leaf area.

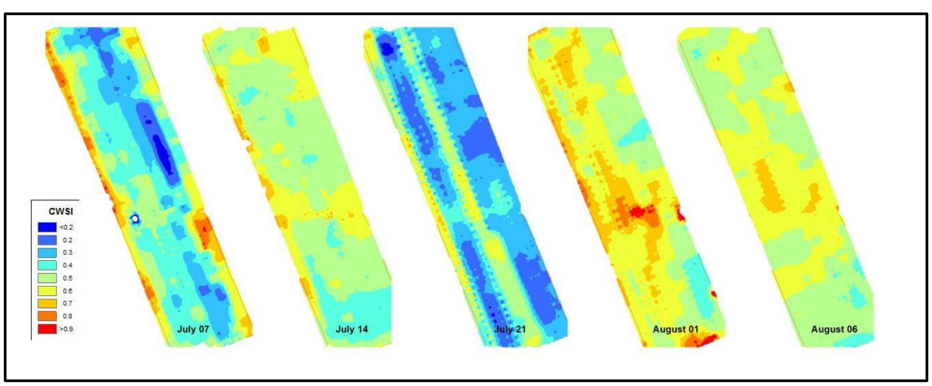



**Figure 14.** Example of CWSI maps in a bi-weekly sequence for a drip irrigated cotton field (Source: Meron, Alchanatis and Cohen, 2012).

CWSI values derived from remote sensors are valuable indicators for the assessment of the spatial variability of crop water status. However, one of the challenges with monitoring a crop's water status through remote sensing is that multiple images throughout a season or during set time intervals are required to monitor changes, which can become costly and not always practical. Likewise, a handheld thermography approach, that utilizes a handheld infrared camera, is also costly, laborious, and unviable for monitoring large areas (Park et al. 2017). As a result, there has been an increased adoption of proximal sensors that can compliment remote sensing or soil data (for example, electrical conductivity) for water management at field scale levels. For example, on a visit to a Macadamia tree orchard in Australia, proximal sensors were being used to evaluate the effectiveness of a sun protectant product on water use and nut yields (Figure 15). Visually, more nut development was occurring on trees with the addition of a sun protectant product, but the ability for the sensors to measure the impact the product was having on water loss on each tree allowed the agronomist and grower to evaluate the merits of the product in season until they could further determine its impact on yield.

The investment in irrigation management, especially variable rate (VR) irrigation, on high value crops such as cotton in Australia or carrot seed production in New Zealand has been increasingly focused on improving pivot systems whereby each sprinkler is individually managed, has high efficient nozzle bodies and utilizes ground sensors to measure soil moisture. During farm visits in New Zealand and Australia, many of the VR irrigation zones developed and implemented have utilized soil data, most specifically electrical conductivity data. Remote sensing data such as NDVI or biomass maps were used by some growers to validate irrigation zones, but many growers and agronomists agree more research on remote sensing imagery is needed to establish how VR irrigation practices can be more proactive to water changes within each zone.

Nonetheless, both soil data and remote sensing data provide more value when combined, but the increased cost of intensive sampling and monitoring to achieve the most value in managing water resources has been better aligned with higher value crops. In the future, irrigation models that utilize remote sensing data such evapotranspiration with other variables including soil moisture and weather data, may provide the ability to optimize the amount of water required by a crop. Consequently, these models could lend to lower cost solutions to managing water resources across all crop types.


**Figure 15.** Telemetry on proximal sap and water flow sensors on Macadamia Trees, QLD, AUS (Source: Author, 2019).

## 3.2 Nutrient Management and Soil Characteristics

Remote sensing can be used to determine soil properties in the upper layer of the soil or assess the variability in a crop canopy due to nutrient deficiencies or other underlying soil variability issues. Mapping soil properties can also offer understanding into improved methods in managing nutrients. One of the most common applications for remote sensing has been for determining spatial and temporal variability due to nutrient deficiencies, particularly nitrogen deficiency and developing VR nitrogen programs. In Canada, their isn't a widespread adoption of the technology for VR fertilizer application. The VR fertilizer adoption rate in western Canada has been reported to be 48% (Steele, 2017). Conversely, a 2017 dealer survey in Ontario by Mitchell et al. (2017) reported that retail dealers estimated 13% of the total acreage in their market area used VR fertilizer; furthermore, satellite or aerial imagery is used by 29% to define management zones.

For many companies that are offering VR fertilizer program services, a foundation of having quality data and in many cases several decades of quality data has been essential to their success. For example, during a visit to SOYL in England, a PA provider in over 15 countries globally, Simon Parrington, commercial director showed how their company was utilizing satellite imagery, such as NDVI and 25 years of electrical conductivity (E.C.) and soil sampling data to develop variable rate nitrogen rate applications (Figure 16). SOYL has found that over 11 seasons of field trials, growers produced an average yield increase of 4.37% (ranging from 3 to 7%) when using variable rate nitrogen over a traditional flat rate (Parrington, 2018). Although growers may be simply adding more nitrogen to achieve higher yields, they are optimizing where the nitrogen is being placed in their fields for the greatest yield return.

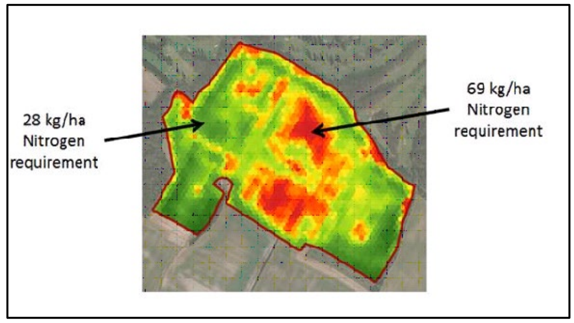



**Figure 16.** Nitrogen variable rate requirements based on satellite imagery (Source: SOYL, 2019)

Throughout my travels and discussions in France, Ireland, the United Kingdom, Australia, Brazil, Canada and the United States, there are still many growers and agronomists that show hesitancy to adopt VR fertilizer practices across all their broad acres. For many of the VR programs in the area, which mostly focused on nitrogen applications, satellite imagery has been the foundation of developing the management zones. In many cases, the satellite imagery alone has not been robust enough to devise management strategies for VR nitrogen fertilizer, especially with highly variable environmental conditions. VR fertilizer programs for other nutrients, such as phosphorous and potassium requires additional soil information, which in turn involves more intensive sampling, and therefore aren't typically the focus of VR programs. In Canada, many VR fertilizer programs have been historically established on Landsat satellite imagery with 30 metre resolution and had not been adequately verified for variability across time and space. As result, this may have generated poor zones and prescriptions maps, limiting the value of remote sensing and VR fertilizer programs to the farmer. Now with current high resolution imagery data to provide more accurate

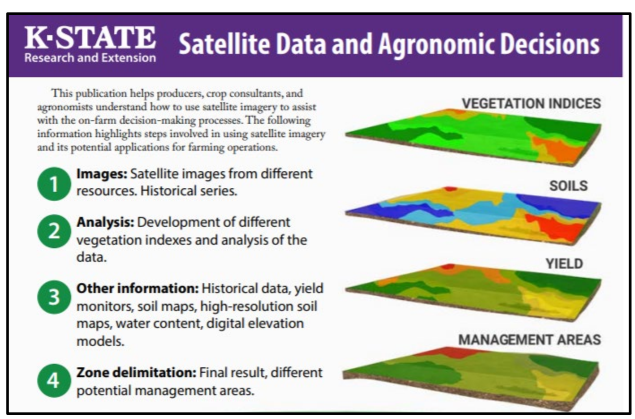



**Figure 17.** Satellite data and agronomic decisions (Source: Ciampitti et al. 2018).

assessments of crop variability, the strength in using remote sensing data such as imagery comes from how its combined with other data such as historical yield data, topography/digital elevation models, electrical conductivity and soil fertility. Universities, such as Kansas State University are developing decision making tools that can help growers and agronomists identify how satellite imagery can be properly utilized with other farm data to assist with agronomic decisions (Figure 17).

Hyperspectral imaging has been increasingly used to investigate soil properties and differentiate micronutrient deficiencies and other nutrient deficiencies such as phosphorous. More specifically, soil imaging spectroscopy, which uses visible and near infrared wavelengths (400–1100nm) and shortwave infrared wavelengths (1100–2500nm) can measure physical, chemical and biological soil properties. The most positive results have been derived from applications of soil properties directly associated to soil chromophores such as iron oxides, clay, soil organic carbon, carbonates and water content (Escribano et al. 2017) (Figure 18). Currently, one of the largest and most diverse global soil visible-near infrared spectral libraries developed by Rossel et al. (2016) includes 12,509 sites globally with reflectance spectra (Figure 19); however, there is a large gap in soil data from Canada.

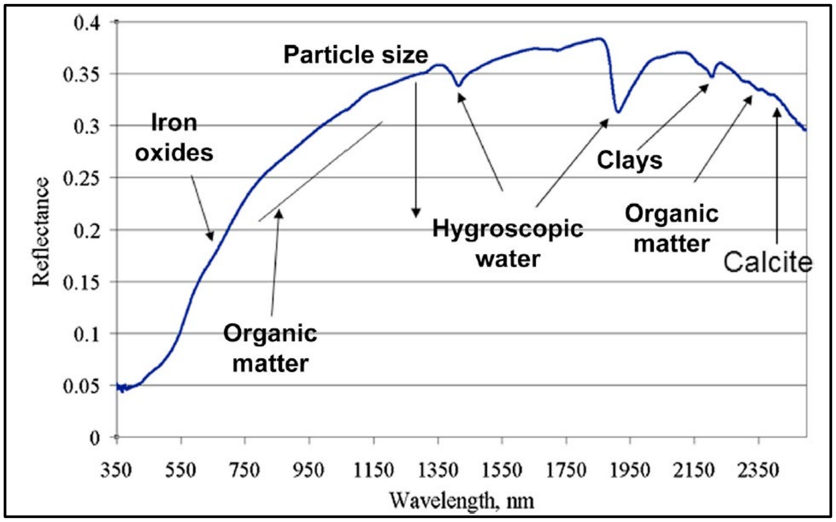



**Figure 18.** Soil spectrum characterizing the major soil chromophores (Source: Ben-Dor et al., 2008, Escribano et al., 2017).

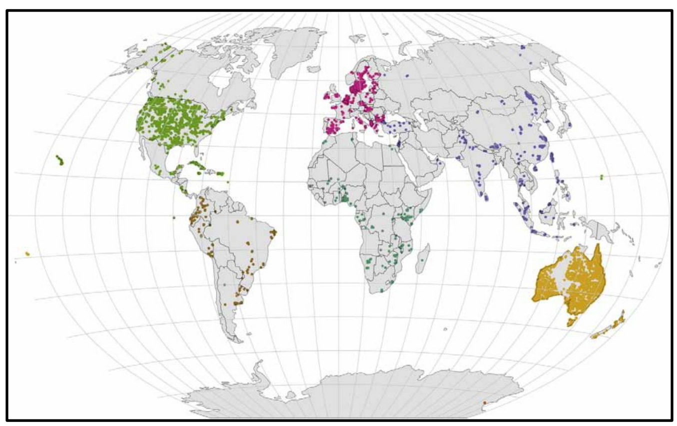


**Figure 19.** Locations of the 12,509 unique sites with reflectance spectra that are in the global database (Source: Rossel et al., 2016).

Attaining high spectral resolution of the upper soil horizon can provide immense insight into the salinity, organic matter, soil moisture, infiltration and runoff capacity of soils (Ben-Dor et al. 2009). For example, Ben-Dor et al. (2002) produced soil surface maps of organic matter, soil field moisture and salinity using hyperspectral imaging and extensive field and lab studies. Electrical conductivity had a high degree of correlation with hygroscopic soil moisture content as measured on the soil surface; subsequently, salt-affected areas (i.e. areas with high E.C. values) had higher hygroscopic moisture content (Figure 20).

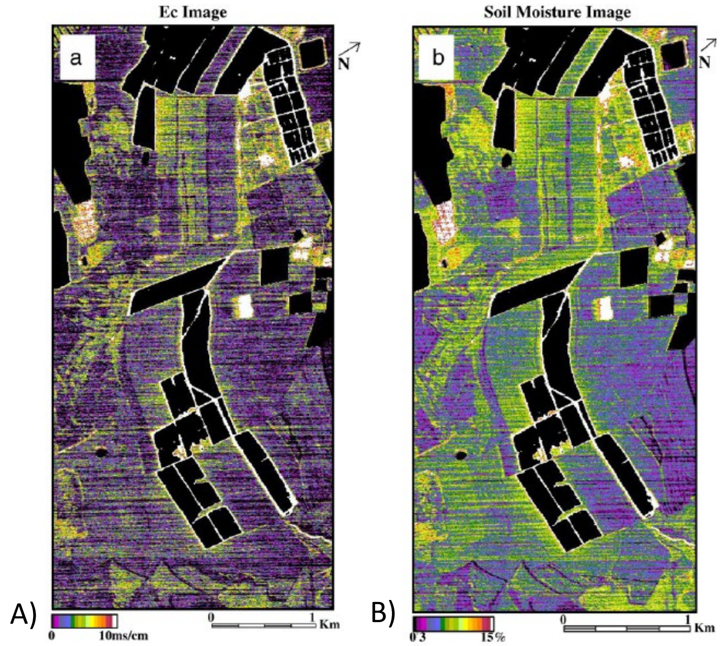



**Figure 20.** Processed DAIS-7915 images of Vertisol soil from Israel showing (A) E.C. and (B) hygroscopic moisture. (Source: Ben-Dor et al., 2002).

Although there is great promise in mapping and monitoring soils through hyperspectral imaging, surface conditions of the soil, water content and crop residue cover impact the spectral response of soil and complicate the analysis (Price and Rundquist, 2009). As more hyperspectral sensors on satellites become available over the next 5 years, there will be new opportunities to collect imaging spectroscopy data of soils and integrate this data with existing data sets or compliment other remote sensing data to expand the information on soil surface properties. These data sets can offer the foundation of soil data to help develop more comprehensive fertilizer programs, without investing significant dollars in intensive testing.

## 3.3 Pest Management

### 3.3.1 Weeds

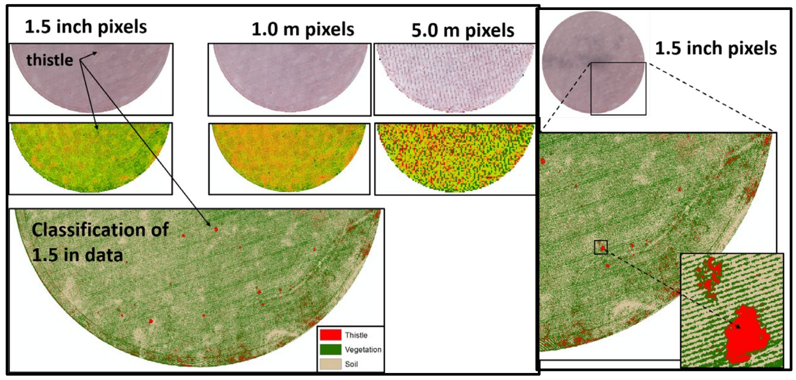



**Figure 21.** Canada thistle detection in a corn field (Source: AgPixel, 2015).

Remote sensing for weed management has been driven by the interest of site-specific applications of herbicides to manage localized populations of weeds and reduce herbicide costs. Weeds are more successfully spectrally differentiated from crops when growing between rows; conversely, there is greater difficulty to separate weeds from crops when they are within the row. However, improvements in spatial and spectral resolutions are influencing the accuracy of mapping individual weed species (Figure 21).

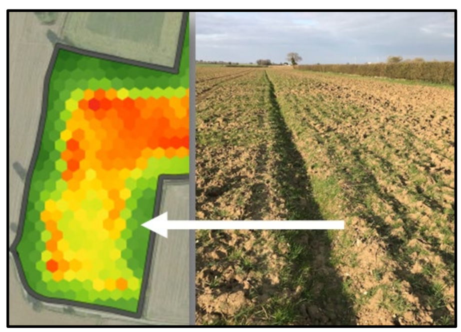


**Figure 22.** Black-grass growing and highlights particularly bad patches on the headlands on overwintered plough (Source: Alexander, 2019).

The use of hyperspectral imagery is contributing to a greater degree of differentiation of different plant species. However, high spatial resolution satellite data (such as GeoEye, 0.5-m pixel) can offer some exceptional detail for looking at weed patches in the field. For example, some agronomy companies in the UK, such as SOYL, are developing variable rate (VR) seeding and herbicide maps for managing black grass (*Alopecurus myosuroides*) based on late season vegetation biomass maps (Figure 22). Increasing seeding rates in both winter cereals and oilseed rape in conjunction with herbicide management has provided a more targeted approach to managing blackgrass.

An interesting development in weed science that was presented at the 2018 Canadian Weed Science Society Annual Conference in Niagara Falls, Ontario is the use of hyperspectral imagery to estimate seed germination of weeds. Matzrafi et al. (2017) used hyperspectral imagery to distinguish between germinating and non-germinating palmer amaranth (*Amaranthus palmeri* S. Watson) seeds with accuracy of 81.9 and 76.4%, respectively (Figure 23 A); furthermore, resistant and sensitive plants to trifloxysulfuron-methyl herbicide were also classified from leaf hyperspectral reflectance with an accuracy of 90.5% and 88.5%, respectively (Figure 23 B,C). The long-term goal for these imaging techniques is to give tools to farmers and agronomists to predict seed germination and provide information on the following year's weed populations and potential risk of infestation to ensure proper management strategies are in place.

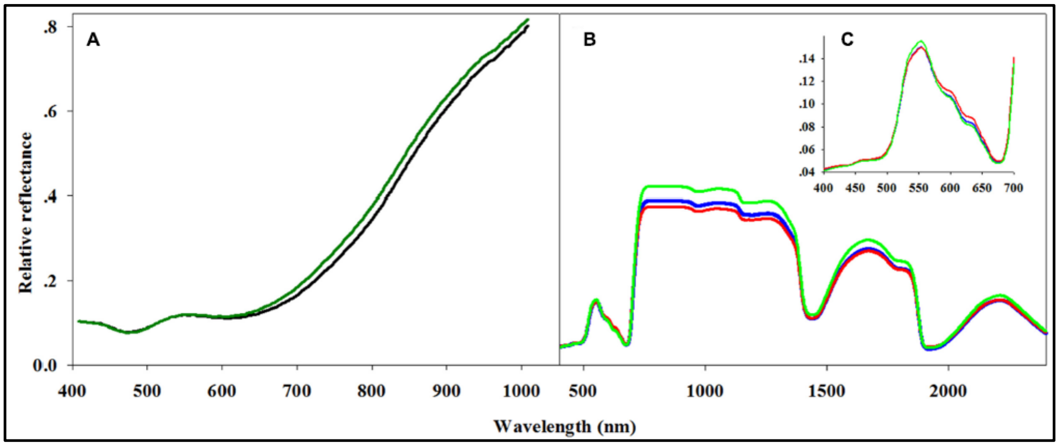
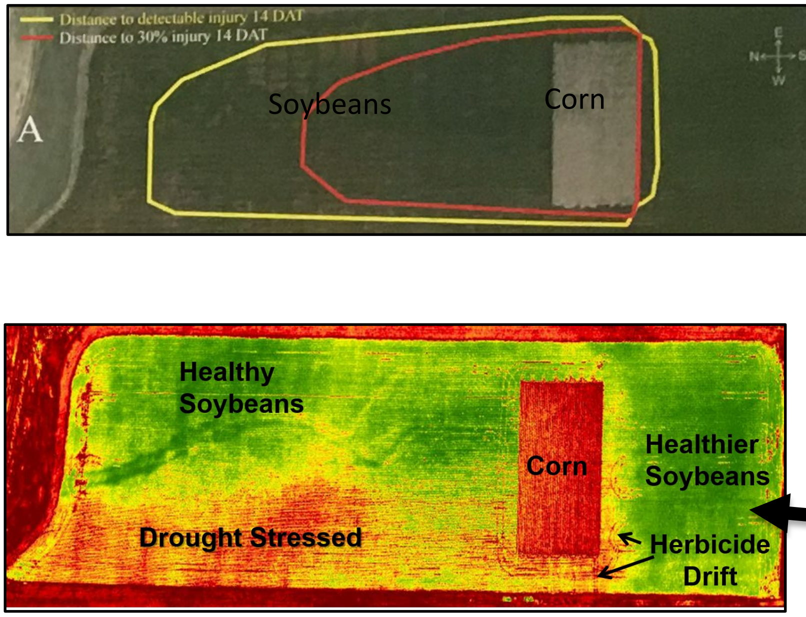



**Figure 23.** Hyperspectral analysis of palmer amaranth seeds and leaves. A) Two seed classes: germinating (dark green line) and non-germinating seeds (black line) B) Three leaf classes: resistant (green line), moderate (blue line) and sensitive (red line) and C) Isolating the 400–700 nm spectral region with the three leaf classes.

Lastly, remote sensing has been used to identify crop production problems, such as herbicide drift. The type of crop damage from herbicide drift, however, can impact the effectiveness of identifying damage with remote sensing. In many cases, it is still important to ground-truth causes for different growth patterns that exist in the field. For example, in a study done at Kansas State University by Peterson et al. (2012) differences in crop growth were observed from the imagery, however, most of the variability appeared to be a function of variability in soil properties and available soil moisture rather than herbicide drift damage (Figure 24). Since the drift injury was only distorted growth and a height reduction, not drastic reductions in biomass or chlorosis, the effectiveness of the imagery to decipher herbicide drift was not as clear.



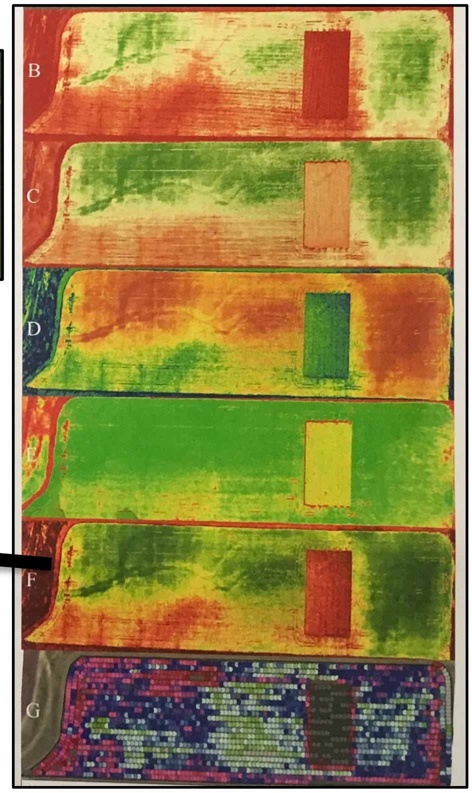




**Figure 24.** A) Google Earth image with visual injury assessment ranges; B-F) Various infrared color separations G: soybean yield (Source: Peterson et al., 2012).

### 3.3.2 Disease

The use of remote sensing can be useful to detect diseases in crops before the onset of infestations (Figure 25). Various imaging techniques such as thermal, chlorophyll-fluorescence, RGB, multi- and hyperspectral imaging have all been applied to detect various plant diseases (2016). In general, high temporal and spatial resolution imagery has been important in the detection of plant diseases. There is complexity in identifying hyperspectral signatures of diseases at a canopy level due to crop morphology and canopy arrangements (Mahlein 2016). Proximal sensing with spatial resolutions <1m has been more frequently adopted to identify symptoms on leaves and plants (Figure 26). Generally,

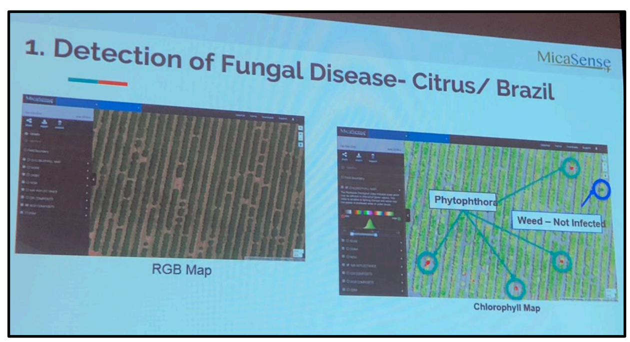



**Figure 25.** Detection of fungal disease in citrus fruit crops with MicaSense sensors on UAV (Source: Author, 2018).

these types of sensors have been more exploited for phenotyping and greenhouse or small field scale sampling.

A)

B)

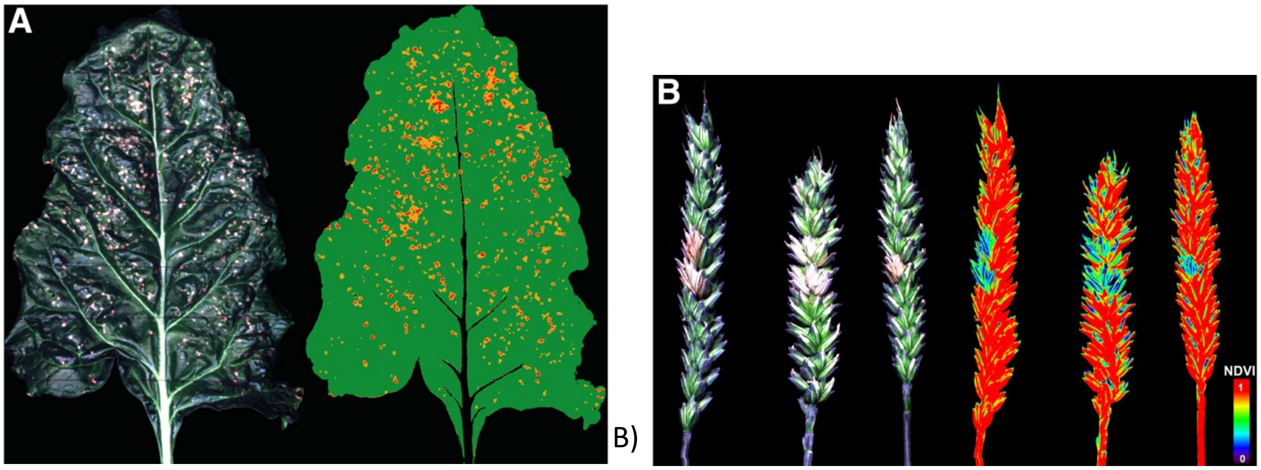



**Figure 26.** Hyperspectral images of fungal plant diseases for disease detection. A) Supervised classification of Cercospora leaf spot on sugar beet. Green color is healthy tissue, red color is necrotic center of leaf spot and yellow color denotes the border of leaf spot (Source: Anne-Katin Mahlein in Mahlein, 2016). B) Wheat heads diseased by Fusarium head blight visualized by normalized difference vegetation index (Source: Anne-Katin Mahlein and Ali Al Masri in Mahlein, 2016).

The spectral properties of plants also varies depending on the type of disease-plant interaction; i.e. plant pathogens that degrade leaf structure (such as chlorotic and necrotic tissue) versus plant pathogens that change the chemical composition through the appearance of fungal structures on leaves (such as hyphae, conidia or urediospores) (Figure 27).

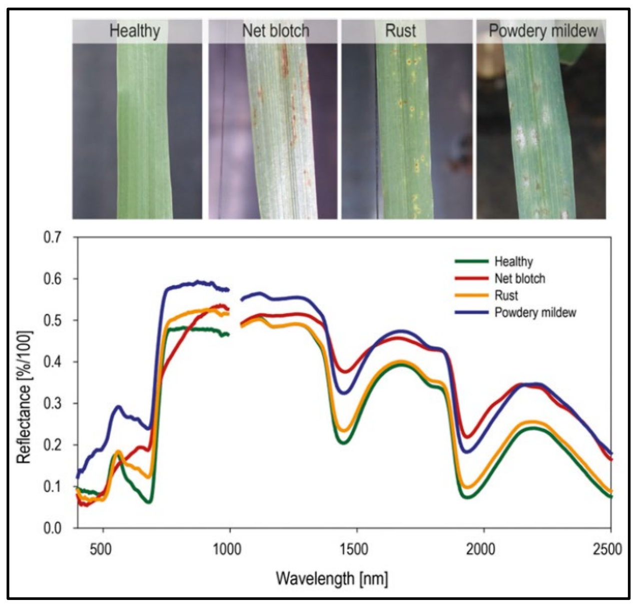



**Figure 27.** Spectral signatures of healthy barley leaves compared to barley leaves diseased with net blotch, rust and powdery mildew (Source: Mahlein, 2016).

Satellite, manned aircraft and UAV imagery have been useful in identifying patches in field that are diseased; however, that information is generally only useful to understand the impact of disease after damage has occurred. Additional research is occurring with hyperspectral imaging with UAVs to identify diseases at low severity ratings, so that detection can lend to decisions regarding the need to apply a fungicide. Significant research in potato production in Canada, United

States and Europe for example are evaluating better imagery tools to identify late blight (*Phytophthora infestans*) infections at low disease levels to improve the timing of fungicide applications. For example, recent research in Dutch potato production which evaluated late blight incidence identified disease severity levels as low as 2.5 and 5.0% of affected leaf area with UAVs (Franceschini et al. 2019).

Furthermore, there is currently an increasing focus in disease management research on assessing the risk of diseases through sensor technologies, by monitoring environmental conditions, crop phenology and disease spore production. In Canada, sensor technologies such as the Spornado, which trap airborne spores are being utilized to determine the risk of sclerotinia in canola and fusarium head blight in cereals. Similarly, in western Canada, a sclerotinia stem rot risk forecast for canola production is being developed to correlate disease levels with weather data and crop characteristics such as crop stage and density as a decision support tool for growers and agronomists. As a result, disease forecast models combined with early disease detection methods and tools, such as remote sensing technologies, will provide significant advantages in managing diseases more successfully and applying fungicides at optimal timings.

### 3.3.3 Insects and Other Pests

Remote sensing has been used to study insect damage in various crops, but despite technological and analytical advances, it remains underdeveloped for studying and managing agricultural insect pests. Generally, infested plants showed noticeably different values for reflectance and vegetation indices, like NDVI, compared to plants not infested; i.e., insect infested plants consistently show lower NDVI values than plants not infested (Bhattarai, Schmid and McCornack 2019). For example, at Kansas State University, research was conducted with 10m resolution satellite data (Sentinel-2) and 17–20 cm resolution manned aircraft data (TerrAvion) to develop NDVI maps for Hessian Fly (*Mayetiola destructor*) infestation in commercial winter wheat fields (Figure 28) (Bhattarai, Schmid and McCornack 2019). Sentinel-2 satellite data was an excellent predictor of Hessian fly infestation in the field which was

**Figure 28.** Severe damage to winter wheat due to feeding by Hessian fly larvae (Source: Arlan Newby, 2015).

also supported by imagery collected from manned aircraft. As research continues in the field of remote sensing and entomology, additional sensors such as LIDAR, thermal and visible-to-shortwave imaging spectrometers are being utilized to look at how plants respond to insect pressure (McCornack 2018).

In the UK, NDVI from satellite imagery is being used for identifying areas of slug damage and fall flea beetle damage in oilseed rape. For example, from the areas of slug damage, targeted applications of pesticide for slug control or increased seeding rates in more slug-prone areas have been utilized (Figure 29). The ban on neonicotinoid insecticides in UK, however, has limited growers on managing flea beetles in oilseed rape. Satellite imagery can be used as a tool to monitor the areas of damage and whether the severity of damage may result in re-seeding.


**Figure 29.** SOYL VR slug treatment map (Source: Farmers Weekly, 2017).

## 3.4 Crop Yield Modelling

One of the first functions of remote sensing in agriculture was estimating yields. There are typically two approaches that use remote sensing data for estimating yield. First is a direct approach, whereby yield predictions are obtained using remote measurements. Second, is an indirect approach whereby remote measurements are incorporated into simulation models for crop growth and development. Numerous methods exist globally for estimating crop yields through remote sensing (Monteith 1977, Moulin et al. 1998; Gallego et al. 2010).

The direct method for predicting yield using remote sensing can be reflectance-based (leaf area or biomass) or thermal-based (stress) (Pinter et al. 2003). In a reflectance-based model, crop yields are estimated by establishing a relationship between field-based yield assessments and vegetation indices, like NDVI, which are calculated during single or multiple dates in the growing season and matched to corresponding crop growth stages (Lobell 2013). For example, when evaluating NDVI in wheat, Feekes growth stage 5 (i.e. when head size is determined and prior to stem elongation) has been shown to have the highest correlation with grain yield (Moges et al. 2004). Conversely, using stress-based models that incorporate reflectance measurements, can improve the accuracy of yield predictions, but many require intensive daily sampling during grain fill to estimate crop stress (Pinter et al. 2003).

The difficulty in adopting direct types of models is they tend to poorly extrapolate to new fields, different varieties or other years. As a result, more fully integrated approaches have been developed that simulate yields through crop models, which commonly require additional information on crop physiological and phenological properties such as crop varieties, seasonal moisture and soil properties (Lobell 2013). Many different types of local vs regional and global scale types of models have been developed. In Canada, the geospatial modelling tool used by Agriculture and Agri-Food Canada (AAFC) to generate yield forecast maps of major Canadian crops (e.g. spring wheat, durum wheat, canola, barley, corn and soybeans) is called the Canadian Crop Yield Forecaster (CCYF). This specific model uses yield predictors such as agro-climatic indices and NDVI, to create monthly forecast maps of yield probabilities. One of the aims of CCYF is to provide an option that may replace or complement the intensive and time-consuming Statistics Canada surveys with a remote sensing yield model-based approach. Chipanshia et al. (2015) evaluated the Integrated Canadian Crop Yield Forecaster model against yield survey data of spring wheat, barley and canola from 1987–2012. The coefficient of variation (CV) distributions for all three crops showed not only more variability in yields in western Canada than eastern Canada, but the prairie census agricultural regions typically had CVs greater than 20%, indicating a large degree of environmental impact on the yields (Figure 30 A). The CCYF model's coefficient of determination ($R^2$) at the census agricultural region level was 0.67, 0.66 and 0.51 for canola, spring wheat and barley, respectively. The predictability of the model improved in census agricultural regions when areas had more climate/weather station data available and a greater percentage of crop coverage (Figure 30 B).

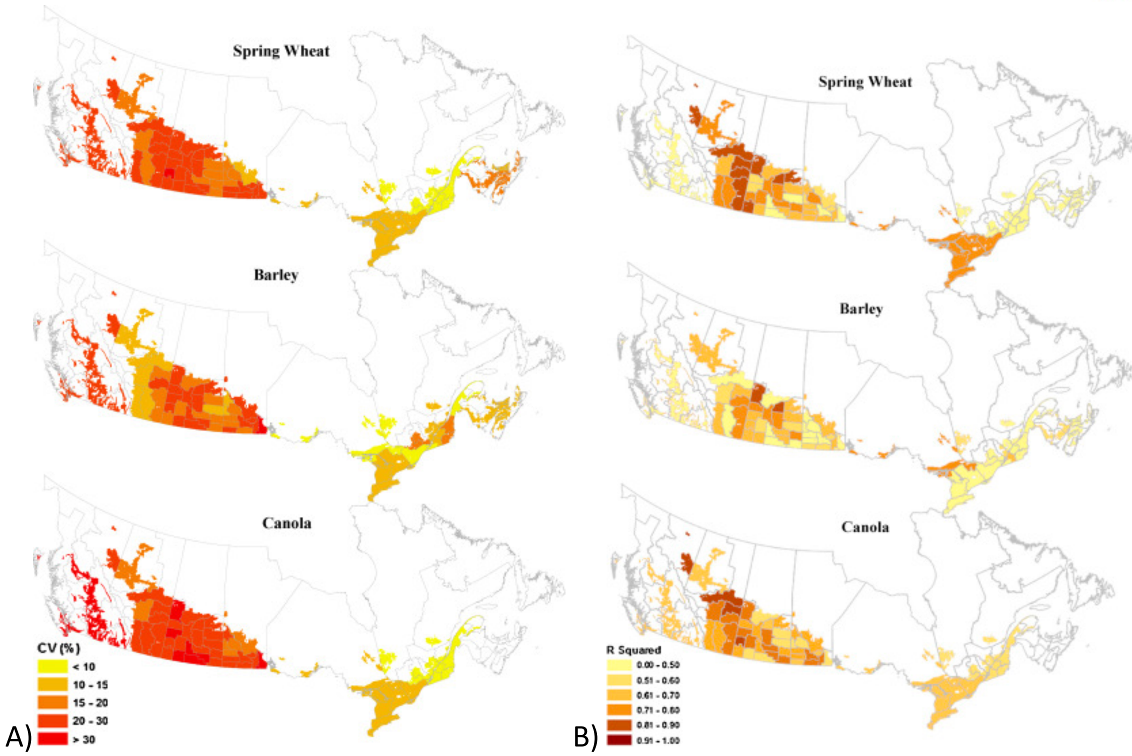



**Figure 30.** A) Coefficient of variation of surveyed spring wheat, barley and canola yields between 1985–2012 at the census agricultural region scale across Canada (Source: Chipanshia et al., 2015). B) Coefficient of determination distribution of model at the census agricultural region level across Canada for wheat, barley and canola (Source: Chipanshia et al., 2015).

## 3.5 Plant Breeding

In plant breeding, phenotyping is done on several thousand small plots to evaluate plants with improved traits. High-throughput field-phenotyping (HTP) in breeding has become increasingly popular to screen a high number of samples with better accuracy and increased efficiency to improve selection of new germplasm. In addition, integrating genomic selection with HTP can not only allow for screening of large populations but can 1) minimize replications 2) scale up selections of large nurseries 3) scale up selections of early generations and 4) increase selection accuracies (Juliana et al. 2018).

For plant breeding trials that are typically done on 1 to 2m$^2$ plots, remote sensing with UAVs and proximal phenotyping equipment has become gradually utilized (Figure 31). During visits to Dr. Jesse Poland's Wheat Breeding Program at Kansas State University and the International Maize and Wheat Improvement Center (CIMMYT) in Mexico, researchers are utilizing high-throughput field-phenotyping data to improve the wheat lines for grain yield. For example, NDVI and canopy temperature have been examined as high-throughput phenotyping data which can then be later integrated with genotypic data to further improve selection of enhanced breeding lines from larger populations.

Similarly, while at Embrapa Cerrados in Brazil, researchers were currently working on developing wheat varieties that utilized sensors to measure heat and drought stress amongst different phenotypes. Three common sensors that have been utilized on either a proximal or UAV platform included thermal, fluorescent and multispectral, measuring CWSI, FV/FM and GNDVI, respectively. Remote sensing has been useful to their breeding program as it provided an opportunity to capture many data points without destroying the plants in the trial. In addition, they were utilizing, phenoVein, a software tool that analyzes leaf veins for characteristics such as length, density, and width, to correlate with their field data to identify wheat varieties with best tolerance to drought.

A) 

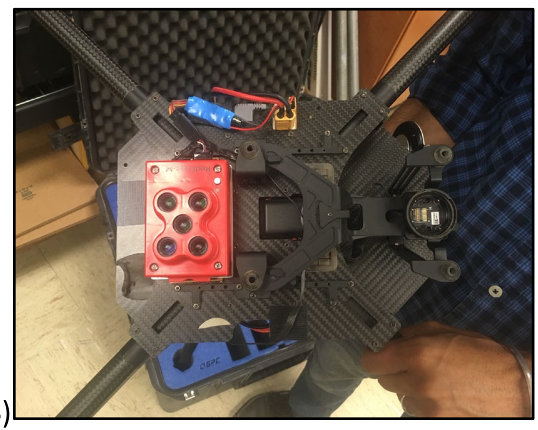
B) 

**Figure 31.** A) PhenoCart platform with NDVI, canopy temperature and georeferenced data at Obregon, Mexico. The platform integrates several commercial sensors, including GreenSeeker for spectral reflectance, an infrared thermometer, and a global navigation satellite system receiver (Source: Author, 2018) B) MicaSense RedEdge M optical sensor on UAV used at Kansas State University Wheat Breeding Program (Source: Author, 2018).

## 3.6 Applications to Canadian Crop Production

Remote sensing has been applied to crop production for over 50 years, and advancements in the application of the technology are continuously being developed to this day. Worldwide, there are many examples of how remote sensing is being used in various crops to manage water, soil, crops, pests and improve crop varieties and production practices. The previous sections have provided some examples that were discovered during my Nuffield Farming Scholarship travels.

While many of the examples that were highlighted can have direct application to Canadian crop production practices, there needs to be further research into the direct benefits for application on Canadian cropping systems. Further evaluation of how the technology interacts with factors that drive variability within the crops grown in Canada, such as our environment, management systems, soil variability and commodity prices, is required. For example, economically it may not be realistic to monitor individual plants of commodity crops like canola or wheat for water or nutrient stress, but there may be better application for high value crops such as fruit orchards and vineyards in Canada. Conversely, utilizing remote sensing data to develop variable rate seeding and fertilizer maps has had value to farmers and agronomists in Canada, albeit the adoption and implementation in Canadian crop production has varying degrees of success. In Canada, a small set of private and public companies involved in generating variable fertilizer and seeding prescription maps typically have exclusive methods. While many use a combination of soil, yield, remote sensing and topography data to develop their maps, there isn't a consensus on what data should be included. Perhaps the best strategy is to seek data that carefully details field variability and allows for development of personalized maps for farm operations. In some cases, this may or may not include remote sensing data.

Current uses for remote sensing technology in Canada have been its application for disease detection in vineyards, orchards and high value crops (i.e. potatoes), the monitoring of field variability in soil and moisture for variable rate applications, weed mapping, and measuring crop biomass and crop yield modelling. The challenge for the Canadian grower is not that there isn't application for the technology, since many applications of the technology exist, but rather a lack of extension of the new research and development from the scientific community to farms to realize the full potential of the technology and economic value to the operation. Even with a growing field of applications from the research community, there are only a few growers and agronomists utilizing remote sensing technology, outside of visually looking at maps to look for field variability.

While the potential for using remote sensing data in Canada in commodity crops for developing disease detection tools, improving management of herbicide resistant weeds, improving or validating management zones for irrigation and variable rate applications, and developing the next generation of crop genetics, the reality is the most of the agriculture industry in Canada is still in its infancy with regards to impactful applications. While other countries are researching applications for the technology, this only highlights the need to do the work in our own industry to develop applications that demonstrate value to farmers and agronomists.

# 4.0 VALUE OF REMOTE SENSING DATA IN CROP PRODUCTION

The adoption of PA has been considered slow, including here in Canada, despite many accounts of the technical benefits that many of the technologies provide to farmers. Several studies (Nowak 1992; Yapa and Mayfield 1978) have indicated many reasons for farmers to be slow adopters of innovation including:

- Shortage of adequate information about technology
- Shortage of confidence in the information about technology
- Critical attitudes and poor technology literacy
- Deficient economic resources to acquire technology
- Poor physical availability of technology
- Shortage of evidence citing clear economic feasibility and profitability

Many PA meetings and conferences have also targeted topics on the adoption and value of PA technologies. During the World Agri-Tech Summit in London, UK, Oct. 17, 2018, there was an entire session devoted to, “Tackling Adoption Barriers: What Value is Digital Agriculture Bringing to the Farm”. One of the key messages from the meeting was that although technology should help drive profitability, productivity and efficiency on farms, the industry needs to improve on articulating the benefits that each PA technology delivers; that is, the economic benefits, but also functional, social and emotional benefits. Furthermore, more collaboration is required amongst technology providers and farmers to showcase how the technology works (i.e. technology transfer).

One of the challenges with identifying the value of PA is that all technologies are lumped together. Lowenberg-DeBoer and Erickson (2019) identified one of the main reasons that the perception of PA adoption is slow stems from the association that PA has with VR technologies, which rarely exceeds 20-25% of farms. The value and adoption of some technologies varies largely depending on the type of technology. For instance, automated technologies (i.e. sectional boom control or section shutoffs) have higher rates of adoption. Terry Griffin, Cropping Systems Economist from Kansas State University has reported similar trends in Kansas (Figure 32). Conversely, the adoption of data collection technologies like yield and soil mapping and remote sensing, has been relatively slow (Griffin 2016; Lowenberg-DeBoer and Erickson, 2019).

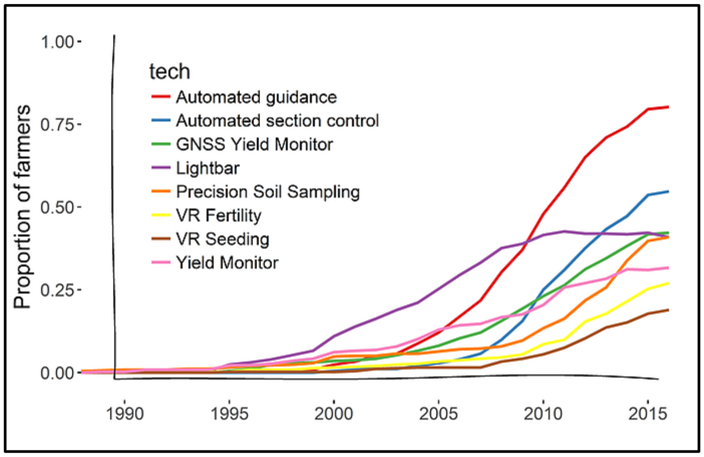



**Figure 32.** Precision agriculture adoption in Kansas, USA (Source: Griffin, 2016).

Remote sensing can provide significant information for crop management decisions but also helps lay the foundation to establish management zones for VR technologies. However, the direct economic value of remote sensing data is difficult to assess as many of the benefits are used in combination with other technologies. As a result, the cost and profitability of the imagery data tends to remain rather unclear. Tenkorang and Lowenberg-DeBoer (2008) reviewed nearly 100 remote sensing research studies, and the vast majority concentrated on technical aspects of the technology (i.e. estimating crop acreage, crop identification, detecting crop stress and predicting yield). Only 12 studies reported economic benefit estimates from use. Although the studies gave substantially mixed estimates of returns from use, (i.e. $2/ha to $200/ha), there was no clear evidence on profitability; although returns gained tended to be a function of adjusting management practices.

Economic returns are one of the most important factors for farmers in adopting PA technologies. To attain more adoption of aerial imagery, the cost of imagery needs to be reflective of its value in the total value of a VR program. In a sit down interview with Ben Boughton (2019), founder and director of Satamap, he captured the behavior of the remote sensing market with an excellent observation: 80% of people are just looking at imagery data, 10% of people are not interested in looking at any imagery data and 10% of people are vested in the data and using it for additional applications. Ben's comments highlight the obstacle with the value proposition of imagery data. If the only value growers or agronomist are getting out of the images is as a visual tool (Figure 33), then the cost of imagery needs to be low and affordable. Although a vast market of imagery products are available, from cameras mounted in planes and unmanned aerial vehicles, to high resolution satellites, one of the greatest hurdles remains how growers and agronomists are to utilize and apply the information profitably. Therefore, the greatest value driven from imagery will be derived by linking spectral and agronomic parameters into economically viable actionable data that influences how crops are managed.

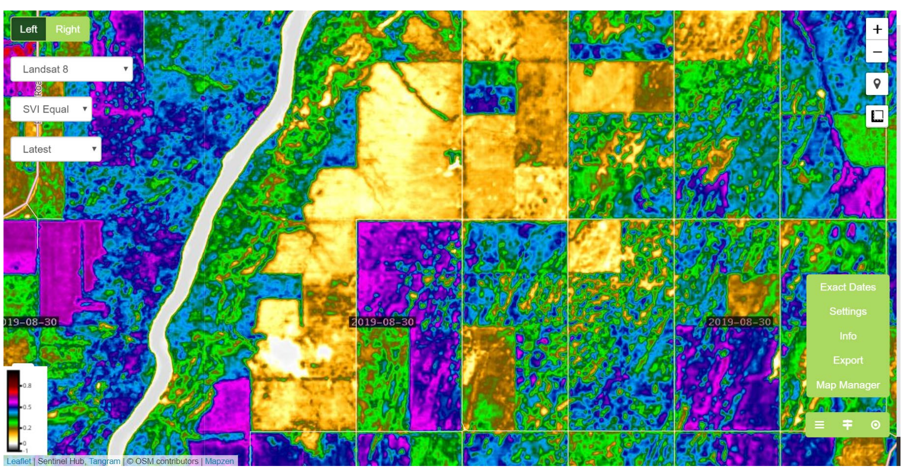



**Figure 33.** Satamap imagery of Peace River, Alberta used by Axiom Agronomy Ltd. for monitoring crop dry down in wheat (Source: Author, 2019).

Most aerial imagery data applications require additional analysis and interpretation to become actionable and usable. This extra piece of data handling is typically what limits most farmers and agronomists from uptake as there are usually additional costs and expertise required to transform remotely sensed data into actionable data. Growers and agronomists are looking for technologies that can provide simple management and production efficiencies. The next step is to turn collections of historical data into actionable items that are simple to understand and implement. Many of these applications, however, are data intensive and requiring combining several layers of information (Figure 34).

Remote sensing is a highly technical field, that requires bridging knowledge of many scientific disciplines. The value and application of remote sensing data to agronomists and farmers will be better realized when its used in larger data sets to describe or predict factors that influence crop production, field variability or risk. Unfortunately, Canada, is still in many respects at the early stages in this approach with very little to no offerings that bridge multiple data sets together to create a value added product. For example, while in the UK, I met with Lucy Wilson from ADAS, a large agricultural and environmental consultancy agency, who developed the Crop Intelligence System (CIS), which delivers remote sensing data to farmers and agronomists. CIS integrated data on light, water and temperature for crop growth as part of a larger attempt to understand the variation in yields within and between fields, farms and years. A program called the Yield Enhancement Network (YEN), established in 2012, which allows for collaboration between farmers, industry and scientists, began combining soil data, and weather data to determine the potential yields for each field in the UK. Farmers and agronomist supply data (i.e. yield data, crop samples, crop management history) to ADAS who in turn analyzes and provides recommendations on the factors limiting yields .The addition of CIS provided growers and agronomists additional information on captured solar radiation, available soil water and accumulated temperature that allows for improved crop monitoring, benchmarking and crop management.

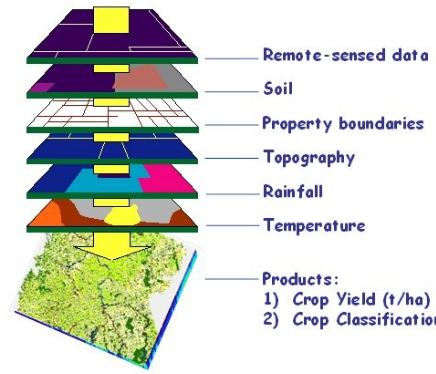



**Figure 34.** Layers of information used to create digital products (Source: Lawes et al., 2018).

In Australia, while visiting the CSIRO (Commonwealth Scientific and Industrial Research Organisation), I was introduced to the research that has gone into the creation of a digital product that collects information from soil water sensors, satellites, soil classes, crop models, economics and commodity prices. The launch of Graincast$^{TM}$ in Australia in 2019 is an excellent example of the capacity for personalized farm data that has a sound scientific basis. Graincast$^{TM}$ includes a wide range of integrated data such as:

- Daily rainfall, temperature and solar radiation data from the Bureau of Meteorology (5 km resolution)
- Soil data from the Australian Soil and Landscape Grid
- Soil water status and grain yield forecasts computed by Agricultural Production Systems sIMulator (APSIM®)

In countries like the UK, US and Australia, I saw the implementation of imagery data into large crop yield and growth models. In Canada, there is a wealth of crop production data, imagery, weather and crop production data that is not being utilized to its potential. In 2015, Kouadio et al. explored the potential effects of climate variability on spring wheat yields in Saskatchewan with the APSIM decision support tool, proposing it had the basis to assist decision making with regards to adapting or mitigating risks under future climatic conditions in western Canada. While the study only described a small segment of crop production in Canada, further attention needs to be addressed on development of these models in Canada to ensure growers and agronomists have decision making tools that aid in managing crop production risks with a greater degree of accuracy than what currently exists.

Crop yield models can provide value to many individuals including farmers, agronomists, scientists, government agencies, commodity firms, banks and insurance companies. The information and data generated from crop yield models can be used to monitor both the economic and environmental performance of farms spatially and temporally. At Rothamsted Research in the United Kingdom, high frequency and high resolution satellite data has been utilized to confirm crop productivity of land and used to benchmark productivity at a farm scale (Figure 35). In the UK, there is significant interest from banks, for example, to use this data to compare and assess farmers with good and bad production and financial practices. Furthermore, insurance companies in Canada and the US, have an interest in farm level

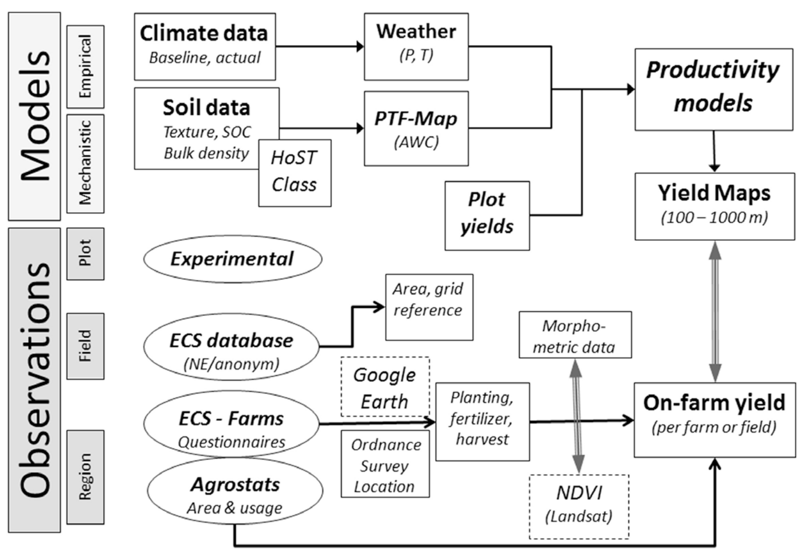



**Figure 35.** Integration of data for on-farm yield evaluation, estimation and improvement (Source: Richter et al. 2016).

yield data for more accurate implementation of crop insurance programs as they rely on more regional or county level data which aggregates several producers' yield data. Further interest in remote sensing data for crop yield models will continue to examine other impacts to yield such as climate change, technology advances, land use and crop management practices.

There is an increasing trend to have transparency in the production and management of food. Remote sensing provides a visual transparency on production practices, that can highlight successes in management or indicate areas of improvement. The value in this transparency is it can provide access to new markets. For example, in Canada, currently, the market access of canola to European Union biofuel markets is dependent on rigorous sustainability requirements including no new land cleared after January 1, 2008 (CCC, 2019). Validation of whether growers have land that meets this requirement can be reviewed through monitoring agricultural land use by programs such as those done by Agriculture and Agri-Food Canada (Figure 36). Conversely, information can be used to determine poor production practices, such as poor crop rotations or land management practices. In the future, this information may have an impact on crop insurance programs, financing programs from banks, land values/land purchasing decisions.

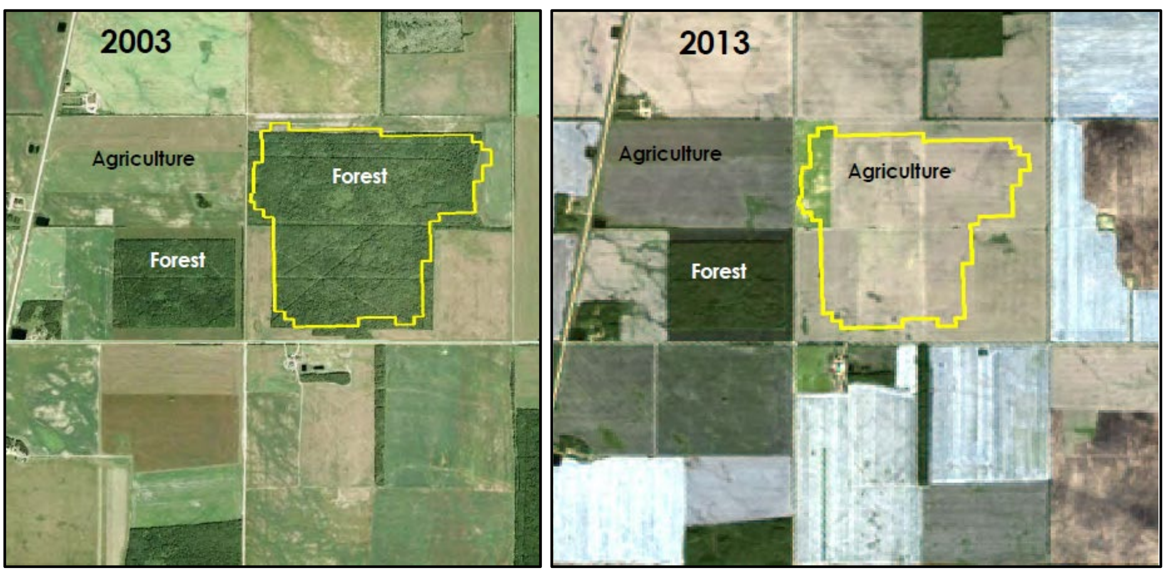



**Figure 36.** Agricultural land use indicators to identify areas converted from forests or wetlands to agriculture use (Source: Campbell, 2016).

# 5.0 CONCLUSION

Remote sensing technology should be viewed as a tool. Before applying any technology tool, it is important to assess whether the technology is the right tool to address the problem or question. Remote sensing has a strong history as a tool for detecting nutrient deficiencies, identifying soil variability, spotting soil water excesses or deficiencies, pest damage and estimating crop yield. Many aerial and satellite imagery products are available on the marketplace that can serve as a key geographic information system layer to develop site specific management. There are various technology tools that can uncover field variability, and remote sensing should be regarded as one tool that can quantify this variability. However, it is still essential that we understand the factors that contribute to the variability, which in the end may require additional sampling and utilization of other technology tools (i.e. proximal soil sensors).

The benefits and applications of remote sensing in PA are yet to be fully realized in Canada. With the vast array of imagery products available, problems with data quality, consistency in data processing times and delivery have impeded the uptake of imagery products. Most of the applications for remote sensing have also typically been utilized within research communities. At the field level, growers and agronomists are looking for imagery that is utilized as part of a decision support tool or model rather than some of the current commercial uses of imagery which are solely visual tools. These digital support tools need to be simple and easily adapted to farms. Farmers and agronomists want real solutions to real problems, not solving problems created by technology. The tools need to be economical, as many farms are operating on low margins, low commodity prices and generally one crop per year.

The usefulness of remote sensing will continue to develop as we continue to use tools to learn more about crop performance variability during the growing season and understand what drives variability on the farm. The greatest benefits from remote sensing will continue to come as we combine imagery data with maps of yield, soil characteristics and fertility to develop sustainable and integrated PA programs.

# 6.0 RECOMMENDATIONS

Discussed in this section are some broad recommendations on developing remote sensing technology applications in Canada that can lead to wider adoption and value.

1. *International Collaboration*

Canada is slow in the development and knowledge of PA technologies when compared to other parts of the world. Given the global nature of agriculture, Canada needs be partnering with other private and public agencies in countries like Australia, UK and USA to develop more widely accessible public and private remote sensing tools for farmers and agronomists.

2. *Precision Agriculture Workshops*

The most useful aspect of PA technology tools is putting it in the hands of growers and agronomists and showing them how to apply that knowledge. A collaboration of commodity groups, post-secondary institutions and private sector need to create opportunities for growers to work with PA tools and understand how they work. For example, providing workshops that show how growers and agronomists can clean and manage yield data on their farms, and how that data can be then used in conjunction with other agronomic geographic information system information to create actionable economic results on farms.

3. *Technology Transfer*

PA work that is done at the research level needs to be scaled to a farm field level so that information does not get lost in research journals. This technology transfer will also help further the development of PA tools and programs as well provide more information on the economic returns of PA tools. The learning curve of technology is highly underestimated and creates an intangible cost to most farms. If a network of technology transfer can shorten the time to learn a new technology, this would allow many farms to consider the adoption and value to their operations. Technology transfer events may include field days, industry panel events/conferences, trade shows with demonstrations, or online forums/webcasts.

### *4. University Precision Agriculture Programs*

A large amount of money has gone into developing PA programs at the college/diploma level. While a good step in the right direction, there is still a large gap in bridging scientific principles of agronomy with scientific principles of PA. Part of creating technology transfer and developing high level PA research in Canada is developing PA programs at universities in Canada. Universities have a community of expertise in computer science, engineering and economics that can also be utilized to share expertise and knowledge in developing technologies for crop production.

### *5. Precision Agriculture Research*

PA agricultural research is not always structured around questions that exist at the farm gate. The appetite for innovation must be set by farmers as well as agronomists so that value is truly provided to farms. The key condition that drives PA is variability, but a broader understanding of what drives variability on farms is needed (i.e. What is the greatest source of variability on your farm?). Variability needs to include not just the soil and crop variability factors, but labour, equipment, time, weather and commodity prices. The implementation of some PA technologies in many cases is dreadfully complex that the value is never fully realized. PA products and programs need to be simple and user friendly, with a clear understanding of how variability can be managed profitably in the short and long term. As a result, additional applied research needs to occur to address the useability and feasibility of PA technologies.

Further, there are emerging fields that use remote sensing that are not being fully adopted yet in the field of crop production. For example, the field of spectranomics which maps the relationships between plant species, canopy functional traits and their spectral properties, will have a significant role in crop production. Currently, spectranomics has been used primarily to classify plant biodiversity in diverse ecosystems like rainforests. In crop production there is value in determining the relationships that exist between the spectral properties of crop species and functional traits, such nitrogen and photosynthetic pigments involved in plant growth. The addition of monitoring chemical traits can offer another source of information that may improve assessing crop stressors.

6. *Crop Modelling/ Crop Assessment and Monitoring*

Models are extremely useful for educating farmers and agronomists. A large part of farming is managing risk. At the crop production level, many times growers and agronomists are working out scenarios to decide on the level of risk to economic reward that management decisions incur. More attention to research and collaboration with the agricultural community needs to be conducted in Canada to look at crop models such as APSIM and Canadian Crop Yield Forecaster to aid in the basis for decision support tools across western Canada. Given the wide range of historical data that exists among many of the universities, federal and provincial governments, there would be great value to growers in western Canada to see that data come alive in as digital tools. In addition, it will create more informed decision making in other ends of the industry such as consultants/agronomists that advise growers on risk and return, grain marketers can track and monitor grain production in regions more carefully, ag-retailers and crop life companies can better plan for the production year based on crop performance in an area and scientific communities understanding how crop yields and production are changing within changing weather patterns.

# 7.0 GLOSSARY

APSIM®: Agricultural Production Systems Simulator, an integrated modelling framework developed to simulate biophysical process in farming systems.
CV: Coefficient of Variation is a statistical measure of the distribution of data points in a data set.
CWSI: Crop Water Stress Index is used to quantify crop water stress based on the difference between canopy and air temperatures.
DAIS-7915: Digital Airborne Imaging Spectrometer with a 79 channel high resolution optical spectrometer to collect information from the Earth's surface in the 0.4 - 12.3 µm wavelengths.
EC: Electrical conductivity of soil is a measurement that correlates with soil properties such as soil texture, organic matter, salinity and other subsoil characteristics. EC is the ability to conduct an electrical current and it is commonly expressed in units of milliSiemens per meter (mS/m).
FV/FM: is a normalized ratio created by dividing variable fluorescence by maximum fluorescence.
GNDVI: Green Normalized Difference Vegetation Index quantifies vegetation by measuring the difference between near-infrared and green light.
GreenSeeker: uses optical sensors to measure and quantify NDVI for variable rate applications of inputs.
HTP: High throughput phenotyping uses sensor technology to measure minimally hundreds of phenotypic data about plants.
MicaSense RedEdge M: is a multispectral sensor/camera that captures five spectral bands (blue, green, red, red edge, and NIR).
µm: Micrometer is unit of measurement for wavelengths of infrared radiation. There are 1000 nanometers in a one micrometer.
NDVI: Normalized Difference Vegetation Index quantifies vegetation by measuring the difference between near-infrared and red light.
NIR: Near-infrared light includes wavelengths between 700 and 1,100 nanometers.
nm: Nanometer is a unit of measurement that is $10^{-9}$ meter, or one billionth of a meter.
$R^2$: R squared or Coefficient of Determination is defined as the proportion of the variance in the dependent variable that is predictable from the independent variable.
RGB: Red-Green-Blue is color model used to reproduce an arrangement of colors.
PA: Precision agriculture is an approach to farming that uses technology to manage crop production site specifically in an environmentally, economically and socially sustainable manner.
SWIR: Short-wavelength infrared includes wavelengths between 1,100 and 3,000 nanometers.
µm: Micrometer is a unit of measurement that is $10^{-6}$ meter, or one millionth of a meter.

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