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AN INVESTIGATION OF GEOSPATIAL TECHNOLOGIES IN PRECISION AGRICULTURE: A CASE STUDY ON A CITRUS ORCHARD IN THE EASTERN CAPE

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Abstract

Citrus production is an input-intensive farming practice that carries a high cost of production. A multitude of both local and global factors continue to put pressure on farmers to produce enough food for local consumption as well as international exports. Despite these challenges production and exports continue to increase, fighting to meet the growing rise in global demand for citrus (Genis, 2018). Growers are continuously in search of anything that may provide them with the 'edge' or an advantage to overcoming some of these challenges (Jupp, 2018). One way in which these issues could be addressed is the use of precision agriculture (PA). Precision agriculture, particularly that of commercial, Unmanned Aerial Vehicle (UAV) based PA, provides growers with solutions to these issues in the form of high quality, near real-time data, and provides access and benefits from technology driven agriculture to growers at all levels (Sishodia *et al*. 2020). The aim of this research therefore was to investigate the potential of high resolution, multi-spectral UAV, and satellite imagery to help citrus farmers manage their inputs better, save costs and increase their yields in a sustainable manner. Supervised image classification using a support vector machine (SVM) was applied to map and classify a citrus farm in the Eastern Cape. The approach aided the identification of *Phytophthora* spp in the section of interest and implies that remotely sensed data can be used to detect changes in citrus health. Guidelines for applying geospatial technologies at farm level were developed to provide a framework for enabling growers to enhance data driven farm management strategies.

CHAPTER I: INTRODUCTION

1.1. Introduction

Citrus cultivation in South Africa has grown over the last decade, and in the 2021/22 growing season, the area under citrus cultivation stood just under 100,000 hectares, driven largely by recurring investments and high export market earnings (CGA, 2023a). The net result being 2.13 million tons of citrus exports for the 2021/22 season. The gross value of production of the citrus industry in South Africa continues to grow and in 2018, it was the third largest horticultural industry in South Africa, after vegetables and deciduous fruits (DAFF, 2018). The industry is comprised of four broad categories namely oranges, easy-peelers, grapefruits, and lemons/limes, grown in the provinces of Limpopo, Mpumalanga, North-West, KwaZulu-Natal, the Northern Cape, the Eastern Cape, and the Western Cape. The production of citrus in South Africa is primarily aimed at export markets, with South Africa being ranked the second largest exporter of citrus globally (Genis, 2018).

The South African citrus sector is vulnerable to a wide array of issues including commercial barriers like strict phytosanitary requirements to certain export countries, market fluctuations, logistical challenges, climate change, high operating costs, and deteriorating infrastructure (ARC, 2000, CGA, 2022). Another major threat to the citrus industry is the availability of water for irrigation, as this can affect the prospects for growth and development of the industry. However, there is an increasing demand for citrus products and one way that some of these issues can be managed, sustainably, is by using precision agriculture (PA) techniques and technologies. Precision agriculture is the enhancement of productivity and profitability through an integrated set of technologies while sustaining the surrounding environment (Elarab, 2016). Citrus production is an input-intensive farming practice that carries a high cost of production (Kane and Lee, 2007). Data obtained from remote sensing techniques has the potential to improve PA approaches within the citrus industry.

1.2. Structure of the Thesis

The thesis is divided into five standalone chapters, with each chapter based on an objective. The first chapter is an introductory chapter that provides a brief outline of the relevant topics and themes that relate to the chapters that follow. The second chapter deals with gaining an understanding of the South African citrus industry, focusing on primary production. The third chapter deals with remote sensing sources and techniques focusing on high-resolution and multispectral satellite and unmanned aerial vehicle (UAV) imagery, and how this data can be manipulated and analysed for use in Precision Agriculture. This chapter includes a review of online based sources such as Fruitlook and explores other potential, free, or paid services that could assist citrus growers. Chapter four presents the results of applying selected remote sensing techniques to mapping and classifying a citrus farm in the Eastern Cape. It aids in identifying the type of horticultural and/or phytosanitary issues that may be present in citrus orchards. The fifth, and final chapter deals with developing guidelines for applying remote sensing techniques to citrus cultivation, focusing on what steps can be taken by growers to obtain actionable insights.

1.3. Research Question

Can high-resolution, and multispectral imagery be used to detect and assess changes in citrus health?

1.4. Aim

To investigate the use of high and low/medium resolution, multispectral, UAV imagery and satellite imagery, for PA practices within an individual orchard.

1.5. Objectives

1. Develop an understanding of the South African citrus industry, focusing on primary production.
2. Identify and assess remote sensing sources and techniques for use in PA.
3. Identify typical horticultural issues in citrus farming, how they manifest and how they can be detected through selected remote sensing techniques.
4. Develop guidelines for applying remote sensing techniques to citrus cultivation. This will include:
    a) The inputs and variables of significance that need to be considered when it comes to obtaining good quality, actionable, remotely sensed data for citrus growers and,
    b) The types of insights a grower would obtain from any output generated.

1.6. Literature Review

1.6.1 Introduction

The citrus industry is arguably one of the biggest employers in South African agriculture (Genis, 2018). It is a labour-intensive industry and according to the DAFF report of 2016, there are over 100 000 people employed throughout the supply chain. The same report estimates that over a million households rely on the citrus industry in South Africa for their livelihoods. The industry has significant job creation prospects: if the export market could expand into Eastern Europe, China, and India, a further 45 million cartons of produce could be exported which would create roughly 50 000 new jobs in the sector (Genis, 2018). Precision agriculture could support this kind of expansion by offering citrus farmers better production efficiency, better managed orchards, increase in quality and quantity of crop yields and better profits (Kane and Lee, 2007; Rokhmana, 2015). This literature review aims to cover material on relevant theoretical topics and some examples of similar applied research. It will discuss PA in South Africa and relevant case studies.

1.6.2. Remote sensing in Agriculture

Agriculture plays a significant role in the economies of almost every country, be it a substantial trading industry for a strongly developed country, or sustenance for an overpopulated, underdeveloped one (Natural Resources Canada, 2016). Food production is important for everyone and the goal of every agricultural agency, and large or small-scale farmer, is to produce food in a cost-effective manner. For a farmer to be efficient, they need to be informed. A viable strategy for farming operations using knowledge and information products, can allow farmers to better understand the health of their crops, soil conditions, potential yield and infestation or stress damage (Natural Resources Canada, 2016). Other stakeholders such as commodity brokers are also interested in farm production and yield estimates for global trade.

The applications of remote sensing are many and varied when it comes to studying the components of supply and demand of agricultural products worldwide (Lillesand *et al*. 2015). Airborne and satellite imagery are tools that are used to classify crops, monitor farming practices, and examine crop health and viability. The most important uses of imagery in an agricultural sense are crop type classification, crop condition assessments, early detection of potential issues and support for PA (Lillesand *et al*. 2015).

Crop type classification, or area inventory, is based on the premise that spectral signatures and textures can be used to identify specific crop types (Lillesand *et al*. 2015). This requires in-depth knowledge of the developmental stages in crop growth, summarised in the form of a crop calendar that highlights the expected development status and appearance of different crops over time. Crop characteristics change throughout the growing season. As such multiple images should be acquired on several dates over the growing season to obtain unique spectral signatures that allow for detailed and accurate crop classification and identification (Lillesand *et al*. 2015).

Crop condition assessments through remote sensing involve the use of spectral band combinations from multispectral and hyperspectral imagery to generate estimated values for variables such as leaf water content, leaf area index (LAI) and other models. Atmospheric correction to the imagery is required so that spectral signatures are represented by spectral reflectance at the surface. Other applications of remote sensing in agriculture include yield estimates, soil characteristics, monitoring, and management practices (Lillesand *et al*. 2015).

1.6.3. Precision Agriculture

Between 1900-1930, the first agricultural revolution took place through increased mechanisation (Dwivedi *et al*. 2017). This was followed by the Green Revolution in the 1990's where new methods of crop genetic modification took place. Precision Agriculture arose from a third wave of modern agricultural revolutions that brought about new technological advancements in farming practices. Precision agriculture or precision farming is defined as an information and technology-based management system for agriculture that aims to identify, analyse, and manage spatial and temporal variability, within and between fields, for optimum sustainability, profitability, and environmental protection (Lillesand *et al*. 2015). Precision Agriculture can improve farm management at field-level with regards to crop science (matching inputs to the needs of the crop, such as fertiliser), environmental protection (reducing the footprint of farming, such as nitrogen leaching) and economics (being more competitive through improved management practices, such as fertiliser and other input usage) (Dwivedi *et al*. 2017).

Management of variability within agricultural industries is what PA strives for, along with the aim of improving short and long-term profitability and the impact that farming has on the environment (Whelan and McBratney, 2006). Site-Specific Crop Management (SSCM), as one form of PA can be defined as "Matching resource application and agronomic practices with soil and crop requirements as they vary in space and time within a field" (Whelan and McBratney, 2006). For the implementation of PA practices to be considered by farmers, the general question of spatial and temporal variability and optimal scale need to be quantified, to present opportunities for better farm management. In terms of spatial variation in soil and crop attributes, it is still difficult to develop in-field variable-rate management plans where the patterns of spatial variation displayed are random. In terms of temporal variation, yield quantities and their magnitude may vary within fields for different crops in different soil units, over time. The availability of real-time yield monitors has allowed for crop yield variability, at a within-field scale, to be estimated over time. Temporal variation may indicate seasonal and/or climate influences on crop yields.

Whelan and McBratney (2006) note that "temporal variability in crop production indicators (i.e., yield) at the within-field scale is often larger in magnitude than spatial variability". What this entails is the need for economic and environmental actions in terms of PA, to be based on both spatial and temporal data and not spatial data alone. The management of variability in agriculture using PA will hinge largely on evidence that rejects the null hypothesis. "The PA system can be considered, therefore, the agricultural system of the twenty-first century, as it symbolizes a better balance between reliance on traditional knowledge and information and management-intensive technologies" (Srinivasan, 2006).

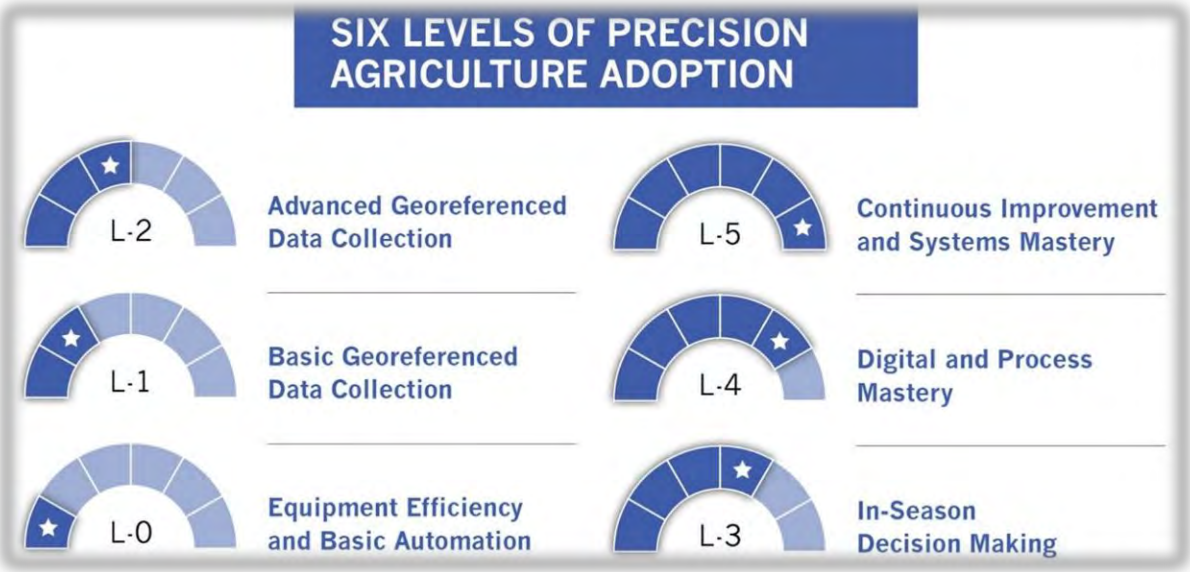


Figure 1: The six levels of Precision Agriculture Adoption (Schrimpf, 2019)

According to the PrecisionAg Institute, the adoption of PA is non-binary, meaning there is no clear divide between PA users and non-PA users. It is best represented on a sliding scale of 6 core levels of adoption, ranging from basic to advanced, that allows current and future levels of adoption to be consistently and effectively quantified (Schrimpf, 2019). The six-level adoption scale focuses on evolving technologies and enduring agricultural practices, covering the aspects of observation, analysis and decision making in planting, spray-applications, and harvesting.

The first level is defined as equipment efficiency and basic automation where technologies being implemented provide little to no data for production planning, but improve operational efficiencies, such as automated tractor steering using Global Positioning System (GPS) (Schrimpf, 2019). The second level is defined as basic georeferenced data collection where at least one layer of spatial data, such as field imagery or soil probe data, is integrated into decision making that aids in inter and/or intra-field assessments. The third level is defined as advanced georeferenced data collection, and it builds on the second level where additional layers of data are compared for improved operational efficiency, typically at centimetre level. This can include information such as yield data, seasonal imagery, and weather data. Agronomic service providers are often employed to assist with the collection and analysis of this information (Schrimpf, 2019). The fourth level, defined as in-season decision making, builds on the previous levels where the data gathered allows growers to measure and manage their production using an evidence-based approach (Schrimpf, 2019). Growers can now collect 'as-applied' data, such as planting, fertilizer application, spraying and scouting data that deepen field knowledge. The fifth level, defined as digital and process mastery is usually achieved after multiple years of data collection that allow for yearly and seasonal comparisons, allowing growers to make operational decisions on-the-fly. Commercial partners are usually involved at this stage (Schrimpf, 2019). The sixth and final level is defined as continuous improvement and systems mastery that builds on the fifth level through the creation and continual implementation of valid data sets (Schrimpf, 2019). New systems and technologies are usually explored that allow growers targeted and effective decision making such as modelling nitrogen management, insect and disease monitoring, weather and soil moisture sensors and imagery that keep growers fully informed and in control of their production (Schrimpf, 2019). To contextualise this research in the sphere of PA, using the above information, it would fit in the third level of PA adoption. The grower in the study area currently makes use of weather data, drip-irrigation, targeted spraying, and soil data for production management of their citrus orchards.

1.6.4. Precision Agriculture in South Africa

Precision Agriculture involves the use of UAVs, satellites, sensors, and Global Positioning Systems (GPS) to observe and measure different temporal and spatial characteristics of different crop varieties (GreenCape, 2018). In 2017, South Africa's UAV market, although in its infancy, was valued at an estimated R2 Billion. Global leaders in UAV technology predict that the agricultural sector will capture the largest share of the market for UAV products (R1,8 billion), thereby suggesting significant future potential for the South African UAV market and use in the agricultural sector (GreenCape, 2018). Unmanned Aerial Vehicles can be used throughout a crop's life cycle and the uptake of technology during a crop's life cycle provides a broader trend for farmers and a data-driven approach for on-farm management purposes. Despite a large increase in remote sensing technologies for PA and the companies that offer these services, there has been some hesitation by farmers to embrace these new technologies. The emergence of these technologies overwhelmed some farmers by their apparent capabilities in PA. This sentiment is changing however, and there is growing interest both locally and globally with regards to the potential for UAVs in the agricultural sector (GreenCape, 2018).

The main reason for uptake of UAV technology in PA is the potential for improved resource use through more precise and effective application of farming inputs. Precision agriculture technologies have also proven time and cost savings to farmers, where in a highly competitive market with rising input costs, production efficiencies are the key to remain viable. One such efficiency is the use of water. The allocation of water for agriculture is set to decrease in the future and PA has a major role to play in helping farmers manage their water resource (GreenCape, 2018). With South Africa being a water scarce country, the efficient use of water in agricultural practices is vital to farming enterprises.

A Scopus search was carried out to identify any scientific research on PA in South Africa. The keywords used included remote sensing, agriculture, UAVs, and precision agriculture, with the timeframe of the search set between the years 2010 and 2020. The search only returned seventeen results of scientific literature pertaining to various form of applied remote sensing and PA techniques in multiple crop settings which shows that there is relatively little published research on PA in South Africa and this research aims to fill this gap.

1.6.5. Case Study: Fruitlook: improving water efficiency through remote sensing.

The GrapeLook initiative was designed to support the table grape and wine producers in the Western Cape by improving their water use efficiency through satellite derived information (Jarmain *et al*. 2018). This initiative, known today as Fruitlook, has expanded and provides weekly updates on crop water use, crop growth and plant nitrogen for the wider agricultural sector. Fruitlook allows farmers access to the latest satellite-based technology to precisely manage their water use and monitor crop production (Jarmain *et al*. 2018).

Fruitlook is funded by the Western Cape Department of Agriculture and allows all registered users free access to spatial data and satellite imagery for their areas of interest. The imagery is updated weekly and offers historical images from 2010 to present. Historical imagery allows farmers to view and compare data from previous seasons to gauge farm performance over time. Fruitlook currently has 700 users, each having access to data that covers roughly 9 million hectares of the Western Cape including data on multiple crop types such as citrus, grapes, pasture crops, grains, vegetables and more (Jarmain *et al*. 2018).

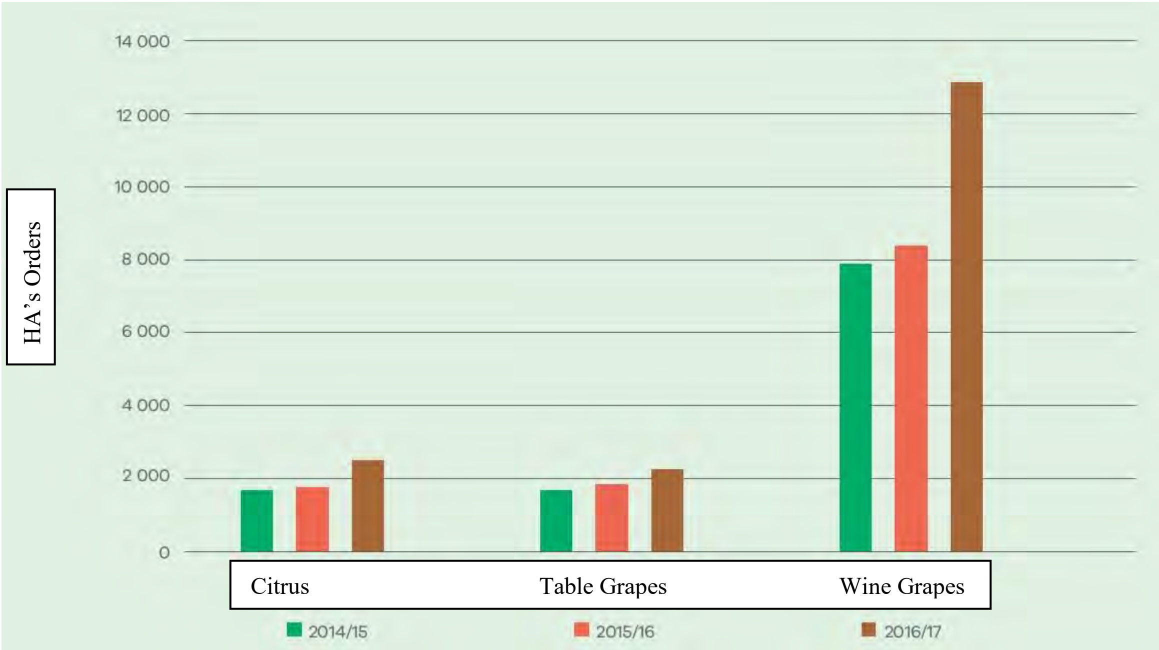


Figure 2: Uptake of Fruitlook in hectares over time (Jarmain et al. 2018)

Figure 2 shows an increase in the use of Fruitlook by farmers for the key commodities of citrus, table grapes and wine grapes in the Western Cape from 2014/15 to 2016/17. A block level questionnaire from early 2018 by the Western Cape Department of Agriculture, indicated that 71 out of 100 respondents had improved their water management by using Fruitlook with the minimum saving being 10% of water used per hectare per season. Table 1 below illustrates the potential savings in ZAR per hectare per season to improve water efficiency by using remote sensing (GreenCape, 2019).

Table 1: Cost-savings for using remote sensing for improved water efficiency (GreenCape, 2019)

Commodity	Savings / ha[19] (ZAR)	Captured hectares	Potential hectares
Apples	817	7 146	17 066
Pears	817	2 062	10 217
Apricots	700	94	2 744
Nectarine	700	341	1 790
Peaches	700	698	6 640
Plums	817	513	4 580

1.6.6. Case Study: Disease identification

A major issue in citrus groves is that of fungal disease (MicaSense, 2017). Fungal diseases can spread quickly if left undetected and can threaten an entire crop. To ensure the success of a citrus crop, careful disease monitoring measures need to be in place. Bruno Holz Gemignani of 3DGEO, flew and collected imagery using a drone and the MicaSense RedEdge sensor to help a citrus farmer in Brazil address a fungal disease issue they were having. MicaSense Atlas was used to analyse the imagery using "NDVI" and "Chlorophyll Map layer".

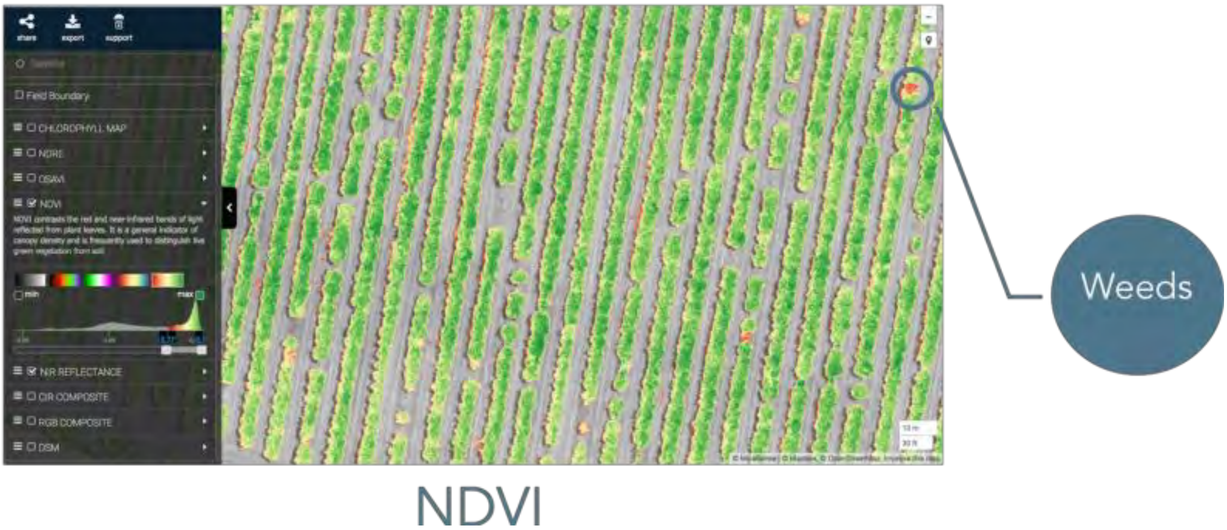


Figure 3: MicaSense Atlas NDVI (MicaSense, 2017)

Gemignani began his analysis by looking at the "NDVI" results. The NDVI (Normalised Difference Vegetation Index) is primarily used to measure the vigour or "greenness" of a plant, as the health of a plant cannot always be determined through NDVI (MicaSense, 2017). The results shown in Figure 3 illustrate a mostly homogenous layer, with the areas affected being identified as weeds. Gemignani moved onto the "Chlorophyll Map Layer" (an index designed specifically to determine the health of plants by indicating areas that may be deficient in chlorophyll) and identified the issue as *phytophthora* spp (root rot), a type of fungal disease that causes a slow decline in tree growth (Citrus Academy, 2017b).

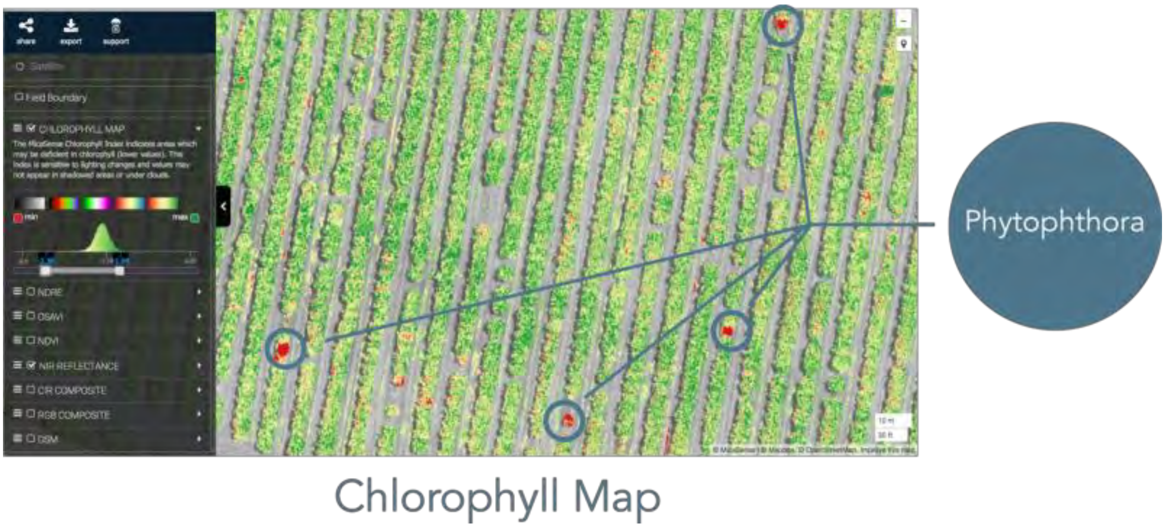


Figure 4: MicaSense Atlas Chlorophyll Map Layer (MicaSense, 2017)

The results shown in Figure 4 show a slightly different picture with multiple trees displaying low values. Using the "geo-location" tool in MicaSense Atlas, Gemignani and the farmer were able to go into the field and confirm the findings. Based on this information the farmer proceeded to remove the plants and prevented any further spread of the disease.

Measuring overall plant health and detecting signs of stress and disease was achieved through the combination of advanced analytics and specific spectral bands from the MicaSense Red Edge sensor. The power of high-resolution multispectral imagery and advanced vegetation indices obtained through remote sensing techniques in this case proved highly useful, as a problem that was not immediately visible to the naked eye was identified and dealt with, ultimately showing the potential for the implementation of PA practices (MicaSense, 2017).

1.7. Research Methodology

Objective 1: Develop an understanding of the South African citrus industry focusing on primary production.

Method:

a) A review of literature on the South African citrus industry was compiled using:
    i. Existing literature and reports

Objective 2: Identify and assess remote sensing sources and techniques for use in PA.

Methods:

a) A review of literature on remote sensing, different sensors and UAV technology was compiled for comparison.
b) Product identification and review, through bench marking, with a focus on open access, high resolution satellite imagery, high resolution UAV imagery and other online resources such as Aeroview and FieldMargin.

Objective 3: Identify typical horticultural issues in citrus cultivation, how they manifest and how they can be detected through remote sensing techniques.

Methods:

a) A review of literature on remote sensing in crop management, focusing on:
    i. UAV and satellite image case studies in various crops.
b) Structured interviews with stakeholders, the farmer, and other researchers were conducted to obtain information regarding pertinent issues faced by citrus farmers, such as the manifestation of:
    i. Environmental/physical issues
    ii. Pest and disease issues
c) Identify a site where typical problems exist and run trials using information obtained from objectives 1 and 2.
d) Carry out statistical analysis on the results.

Objective 4: Develop guidelines for applying remote sensing techniques to citrus cultivation.

Methods:

a) Using information from chapters two, three and four:
    i. Highlight the types of input a grower would obtain from any generated output and,

ii. Highlight he inputs and variables of significance that need to be considered when it comes to obtaining good quality, actionable, remotely sensed data for citrus growers.

This research holds a postpositivist philosophical worldview with a mixed methods approach for data collection and analysis. A mixed-methods approach refers to collecting, analysing, and integrating quantitative and qualitative research and analysis techniques. A mixed-methods approach helps address the issue of complexity in research, especially where measurements of the physical environment and human knowledge need to be understood and combined. By using the strengths of multiple approaches, a more rigorous and complex account of the research can be obtained (Hawthorne, 2017).

Open-ended questionnaires, semi-structured interviews, and UAV imagery were used as primary sources of information. Relevant literature, such as GreenCape, DAFF reports, and satellite imagery were used as secondary sources of South African based information. The researcher attended a field trip to the Sundays River Valley in 2019 and gained valuable insights into the citrus industry through a tour, from nursery through to packhouse, to understand what takes place along different parts of the citrus market value chain.

1.8. Study Area

1.8.1. Geography

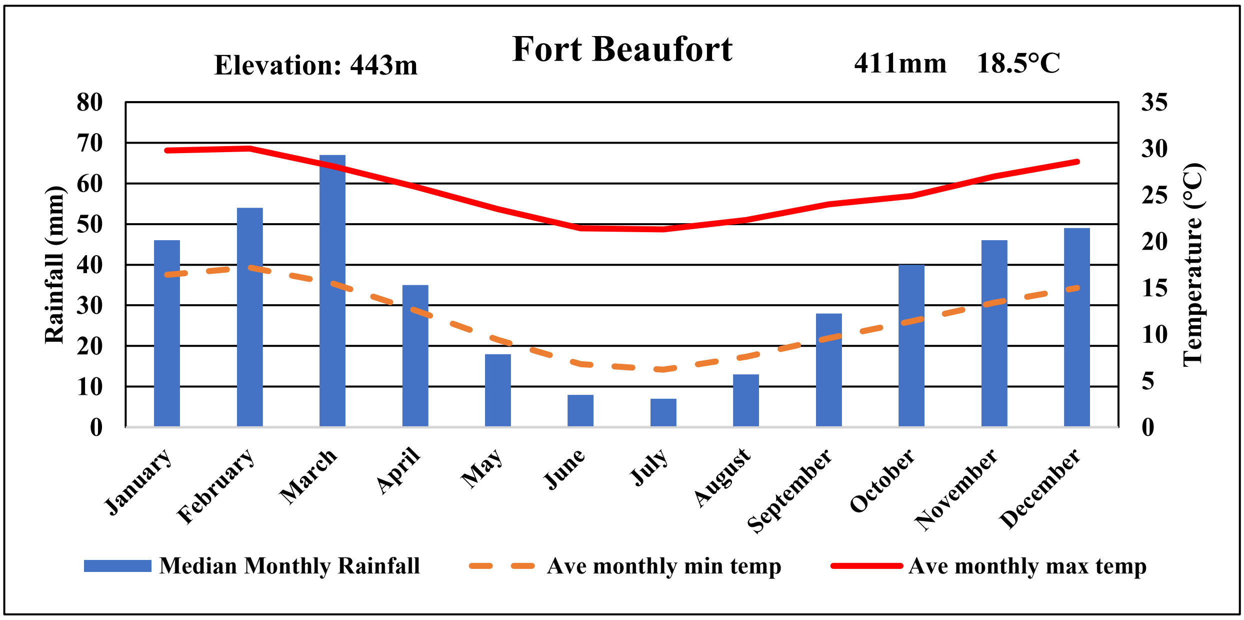


Figure 5: Fort Beaufort Climatograph (Schulze *et al*. 2007)

The study area is in the heart of the Kat River Valley on a farm roughly 14 kilometres South-East of the town of Fort Beaufort along the Kat River, with an altitude of 443 metres above sea level. The farm falls within the southern portion of the Kat River valley in the Raymond Mhlaba municipality in the Eastern Cape. The climate of the area is a local-steppe climate characterised by hot summers and cool winters (Schulze *et al*. 2007). The highest temperatures are in February, with an average monthly maximum of 30°C and an average monthly minimum of 17.2°C. The coldest month is July, with an average monthly maximum of 21.3°C and an average monthly minimum of 6.2°C (Schulze *et al*. 2007). The average annual temperature is 18.5°C and the annual rainfall Figure is 411mm. The Kat River Valley often experiences severe frosts in winter, which is a major threat to citrus farming in the area. Peak rainfall occurs in March with a median value of 67mm, and the least amount of rain falls in July, with a median value of 7mm (Schulze *et al*. 2007).

1.8.2. Agriculture

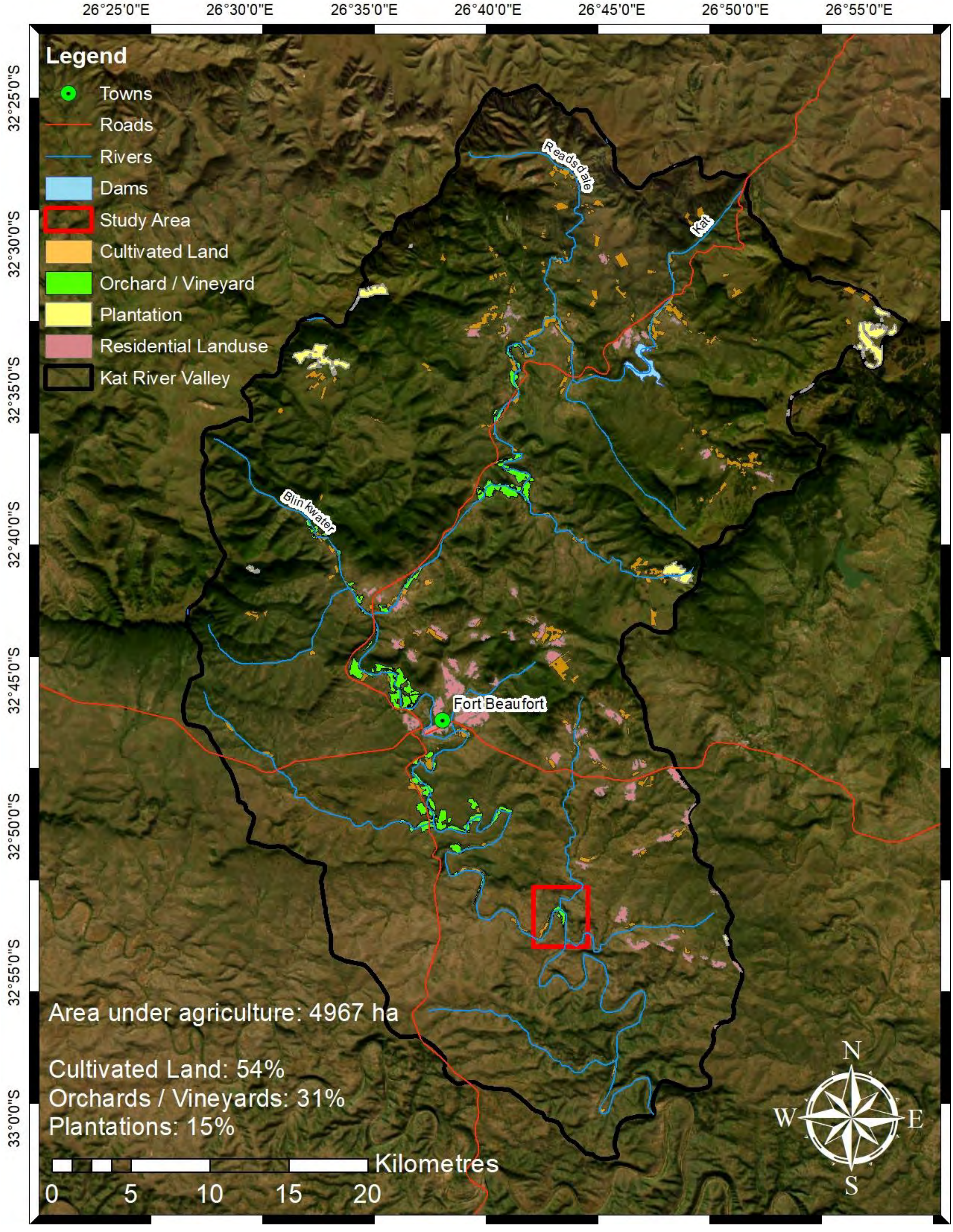


Figure 6: Land use map of the Kat River Valley derived from the NGI 2016 Topo50 dataset

The Kat River Valley has several farming groups, comprised of small-scale, emerging, and large-scale farmers (Farolfi and Abrams, 2005). The main activity in the valley is agriculture, where the majority of commercially irrigated farmland is used for citrus production, which typically takes place on flat river terraces spread throughout the catchment (Holtzhousen, 2006). Small-scale farmers are mostly found in the Upper Kat, each operating on roughly 1 hectare where they mostly produce vegetables. There are also community schemes that grow cotton on a small-scale. Emerging farmers generally tend to be citrus producers, or ultimately become citrus producers. They operate on farms between 20 hectares and 30 hectares in size and are situated in the Middle and Upper Kat. Large-scale farmers are mainly white-owned, commercial-citrus producers, located in the Lower Kat (Farolfi and Abrams, 2005). Citrus is the main agricultural export from the Kat River Valley. Large-scale commercial production covers roughly 874 hectares of the valley, 418 hectares of which are found in the Upper Kat and 456 hectares in the Lower Kat. Emerging farmers occupy 400 hectares and are situated in the Upper and Middle Kat (Farolfi and Abrams, 2005). Twelve thousand five hundred tons of citrus are produced per year by the large-scale farms in the Upper Kat, an average of 30 tons per hectare. Water quality and water allocation are two main concerns for those who depend on the Kat River for daily use (Holtzhousen, 2006).

1.8.3. Citrus export and packaging

Most of the citrus from the Kat River Valley is exported. For most farmers, more than 50% of their production is exported and roughly 70% of the total citrus production in the Valley is exported (Farolfi and Abrams, 2005). Citrus meant for export is graded with scores of 1, 2 and 3. Citrus that scores 1 or 2 are exported to foreign markets and if they score 3, they are sent to local markets. Fruit size and quality grading is carried out by both the Riverside packhouse and KATCO (the Kat River Citrus Co-operative) who are also responsible for marketing, packing, processing, and transporting citrus from the Valley for export. Most international exports from the Valley are sent to Europe, the Middle East, the Far East, and Russia. KATCO has a packing capacity of 58000 bins per year and a total orchard area of between 800 hectares and 1000 hectares (Farolfi and Abrams, 2005).

CHAPTER II: PRIMARY PRODUCTION
IN THE SOUTH AFRICAN CITRUS INDUSTRY

2.1. Introduction

Citrus is South Africa's largest agricultural export product by value and has a share of 8% in terms of total world exports. South Africa is the 11th largest producer of citrus globally but is second only to Spain as the largest exporter of citrus (Genis, 2018). The citrus industry has shown steady growth over the last ten years, with nine successive years of good production between 2010 and 2018 (DAFF, 2018). One hundred and twenty-two million boxes of citrus were exported in 2017 and were produced by roughly 1200 citrus farmers across the country. The total volume of citrus exported in 2018 amounted to roughly one hundred and thirty-six million boxes, the highest recorded export figures in South Africa. A figure of roughly one hundred and thirty-seven million boxes for export was forecast for the 2019 production season (CGA, 2019a). However, due to prolonged drought, the total export figure for the 2019 season was forecast to reach one hundred and twenty-nine million boxes, eight million boxes less than the previous year. Despite this, the industry still managed to contribute around R20 billion in export revenue (CGA, 2019a). This chapter will focus on primary production in the South African citrus industry. It consists of a literature review that aims to look at the history of the South African citrus industry, global and local production, the production areas around the country, important inputs for citrus production, and the issues associated with citrus production.

2.2. Aim:

To develop an understanding of the South African citrus industry focusing on primary production.

2.3. Objective:

a) Review literature on the South African citrus industry using existing literature and reports.

2.4. Literature review

2.4.1. History of the South African Citrus Sector

The first citrus was planted in South Africa in the 17^{th} century (Genis, 2018). Citrus trees arrived from St Helena in 1654, according to the daily journal of the Dutch East Indian Company, which were to be planted in the Company's gardens in Cape Town. These trees yielded fruit in 1661, however, citrus cultivation subsided between 1666 and 1890 (CGA, 2007). Cartwright (1977) discovered anecdotes of citrus planting post-1850 near Grahamstown in the Eastern Cape, Tzaneen in Limpopo, Rustenburg in the Northwest and in some towns in the Western Cape.

The development of agriculture in South Africa by the Dutch and early British settlers was slow. In contrast, California and Florida had a well-developed citrus industry by 1849 around the time gold was discovered in California (Genis, 2018). The influx of gold-diggers to the region created an increase in demand for fruit and food, particularly oranges. American growers successfully exported citrus to Europe in refrigerated shipping containers in 1890 (CGA, 2007). California and Florida, around 1894, were producing 6 million boxes of oranges per annum. A similar story occurred in South Africa around the time gold was discovered. Citrus farmers from Rustenburg would pack oranges into tins and boxes and sell them at Market Square in Johannesburg, in response to the demand for fruit brought about by the influx of miners to the area (Genis, 2018).

The first citrus exports from South Africa were in 1907 and thereafter occurred annually (Genis, 2018). The industry was further bolstered by agricultural inputs from experts in America and the implementation of single-channel marketing, co-operative packaging, generous state support and supportive legislation. In 1910 the first co-operative citrus growers' association was formed by a group of farmers in the district of Rustenburg, and other associations would follow suit (Genis, 2018; CGA, 2007). The Union of South Africa was formed in 1910 and in the period after this formation, agricultural 'estates' were bought by wealthy investors, who lured decommissioned soldiers from the first world war to grow citrus, and although many failed, many were successful in growing lemons, oranges, and grapefruit (Genis, 2018).

Exports began to increase dramatically and in 1922 a union called the "Vrugtekwekers Ko-operatiewe Beurs van Suid-Afrika Beperk" (Fruit Growers' Co-operative Exchange of South Africa Limited) was formed (CGA, 2007). This union represented farmers that grew deciduous fruit, pineapples and citrus and by 1925, one million cases of citrus fruit were being exported. The union did not exist for very long as the deciduous fruit and citrus industries parted ways (Genis, 2018). This paved the way for the formation of the Citrus Exchange (Outspan International) in 1927 which became the sole representative of the South African citrus industry (CGA, 2007).

The exchange became extremely successful and powerful due to the implementation of a single channel marketing system (Genis, 2018). The organization was responsible for coordinating and controlling all exports from the country. This control over the industry allowed for the establishment of remarkable infrastructure ranging from nurseries to cooling and packing facilities, and research laboratories, both locally and abroad. Outspan International had established offices overseas in Europe, North America, and Asia by the mid-1990s (Genis, 2018).

The exchange had launched a strong promotion for Outspan oranges in the mid-1990's, but this campaign ended due to anti-apartheid boycotting in Europe (Genis, 2018). The exchange was deregulated in 1997 and subsequently lost exclusive control over all citrus exports (CGA, 2007). The increasing power of supermarkets in the value chain and private regulation of the industry led to a shift in focus in the sub-sector, from volume to quality which was in line with foreign market demands (Genis, 2018). Quality issues could be managed by the citrus industry body during the regulated era according to Genis (2018), but the fragmentation of the industry, caused by deregulation, forced the systems to break down. European importers ultimately exploited the quality issues that arose from deregulation and discounted all South African citrus.

The industry was in a crisis which was exacerbated by unskilled export agents who could not handle the tough market conditions (Genis, 2018). Low export earnings from a multitude of local and global issues saw a R600 million decline in export earnings in the year 2000. Many industry stakeholders advocated for the use of the single marketing channel system as it had always been effective at regulating the industry, leaving little room for crises to occur. This led to the establishment of a producer's organisation named Citrus Southern Africa who were responsible for regulating the activities of private exporters (Genis, 2018; CGA, 2007).

The deregulation that had occurred earlier led to the separation of citrus farmers into small growers and larger commercial growers (Genis, 2018). The commercial farmers began exporting and marketing on their own, as well as establishing their own packing sheds, moving away from cooperative packing sheds. Citrus black spot (CBS) became another source of differentiation between farmers. Orchards in the Western Cape were free of CBS and became lucrative for producers there as they gained access to North American markets. Export volumes increased from 30,000 to 1,5 million cartons from 1997 to 2002 (Genis, 2018).

In 1997, the Citrus Growers Association (CGA) was formed by growers who were concerned by the underperformance of the Citrus Board in terms of the downsizing and discontinuation of certain functions they were responsible for (Genis, 2018). The CGA is mandated to set standards for quality of fruit, expand and maintain access to overseas and local markets, participate actively in research and development, represent growers and drive transformation through the industry, for all stakeholders including government, research institutions, suppliers, and exporters (CGA, 2007).

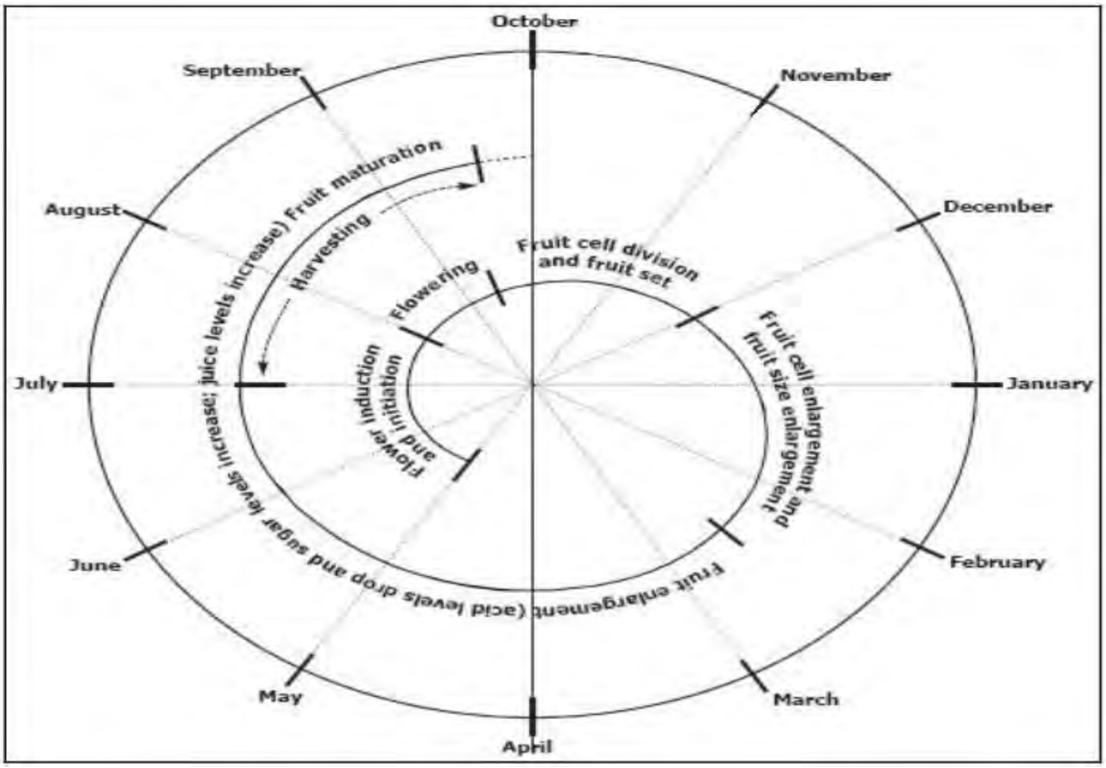
2.4.2. Citrus Plant Production

Critical to this research, is identifying the various factors that can affect spectral properties of citrus plants, as they link to the interpretation of results from aerial imagery and therefore inform management practices. The factors include citrus phenology, climate and soil, pests and diseases, irrigation and moisture, plant manipulation, and scouting. In Chapter 4, a combination of this information, coupled with remote sensing techniques, were used to develop a methodology to assess the state and health of a citrus orchard in the Eastern Cape.

For the purposes of production and marketing, South African citrus is divided into four broad categories, namely soft citrus, grapefruit, lemons and limes, and oranges. Each category has different cultivars and varieties (Anon, 2012a). A cultivar can be described as a group of cultivated plants with distinctive characteristics. The term variety is used more for marketing purposes and describes different cultivars as often having similar characteristics. Commercial citrus production relies on efficient and cost-effective management practices that factor in the selection of superior and high yielding varieties, the needs of consumers, and sustainable orchards (Citrus Academy, n.d.). The economic lifespan of citrus orchards ranges between 18 to 30 years and can often be as high as 30 to 60 years in hot and dry areas. Citrus is a long-term crop that needs to consistently produce high yielding and quality fruit, to remain profitable (Citrus Academy, n.d.).

Citrus trees are planted in rows in orchards. The distance between each tree, between and within rows is called ‘tree-spacing’. Tree spacing dimensions are determined by several factors including soil type, climate, and variety (Citrus Academy, n.d.). Standard tree spacing is usually 6 metres between rows and 3 metres within rows, resulting in 555 trees per hectare. Seedlings are usually planted for commercial citrus and generally take three or more years to produce market grade citrus. Depending on the cultivar and variety, per hectare yields steadily increase to 40 t/ha to 70 tons per hectare after 4 to 7 years. This level of production will remain relatively constant until the trees start to naturally decline, if orchards are carefully managed (Citrus Academy, n.d.).

2.4.2.1. Citrus Phenology



Stage	*Description*	*Time Period*
Flower Induction and Initiation	Flower initiation is the induction and differentiation of vegetative buds into flower buds at a cellular level, and cannot be seen with the naked eye.	May to July
Flowering	Flowering or "bloom" is when blossoms appear on the tree.	August to Mid-September
Cell Division and Fruit Set	Cell division is the period when cells making up the fruit increase in number. Fruit set is the period from flowering or "bloom" until the end of fruitlet drop, after which the final fruit load is determined.	Mid-September to November
Cell Enlargement and Fruit Growth	Cell enlargement is the period during which cells making up the fruit increase in size. Fruit growth is the period during which the fruit grows and develops.	December to Mid-February
Fruit Maturation and further Fruit Growth	During this period fruit enlarges further and matures internally, meaning that the flavour, sugars and acids reach their optimum levels.	Mid-February to September
Harvest		July to September

Figure 7: Phenological stages of the Valencia orange (Citrus Academy, 2017a)

Figure 7 illustrates the phenological stages of the Valencia orange, a description of what takes place at each stage, and the associated production practices during each stage. "Phenology is defined as the different stages of vegetative and reproductive growth, and development, including that of the various fruit growth stages" (Marais, 2017). The period between flower induction and harvesting is referred to as the 'citrus season' and it differs between the various citrus cultivars. For the Valencia orange, the citrus season generally begins from the period of flower induction and initiation around the beginning of May, to harvesting, around the end of the following September (Citrus Academy, 2017a). The understanding of citrus phenology is vital for the actions and practices employed in citrus production. An example of this would be the correct timing of fertiliser for optimising flowering, cell enlargement and fruit maturation (Anon, 2012a).

2.4.2.2. Climate and soil requirements

Citrus trees cannot tolerate high levels of frost due to their subtropical origin (ARC, 2000). For this reason, South African citrus production is confined to areas with near frost-free and mild winters, and where temperatures seldom drop below 3°C. Commercial citrus production is generally confined to areas with clearly defined warm-wet and cool-dry seasons, and altitudes well above sea-level (Gaskins, 1984). In terms of soil requirements, production, development, and growth of citrus trees, depend on the physical characteristics of soil such as density, texture, drainage, structure, water-holding capacity, soil depth, erodibility, homogeneity, and infiltration (ARC, 2000). The depth of the root system and water uptake by plants is determined by the physical properties of the soil. Citrus can be grown in a wide range of soil types, but ideal soils should be well aerated, fertile and should have a pH between 6 and 6.5 (ARC, 2000). Citrus roots grow to a depth of 1m and a width of 2m beyond the tree's dripline. Greater growth and plant yield depend on greater effective depth of root systems because a greater volume of soil can be exploited by the roots (ARC, 2000). Root development can also be restricted by soils with low nutrient and water content. If any limiting factors such as gravel or mottled clay or sandy layers are found within 1m of the soil surface, the normal spread of roots and effective depth for root development may be affected (ARC, 2000).

2.4.2.3. Irrigation and Fertiliser requirements

Moisture availability is a limiting factor in citrus production (ARC, 2000). Reliable irrigation is a major requirement for production, to ensure that growth and production is not supressed by moisture stress. Waterlogging or oversaturation occurs where drainage is restricted by certain layers in the soil. Weather conditions dictate the amount of water a tree requires. If soils are saturated and are poorly drained, root rot may set in, shortening the life of the tree. A shortage of water may result in excessive drop of fruitlets and flowers, out-of-season fruit setting, flowering, or acidic fruit, depending on what time of season moisture stress occurs. Signs of stress may not be initially visible on a stressed tree. A sign for water stress is a slight leaf wilt (ARC, 2000).

Nutrient absorption through fertiliser applications is essential for maximising the potential of commercial citrus (Walsh and Lacey, 2019). There are general guidelines on the correct timing and amounts of fertiliser required, based on variety and yield, which account for nutrient removal by tree growth, the fruit, and environmental losses. Other factors that need to be taken into consideration when applying fertilisers are the age of the orchard, soil characteristics and irrigation (Walsh and Lacey, 2019). Table 2 below shows the percentage of nutrient applications that should be applied at different citrus phenological stages, annually.

Table 2: Annual nutrient application percentages per phenological stage (Walsh and Lacey, 2019)

	Nitrogen	Phosphorus*	Potassium	Calcium
Pre-bloom to flowering	40-50%	100% (50%)	30-40%	70-80%
Cell Division	25%	50%	30-50%	
Cell Expansion	25%		30%	20-30%

* Figures in brackets refer specifically to phosphorous applied through fertigation

Regular nutrient analysis is a good way to monitor the effectiveness of fertiliser and nutrition programs on soil chemistry and in turn, tree nutrient levels (Walsh and Lacey, 2019).

2.4.2.4. Plant manipulation

The majority of South African citrus is exported and sold through local supermarkets, juice processors, hawkers, and manufacturers, with each market having their own set of external and internal fruit quality requirements (Citrus Academy, 2017b). Most overseas consumers prefer fruit that is large and sweet, is blemish free and is easy to peel. Fruit trees do not naturally produce fruit of such a standard and a certain amount of plant manipulation is required to produce good quality fruit. Plant manipulation refers to different physical and chemical management and treatment methods of citrus trees to produce a set of desired outcomes, that contribute to the production of good quality fruit (Citrus Academy, 2017b).

Production factors such as soil and irrigation, pests and diseases, and plant nutrition should always be considered as controllable factors (Citrus Academy, 2017b). If any issues were to arise from any of the above production factors, they would need to be identified and addressed before applying any plant manipulation methods, to help improve the issue. There are a variety of internal and external factors that affect the overall health and growth of citrus, which in turn affects the outcomes produced through plant manipulation techniques. Good knowledge of citrus and experience in understanding local climatic conditions and tree management techniques, aids in producing desired outcomes through plant manipulation techniques (Citrus Academy, 2017b).

Plant manipulation methods are split into two categories which are physical, and chemical manipulation, with some methods falling under both categories, such as fruit thinning (Citrus Academy, 2017b). Physical manipulation involves forms of manual intervention such as cutting back and removing certain parts of the tree to improve aspects such as light interception, and the shape and size of trees. This method includes pruning, girdling, skirting and fruit thinning, and makes use of a variety of tools such as shears, saws, knives, hedgers, toppers, and associated safety equipment. Chemical manipulation makes use of various hormones and chemicals to achieve aspects such as improving fruit set, increasing fruit size, fruit thinning and delaying harvesting (Citrus Academy, 2017b).

2.4.2.5. Horticultural issues: Pests, diseases, and associated management practices

Of all global fruit crops, citrus is the most extensively cultivated, and like many of the tropical and subtropical crops, citrus plays host to many pests and diseases (Jaouad *et al*. 2020). The success of commercial citrus production lies in the management of pests and diseases (Citrus Academy, 2017b). Pests and diseases can cause varying amounts of damage to citrus trees, the fruit, and exports, due to the restrictions imposed by certain countries on strict phytosanitary requirements. Some diseases cause lower fruit quality and yields, and some can cause insurmountable damage that leads to loss of productive orchards. Pest and disease control requires continuous scouting and monitoring to strengthen control methods, reduce the use of pesticides and avoid potential financial disaster (Citrus Academy, 2017b; Jaouad *et al*. 2020).

Citrus pests are organisms that negatively affect the quality and quantity of fruit produced through their feeding and/or reproductive habits (Citrus Academy, 2017b). Not all insects are pests, for example *Aphytis* and *Comperiella* wasps, and *Chilocorus nigritus* ladybird beetles, have parasitic or predatory behaviours that aid in pest control. There are different types of damage that pests can cause, and these include stinging, biting, or chewing plant parts, laying eggs in or on plant parts and other actions that cause pests to act as vectors for other diseases (Citrus Academy, 2017b). Common citrus pests of South Africa include, but are not limited to, false codling moth (FCM), mealybug, fruit fly and thrips. Citrus pests can be controlled in many ways that include the use of contact and systemic chemicals, insect and pheromone-based techniques, traps, and cultural control methods (Citrus Academy, 2017b). While chemical sprays are highly efficient at controlling pests, they often have adverse effects on beneficial insects. A balance exists between pests and their natural enemies which can be disturbed through the overuse of pesticides, resulting in the need to spray more frequently, which in turn can become a rising cost for farmers (ARC, 2000). Table 3 below provides details and symptoms caused by some of the common pests found in South African citrus.

Table 3: Common citrus pests, details and their symptoms (Lacey and Broughton, 2020)

Identification	Pest	Details	Symptoms/Damage caused
	False codling moth (*Thaumatotibia electorate*)	False codling moth (*Thaumatotibia leucotreta*) is native to sub-Saharan Africa and is found in all citrus production areas in Southern Africa. Eggs are laid singly on the surface of the fruit and resemble a saucer-shaped dome. After a few days the eggs hatch and the neonate larvae finds a suitable place to penetrate the fruit. All five instars of larval development take place inside the fruit. Once the final instar (fifth) is ready to pupate, it exits the fruit and drops to the ground where it pupates in the top layer of the soil. The moths emerge after a couple of weeks.	Larval penetration holes in the fruit can only be found through thorough inspection. In green citrus fruit the peel around the penetration hole eventually assumes a yellow colour. On ripe fruit this area is orange, but eventually becomes sunken and brown as the damage tissue decays. The mature larvae enlarge the hole to leave the fruit and pupate. Excreta can be found within the larvae tunnels in the fruit. An infested fruit usually falls from the tree 3-5 weeks after penetration by the larvae.
	Mealybug (*Planococcus citri*)	Mealybugs are up to 3mm long and are found on naval ends and under calyxes of fruit, as well as between touching fruit and leaves. Long tailed mealybugs have long white 'hairs' extending from the tail region, whereas citrus mealybugs do not.	Deformation and / or yellowing of leaves, sometimes followed by defoliation. The overall effect is a reduction of photosynthesis and therefore the yield. Flowers and fruit often drop off.
	Fruit Fly (*Ceratitis capitata*)	Attacks most citrus, especially mandarins and oranges. It is a highly polyphagous species whose larvae develop in a very wide range of unrelated fruits	The presence of small piercing holes in the fruit indicates that eggs were laid under the fruit skin and that maggots, up to 8mm long, may be present. The maggots tunnel into the fruits and cause rotting, often resulting in premature ripening and fruit drop.
	Thrips (*Thysanoptera*)	Thrips are small, slender, soft-bodied insects just visible to the naked eye. Adults are only about 2mm long.	Damage around the calyx appears as silver white blemished areas when fruit is small, which may become brown when exposed to the sun later in the season. Severe scarring of fruit can occur up to 13 weeks after petal fall, after which the damage appears as scribbling and finally as stippling or russet in mature fruit. Young citrus plants can be stunted by severe foliage damage

The physiological functions of healthy and normal citrus plants include absorption of nutrients and water, transpiration and photosynthesis, cell division and cell growth, and the development of plant organs such as buds, flowers, and fruit (Citrus Academy, 2017b).

Diseases can be classified as biotic and abiotic, and are caused by micro-organisms such as viruses, fungi, and bacteria which impair the physiological functions of a plant. Citrus diseases have three separate classifications which are soil-borne diseases, fruit and foliar diseases, and graft-transmissible diseases. Unlike pests which can be detected more immediately, diseases often only appear when the plant begins to show symptoms of being affected (Citrus Academy, 2017b). Common diseases in South African citrus include but are not limited to *Phytophthora* spp, CBS, citrus huanglongbing (HLB) also known as citrus greening. False codling moth and CBS provide the biggest challenges in terms of market access, as most markets have stringent laws that govern the importation of citrus from areas where FCM and CBS are present (CGA, 2020).

The common symptoms of disease pressure shown by plants include discolouration, dieback, gum formation (gummosis), wilting and post-harvest fruit rot (Citrus Academy, 2017b). Discolouration can be detected through changes in leaf or fruit colour, for example, a symptom of *Phytophthora* spp is foliage chlorosis, caused by inefficient water and nutrient uptake resulting from root system damage. *Phytophthora* spp can also cause plants to wilt, as it affects the ability of water and nutrients to pass through a plants transportation system. Gummosis forms part of a plant's natural defence mechanism and is often induced by environmental stress factors such as flooding, infection, insects, and mechanical injuries (Citrus Academy, 2017b). Table 4 provides more detailed explanation of the above-mentioned diseases in citrus.

Table 4: Common citrus diseases; details, symptoms, and control methods (Citrus Academy, 2017b)

Disease Name	***Identification***	***Details***	***Symptoms and Damage Caused***	***Prevention/Control***
Citrus Black Spot	 	• Infection is favoured by warm, wet conditions in summer, presence of susceptible fruit, and presence of abundant inoculum • While conidia (asexual spores) may cause infection, the primary source of infection is ascospores (sexual spores) produced on leaf litter on ground • Ascospores are forcibly ejected during rains or irrigation onto fruit • Fruit are susceptible for 4-5 months after petal fall • Although infection occurs when fruit are young, fungus remains latent for long period and symptoms may not appear until fruit mature	• Necrotic lesions on fruit that make them unacceptable for fresh market • With severe infection extensive premature fruit drop occur that reduces yields of fruit for processing	• Reduce inoculum by removing infected material by means of pruning or removal of sick trees • Apply fungicides in preventative chemical programs • Pick when fruit mature and do not harvest after August in the summer rainfall areas
Citrus Greening Disease	 	• Bacterial disease • Results in a chronic decline of citrus • Citrus Psylla (Trioza) are vectors of the bacteria	• Leaf veins initially turn yellow • Leaf symptoms may resemble zinc deficiency • Disease begins in one branch or section of larger trees and gradually spreads throughout the tree • Leaves are small, point upright, and show chlorosis • Fruit are small, misshapen, have sour or bitter flavour, and remains green on one side • Seeds in symptomatic fruit are usually aborted • Premature fruit drop occurs	• Control of vector (Psylla) • Removal inoculum source by pruning branches with symptoms and controlling re-growth • Removal of whole tree
Disease Name	***Identification***	***Details***	***Symptoms and Damage Caused***	***Prevention/Control***
Phytophthora (Phytophthora citrophthora)	 	• Fungal disease • Affects plant parts below and above ground (root systems, trunks, branches, leaves, blossoms and fruit) • Especially prevalent during prolonged rainy periods • Trees with bud union below or close to soil and trees in poorly-drained soil that may cause anaerobic conditions are highly susceptible	• Poor growth, smaller trees • Nutrient deficiencies due to damage to feeder roots • Gumming • Lower yield and smaller fruit	• Preventative practices, including use of resistant rootstock and planting in well-drained soil • Recommended control practices include budding seedlings high, avoiding wounds, and keeping soil off lower trunk • Soil fumigation of seedbeds should be practiced in field nurseries • Chemicals with preventative and curative action are registered

2.4.2.6. Scouting

Scouting is the general observation of plants and orchards, looking for signs and symptoms of pest or disease presence in strategic locations within orchards, and recording observations of what is present and the extent thereof (Citrus Academy, 2017b). Scouting is an exercise that is repeated throughout the growing season and is done in conjunction with crop nutrient and water status and weed density. Traditional scouting is usually done by an individual with high competency and a good understanding of the principles of scouting. More experienced scouts typically perform an 'impression survey' which involves a general examination of orchard condition. A more favourable approach is a structured scouting procedure that involves selecting permanent data trees, unit inspections, pest traps, cursory examinations, recordkeeping, and reporting (Citrus Academy, 2017b). The structured approach allows for active pest and disease control and predicting the occurrence of pests and diseases at different phenological stages.

2.4.2.7. South African citrus harvesting periods

Table 5 illustrates the different varieties and harvesting periods for each of the four citrus categories. For soft citrus, the earliest to ripen and harvest is the Satsuma, generally harvested between the beginning of March and the end of August (ARC, 2000; Sikuka, 2020a). The premier Mandarin of the world, the Clementine, is harvested between mid-April and the end of June. The last to harvest is the Nadorcott, between June and August. The main production areas for soft citrus are in the Eastern and Western Cape (Sikuka, 2020a).

The Marsh, Rose, and Star Ruby cultivars of grapefruit are generally harvested between the end of March or mid-April, to the middle or end of June, sometimes as late as September for the Star Ruby (Sikuka, 2020a). Grapefruits are mostly produced in Limpopo, Mpumalanga, KwaZulu-Natal, and the Eastern Cape. The Eureka cultivar of the lemon category is harvested between mid-February to mid-July for the warmer areas, and mid-March to mid-August/September for the cooler areas. Lemons are mainly produced in Limpopo, Mpumalanga, KwaZulu-Natal, the Eastern Cape, and the Western Cape. Popular orange cultivars are Navels, mid-seasons, and Valencias. These orange cultivars have different harvesting periods that generally run from March for Navels to the end of September/mid-October for Valencias. The main production areas for oranges are in Limpopo, Mpumalanga, KwaZulu-Natal, the Eastern Cape, and the Western Cape (Sikuka, 2020a).

Table 5: Citrus varieties and harvesting periods for the four categories of South African citrus (Sikuka, 2020a)

Citrus Type	Varieties
Grape fruit	Star Ruby, Marsh, Rose, Flame, Nelspruit Ruby (Nelruby), Flamingo
Oranges	**Valencias** - Delta, Midknight, Turkey, Oukloon (Olinda, Late), Du Roi, Benny. **Navels** - Palmer, Bahianinha, Washington, Robyn, Navelina, Lane Late, Newhall, Cambria, Cara Cara, Rustenburg, Autumn Gold
Mandarins/ Tangarines	**Clementine** - Nules, Marisol, SRA, Oroval, Esbal, Clemenpons, Oronules. **Mandarin –** Tango, Nadorcott (Afourer), Nova, Or (Orri), Minneola, Mor , B17, Tambor , Naartjie, Thoro Temple, Sonet, B24 (African Sunset) **Satsuma** - Miho Wase, Owari, Kuno, Miyagawa Wase, Okitsu Wase, Aoshima.
Lemons/Lime	Eureka, Eureka SL, Lisbon, Limoneira, Genoa

Citrus	Harvest Period
Marsh Grapefruit	March to June
Star Ruby Grapefruit	April to September
Navel Oranges	March to July
Valencia Oranges	July to September
Mandarins/Tangarines	March to August
Lemons/Lime	February to September

2.4.2.8. The South African citrus market value chain

The links in the citrus market value chain are production, picking, packing, transport, harbour handling, shipping, receiving and transport, and sales (Citrus Academy, 2017a). Production refers to all the steps taken to the point where fruit is visible on the trees. These steps include variety and cultivar choice, planting, plant maintenance, and crop protection, and are aimed at producing fruit of a high quality. It is a capital-intensive phase of the value chain, as growers need to pay for orchard establishment, land preparation, irrigation, seedlings, and equipment. Other input costs that arise in this phase are water, fertilisers, fuel, salaries, and plant protection products. Quality and volume are two important factors that drive production. In essence, a grower needs to produce enough fruit to justify capital and input expenditure (Citrus Academy, 2017a). This research aims to assist growers at the production stage of the value chain, through improved management of inputs.

Picking is the next phase of the value chain, and it involves harvesting the fruit and sending it for packing (Citrus Academy, 2017a). This phase is also cost intensive as it requires labour and equipment. The packing process involves grading, washing, treating, sorting, waxing, wrapping, and labelling. The fruit is then packed into cartons, put onto pallets, and inspected before being exported (Citrus Academy, 2017a). The next phase is transport, where fruit is moved from the packhouse to the port where it will be shipped from. Depending on the cultivar and the market, citrus can be transported by rail, on a flatbed trailer or in refrigerated trucks. Distance and transport method dictate the cost in this phase (Citrus Academy, 2017a).

Harbour handling takes place before the fruit is loaded onto a ship (Citrus Academy, 2017a). It is often kept in a fruit terminal with cooling facilities as the fruit may need to be put in storage for a short period. Fruit is loaded onto ships in loose pallets or containers during this phase. Fruit temperature needs to be maintained and may also undergo a cold sterilisation treatment depending on the target market (Citrus Academy, 2017a). Sales is where the fruit is sold to the customer once the retailer adds their profit margin. All costs up to the point of sales are incurred by the grower. Other costs that are incurred by growers are the export and import agent commission, as well as levies and inspection fees paid on export fruit (Citrus Academy, 2017a). Table 6 below shows the percentage breakdown of the total cost incurred per phase of the citrus market value chain.

Table 6: The cost percentage incurred by growers along the citrus market value chain (Citrus Academy, 2017a)

1&2 – Production and Picking	11.5%
3 – Packing	13%
4 – Transport	1.5%
5 – Harbour Handling	3.5%
6 – Shipping	18.5%
7 – Receiving and Transport	13%
8 – Sales	30%
Other Costs	9%
Total	**100%**

2.4.2.9. Factors affecting the citrus market value chain

DAFF (2018) highlights some of the challenges associated with citrus production. Small-scale farmers are unable to keep up with the rising cost production caused by increasing food safety and traceability requirements. Cumbersome legislative requirements such as water, labour, skills development, and environmental laws are causing citrus operations to become less profitable. DAFF (2018) also suggests that a global harmonisation of standards should be implemented. This could entail an 'inspected once – accepted everywhere' scenario to alleviate some of the additional costs and administration that impact grower returns. This could prove difficult to implement as different growing regions globally have their own unique set of issues or factors that influence the import/export of agricultural produce (ARC, 2000).

The emerging sector continues to face challenges despite support received from various partnerships. Improvement in this regard is required by government support programmes, credit policies of lending institutions, and collateral in the form of title deeds. A 'Strengths

Weaknesses Opportunities and Threats' analysis by DAFF (2018) highlights climate change, traditional export market saturation, high capital costs, degrading infrastructure, increased competition, and water scarcity as some of the threats and weaknesses the industry faces.

The Chief Executive Officer of CGA's annual report of 2020, highlighted market access, climatic factors, and logistics as some of the key issues affecting citrus production in South Africa (CGA, 2020). Despite adopting well researched, costly, and time-consuming methods to remain compliant, strict phytosanitary protocols by some trading partners continue to hinder the progress made by South African citrus growers to export their citrus in line with the volumes they produce. Market access is therefore one of the key areas to continue addressing for the CGA and the growers it represents (CGA, 2020).

Logistical challenges in the form of poor road quality and port labour disputes also hamper export efforts. The use of railways as a means of transportation is an option being explored by the CGA and is a key area for development as it may alleviate some of the logistical pressures in the northern growing regions of South Africa (Letsitele, Hoedspruit, Tzaneen, Musina) that are further from the shipping ports than other production areas. Exporting citrus from the Maputo port in Mozambique has also been identified as a viable option for citrus exports as it would reduce the pressure on the Durban port and the high volume of citrus generally exported from there (CGA, 2020).

2.5. Results

2.5.1. Global citrus production

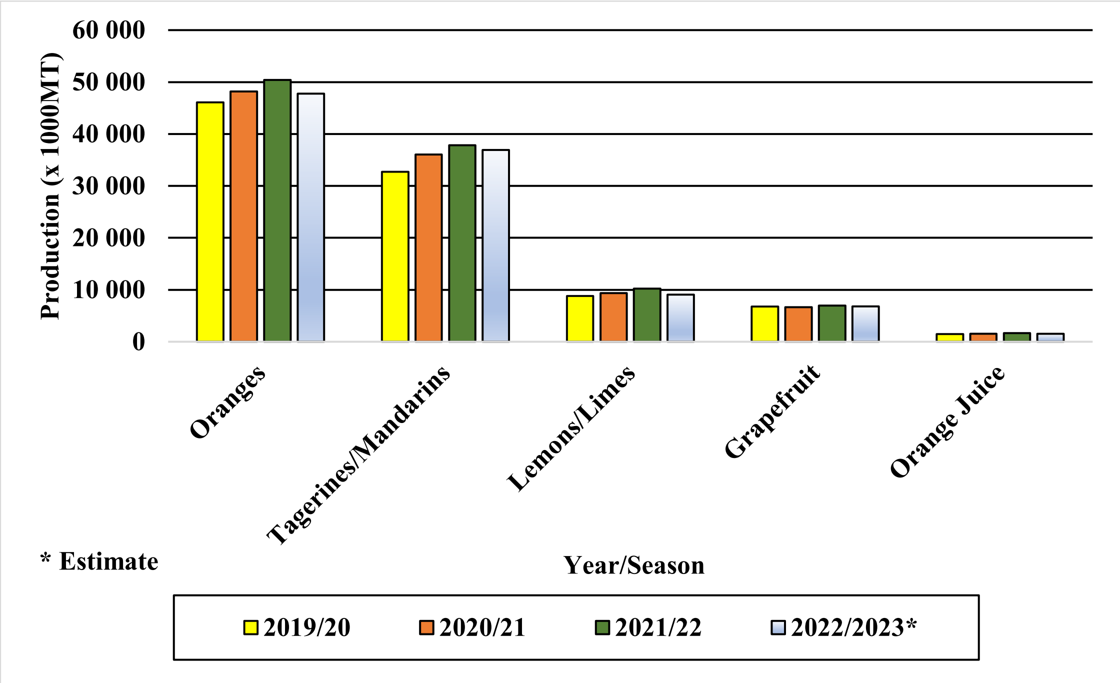


Figure 8: Global citrus production (FAS, 2023)

The global production of oranges stood at roughly 46.1 million tons for the 2019/20 season, a decrease of about 7.8 million tons from the 2018/19 season. This was due to unfavourable weather conditions, particularly in Mexico and Brazil, leading to smaller crops being produced (FAS, 2021). The 2020/21 season showed some improvement and resulted in a 2.5-million-ton increase to 48.1 million tons, as more favourable weather in Brazil and Mexico led to increased production (FAS, 2022). Orange production further increased in the 2021/22 season to roughly 50.5 million tons but is forecast to decrease to 47.5 million tons for the 2022/23 season. This is due to climate related factors affecting production in the EU and Turkey (FAS, 2023).

Soft citrus production (Tangerines/Mandarins) globally, dropped slightly, by 300 000 tons to 31.9 million for the 2019/20 season, with lower production occurring in the USA, the EU, Turkey, and Morocco (FAS, 2021). A strong resurgence took place in these markets in 2020/21 season and saw production rise to roughly 35 million tons (FAS, 2022). The continued growth trend continued in the 2021/22 season with production standing just under 38 million tons, but the forecast for 2022/23 shows a decline in the abovementioned markets due to unfavourable weather conditions (FAS, 2023).

Grapefruit was initially forecast for 7 million tons in the 2019/20 season, but unfavourable weather conditions in the USA and Mexico kept the global production figure at roughly 6.8 million tons, the same amount being achieved in the 2020/21 season (FAS, 2021; FAS, 2022). Production in the 2021/22 season saw a slight increase to 6.9 million tons, and forecasts for the 2022/23 season have production at 6.7 million tons (FAS, 2023). Production is relatively flat across recent marketing years, attributed to fluctuating weather conditions across the major production markets of China, Mexico, Turkey, and the USA.

In the 2019/20 season, the global lemon/lime production figure stood at 8.4 million tons due to lower production in the EU, Turkey, the USA, Mexico, and Argentina (FAS, 2021). Production in the 2021/22 rose to a record 9.9 million tons, attributed to higher production in the marketing countries of Mexico, Turkey, and the USA, and record global consumption (FAS, 2022). Global lemon/lime production is forecast to decrease by 7% to 9.3 million tons, and like the other citrus groups, it is attributed to higher input costs and unfavourable weather conditions (FAS, 2023).

2.5.2. South African citrus production

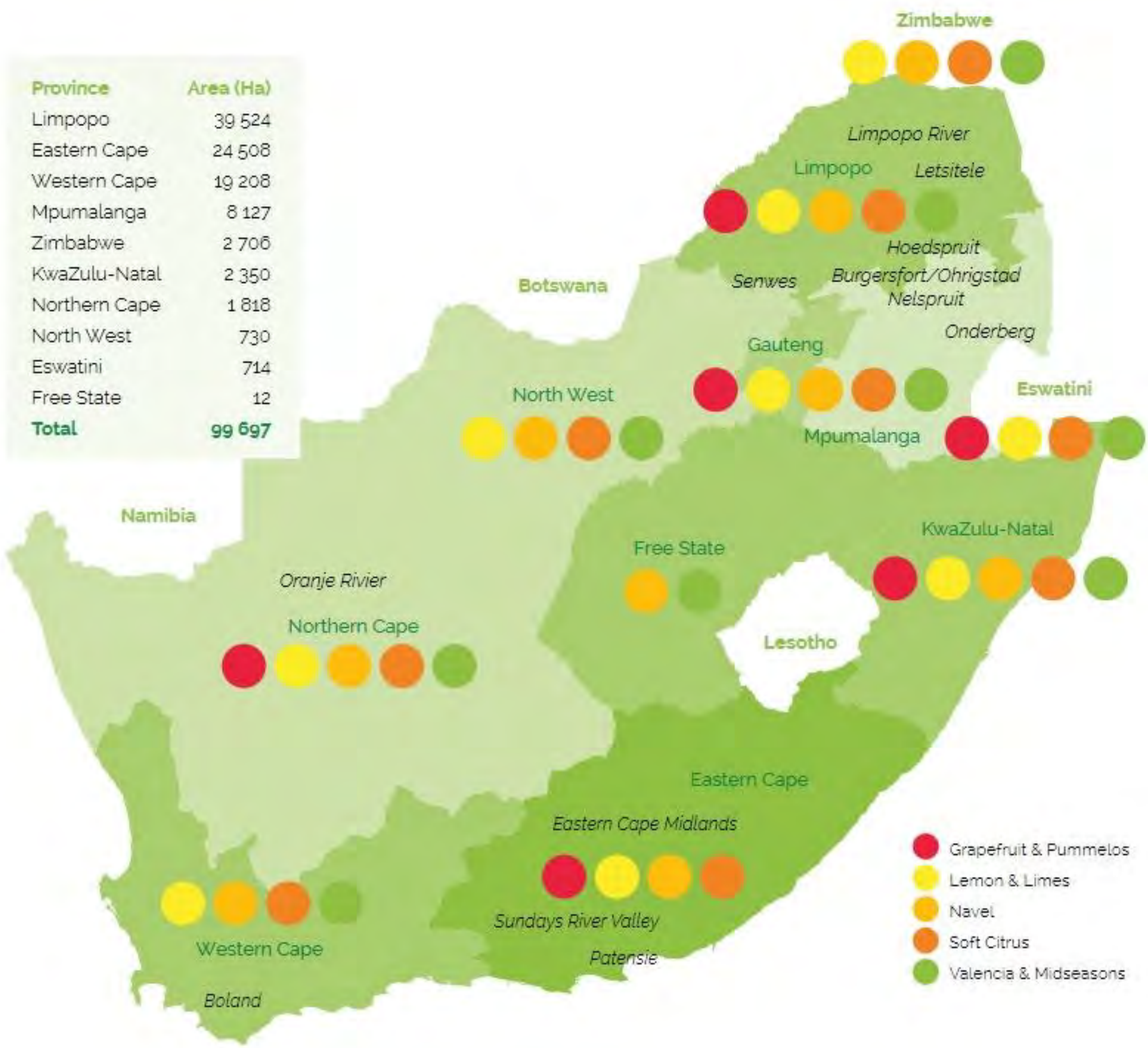


Figure 9: Map of the citrus production areas in South Africa (CGA, 2023a)

The industry is comprised of four broad categories namely oranges, grapefruits, lemons/limes, and soft citrus which are grown mainly in the Eastern Cape, Limpopo, Western Cape, Northern Cape, North-West, KwaZulu-Natal, and Mpumalanga provinces as stated previously (Sikuka, 2020a). Of the provinces in which citrus is grown, Limpopo and the Eastern Cape are the largest, accounting for 40% (39,524 hectares) and 25% (24,508 hectares) of the total area planted, respectively. These are followed by the Western Cape 19% (19,208 hectares), Mpumalanga 8% (8,127 hectares), KwaZulu-Natal 3% (2,450 hectares) and the Northern Cape 2% (1,818 hectares) with the total area under production standing at 99,697 hectares (CGA, 2023a; CGA, 2023b).

2.5.3. South African citrus exports and target markets

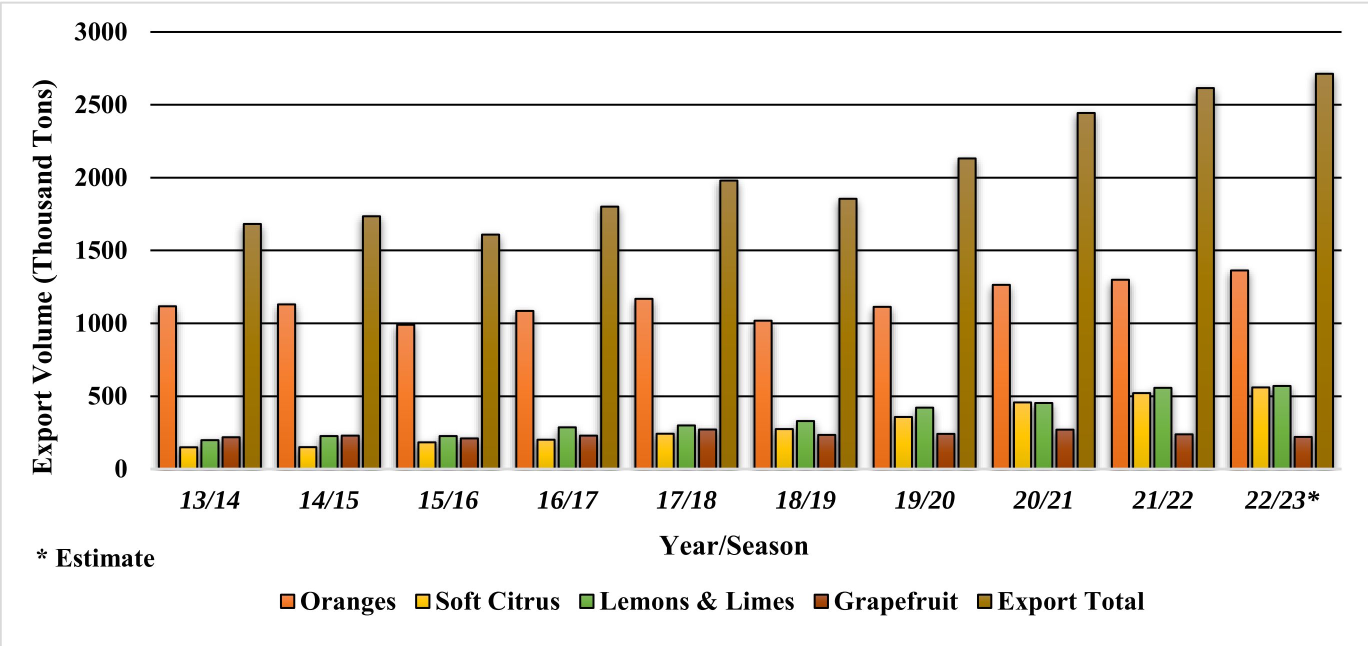


Figure 10: South African citrus exports (FAS, 2023; CGA, 2023b)

Figure 10 above shows South Africa's historical and current citrus exports. South Africa exported a total of 2.13 million tons of citrus in the 2021/22 season (CGA, 2023b). In this season, a total of roughly 1.3 million tons of oranges were exported from South Africa, accounting for nearly 30% of global trade, with exports targeted mainly at the traditional export markets including the EU, Russia, and Asia (FAS, 2023; CGA, 2023b). Lemons/limes exports totalled 557 thousand tons, grapefruit totalled 238 thousand tons, and soft citrus totalled 521 thousand tons. Aside from grapefruit, all citrus export groups have shown an increase in the last four years, with further growth in exports predicted for the 2022/23 season.

Figure 11: <u>South African citrus target markets and percentage exports (CGA, 2023a)</u>

Figure 11 shows the percentage exports of each of the four categories of citrus to various countries around the world in the 2021/22 season (CGA, 2023a). In terms of orange exports, the EU, Asia/South-East Asia, and the Middle East accounted for 77% of South African citrus, followed by the USA and Russia with 9% and 7% respectively. Europe and Asia/South-East Asia imported most of South Africa's grapefruit in the 2021/22 season, accounting for 77% of all grapefruit exports. South Africa's soft citrus (Mandarins) was imported mostly by the UK, the EU, and the USA, accounting for 59% of all soft citrus exports. Lastly, the Middle East and the EU accounted for 68% of all lemon exports (CGA, 2023a).

Predictions for the 2022/23 season are that South African citrus production and exports will increase, as a good rainy season allowed for sufficient irrigation in major production areas, and several newly planted areas reaching full production (FAS, 2023). The South African citrus sector continues to face several challenges including accelerated farming input costs, phytosanitary requirements, inflation pressure on consumers in key markets, high shipping costs, and infrastructure inefficiencies, resulting in reduced profitability and restrained investment (Esterhuizen and Caldwell, 2022).

2.5.4. Fort Beaufort Citrus Production

At present, roughly 800 hectares to 1000 hectares of land is being used for citrus production in the Kat River Valley (I. Sparks, pers comm, 16/01/2020). Exports from the valley vary between 1.1 million cartons and 1.5 million cartons of citrus, which equates to roughly 16,500 tons and 22,500 tons of citrus respectively. At the beginning of 2020, a new packing shed was built, which allowed up to 2 million cartons to be packed at the facility. According to I. Sparks (pers comm, 16/01/2020) the main issues being faced by farmers in the Kat River Valley, from a phytosanitary point of view, are scale, thrips, mealie bug, phytophthora, FCM and CBS. Soft citrus from the valley is usually exported from Cape Town but given the logistical issues that occur at the various ports from time to time, any of the ports are used for all citrus exports from the valley, it largely depends on which port is open and operating at the time (I. Sparks, pers comm, 16/01/2020).

2.6. Discussion

South Africa is a prominent global producer and exporter of a variety of subtropical, deciduous, and citrus fruits (Phaleng *et al. 2019*). Based on the export figures shown in table 7, South African citrus showed considerable growth from the 2015/16 season through to the 2017/18 season, which led to a record season in 2017/18 for the South African citrus sector that stemmed from an increase in production, as well as record exports from all four citrus categories (Sikuka, 2020b). John Edmonds' article 'Southern African Export Season' for the South African Fruit Journal, cited 2019 as being "an off year" with the actual export volume for citrus totalling around 1.8 million tons, down by about 125 thousand tons from the previous season (Edmonds, 2020; Sikuka, 2020b). Oranges were down by 22% to 1.1 million tons and grapefruit was down 14% to 258000 tons. The Northern growing regions of Senwes, the Limpopo River, Zimbabwe, Hoedspruit and Eswatini had the lowest yields, particularly amongst oranges, with smaller fruit, wind scarring and poor colour development (Edmonds, 2020). Soft citrus and lemons, however, were up slightly by 17% (350000 tons) and 13% (295000 tons), respectively through increased demand and steady supplies to the Middle East, the UK, and European markets. Drought, market access and logistical challenges were mostly to blame for the decline in total citrus production and exports for the 2018/19 season.

Record exports, year on year, have been achieved since 2019 and in the 2019/20 season, exports reached around 2.1 million tons of exported fruit (FAS, 2021). Despite the onset of the COVID-19 pandemic during the 2019/20 season, early engagement with stakeholders at the port terminals allowed for citrus exports to be mostly fluid through the Port Elizabeth, Coega, and Durban ports operating at 100% capacity (Brooke, 2021). The Cape Town port saw rising COVID-19 infections though, and only ended up operating at 60% capacity which affected all shipping and created a large backlog and extensive delays. The growth during the 2019/20 season was mostly attributed to increased demand for citrus, due to the immune boosting properties of the vitamin-c contained in citrus, as well as good investment returns and profit margins (Brooke, 2021). South Africa also managed to gain greater access to the USA market by being allowed access to all ports in the USA, as opposed to having access to only four ports previously. It allowed for greater fruit spread and opportunities to reach more consumers (Sikuka, 2020b; Phillip, 2020).

The 2021/22 production season in South Africa was marred by multiple global and local travesties beginning with the Russian invasion of Ukraine that begun the disruption of the logistics supply chain to the growing Ukraine market (CGA, 2023a). Continual lockdowns in China due to new spikes in COVID-19 further impacted global shipping, resulting in significant congestion and hiked shipping rates. Unprecedented rain in April/May 2022 in KwaZulu-Natal devastated the city of Durban and surrounds. The access road to the Durban container terminal was washed away and halted shipping for many days. Lastly, the EU, arguably South Africa’s largest export target market, implemented new, stringent laws on the shipping of citrus that specifies a mandatory cold treatment and precooling processes, for up to 25-days before importation. The CGA (2023) argues that this new regulation was implemented with no regard for scientific evidence and could not be implemented by any of the member states, nor by the EU themselves. Hundreds of millions of rands were wasted as citrus was held up at ports for extended periods of time, and in some cases dumping of fruit had to take place. A dispute was lodged with the World Trade Organisation shortly thereafter, but to-date no progress has been made in finding a resolution (CGA, 2023a).

2.7. Conclusion

South African citrus has a long and rich history, dating back to the 17th century when citrus first arrived from St Helena and was planted in the Dutch East Indian Company's gardens in Cape Town in 1654. The CGA was formed in 1997, and to date, continue their responsibilities of setting standards for fruit quality, expansion and sustained access to overseas and local markets, research and development, representing their growers and driving transformation through the sector (Genis, 2018). South Africa has a well-established market chain, that continues to expand and improve. Logistical challenges do sometimes hamper the efforts for the citrus sector in the form of poor roads and port labour disputes, but government and other stakeholders are continuously engaged in this regard by the CGA, to assist growers with their produce and their exports. Some of the other issues that plague the sector include market access, strict phytosanitary requirements, a high cost of production, increased competition, and water scarcity. Despite the various challenges in the South African citrus sector, production and exports continue to increase, meeting the growing rise in global demand for citrus. This research aims to address some of the issues at the production stage of the value chain through improved management of inputs, informed by remote sensing techniques.

CHAPTER III: REMOTE SENSING TECHNIQUES AND APPLICATIONS FOR USE IN PRECISION AGRICULTURE

3.1. Introduction

"Remote sensing is the art and science of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation" (Lillesand *et al*. 2015). A variety of different sensors allow for 'remote' data collection which can be analysed to obtain further information about the phenomena, areas or objects being investigated. In terms of agricultural applications, the focus is on electromagnetic energy distributions from the earth's surface and the way that these data acquired from airborne and spaceborne sensors can be used to provide information on the areas of interest (Lillesand *et al*. 2015). Precision Agriculture provides a modern and scientific approach to agricultural production, and it offers many potential benefits including improved crop quality, sustainability, productivity, profitability, and food safety (Liaghat and Balasundram, 2010). A rising global population has invoked the need for increased agricultural production and improved resource management. For this to take place, reliable data pertaining to the quality, quantity and location of agricultural resources would need to be obtained, which can be achieved through remote sensing technologies. Remote sensing technologies have the capability to detect and characterise crop and soil data and can be used to guide economic and agronomic decision making (Liaghat and Balasundram, 2010).

3.2. Aim

Develop an understanding of remote sensing and how it relates to precision agriculture.

3.3. Objectives

a) Review literature on remote sensing for comparison of available products for PA.
b) Product identification and review through benchmarking, focusing on high-resolution satellite imagery, high-resolution UAV imagery and other online resources such as Aeroview and FieldMargin.

3.4. Literature review

3.4.1. The role of remote sensing in precision agriculture

Precision agriculture is a modern technological approach to agricultural production that strikes a balance between management-intensive technologies and reliance on traditional knowledge (Liaghat and Balasundram, 2010). There is a rising global commitment by farmers to reduce excessive chemical applications on their lands and to use PA techniques as the framework to become more sustainable. This framework has the potential to aid farmers in production, productivity, efficiency, and profitability in a long-term, site-specific manner, as well as offering wider economic, social, and environmental benefits (Liaghat and Balasundram, 2010).

Precision agriculture uses a systems approach that utilises a combination of technologies like geographic information systems (GIS), computer modelling, global positioning systems (GPS), remote sensing, and variable rate systems for improved crop management in a non-destructive way (Liaghat and Balasundram, 2010). Remote sensing allows us to 'see the invisible' as the imaging sensors on-board different satellite and airborne systems can detect shortwave and longwave radiation in the electromagnetic spectrum, that is invisible to the human eye (NOAA, 2018).

Since the 1990's there have been major advances in GIS, GPS, remote and proximal sensing technology, and these have made major contributions to PA technologies (Yang, 2018). The adoption of PA has been relatively slow, but as a farming strategy, PA is changing the ways farmers operate and manage their fields. Improvements in spectral, spatial, and temporal resolutions in both satellite and airborne imaging sensors, brought about a steady increase in remote sensing applications in PA since the 1990s (Yang, 2018). Remote sensors allow farmers to have a bird's eye view of the crops growing in a single field or the farm in its entirety. Aside from ground-based sensors for monitoring soil and crop growth, remotely sensed imagery has become a popular way of monitoring crop-growth variability and soil, as it allows for a continuous view of all fields over an area of interest (Yang, 2018).

3.4.2. The process of remote sensing

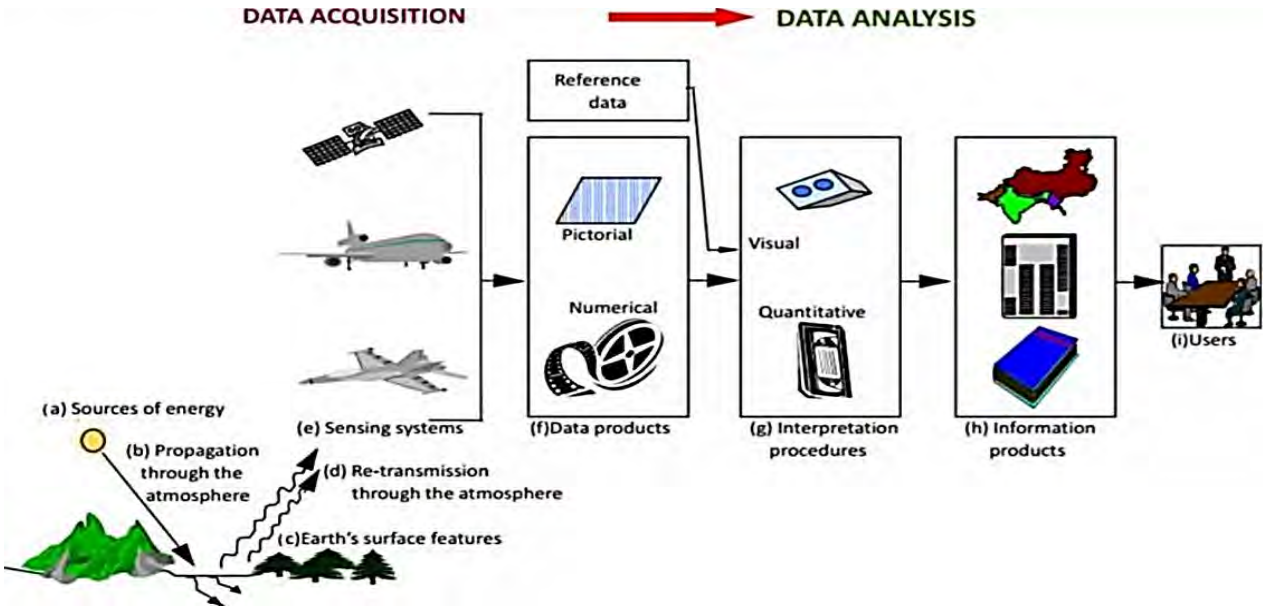


Figure 12: The remote sensing process (Lillesand *et al*. 2015)

Data acquisition and data analysis are the two basic processes involved in remote sensing (Lillesand *et al*. 2015). Data acquisition makes use of sensors to record variations in emitted and reflected electromagnetic energy from the earth's surface and follows processes (a) to (e) illustrated in Figure 12. Data analysis follows processes (f) to (i) and makes use of specialised software for image interpretation and analysis, accompanied with 'reference data' (ground-trothed data, crop statistics and soil maps) that allows analysts to extract certain information about the target resource or area of interest. The information is then compiled into tables, maps or spatial data which can be combined or merged with other layers of spatial data in a GIS. Lastly, the information is supplied to end-users who use the information to help inform their decision-making (Lillesand *et al*. 2015).

3.4.3. The electromagnetic spectrum

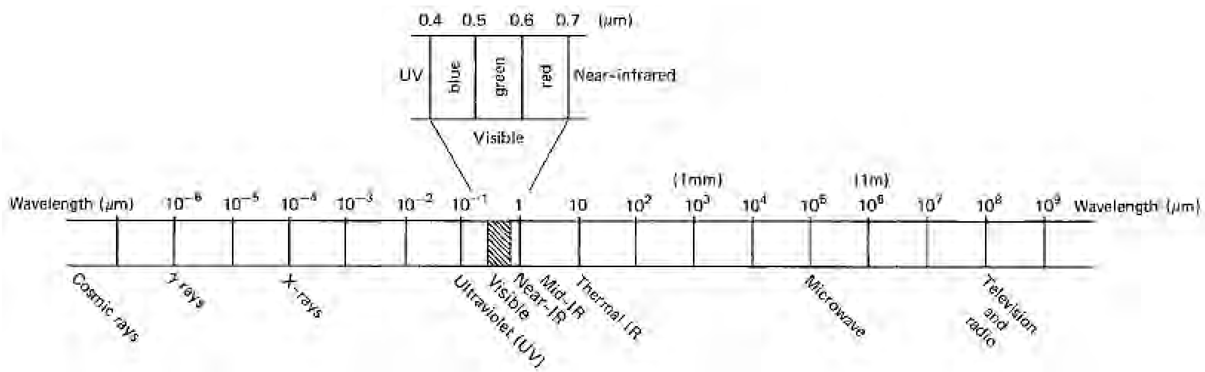


Figure 13: The electromagnetic spectrum (Lillesand *et al*. 2015)

Sensors measure different wavelengths of electromagnetic radiation, and the total range of wavelengths are referred to as the electromagnetic spectrum (Tempfli *et al*. 2009). The different portions of the spectrum are referred to by name and they include cosmic rays, gamma rays, x-rays, visible light, infrared radiation (IR), microwaves, and radio waves, measured in microns (µm). These portions represent a range of wavelengths along a continuum, meaning that there are no clear boundaries between each of the portions. The wavelengths between each portion increase along the spectrum, meaning that cosmic rays have shorter wavelengths and radio waves have longer wavelengths (Tempfli *et al*. 2009).

Different portions of the spectrum are used in different ways in terms of earth observation, primarily regarding the type of information gathered and amount of geospatial data acquired (Tempfli *et al*. 2009). Most practical remote sensing applications make use of the visible and infrared portions of the spectrum. The visible portion only represents a very small fraction of the spectral range. This range consists of the primary colours red, green, and blue and allows us to visualise objects and our surroundings (Tempfli *et al*. 2009). Infra-red radiation that occurs beyond the red region of the spectrum, can be used to distinguish different types, and the healthiness of vegetation, by analysing near (NIR) and mid-infrared radiation.

Healthy vegetation reflects more NIR while unhealthy vegetation reflects less NIR, making it a useful wavelength region to analyse and determine the healthiness and stress-levels of vegetation (Tempfli *et al*. 2009). Another very useful wavelength region to analyse is ‘red edge’ which is the furthest extent of light in the red region of visible radiation (MicaSense, 2020a). Red-edge light is sensitive to the background effects of soil, leaf area variability and chlorophyll content. It has documented use cases in analysing leaf chlorophyll content, nitrogen uptake, plant vigour, fertiliser demand and stress detection (MicaSense, 2020a).

3.4.4. Sensing of electromagnetic energy and energy interactions

A ‘remote sensor’ is an instrument that is used to detect, quantify, and record electromagnetic energy, which is then transmitted in analogue or digital format to a ground-based receiving station (Tempfli *et al*. 2009). There are two types of sensors used to measure radiation, ‘active’ and ‘passive’ sensors. Active sensors produce and emit their radiation onto features of interest and record the reflected radiation from that surface, while passive sensors detect naturally occurring radiation. An example of an active sensor would be taking a photograph with a camera using a flash, while a passive sensor would be taking a photo with the same camera but without the flash (Tempfli *et al*. 2009).

All radiation, irrespective of its source, passes through some portion of the atmosphere. This creates variation in the magnitude of radiation being measured and the path length of radiation through the atmosphere. These variations differ between different sensors and the mechanisms of this variation occur through ‘scattering’ and ‘absorption’ of radiation in the atmosphere (Lillesand et al. 2015). Scattering is the random diffusion of radiation through interaction with other particles in the atmosphere. Three types of scattering exist, and they are ‘Rayleigh’, ‘Mie’ and ‘nonselective’ scattering. Absorption, in contrast to scattering, is the loss of energy to different constituents in the atmosphere, such as ozone, water vapor and carbon dioxide (Lillesand et al. 2015).

Another factor influencing the ‘sensing’ of radiation is the interaction of energy with earth surface features (Lillesand et al. 2015). This includes reflection, absorption, and transmission, which in turn influence the spectral reflectance curves of objects or features on the earth’s surface. A spectral reflectance curve is a graph that depicts the spectral reflectance or response of an object or feature as a function of wavelength. This indicates the spectral characteristics of an object and guides the choice of remote sensing data collection by looking at the wavelength region the object or feature falls within (Lillesand et al. 2015).

Some features on the earth’s surface have very distinctive spectral reflectance characteristics or spectral signatures which could be considered ‘unique’ and ‘absolute’ (Lillesand et al. 2015). This is not the case for most phenomena in the natural world and as such we refer to these characteristics as spectral response patterns, meaning that remote sensor measurements for different features are not necessarily unique and absolute. For example, the characteristics of snow, water, vegetation, and soil, differ in spectral reflectance are therefore spectrally separable in this regard (Lillesand et al. 2015). The degree of separation, however, varies between and among different regions of spectra which gives rise to spectral response patterns. The variability in patterns is further exacerbated by spatial and temporal effects on spectral characteristics of earth surface features or objects (Lillesand et al. 2015). When the spectral characteristics of a feature or object change over time, this is referred to as a temporal effect. A spatial effect refers to identical features or objects having different characteristics in different places at a given point in time (Lillesand et al. 2015).

3.4.5. Vegetation analysis through vegetation indices

Vegetation indices are “quite simple and effective algorithms for quantitative and qualitative evaluations of vegetation cover, vigour and growth dynamics, among other applications” (Xue and Su, 2017). Vegetation indices can provide useful information in applications such as biodiversity conservation, environmental monitoring, agriculture, and other fields. This information provides macro and micromanagement strategies for agricultural production on an objective basis (depending on resolution). The application of remote sensing techniques and the vegetation indices extracted from them rely on the platforms and instruments used, which determines what issue can be best addressed by a solution (index) (Xue and Su, 2017).

The remote sensing of vegetation involves obtaining different reflected light spectra from plant canopies. Different plants, at different growth stages and under different forms of stress, have different levels of spectral reflectance (Xue and Su, 2017). Spectral reflectance is determined by the chemical and morphological characteristics of the leaf surface. The light spectra measured through remote sensing are ultraviolet light (UV) with its wavelength ranging between 10-380nm, visible light (red, green, and blue) with wavelengths between 620-750nm, 495-570nm and 450-495nm respectively and near and mid-infrared light with wavelengths between 850-1700nm (Xue and Su, 2017).

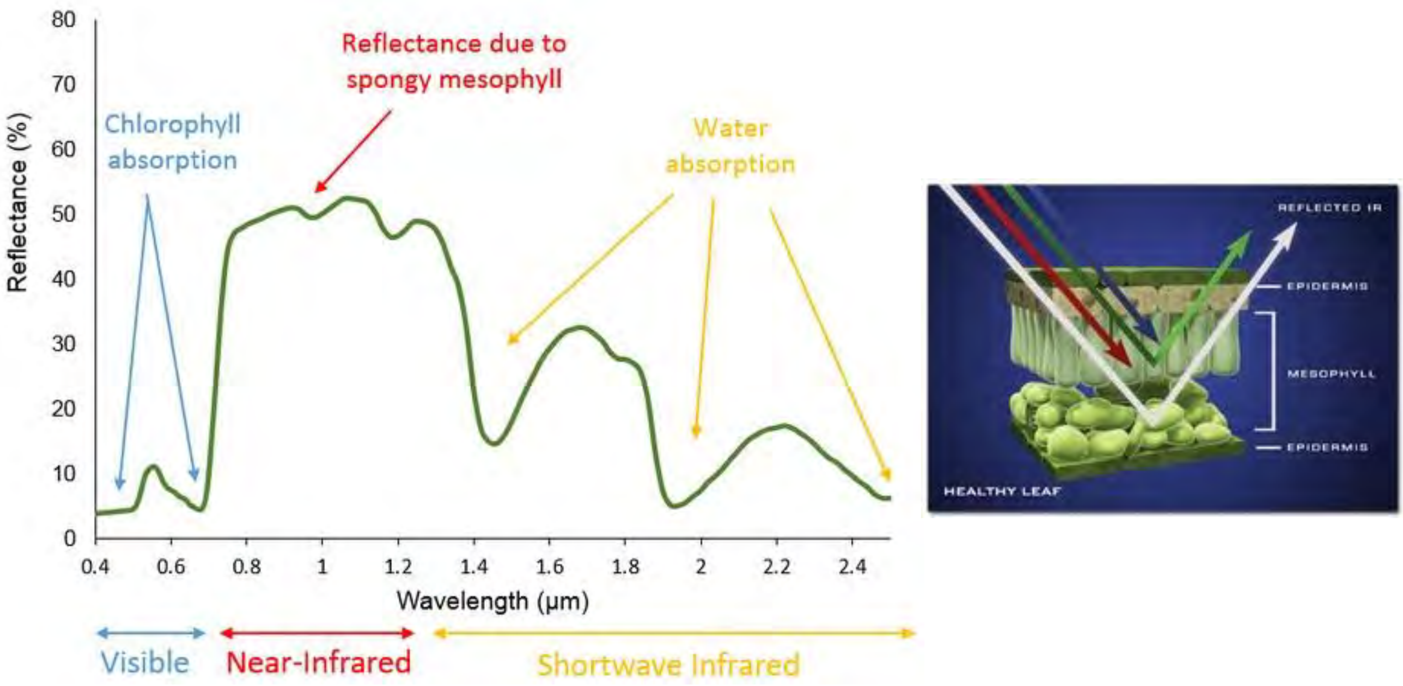


Figure 14: The vegetation spectrum (Harris Geospatial, 2020)

Figure 14 above shows the vegetation spectrum and illustrates how radiation and vegetation interact. Most of the absorption taking place through chlorophyll pigments in leaves, occurs in the blue and red portions of the visible wavelengths, with strong reflectance in the green and NIR portions (why we see healthy vegetation as green) (Harris Geospatial, 2020). Near-infrared radiation has a much higher reflectance than in the visible portions, attributable to the cellular structure of leaves. Healthy vegetation is identified through low visible reflectance and high NIR reflectance, while unhealthy vegetation has higher visible reflectance and lower NIR reflectance (Harris Geospatial, 2020). Vegetation indices obtained from the mid-infrared, NIR and shortwave infrared (SWIR) regions have been widely studied and have been used to show a range of characteristics beyond growth and vigour, such as water content, carbohydrate and sugar content, pigments, and protein content among others (Xue and Su, 2017).

$$Normalized\ Difference\ Vegetation\ Index\ (NDVI) = \frac{Band\ 5_{(NIR)} - Band\ 3_{(Red)}}{Band\ 5_{(NIR)} + Band\ 3_{(Red)}}$$

$$Normalized\ Difference\ Red\ Edge\ Index\ (NDRE) = \frac{Band\ 5_{(NIR)} - Band\ 4_{(RedEdge)}}{Band\ 5_{(NIR)} + Band\ 4_{(RedEdge)}}$$

Figure 15: The NDVI and NDRE equations (MicaSense, 2022)

One of the most widely implemented vegetation indices calculated from multispectral imagery is the Normalised Difference Vegetation Index (NDVI) (Xue and Su, 2017). It is calculated as a normalised ratio between the NIR and red regions of light spectra and is primarily used to characterise canopy growth or crop vigour but can also be used to estimate differences in soil water availability, foliar nutrient content, and yield potential. The intensity of light reflectance in the NIR region increases and decreases in the red region, as vegetation becomes healthier (MicaSense, 2022). Normalised Difference Vegetation Index values range between 1 and -1, with higher values (around 0.9) typically indicating high plant vigour, and lower values (0.5 and below) showing lower plant vigour. It is effective in assessing spatial and temporal differences in above-ground biomass, including canopy density variation during early and mid-growth stages, but loses sensitivity at high levels of canopy density (MicaSense, 2022).

The Normalised Difference Red-Edge Index (NDRE) index is similar to NDVI with the exception being that the red band is replaced by the red-edge (RE) band in the equation seen in Figure 15 above. It is sensitive to the chlorophyll content present in leaves, soil background effects, and variability in leaf area (MicaSense, 2022). The NDRE index, like NDVI, has values that range between 1 and -1, where high NDRE values represent higher levels of leaf chlorophyll content than lower values. In this equation, soil typically has the lowest values, followed by unhealthy plants in transitional values, and healthy plants with the highest values (MicaSense, 2022). Chlorophyll is mostly absorbed in the red-light band and does not penetrate leaves as much as green and RE light. Light in the RE waveband is therefore more sensitive to medium-high levels of chlorophyll content (MicaSense, 2022). The NDRE index serves as a much better indicator of vegetation health/vigour for crops that accumulate high to critical levels of leaf cover or chlorophyll content than NDVI, as red-edge light is more translucent that red light, making it less likely to be absorbed completely by a plant canopy. The NDRE index is suited to intensive management applications for these reasons and can be used in applications such as stress detection, fertiliser demand and nitrogen uptake (MicaSense, 2022). The vegetation indices that were used in this research were NDVI and NDRE.

3.4.6. Satellite imagery

There are a multitude of satellites orbiting the earth, collecting, and providing useful, remotely sensed, agricultural data with continuous improvement in the amount and quality of data available for PA (Sozzi *et al*. 2018). Satellites can be polar orbiting or geostationary, solar, or nuclear powered, and can be low, medium, or high orbiting satellites, which relates to the distance they cover, their resolutions, and their return interval times (NOAA, 2018). There are multiple satellite sensors with different capabilities which include, but are not limited to, RADAR (Radio Detection and Ranging), thermal, multispectral, visible, and short-wave infrared (SWIR) sensors, that allow for the detection and monitoring of crop and soil characteristics throughout growing seasons (Sozzi *et al*. 2018).

Due to the vast amount of satellite data available for PA, a comparative analysis is required to determine which products best suit the needs of a farmer (Sozzi *et al*. 2018). The most important factors to consider are the spatial resolution of imagery which should be based on field size (≤ 30 metres), satellite revisit time (≤ 30 days), spectral resolution (visible and NIR wavelengths measured), and the computational power required to process the data. Commercial satellites have different characteristics based on the factors above, as well as different prices per unit (hectares) (Sozzi *et al*. 2018). These factors aid in determining the cost-effectiveness of different satellite data for farmers.

3.4.7. UAV imagery

Unmanned Aerial Vehicles, also known as unmanned aerial systems (UAS's) refer to airborne platforms that are remotely controlled by a human operator (Muchiri and Kimathi, 2016). Unmanned Aerial Vehicles can be used in many ways such as filmmaking, communications, search and rescue, agriculture, and military operations. From a PA point of view, UAVs collect high-resolution, real-time imagery at a relatively low operational cost that allows farmers access to instantaneous crop health and yield monitoring, terrain analysis, weed mapping, salinity/yield/density mapping, topography, and boundaries (Rokhmana, 2015). Three common types of UAVs are associated with agricultural uses, and they are 'multi-rotor', 'fixed wing' and hybrid UAVs known as VTOL's (Vertical Take-Off and Landing) that have propellers as well as wings (Miller and Adkins, 2018). Fixed wing and VTOL UAVs typically have longer flight times that multirotor drones as they have fewer propellors being powered by a single battery and allows them to cover much larger areas than multirotor UAVs. Multi-rotor UAVs take off and land vertically and are easier to manoeuvre than fixed-wing UAVs as they can hover over certain areas or features, whereas a fixed-wing cannot.

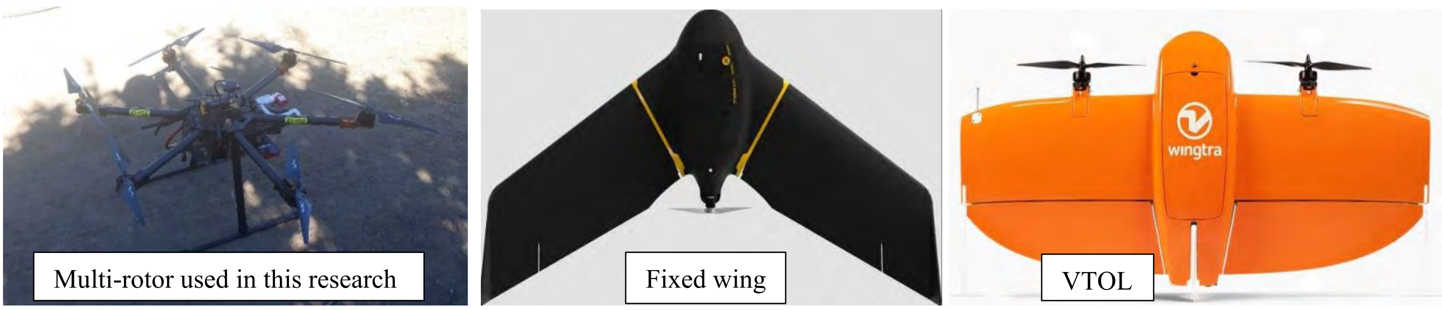


Figure 16: Types of UAVs (Miller and Adkins, 2018)

The benefits of using UAVs for PA are that they are cost-effective, provide sub-meter geometric accuracy, can be operated by local employees, and can capture a relatively large amount of data per unit time (Rokhmana, 2015). The attractiveness of UAVs for use in agricultural applications lies in the ability to obtain high spatial and temporal resolutions (sub-metre pixel resolutions) which allows for different practical applications such as plant growth, evapotranspiration modelling, vigour dynamic assessments, water status sensing and many more (Xue and Su, 2017). This research made use of multispectral imagery obtained by a MicaSense Red-Edge sensor mounted onboard a customised quadcopter UAV.

3.4.8. Other resources

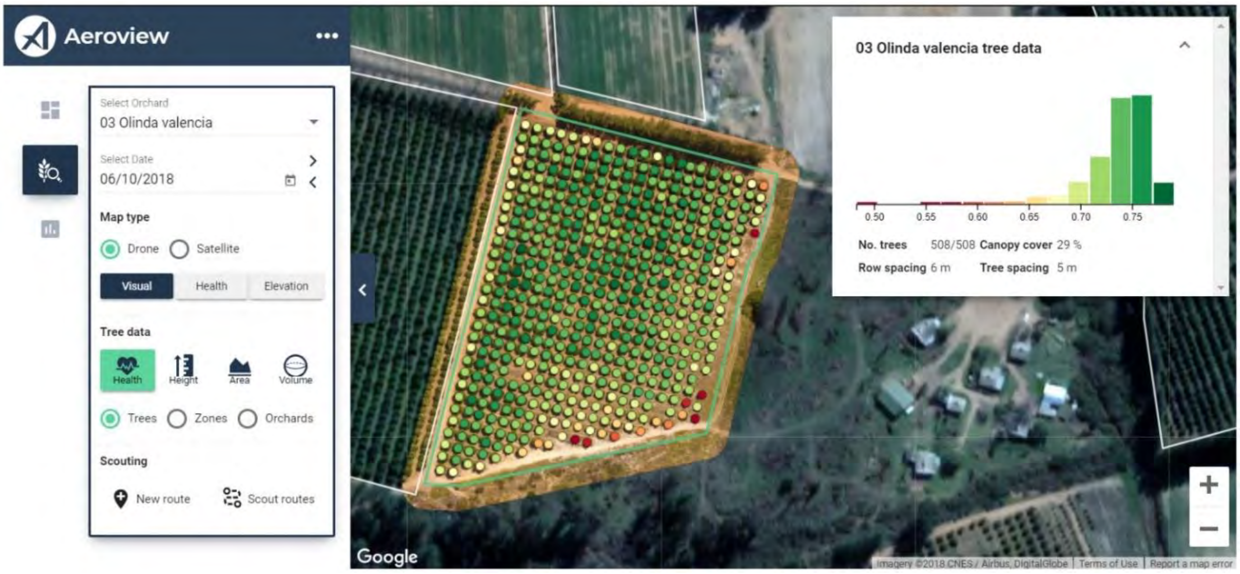


Figure 17: Example of the Aeroview application interface (Rubin, 2019)

Aeroview, designed and managed by the South African-based company Aerobotics, is a web-based application that allows farmers access to UAV and satellite imagery, as well as scouting data for crop monitoring, planning, and reporting (Rubin, 2019). Aeroview InField is a mobile application that syncs with Aeroview for ground-based data collection and crop monitoring, and includes features such as GPS referenced scout data, scouting task assignments and detection of in-field issues. For example, if a farmer were to identify a visibly stressed tree/crop from data collected by a UAV they could log either pest, disease, irrigation or weed issues for that tree while scouting in-field, and ultimately generate reports for that scouting event (Rubin, 2019).

Table 8 below shows the pricing options for different packages offered by Aerobotics for their Aeroview platform (Rubin, 2019). The ‘SMART-Scouting’ package offers full access to the Aeroview platform, access to satellite imagery and scouting reports, for free. The ‘Orchard Monitoring’ package offers everything from the ‘SMART-Scouting’ package but includes a single UAV flight per season, per-tree monitoring, reporting and data exports, premium training, and client support, for R250 per hectare. The ‘Seasonal’ package offers the same features as the ‘Orchard Monitoring’ package but includes an extra two drone flights per season and access to Beta features, for R600 per hectare (Rubin, 2019).

Table 7: Aeroview package and pricing guide (Rubin, 2019)

Package	Includes	Cost	
SMART-Scouting (Satellite Data Package)	Unlimited scouting on Aeroview Scout • Full Aeroview platform access • Regular satellite health maps • Scout reports Complete Farm Digitisation (CFD)	Free	
Orchard Monitoring Package	Everything in SMARTScout • 1 flight per season by a certified drone pilot • Per-tree monitoring and premium features • Farm reporting and data exports • Premium training and client support	SA - R250 / ha RoW - $26 / ha EU - Euro 24 / ha US - $12 / acre	*1 flight per block
Seasonal Package	Everything in Orchard Monitoring Package • Extra 2 drone flights per season = triple the data! • Per-tree monitoring + early access to Beta features • Farm reporting and data exports • Premium training and client support	SA - R600 / ha RoW - $84 / ha EU - Euro 72 / ha US - $36 / acre	*3 flight per block

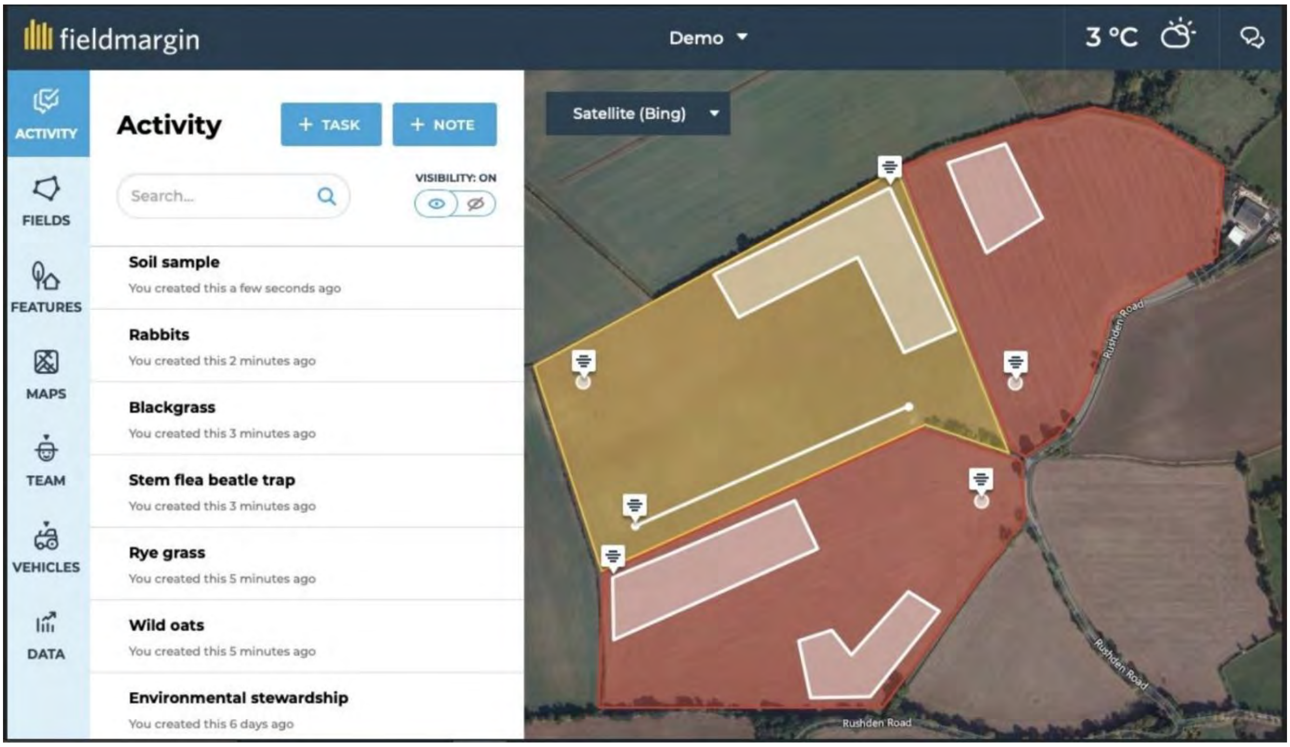


Figure 18: Example of the Fieldmargin interface (Fieldmargin, n.d.)

'Fieldmargin' is a tool that can be used by farmers to manage their lands on a mobile platform (Fieldmargin, n.d.). This application works in a similar way to Aeroview with the exception that it does not allow for the incorporation of UAV data and strictly uses satellite imagery (only in its top tier package option). Fieldmargin allows users to create digital maps of their farms, plan and share field jobs based on required inputs like fertiliser, create farm reports and remote farm monitoring. This application is suited to different types of agriculture such as vineyards, forestry, horticulture, arable crops, and livestock (Fieldmargin, n.d.)

Figure 19: Fieldmargin package and pricing guide (Fieldmargin n.d.)

Figure 19 above shows the four different package offerings from Fieldmargin, the pricing of which was noted in the year 2019. The different packages offered are the ‘Free’, ‘Essential’, ‘Plus’ and ‘Pro’ that can be billed monthly or annually. Each package progressively includes more features particularly with ‘reporting’ and ‘work planning’ features. The standout feature that it includes is the ‘field health’ tool that allows for crop health monitoring and map comparisons from previous seasons or at earlier stages in the growing seasons using Sentinel-2 imagery. This feature is only included in their ‘Pro’ package that is billed at R360 per month on an annual subscription and R480 on a monthly subscription.

3.4.9. PA technologies in citrus production

Various UAV technologies have been applied in PA such as water deficiency identification, site-specific herbicide applications, and disease detection (Tsouros *et al*. 2019). Common applications of UAV based PA include weed management and mapping, irrigation management, vegetation growth monitoring and yield estimation, crop spraying, vegetation health monitoring, yield estimation, and soil analysis. There are several problems associated with conventional methods of weed control (herbicide use) including competition for resources, the evolution of resistant weeds to certain herbicides, an environmental pollutant and the cost incurred by spraying entire fields uniformly (Tsouros *et al*. 2019). By generating weed cover maps using UAVs, site-specific weed management can be attained, as fields are divided into management zones where areas of weed pressure can be precisely targeted, which aid in alleviating some of these issues. Vegetation growth monitoring and yield estimation are also areas where UAVs are used in agricultural production (Tsouros *et al*. 2019). One of the major obstacles in increasing agricultural productivity is the lack of a means for systematically monitoring progress in cultivation, which is further compounded by variable weather conditions that alter crop micro-climates. The collection of UAV data, regularly, allows for increased and improved opportunities to monitor crop growth and record variability in various crop phenotypes and field parameters, that allow growers to effectively plan their management strategies and identify any possible errors (Tsouros *et al*. 2019).

Crop health is an important metric that requires monitoring as significant economic losses due to yield and quality reduction can be caused by diseases (Tsouros *et al*. 2019). Scouting is typically performed by field experts which can be a tedious, time-consuming effort. The application of pesticides, when uniformly applied, can also be expensive. The detection of diseases through UAV imagery provides a non-destructive way to identify diseases at an early stage through changes in crop biomass and provide a means for targeted spraying using prescription maps generated from UAV imagery (Tsouros *et al*. 2019).

The irrigation of crops currently consumes 70% of available water, worldwide (Tsouros *et al*. 2019). The use of UAVs for precision irrigation allows growers to implement a technique whereby crops can be irrigated in the right places, at the right time, in the right quantities using specialised sensors that can illustrate soil morphology and help growers to divide fields into management zones for precise application of water for irrigation. Crop spraying is another element of PA where UAVs can play an important role in crop management (Tsouros *et al*. 2019). Conventional methods for chemical application include boom sprayers and knapsacks which, though effective, can lead to pesticide losses in certain cases, can be time consuming, and can also lead to chemical exposure in the case of knapsack spraying. By using UAVs for chemical application, operator exposure is lowered, and pesticides can be applied timely and in a spatially efficient manner without affecting yield (Tsouros *et al*. 2019).

3.5. Results

3.5.1. Product Identification and Review

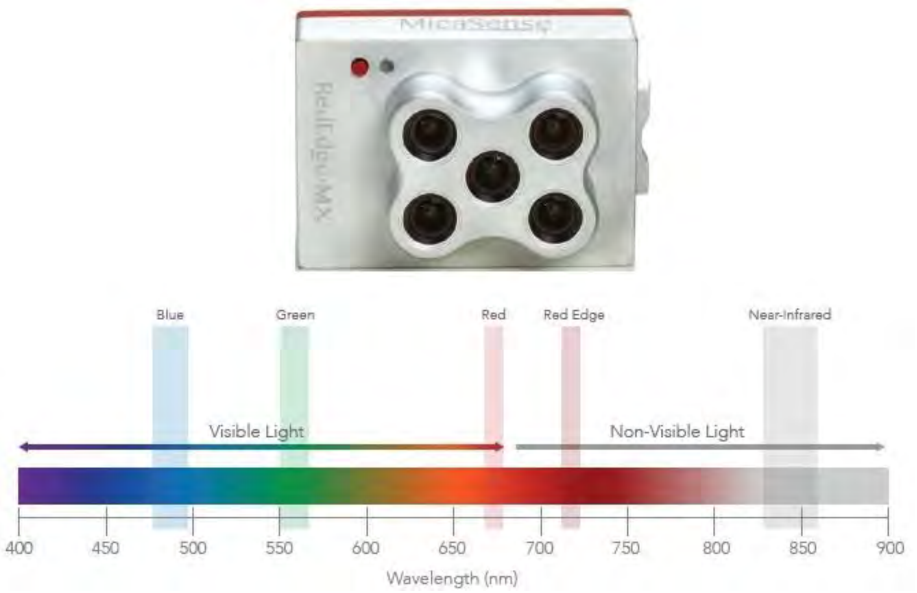


Figure 20: MicaSense RedEdge MX sensor (Micasense, 2020b)

Figure 20 above shows an image of the MicaSense RedEdge MX sensor used to conduct the UAV surveys in this research. It is a highly durable multispectral sensor that has documented use cases in phenotyping, crop health mapping, water management, disease identification, advanced crop scouting and more (MicaSense, 2020b). Its key features are that it has five calibrated, high resolution spectral bands that measure narrow portions of the electromagnetic spectrum (blue – 475nm, green – 560nm, red – 670nm, red-edge – 720nm and NIR-840nm) and a ground sampling distance (GSD) of 8cm per pixel at an altitude of 120m, allowing for calculation of crop health indices and advanced analytics. (MicaSense, 2020b).

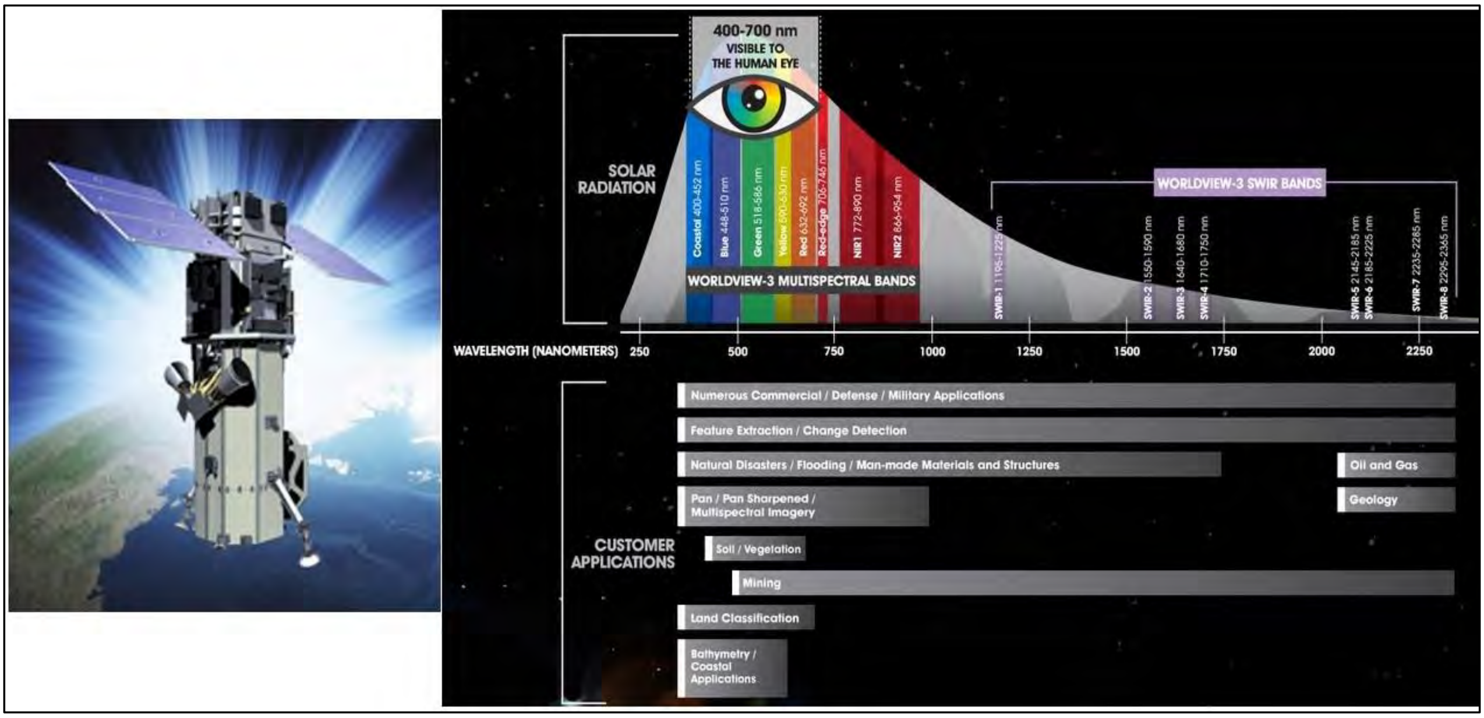


Figure 21: WorldView-3 satellite (Maxar, 2019)

Figure 21 above shows the WorldView-3 satellite and its spectral specifications. The satellite was licenced by NOAA (National Oceanic and Atmospheric Administration) and was launched in 2014 on the 13th of August (Maxar, 2019). The satellite is a super-spectral, commercial, multi-payload, high resolution sensor. It operates at an altitude of 617km, has the capability to obtain around 680000 square kilometres worth of imagery per day, and has an average temporal resolution of 'less than a day'. WorldView-3 offers 30-centimetre panchromatic imagery, 1.24 metre multispectral imagery and 7.5 metre SWIR imagery. The satellite has documented use cases in defence and intelligence, consumer mapping, global development, earth observation and many more (Maxar, 2019).

Figure 22: Planet's satellite constellations (Planet, 2020)

Figure 22 above shows the various constellations of satellites under the Planet brand. It consists of 'Planetscope', 'Rapideye' and 'Skysat' imagery. Planetscope imagery is obtained from over 130 polar orbiting 'dove' satellites has a resolution of 3 metres and consists of four band namely blue, green, red and NIR (Planet, 2020). Rapideye imagery consists of five bands, like Planetscope imagery but with the inclusion of a red-edge band, all at a resolution of 5 metres. Lastly, Skysat imagery consists of five bands like Planetscope imagery, but includes a panchromatic band which has a resolution of 72 centimetres that allows for pansharpening. Pansharpened multispectral Skysat imagery has a resolution of 80 centimetres and an analytic resolution of 1 metre. Planet imagery has documented use cases in agriculture, research, insurance, defence and intelligence, emergency management and many more (Planet, 2020).

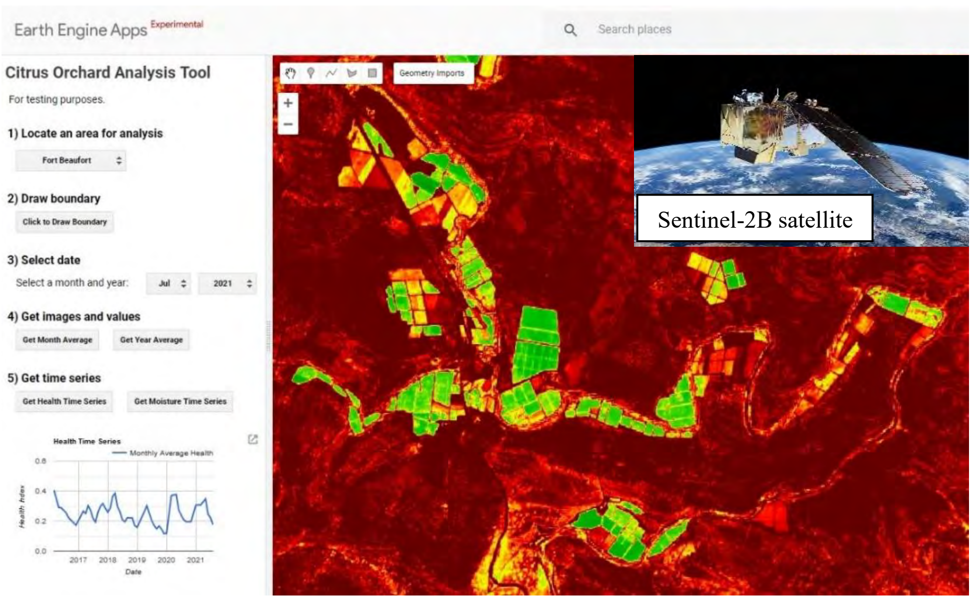


Figure 23: Google Earth Engine using Sentinel-2 imagery (Gorelick *et al.* 2017)

Figure 23 above shows the interface of a citrus orchard management tool, designed by a Rhodes University colleague, in Google Earth Engine (GEE), a free to use software. GEE's Application Programming Interface (API) allows users to create various JavaScript or Python commands that extract satellite imagery to use in different remote sensing use cases, such as change detection (Gorelick *et al.* 2017). In this study, the application extracts Sentinel-2 multispectral imagery for monitoring vegetation vigour and leaf moisture content through two vegetation indices (VI), the normalised difference vegetation index (NDVI) and the normalised difference water index (NDWI). The Sentinel-2 satellite constellation consists of 13 bands that cover the visible and infrared portions of the electromagnetic spectrum, with spatial resolutions between 10 and 60 metres. The application allows users to pan to an area of interest and extract monthly or annual NDVI and NDWI data, as well as time series VI data over a five-year period.

3.6. Discussion

3.6.1. Benchmarking satellite imagery

Low, medium, and high-resolution satellite imagery was acquired for this research, to compare and determine their viability for precision agriculture. The highest resolution satellite imagery acquired was DigitalGlobe's WorldView-3, 8-band bundle, that included a 30-centimetre panchromatic band and 8 multispectral bands that were 1.24 metres in resolution. This was kindly supplied by Alex Fortescue, the manager of Maxar Africa. 'PlanetScope' imagery was also acquired for this research, under an educational license made available by Professor Ian Mieklejohn, the Head of Department for Geography at Rhodes University. It comprises four visible bands and a NIR band, all with a resolution of 3 metres. Lastly, Sentinel-2 imagery was acquired through a script written in GEE by a colleague at Rhodes University.

Tables 9 and 10 below show some of the commercial and open-source (free) satellites, their characteristics, and their pricing. All satellites listed provide multispectral imagery, and have spectral resolutions between 420 and 1040 nanometres, well suited to the calculation of various vegetation indices (Sozzi *et al*. 2018). Landsat 7/8 and Sentinel-2 are the only open-source imaging platforms in the lists below, both of which were used in this research. Despite the low cost of per hectare imagery, most commercial platforms that provide imagery with a resolution lower than 10 metres, charge clients based on a minimum order area, typically 10000 hectares for the higher resolution satellites, which affects pricing as well as the download costs of imagery due to large file sizes. The computational demand refers to the download cost per area unit derived from an average cost of 4G mobile broadband across 41 countries (Sozzi *et al*. 2018).

Spatial resolution should be the main factor to consider when choosing data from a satellite platform as it infers the quality of data being obtained but this is again influenced by factors such as price and revisit times of high-resolution satellites. Sozzi *et al*. (2018) in their analysis, have benchmarked the price for satellite data at USD$30 per hectare, based on the minimum order area for data and the estimated advantages for precision agriculture, the imagery offers. Sozzi *et* al. (2018) calculated that the break-even point for imagery, in terms of farm size, is 17 hectares for high resolution imagery, and between 370 and 470 hectares for sub-meter resolution imagery. Ultimately, the end user would need to decide if a particular satellite could give them the good quality data they require at an affordable price, whilst factoring in issues such as the minimum order area, download costs, revisit times, and spatial resolution.

Table 8: Features of different commercial and open-source satellites (Sozzi et al. 2018)

	Spatial resolution *m*	Spectral resolution VIS/NIR *nm*	Radiometric resolution *bits pixel^{-1}*	Revisit time *dd*
Deimos-2	0.75	466-697/770-892	10	2
Dove (Planet)	3	420-700/770-900	16	1
GeoEye-1	0.5	450-690/780-920	11	3
Kompsat-2	1	450-690/760-900	14	6
Kompsat-3	0.7	450-690/760-900	14	3
Kompsat-3A	0.55	450-690/760-900	14	3
Landsat-7/8	15	450-690/770-900	8-12	8
Pleiades-1A/1B	0.5	430-720/750-950	12	1
RapidEye	5	440-685/690-850	12	5.5
Sentinel-2	10	458-680/785-900	16	5
Spot-6/7	1.5	455-695/760-890	12	1
WorldView-2/3/4	0.3-0.5	450-690/770-1040	11	1

Table 9: Pricing guide for satellite data (Sozzi et al. 2018)

	Minimum order area *ha*	Price per unit *$ ha^{-1}*	Minimum area price* *$*	Computational demand *KB ha^{-1}*
Deimos-2	10 000	0.060	700	50
Dove	10 000	0.012	218	8
GeoEye-1	10 000	0.275	2850	100
Kompsat-2	2 500	0.055	237.5	20
Kompsat-3	2 500	0.110	375	50
Kompsat-3A	2 500	0.160	500	100
Landsat-7/8	3 700 000 (one scene)	0	100	0.5
Pleiades-1A/1B	10 000	0.213	2225	100
Rapideye	10 000	0.012	218	4
Sentinel-2	1 200 000 (one scene)	0	100	0.63
Spot-6/7	10 000	0.045	550	8
WorldView-2/3/4	10 000	0.275	2850	130

3.6.2. Benchmarking UAV imagery

Rapid expansions are taking place in terms of UAV use for precision agriculture; however, many limitations continue to prevent them from being used more widely (Tsouros *et* al. 2019). The lack of a standardised workflow is one such hindrance and generally leads to ad-hoc procedures being implemented when it comes to PA applications. Skilled personnel are also required when it comes to the data intensive procedures that take place when exploiting and analysing aerial imagery. As such a farmer may require training or must seek expert assistance at a cost which may discourage 'small' farmers, from making use of this technology (Tsouros *et al*. 2019).

Investing in a UAV as well purchasing the necessary sensors and software, may also prove very costly for farmers for those who would seek to drive their own UAV surveys (Tsouros *et al*. 2019; Jupp, 2018). Regulations around the airspace sector for UAVs can also be highly restrictive in certain countries, South Africa being one of these. Commercial UAV operators in South Africa are required, at a minimum, to possess a remote operating certificate (ROC), a letter of approval (RLA) for each UAV registered under the ROC, a remote pilots license (RPL), and insurance (Jupp, 2018). The process to obtain each of these is often tedious, costly, and take extended periods of time to obtain. These requirements also incur renewal fees every one to two years, adding additional costs to a commercial UAV operation (Jupp, 2018).

Other limitations include flight timing under optimal weather conditions, and limited flight times of multirotor UAV's that are typically used for surveying (Tsouros *et al*. 2019). The rapid advancements that are taking place with UAV technology should alleviate some of these limitations in the future. The improvements should help to ensure that farmers will benefit more from UAVs for PA into the future (Tsouros *et al*. 2019).

Application		Sensor		Processing method				
				Photogrammetry	Machine Learning	Vegetation Indices	ML & VIs	Other
Weed mapping	12.5%	RGB	73%	12.50%	62.50%	12.50%	0.00%	12.50%
		Multispectral	27%	0.00%	100.00%	0.00%	0.00%	0.00%
Monitor growth	65.6%	RGB	30%	42.11%	31.58%	10.53%	0.00%	15.79%
		Multispectral	59%	13.89%	25.00%	38.89%	8.33%	13.89%
		Hyperspectral	6%	25.00%	25.00%	25.00%	25.00%	0.00%
		Thermal	5%	0.00%	33.33%	66.67%	0.00%	0.00%
Monitor health	6.3%	RGB	20%	0.00%	100.00%	0.00%	0.00%	0.00%
		Multispectral	80%	0.00%	25.00%	25.00%	50.00%	0.00%
Irrigation management	5.2%	Multispectral	60%	0.00%	0.00%	33.33%	66.67%	0.00%
		Thermal	40%	0.00%	50.00%	0.00%	0.00%	50.00%

Figure 24: Sensor usage and processing techniques in UAV based PA (Tsouros et al. 2019)

Figure 24 shows the most common applications for UAV based PA including sensors used and the processing methods used to manipulate and analyse imagery. Weed mapping, growth monitoring, health monitoring and irrigation management are the four most common uses for UAV imagery in PA, with crop growth monitoring being the largest of the four applications (Tsouros *et al*. 2019). Various processing techniques are used to exploit UAV imagery, but the three most common techniques used are photogrammetry, machine learning and vegetation indices. Machine learning is the most widely used processing method for analysing UAV imagery and it forms part of the application of artificial intelligence whereby computer algorithms are designed to continuously learn from data inputs and produce results from an automated process (Tsouros *et al*. 2019). In this research, a combination of supervised image classification, machine learning techniques, and vegetation index data, were used to assess orchard health on a citrus farm in the Eastern Cape.

UAV and satellite imagery are used in similar ways when it comes to vegetation mapping thus making them complementary sources of information, rather than opposing technologies (Micasense, 2020c). The Aeroview platform from Aerobotics for example, offers both satellite and UAV imagery for crop health monitoring. The cost of imagery, information accessibility, spatial and spectral resolutions and atmospheric influences are some of the major differences between satellite and UAV based imagery. One of the greatest advantages of satellite imagery is that they generally provide greater temporal resolutions than UAV based imagery, including the availability of historical data. The insights that can be provided by historic satellite imagery, as well as the different spectral resolutions between satellites and UAVs allows different issues to become more evident through satellite imagery than UAV imagery, and vice-versa (Micasense, 2020c). UAV imagery has its greatest advantage in the high spatial resolutions they offer, usually higher than 10 centimetres per pixel, while open-access satellite data from Landsat and Sentinel have resolutions less than 10 metres per pixel (Micasense, 2020c). Imagery preference depends on the application for which it is required but this does not mean that both platforms cannot be used simultaneously.

3.7. Conclusion

Precision Agriculture provides a modern and scientific approach to agricultural production, and it offers many potential benefits including crop-quality, sustainability productivity, profitability, and food safety (Liaghat and Balasundram, 2010). Precision agriculture uses a systems approach that combines technologies like GIS, computer modelling, GPS, remote sensing, and variable rate systems for improved crop management in a non-destructive way (Liaghat and Balasundram, 2010). A rising global population has invoked the need for increased agricultural production and improved resource management. For this to take place, reliable data pertaining to the quality, quantity and location of agricultural resources would need to be obtained, which can be achieved through remote sensing technologies. There are many differences between satellite and UAV imagery, and the choice by farmer for adopting either, or both applications, depends on the spatial resolution and the cost of the imagery. Spatial resolution should be the main factor to as it infers the quality of data being obtained, but this is again influenced by factors such as price and temporal resolutions of imagery (Sozzi *et al*. 2018). Based on the review of available remote sensing sources and techniques for PA, Planetscope imagery was chosen for analysis in this research, alongside WorldView-3, and UAV imagery. These choices were driven by the need to identify the suitability of various sensors based on their spatial resolution. Results of the analysis performed on all the imagery will be shown in the results section of Chapter 4.

CHAPTER IV: HORTICULTURAL ISSUES IN CITRUS – MANIFESTATION AND DETECTION WITH REMOTE SENSING TECHNIQUES

4.1. Introduction

Of all the global fruit crops, citrus is the most extensively cultivated, with predictions for the 2020/21 season standing at roughly 96.8 million tons of citrus produced globally, between all four citrus categories (FAS, 2021). Citrus, like many tropical and subtropical crops, play host to numerous pests and diseases, some of which are highly destructive, and have the capability to heavily impact production (Jaouad *et al*. 2020). The food and agriculture organisation of the United Nations (FAO) estimates global crop production losses due to pests, to be between 20% and 40% (Sarkozi, 2019). The global economy loses around USD$220 billion each year to plant diseases and around USD$70 billion to invasive insects. The productivity and resilience of agricultural systems also continues to be jeopardised by current and future climate scenarios, as well as a rising global population (Segarra *et al*. 2020).

The application of advanced technologies, namely PA, will be crucial in approaching issues on yield improvement, managing crop variability, and reducing environmental impact (Segarra *et al*. 2020). The aim of this chapter was to develop a methodology for assessing citrus tree health using PA, with a view to aid citrus farmers. This was achieved by combining information on primary production in citrus from chapter two, and remote sensing techniques from chapter three, to inform the development of a remote sensing workflow to assess tree health in a citrus orchard.

There are many oomycetes and fungal pathogens that citrus crops are susceptible to (Jaouad *et al*. 2020). These include *phytophthora* spp and *fusarium* spp, as well as postharvest pathogens such as *alternaria citri* that can affect fruit during storage and cause substantial losses in many citrus producing countries. Understanding the biology of individual pathogens is required to develop effective management programs and the maintenance of productive orchards. Pest control using pesticides has enabled growers to control the effect of pests through modified production systems that increase their crop productivity (Jaouad *et al*. 2020).

Integrated pest management (IPM) combines multiple strategies to alleviate losses due to pathogens and pests based on economic and environmental considerations (ARC, 2000). IPM strategies include prevention, avoidance, scouting, and control using one or more interventions. Traditional methods of scouting, which were referred to in Chapter 2, typically involve an experienced individual performing ‘impression surveys’ which is a general assessment of pest, disease and weed presence among other agronomic factors, that are repeated at critical stages in a cultivars phenological cycle. This can be a time-consuming, labour intensive and expensive process (Donmez, Villi, Berberoglu and Cilek, 2021). Remote sensing technologies have the potential to automate crop monitoring practices, like scouting, which in turn offers growers a cost-effective and practical service in their crop management strategies.

4.1.1. Remote Sensing in Precision Agriculture Applications

There has been a growing global interest in PA as it provides a set of unique set of tools, capable of meeting the needs of producers and consumers in a sustainable manner (Delavarpour *et al.* 2021). Precision Agriculture practices and associated technologies have grown significantly in recent years, with the global market forecasted to reach USD$43.4 billion by 2025. Remote sensing technology allows farmers to collect, process and interpret crop and soil health at optimal production stages in a cost-effective and convenient manner. Remote sensing has the capability to allow for early detection of potential issues and provide opportunities to address them before economic thresholds are met (Delavarpour *et al*. 2021). The purpose of crop monitoring is to record phenotypic traits that reflect potential issues in crops or fields and identify these timeously in the growing season. High-resolution aerial imagery can aid in sustainable crop and risk management, as well as in global markets, various policies and decision making, by helping growers evaluate crop growth status, soil conditions and plant health. This chapter will engage various aspects of remote sensing in PA, but particularly that of crop health monitoring (Delavarpour *et al*. 2021).

Plant stress symptoms appear in the infrared range of the electromagnetic spectrum several days before they appear in the visible range (Delavarpour *et al*. 2021). Many growers and agronomists use traditional ground-based methods and other tools to scout and monitor crop growth and density. As mentioned by Donmez *et* al (2021), these methods can often be tedious, time consuming, destructive, and expensive. Traditional scouting might also lead to certain areas being neglected due to large land or field portions not being covered, and ultimately losses in yields at a later stage (Delavarpour *et al*. 2021). One of the driving factors behind the implementation of UAV based remote sensing, is the time that can be potentially saved through the automation of crop monitoring, making the technology cost effective for farmers (lost Filho *et* al. 2020). Remote sensing of crops generally assesses the visible and near-infrared spectral ranges of light, where photosynthetically active radiation can be measured, with most studies referring to the 400-1000 nanometre (nm) range. Any biotic or abiotic factor that induces a physiological response that affects a plants ability to photosynthesize will lead to changes in leaf reflectance within this spectral range, thereby making it a great candidate for remote sensing (lost Filho *et al.* 2020).

Numerous studies showcase the potential of both UAV and satellite imagery in PA, both individually and comparatively, for multiple crops. According to research conducted by Delavarpour *et al.* (2021) on UAV characteristics for PA, more than 50% of research papers on UAV use in agriculture, from the Web of Science, were published after 2016 and 90% of papers were published after 2013. This serves as an indication that researchers, growers, and the PA industry are beginning to recognize the benefits of remote sensing technology as a beneficial tool in crop management (Delavarpour *et al.* 2021). The following case studies demonstrate the use of remote sensing, from a UAV and satellite imaging perspective, in citrus, olive and macadamia orchard monitoring, and management.

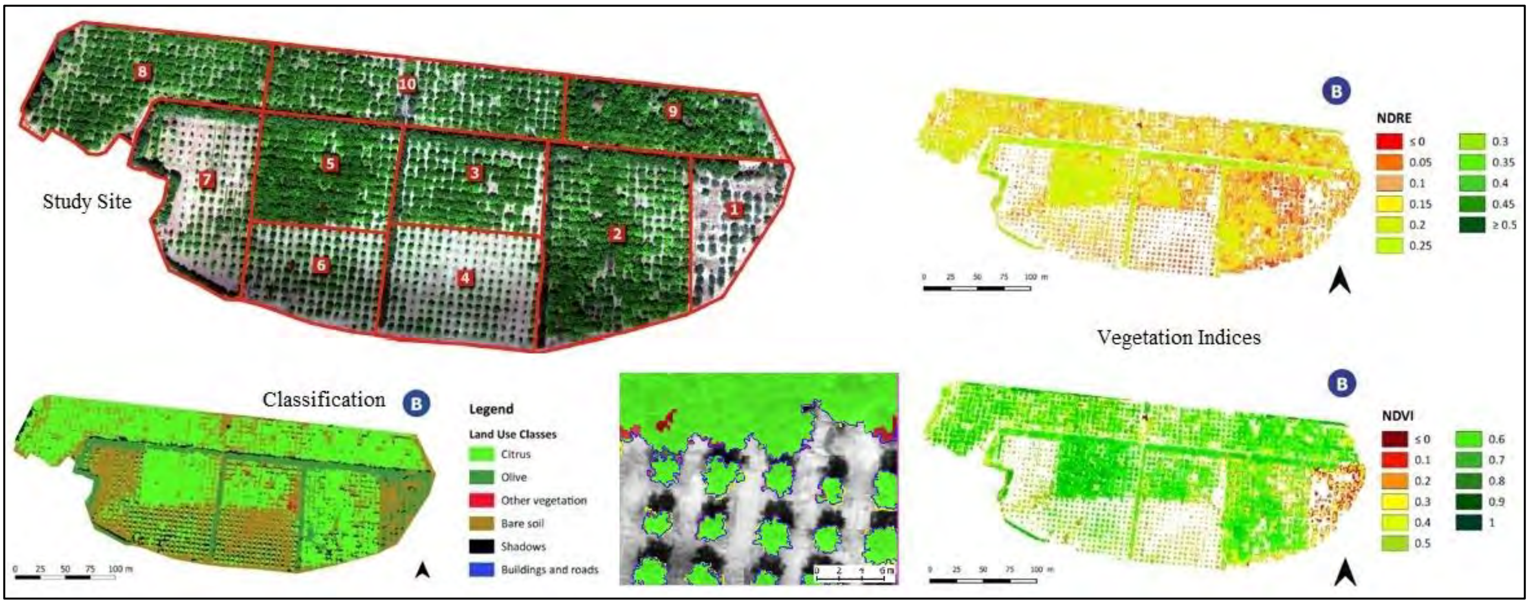


Figure 25: Monitoring vegetation vigour in heterogeneous citrus and olive orchards (Modica *et al.* 2020)

Modica *et al.* (2020) used a multiscale approach of geographic object-based image analysis (GEOBIA) and vegetation indices, to monitor vegetation vigour through the detection and extraction of citrus and olive orchard tree crowns, using multispectral UAV imagery. Figure 25 illustrates parts of the results of their research in a PA context (Modica *et al.* 2020). Their GEOBIA approach, coupled with regular planting patterns and minimal canopy overlap, allowed them to focus their analyses on cultivated sections only, excluding shadows and bare ground to obtain a better description of vegetative health.

The results of their NDVI and NDRE vegetation indices and vigour maps allowed for the identification of both healthy and unhealthy orchard zones (Modica *et al.* 2020). The unhealthy zones were characterised by plants with low density foliage and planting in unfavourable soil. The workflow proved to be effective in applying it to complex datasets with different spatial resolutions and levels of heterogeneity, and ultimately allowed for the creation of a relatively repeatable GEOBIA model (Modica *et al.* 2020).

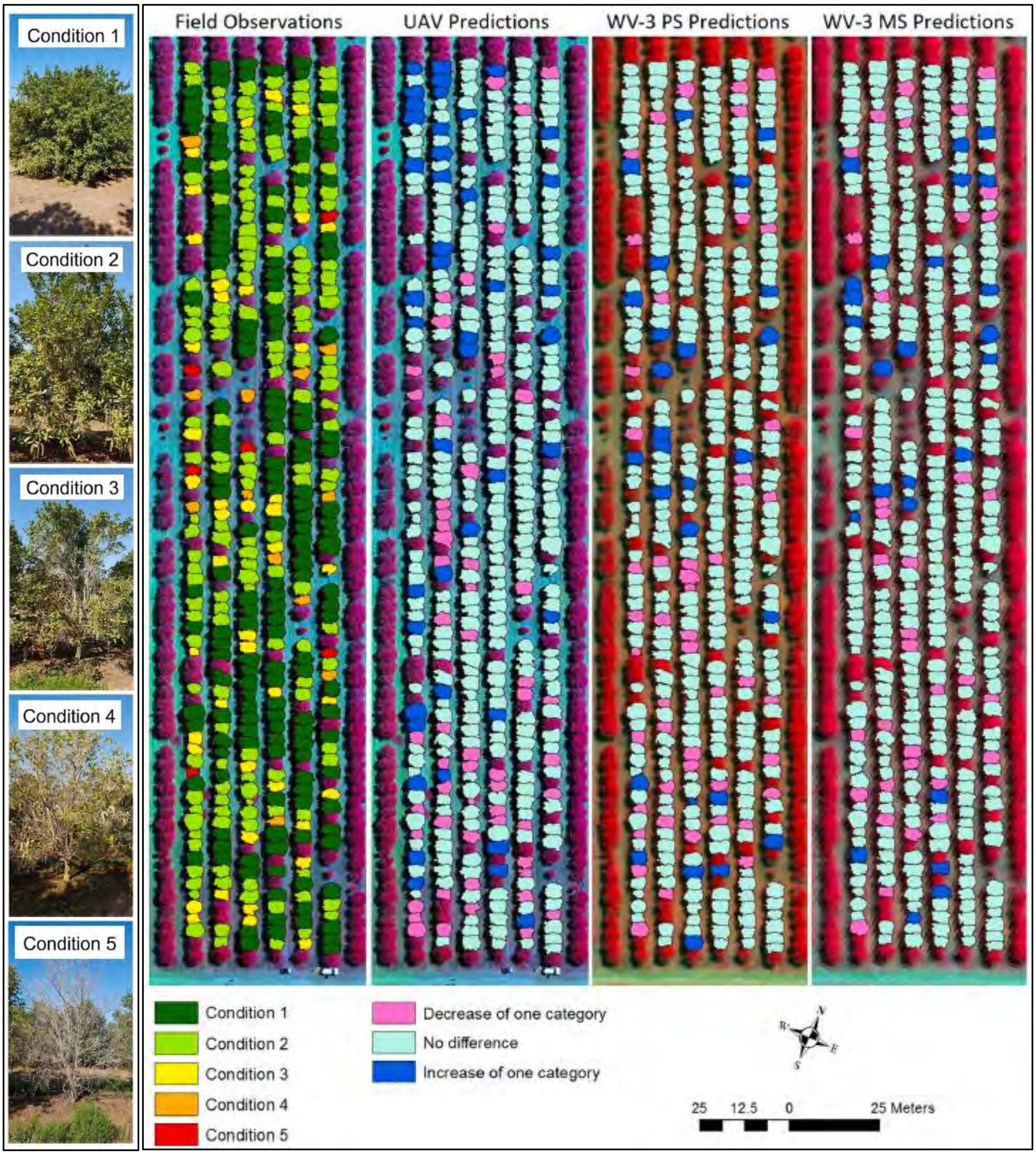


Figure 26: Assessing conditions of macadamia trees (Johansen *et al.* 2020)

Figure 26 presents a section of the results of research conducted by Johansen *et al.* (2020), who used a machine learning approach, coupled with different vegetation indices to extract tree crowns, and map the condition of different macadamia varieties using multispectral UAV and

WorldView-3 satellite imagery. The WorldView-3 imagery produced a more accurate tree condition assessment compared to the UAV imagery but proved challenging when used to delineate individual macadamia tree crowns, given the lower spatial resolution of its multispectral bands and the hedgerow structure of the macadamia orchard. Johansen *et al*. (2020) were able to discriminate and delineate individual tree crowns, more accurately using the higher spatial resolution UAV imagery, which was subsequently used to delineate tree crowns on the WorldView-3 imagery. Other studies have also found it difficult to extract data such as tree crowns from vegetation occurring in a hedgerow (Johansen *et al*. 2020). Both sets of imagery enabled the classification of macadamia tree conditions at a given point in time, for an individual tree variety, correctly or within an offset of one category, greater than 98.5% of the time. However, individual models trained on a single macadamia variety could not be used to successfully classify other varieties at different phenological stages (Johansen *et al*. 2020).

Their research provides a good foundation for converting this workflow into an operational approach for growers to map and monitor macadamia trees at farm and orchard level. Future research, suggested by Johansen *et al*. (2020) is the development of field based quantitative assessment methods for increased objectivity and ranges of condition categories to improve macadamia mapping and monitoring. Automated tree crown delineation is another suggested method, for example using known tree row-spacings along a hedgerow, and tree crown spacing. The testing of new deep learning approaches to validate their robustness against different qualities and quantities of training data is another future research direction (Johansen *et al*. 2020).

4.2. Materials and Methods:

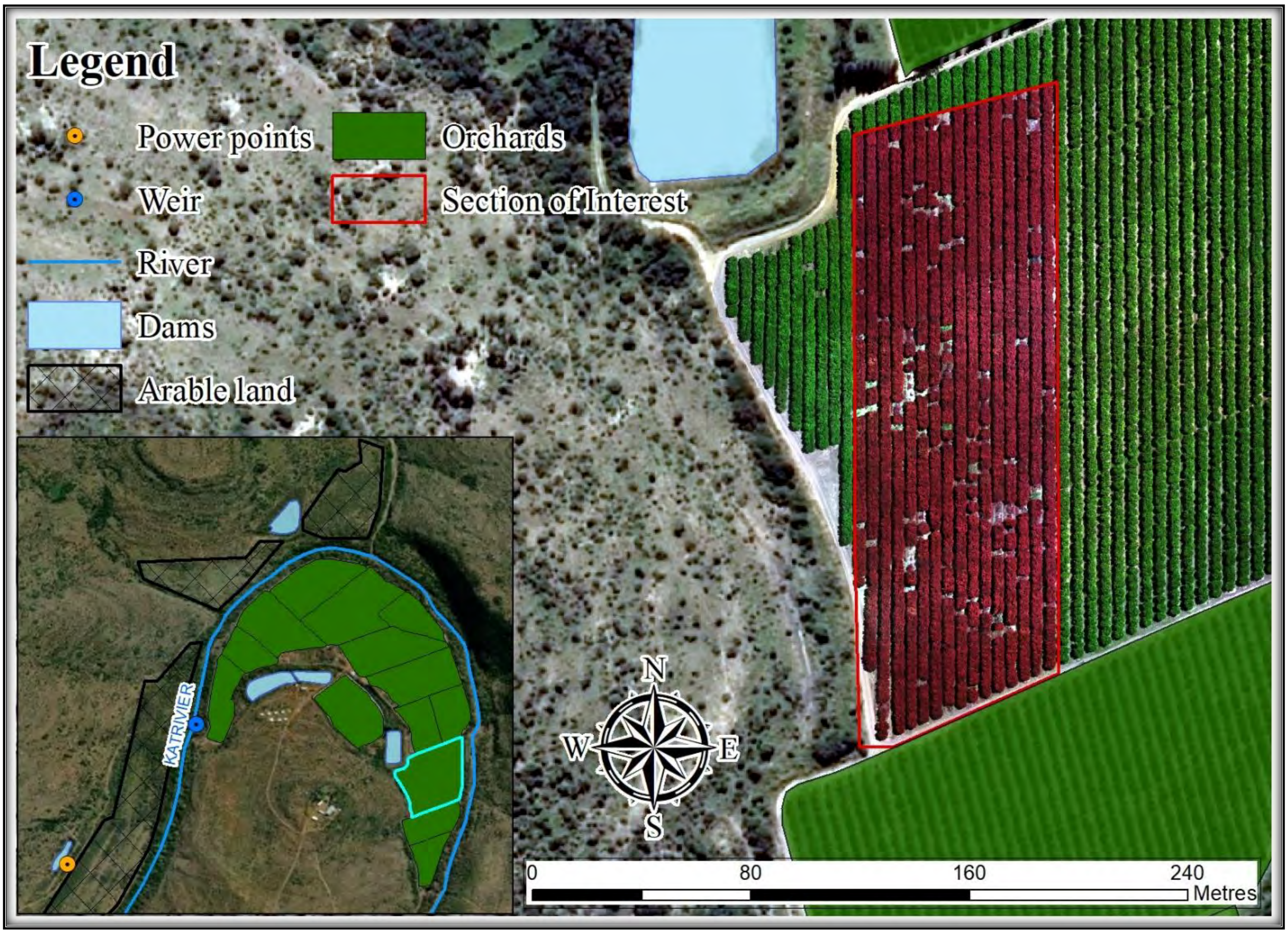


Figure 27: Location of the study site in the Raymond Mhlaba municipality. The citrus lands are located along the Kat River and depend on the Kat River irrigation scheme for irrigation

Figure 27 above shows a map of the citrus farm where this research was conducted. The farm lies in the Southern portion of the Kat River Valley, roughly 15 kilometres south-east of the town of Fort Beaufort. A variety of citrus is grown on this farm including lemons, navels, and mandarins, with the main varieties being navels, clementines and satsumas, on roughly 80 hectares of land. Clementines were the variety under observation in the section of interest shown in Figure 24. The trees in this orchard were planted with a 3.5 metre spacing distance within-row, and 5 metre spacing between-row. This Clementine orchard covers an area of roughly 2 hectares and has a hedgerow structure, where tree canopies overlap.

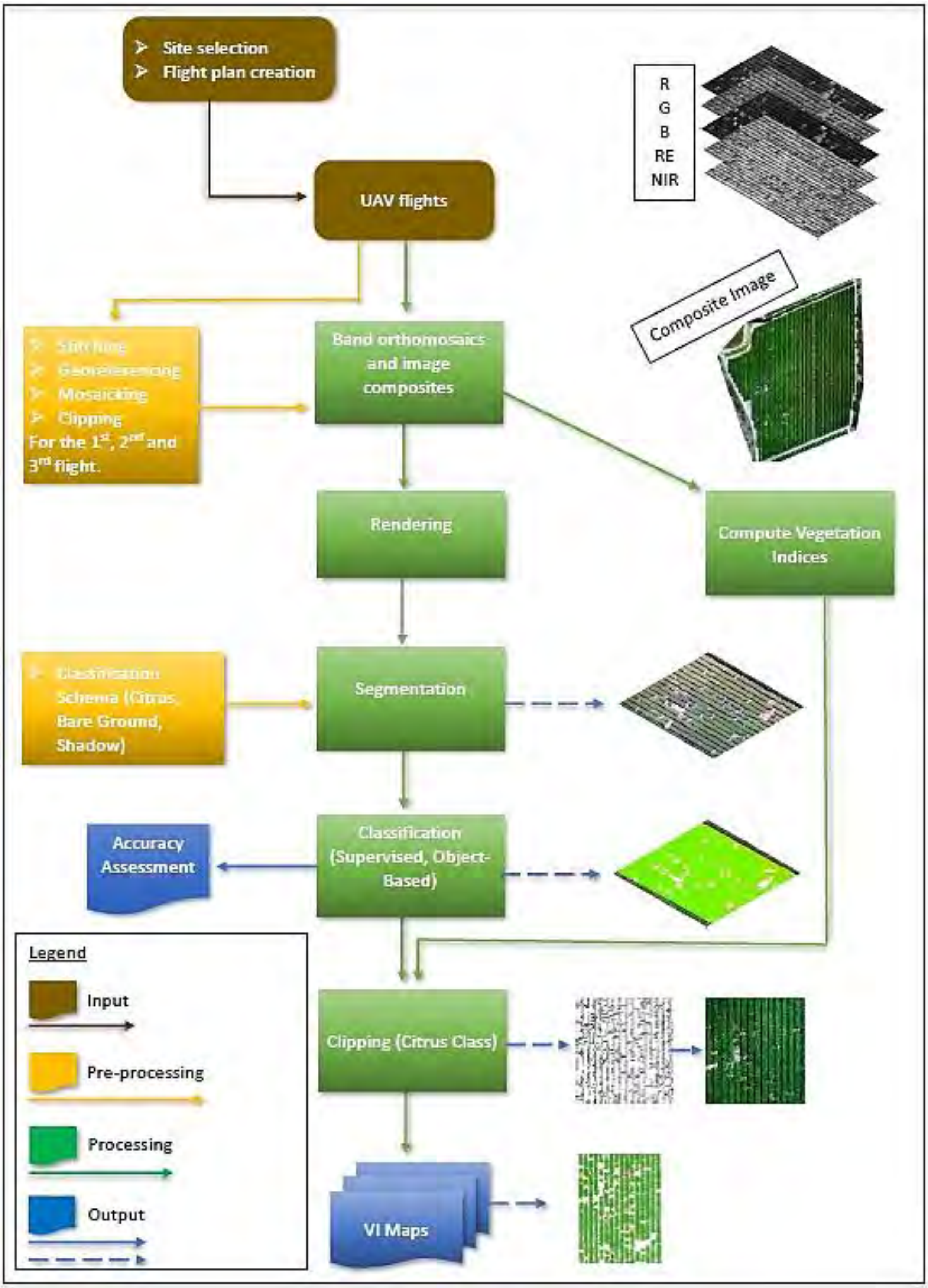


Figure 28: Workflow process for vegetation health monitoring on a citrus farm in the Eastern Cape

4.2.1. Data Collection

The UAV surveys were carried out by a custom built, licensed, and registered multirotor UAV, fitted with the MicaSense Red-Edge MX multispectral camera for data capture, referred to earlier in chapter three. Flight plans were created and executed using Map Pilot and were conducted at a height of 120m, with a 75% front and side overlap. Each of the five spectral bands (red, green, blue, RE and NIR) onboard the multispectral camera produced an individual image tile. The UAV imagery was captured on the 13th of September 2019, the 1st of October 2019, and the 30th of May 2020. The imagery was stitched together using PIX4D Mapper to create multi-band, georeferenced orthomosaics, which were used to compute vegetation indices for the section of interest.

As mentioned in chapter three, all satellite imagery used in this research were provided by third parties. The 8-band multispectral package offering from Maxar contained a coastal, blue, green, yellow, red, red-edge and two infrared bands, as well as an added panchromatic band. The WorldView-3 raster image pre-processing (orthorectification and radiometric correction) was completed by Maxar, using a relatively new technology designed for early tree stress detection through atmospheric compensation (AComp) (Maxar, 2019). Lastly, the 4-band multispectral package offering from Planet, which included a blue, green, red, and infrared bands was used. Due the costs and logistics involved for acquiring commercial satellite imagery, this analysis made use of only one set of satellite imagery per provider. This meant that a time-series analysis and comparison of vigour maps through vegetation indices between the different multispectral image sets was not possible. Analysis of the available imagery allowed for depiction of the progression of stressed or unhealthy plants in the section of interest.

The landowner from the site on which the study was conducted was selected based on willingness to participate via the KATCO (Kat River Citrus Co-Operative) research office and was seen by the KATCO technical manager as a typical citrus farm for the Fort Beaufort area. A semi-structured interview was conducted with the farmer to obtain general information about the farm such as the varieties of citrus being grown, inputs and relative costs, issues being faced on the farm, and perceptions around the topic of PA. The landowner also gave guidance with regards to a *Phytophthora* spp issue facing a particular orchard and recommended it as a suitable study site where anomalies would likely be detected. The responses can be seen in Table 11 in the results section of this chapter.

4.2.2. Data Processing and Analysis

Based on the benchmarked results for UAV and satellite imagery from chapter three, supervised image classification (object-based image analysis) using a machine learning approach - Support Vector Machine (SVM), was applied to perform the analysis of the imagery. Machine learning models (ML) are powerful data driven frameworks that provide generalised, yet accurate solutions to complex relationships between large numbers of variables (Hong Kok *et al*. 2021). SVM is an ML model used for classification and regression analysis that works by deriving an optimal separating hyperplane that separates data into different classes (Hong Kok *et al*. 2021; Shrestha, 2023). The strength of SVM models, particularly in landcover classification lies in their robust ability to classify homogenous and heterogeneous landcover types using a limited amount of training data. However, since SVM models are supervised classifiers, they are susceptible to dimensionality issues, and can potentially lead to noisy and mislabelled data (Hong Kok *et al*. 2021; Shrestha, 2023). The overall success of SVM models depends on how well the process is trained.

The images were firstly ‘clipped’ to the section of interest seen in Figure 27 and were then rendered from 32-bit imagery to 8-bit imagery to allow for ‘segmentation’ of the imagery. The steps that follow were performed in ArcGIS Pro 2.4 using the ‘Image Classification Wizard’. The first step involved the segmentation of the imagery which is the process of grouping neighbouring pixels together based on their similarity, to create objects that are then used in image classification (ESRI, 2023).

Once segmentation was complete, the next step was to create training samples in a ‘classification schema’ to ‘train’ the image classifier. Three different classes were created, namely, ‘citrus’, ‘shadows’ and ‘bare ground’ classes and then digitized based on the segmented imagery (ESRI, 2023). The next step was to ‘train’ the classifier once all the desired samples were selected. The SVM classifier which maps input data vectors into higher dimensional feature space to optimally separate the data into different classes, was used for this step.

Once the classifier was trained, the next step was to classify the image into the three separate ‘citrus’, ‘bare ground’ and ‘shadow’ classes. Upon completion of the classification an accuracy assessment was performed to evaluate the correctness of the classified result (ESRI, 2023). Using the classified image, a ‘raster-to-poly’ function was applied, where all the polygons from the ‘citrus’ class were selected, merged, and used to ‘clip’ the data from the multispectral imagery, to isolate only the vegetation, and 'mask' out the bare-ground and shadows in the imagery. Vegetation indices were then computed on the final image output to make observations on the status of tree health in the section of interest.

Lastly, one-hundred random points were generated using the 'compute confusion matrix' tool in the image classification wizard. The high-resolution 'RGB' imagery was used as the reference dataset for classifying each point in each image dataset, to indicate whether the point fell under an area of 'citrus', 'bare ground' or 'shadow' derived from the classified imagery. The purpose of this was to illustrate the accuracy of the program's classification of the imagery versus the ground truth, giving an overall accuracy of the image classification.

4.3. Results

Table 11 shows a summary of responses given by the farmer to questions raised in a semi-structured interview. In terms of farm inputs, labour is the main and most costly input, followed by chemicals and fertilisers. Different horticultural issues plague different sections of the orchards, the main issues being *Phytophthora* spp, thrips, mealie bug and poor water quality. The farmer is also open to the idea of using PA techniques and technologies to aid in orchard management with the view that these techniques may result in improved yields, effective use of chemicals and improved plant health. The farmer mentioned that any amount of money would be willingly spent to implement PA techniques, if the costs do not outweigh the potential benefits. The presence of thrips and *Phytophthora* spp were noted as part of the initial observations within the section of interest. After conducting the first flight over the orchard in the section of interest, a follow up visit was conducted to demonstrate the initial findings to the farmer. Upon conducting a scouting exercise, the farmer, together with the local agronomist, confirmed that the issue identified through the vegetation analysis presented in Figures 28 and 29, was the effect of *Phytophthora* spp. A few trees had either died or had been removed by the grower, and a number were showing visible signs of stress at differing levels of severity.

Table 10: Citrus farmer interview responses

Citrus type	Area	Inputs	Issues	PA Uptake?	Reason	Amount willing to spend on PA
Nardocotts, Satsumas, Lemons, Navels, Late Navels, Clementines	80ha	Labour, Chemicals, Fertilizer, Diesel, Electricity	Different issues affecting different varieties. phytophthora, thrips, mealie bug and poor water quality	Yes	Improved yield, effective use of pesticides, fertiliser, and improved plant health	Any, if costs do not exceed the benefits, or improvements in input usage and yields.

Table 12 shows a summary of metadata for all three imaging sensors used in this research. The MicaSense Red-Edge MX sensor onboard the UAV used in this research provided imagery with a GSD of 8cm. The WorldView-3 image was a pansharpened, false colour image, with a GSD of 30cm. It has a photochromatic band at 30cm and multispectral bands at 1.24m GSD. The Planetscope image had a GSD of 3m for all four bands. The WorldView-3 and Planetscope satellites have a daily return interval for data collection, while UAV imagery is typically provided as an 'on-demand' service. Based on the figures shown by Sozzi *et* al. (2018) in tables 10 and 11 of chapter three, the WorldView-3 and Planetscope satellites have a minimum order area of 10,000 hectares each, while UAV imagery is typically charged on a per hectare rate. The 8-band WorldView-3 imagery package comes in at the highest cost of ZAR49,500, followed by the Planetscope imagery at ZAR2,000, and the UAV imagery at an average of ZAR350. The two commercial satellite platforms require that users purchase imagery at a minimum order area of 10,000 hectares, hence the higher prices.

Table 11: Metadata comparison between the different imaging sensors used in this research

	MicaSense Red-Edge MX	DigitalGlobe (WorldView-3)	Planetscope
Number of bands	5	8	5
Spectral resolution	475nm to 840nm	375nm to 927nm	431nm to 885nm
Frequency	On-demand	Daily	Daily
Spatial resolution	8cm	1.2m	3m
Minimum order area (Hectares)	1	10,000	10,000
Minimum area costs (ZAR)	350	49,500	2,000

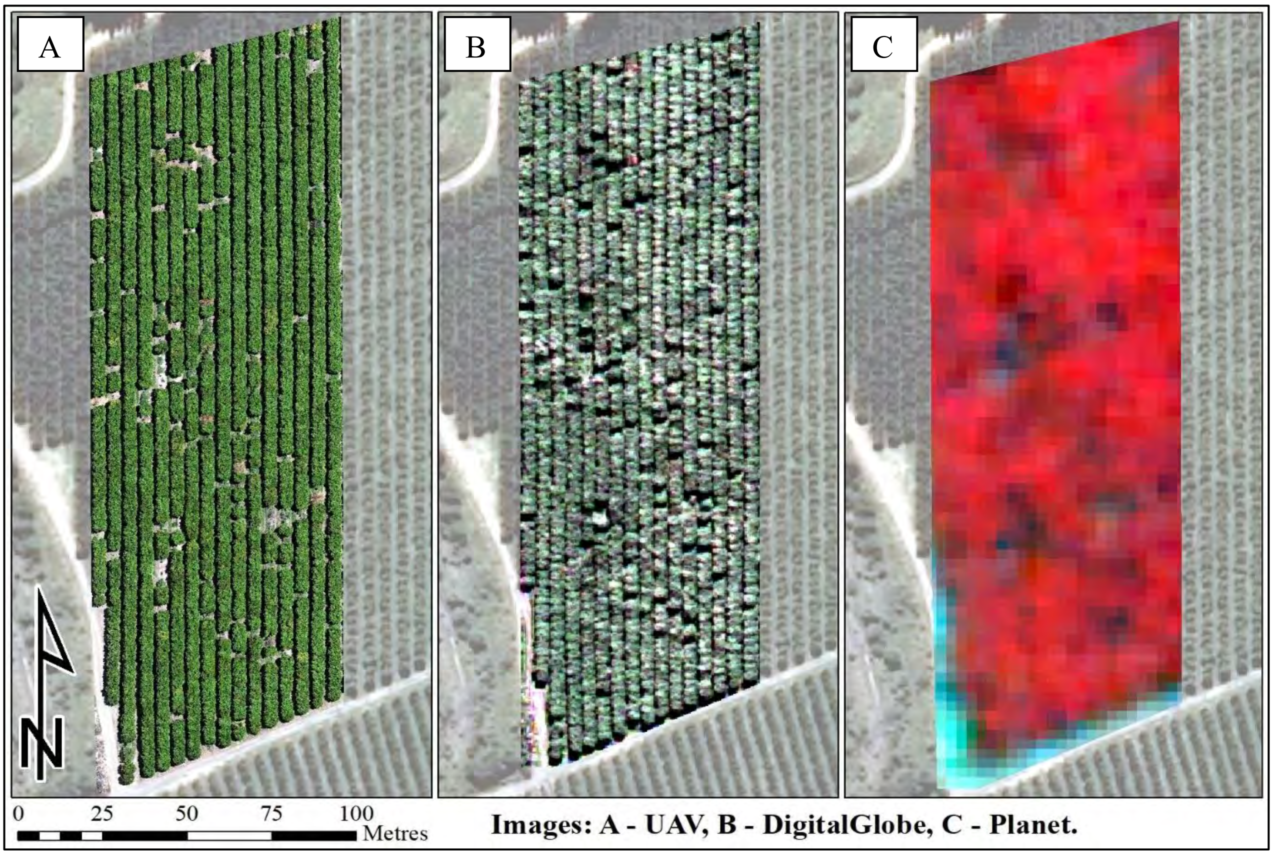


Figure 29: Spatial resolution comparison between the different image sets

Figure 29 shows a side-by-side spatial resolution comparison of the UAV (A), WorldView-3 (B) and Planetscope (C) imagery used in this research. The 3.5m and 5m tree spacing 'between' and 'within' rows respectively, that Figure 25 alluded to imply that the satellite imagery should be able to allow for differentiation between citrus, bare-ground, and shadows. However, the hedgerow structure or overlapping tree canopies of the orchard, made it difficult to differentiate between these three classes in the section of interest. Only the high-resolution UAV imagery proved suitable for more accurate delineation of the citrus hedgerows and extraction of the vegetation indices.

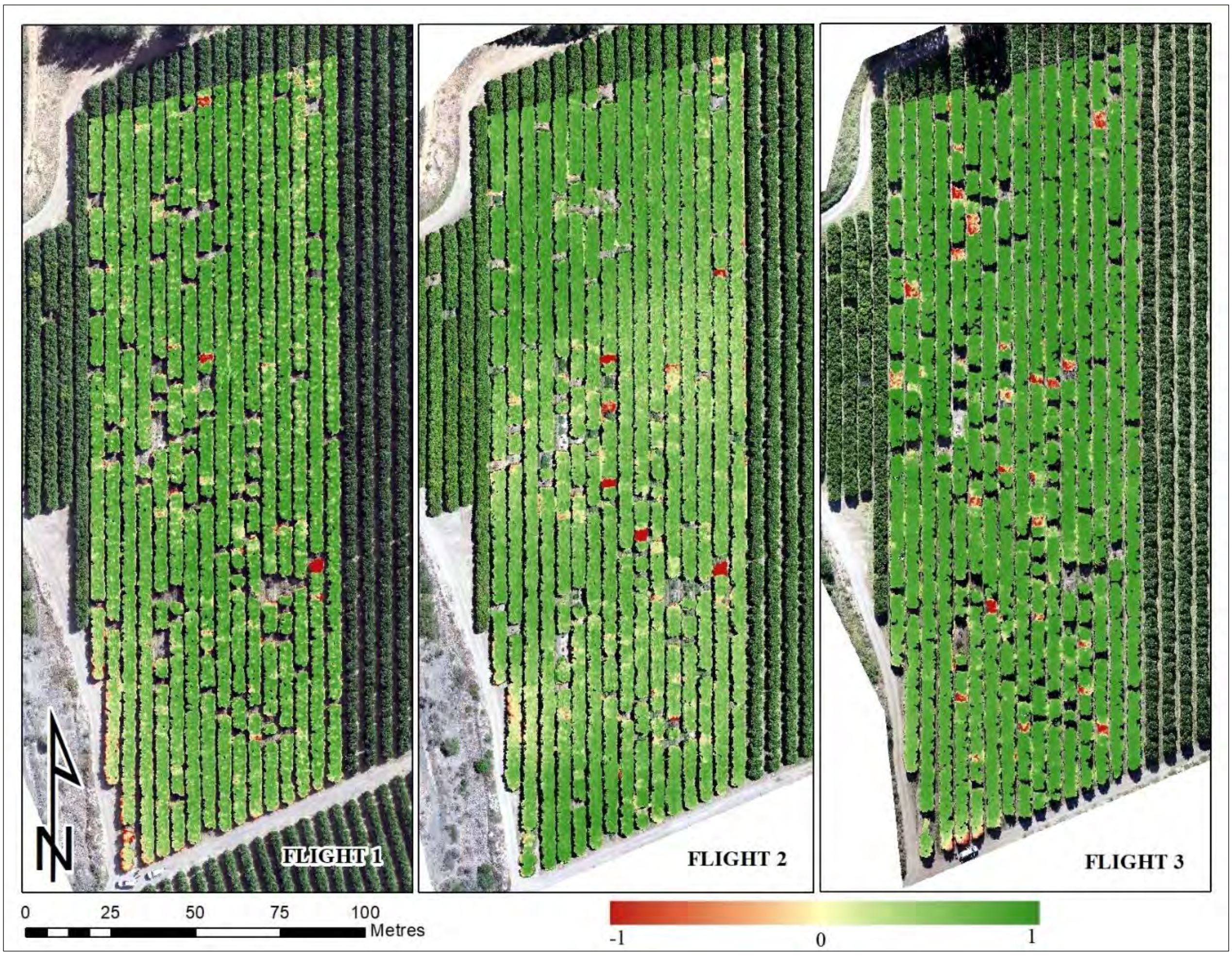


Figure 30: UAV Normalised Difference Vegetation Index Results

Figure 30 above shows the results of the NDVI extracted from the UAV imagery from each flight. The healthy clementine plants have higher NDVI values, closer to 1 and are green in colour, while unhealthy or stressed plants have lower NDVI values, closer to -1 and are yellow to red in colour. There is a clear progression of visibly stressed trees from flight one to flight three indicated by the increasing number of trees with lower NDVI values. Trees with lower NDVI values tend to be concentrated near areas where previously stressed or unhealthy trees were located and have since died or been manually removed by the grower.

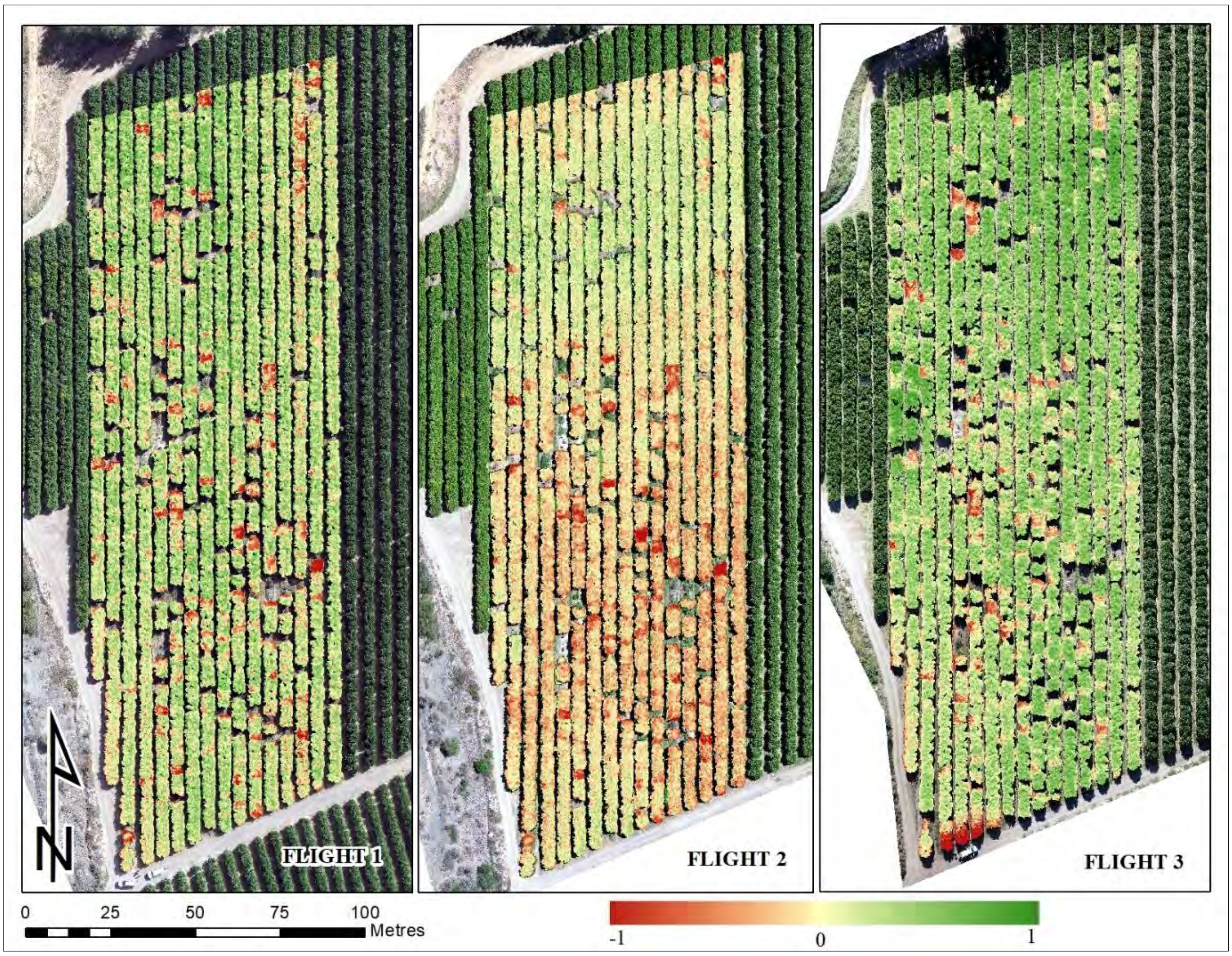


Figure 31: UAV Normalised Difference Red-Edge Index Results

Figure 31 above shows the results of the NDRE extracted from the UAV imagery from each flight. The healthy clementine plants have higher NDRE values, closer to 1 and are green in colour, while unhealthy or stressed plants have lower NDRE values, closer to -1 and are yellow to red in colour. Like the results of the NDVI, there is an increasing number of stressed trees from flight one through to flight three. The results of the NDRE imagery show a greater volume of stressed or unhealthy trees in each set of images versus those of the NDVI sets, which is attributed to the sensitivity of the index to chlorophyll content, as it reflects more RE light than it absorbs, as mentioned in chapter three.

Both sets of UAV imagery were displayed as 'stretched' along the indices with ranging values, as opposed to classified results at 'break points' along each index. This due to the flights being conducted at different times of the day and in different stages of the season, without the use of reflectance panels from the first flight, meaning that each image set in the time series is not radiometrically calibrated to a baseline reflectance level (AgEagle, 2020). Image calibration will be discussed further in the discussion section of this chapter.

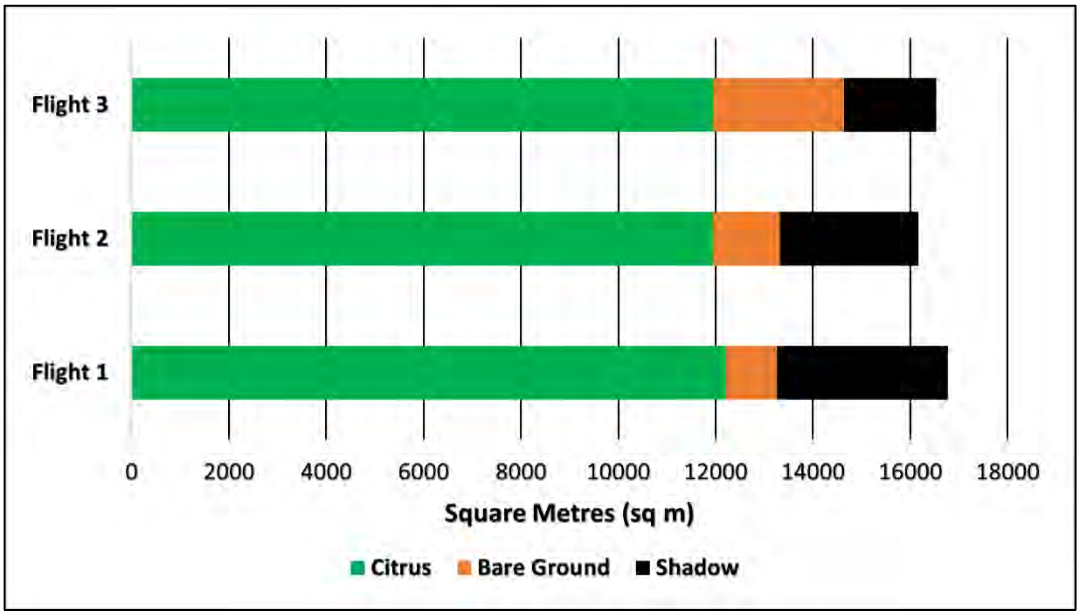


Figure 32: Vector data area derived from the results of image classification

Figure 32 above illustrates the results of the 'raster to poly' function from the classified result of each flight, where the geometry of each class 'citrus', 'bare ground' and 'shadow' was calculated. The general trends shown in the graph above show a decline in the area attributed to citrus from an area of roughly 12200 square metres, to around 11900 square metres from flight one to flight three, and an increase in the 'bare ground' class from roughly 1000 square metres to 2500 square metres. The area attributed to 'shadows' shows a decrease in values from flight one to flight three. This is likely due to the difference in the time of day each flight was conducted, as can be seen in the top sections of either Figure 28 or 29 looking at the shadows cast by nearby trees surrounding the orchard.

Table 13 shows the statistics derived from the accuracy assessment of the UAV image classification. The Kappa coefficient measures the degree of agreement between a pair of variables collected on two different occasions, frequently used as a metric of interrater agreement (Xia, 2020). In this accuracy assessment, the two pairs of variables relate to the program's classification of the imagery and the ground truth data. For the first flight, an overall accuracy of 95% and a Kappa of 89.36% were obtained, followed by 97% overall accuracy and 93.06% Kappa for the second flight, and lastly 99% overall accuracy and 97.84% Kappa for the third flight.

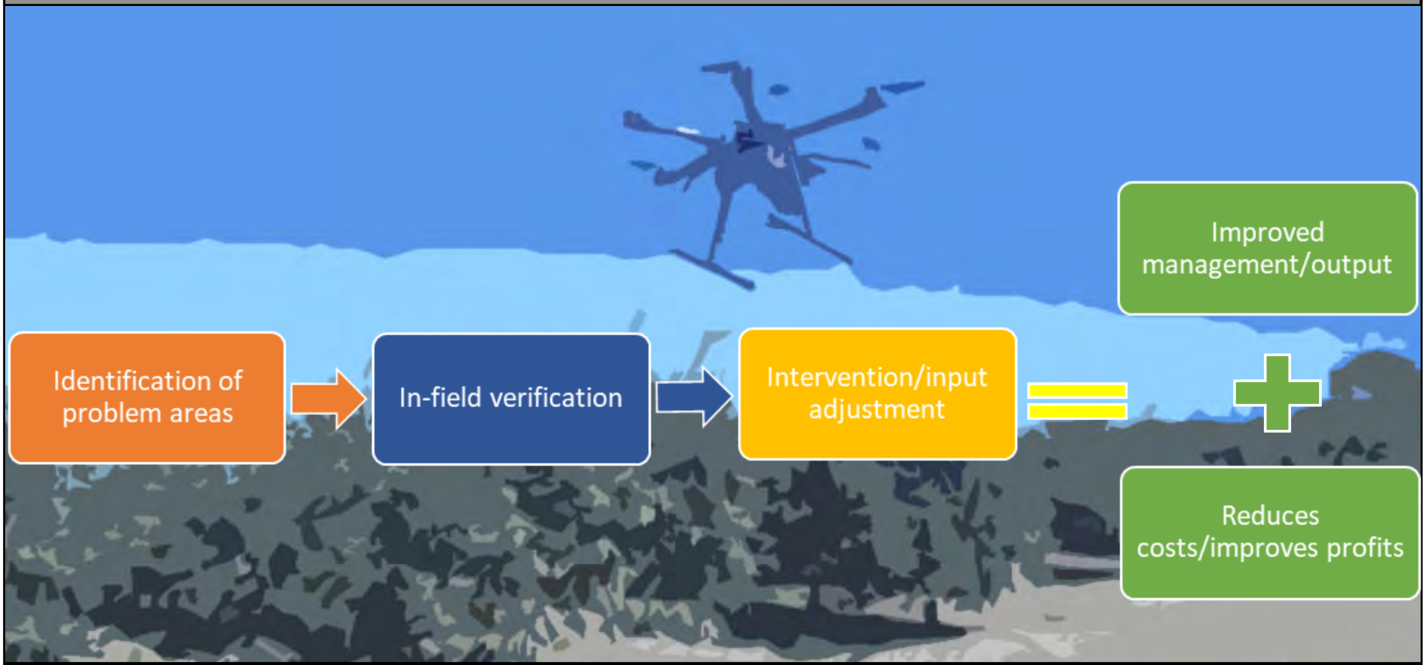
Table 12: Image classification accuracy assessment of the classified UAV imagery versus the reference/ground truth

Classified/Mapped vs. Reference/Ground Truth

Class	Citrus	Bare Ground	Shadow	Total	User Accuracy	Kappa
1st Flight						
Citrus	67	1	2	70	95.71%	0
Bare Ground	0	9	0	9	100.00%	0
Shadow	1	1	19	21	90.48%	0
Total	68	11	21	100	0.00%	0
Program Accuracy	98.53%	81.82%	90.48%	0.00%	95.00%	0
Kappa	0	0	0	0	0	89.36%
2nd Flight						
Citrus	71	0	3	74	95.95%	0
Bare Ground	0	9	0	9	100.00%	0
Shadow	0	0	17	17	100.00%	0
Total	71	9	20	100	0.00%	0
Program Accuracy	100.00%	100.00%	85.00%	0.00%	97.00%	0
Kappa	0	0	0	0	0	93.06%
3rd Flight						
Citrus	70	0	0	70	100.00%	0
Bare Ground	0	17	1	18	94.44%	0
Shadow	0	0	12	12	100.00%	0
Total	70	17	13	100	0.00%	0
Program Accuracy	100.00%	100.00%	92.31%	0.00%	99.00%	0
Kappa	0	0	0	0	0	97.84%

4.4. Discussion

Grower challenges and perceptions: Labour, fertilizer and other chemicals are the costliest inputs. Multiple horticultural issues plaguing the orchards. Open to the idea of implementing PA techniques with the view to improve yield, plant health and effective use of pesticides, if the intended benefits do not outweigh the costs.



Benefits: Early detection of potential issues and early opportunities to address these. Provides an objective approach to scouting that is both timesaving and cost effective.

Limitations: Substantial cost to implement these technologies. The RS approach must account for physiological processes taking place during the growing season. Proper flight planning, georeferencing and image calibration is required for accurate analysis.

Figure 33: Conceptual model of this research: a workflow addressing the combined findings from farmer interviews and the applied remote sensing technique

4.4.1. Interpretation of Results

This research has demonstrated the use of geospatial technologies in PA for the South African citrus industry. The aim of this research was to investigate the use of high and low/medium resolution, multispectral, UAV (Unmanned Aerial Vehicle) imagery and satellite imagery, for PA in the South African citrus industry, and to determine whether the data could be used to detect and assess changes in citrus health. By way of a summary of findings - a conceptual model of the research results is presented in Figure 33. The workflow is derived from the challenges faced by the farmer and how this PA technique can be implemented to alleviate some of these challenges using geospatial technologies.

In table four, chapter two, a list of common diseases in citrus with associated symptoms and control methods is presented, containing information pertaining to *Phytophthora* spp among other diseases prevalent in South African citrus. *Phytophthora* spp is a fungal disease that affects plant parts above and below ground including root systems, leaves, branches, and fruit (Citrus Academy, 2017b). It is prevalent during prolonged periods of rain and affects plants with bud unions below, or close to the soil, as well as where planting takes place in poorly drained soils where anaerobic conditions are more likely to occur. Visible symptoms of *Phytophthora* spp include but are not limited to poor growth, smaller trees, nutrient deficiency, gumming, lower yields, and smaller fruit (Citrus Academy, 2017b).

The high-resolution UAV data allowed for a more accurate delineation of the citrus hedgerows in the section of interest, isolating the vegetation from the soil and ultimately the extraction of vegetation indices. The results from Figures 28 and 29 show a clear progression in the observed number of unhealthy trees, more-so through the results of the NDRE calculation compared to the NDVI results. This observation is further supported by values seen in Figure 30, which depict a decrease in the area attributed to citrus and an increase the area attributed to bare ground from flight one to flight three. The UAV imagery was ultimately successful in picking up the *Phytophthora* spp infestation plaguing the section of interest in this clementine orchard and implies that remotely sensed data can be used to detect changes in citrus health. *Phytophthora* spp is one of the main horticultural issues affecting this farmer's orchards, as seen in table 11, which he has addressed by removing dead or visibly infected trees from orchards when found during scouting activities. The Kappa values from table 13 suggest that the method used to identify the *Phytophthora* spp infestation is robust and reliable and could therefore be applied with some certainty. The farmer has been unable to stem the spread of the pathogen to date, which the farmer believes is likely due to poorly drained soils and poor water quality from the Kat River that runs through the farm, which he depends on for irrigation through the Kat River irrigation scheme (Holtzhousen, 2006).

The same object-based approach was used to analyse the satellite imagery but similar challenges to those of Johansen *et al*. (2020) in segmenting and classifying features from their WorldView-3 satellite imagery, were faced. Given that their approach was to classify individual macadamia tree condition, the delineation of tree crowns was required. Only the high-resolution UAV imagery proved suitable to aid in the semi-automated detection and delineation of tree crowns, and to a certain extent, overcome the difficulty in ascertaining where to separate neighbouring trees within a hedgerow. In this case study, a suitable dataset to use for classifying the satellite imagery into 'citrus', 'shadows' and 'bare ground' classes could not be generated. The GSD of the satellite imagery may have been less than or similar to the 'between' and 'within-row' spacing of the trees in this orchard, but the hedgerow structure of the orchard made it difficult to differentiate between trees, shadows, and bare ground between the rows. The lower resolutions of the WorldView-3 and Planetscope imagery mean that these data are not suited for PA within a single orchard where hedgerows are present. Their use cases are more suited to generalised applications like single crop types covering a larger area (Johansen *et al*. 2020; Delavarpour *et al*. 2021). As mentioned earlier in the results section of this chapter, the presence of thrips and *Phytophthora* spp were observed in the section of interest and attempts were made to score trees with varying levels of stress and apply this to the aerial imagery, similar to the research done by Johansen *et al*. 2020. However, the hedgerow structure of the orchard made it difficult to apply these scores at an individual tree level. Though this research does not focus on individual tree condition assessments, from a PA perspective it would be important to have this level of information, which could allow for immediate action by growers and farm managers in terms of identifying any issues that may be present from an early stage and allow them to perform targeted applications (Johansen *et al*. 2020).

There was a difference of one month between the first and second flight, and six months between the second and third flight. The first flight was conducted at the beginning of flowering and the second flight was conducted when the plants were at the end of flowering. The third flight was conducted during the fruit maturation stage, shortly before harvest. It is important to consider the phenology of citrus, as the physiological processes occurring at these stages can influence the overall condition of citrus trees (Johansen *et al*. 2020). As mentioned earlier in this chapter, lost Filho *et al*. (2020) state that any biotic or abiotic factor that induces a physiological response, affecting a plants ability to photosynthesize, will lead to changes in leaf reflectance, making it a great candidate for remote sensing. Phenology, weather, pests, and diseases are aspects which can affect the spectral characteristics of any crop, as such, it is important to factor in these variables when collecting remotely sensed data in agriculture to aid in the development of effective management programs that maintain orchard productivity (Johansen *et al*. 2020: Jaouad *et al*. 2020).

4.4.2. Implications of Results

Producing food in a cost-effective manner is the goal of every farmer, and for them to be efficient, they need to be informed (Natural Resources Canada, 2016). As mentioned throughout this research, there are multiple use-cases for applying remote sensing techniques in PA (Lillesand *et al.* 2015; Xue and Su, 2017). These include, but are not limited to irrigation water management, soil moisture, nutrient, disease and weed management and crop monitoring. These techniques and technologies provide farmers with insights relating to the health of their crops, soil conditions, potential yield and infestation or stress damage.

The findings of this work support the idea presented by Delavarpour *et al*. (2021) - that remote sensing technologies have the capability to detect horticultural issues at an early stage, providing growers with opportunities to address them before economic thresholds are met. Symptoms of stress typically appear in the infrared range of the electromagnetic spectrum much earlier than the visible range, which is where photosynthetically active radiation can be measured. Many growers and agronomists use traditional ground-based methods and other tools to scout and assess crop growth, pest, disease and weed presence among other agronomic factors, which is repeated at critical stages in a cultivars phenological cycle, sometimes referred to as 'impression surveys' (Delavarpour *et al*. 2021: Citrus Academy, 2017b). These methods are often tedious, time consuming, destructive, expensive, and may lead to certain areas being neglected. A driving factor behind implementing remote sensing technologies in agriculture, is the time that can potentially be saved through the automation of crop monitoring, making the technology cost effective, objective, and practical for growers (lost Filho *et al*. 2020).

Numerous geospatial technologies are readily available and are certainly in use, but for both satellite and UAV imagery in particular, the cost to implement these technologies is still quite substantial (Sozzi *et al.* 2018). In chapter three, tables 10 and 11 refer to the characteristics and costings for different commercial and open-access satellite imaging platforms. The benchmarked price for satellite imagery is USD$30 per hectare according to Sozzi *et al*. (2018) based on the predicted advantages the imagery could offer from a PA point of view. The break-even point for high-resolution imagery, is 17 hectares, and an average of 420 hectares for low resolution imagery. In terms of UAV imagery, using local examples, the average cost per hectare stands at roughly ZAR350 per hectare for commercial, UAV-based surveying and crop spraying, excluding accommodation and travel. The cost of undertaking the UAV data collection for this research amounted to ZAR5500 per flight. The service provider typically works on a sliding scale in terms of pricing, and although the surveyed area for this research was relatively small, they would have been able to fly 100 hectares for the same amount. A grower's main consideration should be spatial resolution when choosing an imaging platform from which to obtain good quality data, while bearing in mind other factors such as price, satellite revisit times, minimum order area and download and analysis costs (Sozzi *et al.* 2018).

4.4.3. Limitations

There were two notable limitations that arose during the data collection stage of this research. Firstly, the chosen dates for flights could have been spread out more, to coincide with the different stages in the clementine orchards phenological cycle. This would have provided an improved means for observing the different physiological processes, as well as detecting stress at each phenological stage via remote sensing. Secondly, optimal flight planning and timing could have allowed for better training of the image classifier. In Figures 28 and 29, there is variability in terms of the shadows present. Each flight was performed at different times of the day, as well as in different seasons. Johansen *et al*. (2020) mention that, for large areas, using a fixed-wing UAV to collect data as close as possible to solar noon, and by covering an area as quickly as possible, could help to avoid this issue.

Growers who would want to conduct their own UAV surveys would need to apply for an ROC, purchase and register their aircraft, apply for RLA's for each craft through the South African Civil Aviation Authority (SACAA). They would also need to obtain an RPL. All these requirements come at a significant cost (Jupp, 2018). Aside from regulatory compliance being a limitation, other limitations would be investing in the various technologies used for PA, including UAV's, sensors, and processing software. It is worth noting that it also takes a considerable amount of time and expertise to plan UAV missions, fly the UAV and to download, process and analyse the data collected. From start to finish this process can take someone with the technical expertise about two days to conduct, which would certainly prove to be a limitation to most growers wanting to implement their own surveys (Modica *et al*. 2020).

Given that this research required the services of a UAV, the budget only allowed for assessment of one orchard to demonstrate the principles of the approach, with the intention that its suitability for use on different orchards, on different farms, would be determined. Purposive sampling was used to get results with some certainty and to maximise the time available from the UAV pilot and his equipment. This was the extent of the sampled research that could be obtained considering the budget and logistical constraints, not to mention the restrictions imposed by COVID during data collection. However, the small sample size remains a limitation to this research.

4.5. Conclusion

Chapter four presents the results of applying selected remote sensing techniques to mapping and classifying a citrus farm in the Eastern Cape. It aided the identification of issues present in this section of interest, namely *Phytophthora* spp. The vegetation index data derived from the high-resolution UAV imagery show a clear progression in the observed number of unhealthy trees from flight one to flight three, more-so through the results of the NDRE calculation compared to the NDVI results. Cost-effective agricultural production is the goal of every farmer, and for them to be efficient, they need to be informed (Natural Resources Canada, 2016). A driving factor behind implementing remote sensing technologies in agriculture, is the time that can potentially be saved through the automation of crop monitoring, making the technology cost effective, objective, and practical for growers (lost Filho et al. 2020). There are many geospatial technologies for PA, readily available and in use, but for both satellite and UAV imagery in particular, the cost to implement these technologies is still quite substantial (Sozzi *et al.* 2018). There is much to consider in terms of adjusting flight timing and data capture at optimal stages along a cultivars phenological cycle. Other considerations include geometric and radiometric calibrations to the UAV imagery for greater spectral and spatial accuracy (Modica *et al*. 2020: Johansen *et al*. 2020). Guidelines for applying geospatial technologies in PA will be discussed in the fifth and final chapter.

CHAPTER V: GUIDELINES FOR APPLYING GEOSPATIAL TECHNOLOGIES IN PRECISION AGRICULTURE TO CITRUS CULTIVATION

5.1. Introduction

Agriculture is an engine of growth for most developed and developing nations, providing humankinds most basic needs (Sishodia *et al*. 2020). Technological advancements, particularly through the Green Revolution period, have allowed for improved crop productivity and food security, particularly for developing countries. Since the 1960's, the global population has doubled, and food demand has tripled, and global agricultural production has managed to meet these demands with a mere 30% increase in cultivated area (Sishodia *et al*. 2020). The demand for food and other agricultural products is forecast to increase more than 70% by the year 2050. Intensified agricultural production through the increased use of pesticides, fertilizers and water would likely play a role in meeting this increased demand, given the limited availability of arable land (Sishodia *et al*. 2020). The intensified, and often excessive and inefficient use of these inputs, including natural resources, can cause environmental degradation and economic losses. For an agricultural production system to be economically and environmentally sustainable, techniques must be developed that enable increased production while increasing input use efficiency and reduction of environmental losses. Precision Agriculture is a management strategy that enhances crop production and reduces nutrient losses and environmental impacts through improved application of water, pesticide, fertilizer, and other inputs (Sishodia *et al*. 2020).

Agriculture can be seen as going through a fourth revolution that encompasses advances in information and communication technologies, as well as emerging technologies such as remote sensing, artificial intelligence, global positioning systems and geographic information systems that aid the optimisation of agricultural operations (Sishodia *et al*. 2020). Remote sensing systems, coupled with information technologies generate large quantities of spectral data that are processed through emerging data processing techniques such as artificial intelligence and machine learning. These geospatial technologies form part of PA and aid in agricultural decision-making processes (Sishodia *et al*. 2020). Based on the experience of using UAVs in this research - this chapter will put forward guidelines for applying geospatial technologies in PA at farm level, focusing on the inputs and variables of significance that need to be considered when it comes to obtaining good quality, actionable, remotely sensed data for citrus growers, as well as the types of insights a grower would obtain from the output generated.

5.1.1. Addressing farm management issues through remote sensing

The population of South Africa is forecast to increase to eighty-two million people by the year 2035, and the World Wide Fund for Nature predicts that food production, or imports, will need to more than double if it is to feed its growing population (Jupp, 2018). Farmers play a critical role in, driving trade and employment, feeding nations, supporting industrial growth, and contributing to a country's gross domestic product. Farming, however, remains a business and requires farmers to maintain steady incomes to provide for their families, maintain a profitable business and to pass on their successful businesses to future generations, all while navigating a multitude of global variables such as global markets, climate change, environmentally aware consumers, and the conservation of natural resources (Jupp, 2018).

Growers are continuously in search of anything that may provide them with the 'edge' or an advantage to overcoming some of these challenges. Some growers have achieved this 'edge' through obtaining high grade information about their lands or crops and have realised the potential that commercial UAVs have to offer their businesses. Some however, have not, and are often vulnerable to issues that they perceive to be out of their immediate control. They often lack viable strategies to tackle issues as a season progresses and end up spending valuable time on mundane tasks (Jupp, 2018). Some growers perceive UAVs to be toys, used largely for recreational purposes. This perception is rapidly changing due to technological advances in the UAV space where the services being offered by highly sophisticated and technological, commercial platforms, are being realised. Commercial UAVs are becoming indispensable management tools, with the value of global commercial UAV services standing at around USD$32 billion in agriculture alone.

Many successful growers are currently making use of PA techniques and technologies including GPS guided tractors, yield monitors onboard combine harvesters, chemical applicators, and commercial UAV surveys (Jupp, 2018). Unmanned Aerial Vehicles provide high resolution imagery that surpasses that of most other available aerial platforms while being more affordable, versatile, and safer to obtain. The information obtained from UAVs provides growers with opportunities to immediately mitigate against the unpredictable and has transformed a traditionally 'data-poor' industry into one where growers can make analytical, rather than intuitive decisions based on real-time, high-quality data (Jupp, 2018).

According to Jupp (2018) farmers typically face three core problems. These are, lack of timeous and accurate information about their crops and soils, insufficient time for productive tasks, and inefficient farm management practices. Traditional ways of crop monitoring and managing farm productivity often involve walking or driving around fields, a time intensive exercise that usually only represents a fraction of the total cultivated area and does not allow sufficient time for farmers to react to various issues (Jupp, 2018). Prior to UAV surveys being commercially available, growers made use of satellites or aircraft for more effective area-wide surveys. The information derived from these platforms, however, are usually slow in terms of data returns, costly, can be affected by weather, and typically only suit larger farm operations due to the field of view and spatial resolution (Jupp, 2018; Sozzi *et al*. 2018). Until recently, the quantity and quality of data being collected at farm and field level on the state of crops and soils meant that growers would be routinely vulnerable to a myriad of both local and global issues.

These three core issues often have a cumulative effect that exposes growers to high levels of bankruptcy risks where lower levels of income are had due to poor harvests over a single season, or number of seasons. Many growers implementing traditional farming methods remain financially constrained, even when good harvests are had, and have limited options to take on new financial demands, leading to resistance to new changes and approaches to farming (Jupp, 2018). Precision agriculture, particularly that of commercial, UAV based PA, provides growers with solutions to these three core problems in the form of high quality, near real-time data, and provides access and benefits from technology driven agriculture to growers at all levels.

5.2. Guidelines for implementing geospatial technologies.

Precision Agriculture is a management approach that seeks a better balance between the reliance on traditional approaches and technologically intensive systems to farm management strategies (Srinivasan, 2006). It should not be seen as a prescriptive technology. Srinivasan (2006) refers to three critical criteria required for the successful implementation of PA. These are, visibly significant spatial and temporal, soil and crop condition variability, the identification and quantification of these variables, and the ability to adjust and effectively distribute inputs to improve productivity, profitability and minimise environmental degradation. Developing cost-effective methods to acquire the above information, developing site or field specific recommendations, data collection and analysis tools and appropriate scales for measurement and analysis, form part of the pre-requisites for implementing PA (Srinivasan, 2006). The guidelines for implementing geospatial technologies that follow, were derived from information obtained from the previous chapters, particularly that of the workflow process for vegetation health monitoring (Figure 26) and the conceptual model (Figure 31) of this research, that inform or illustrate each stage of the model.

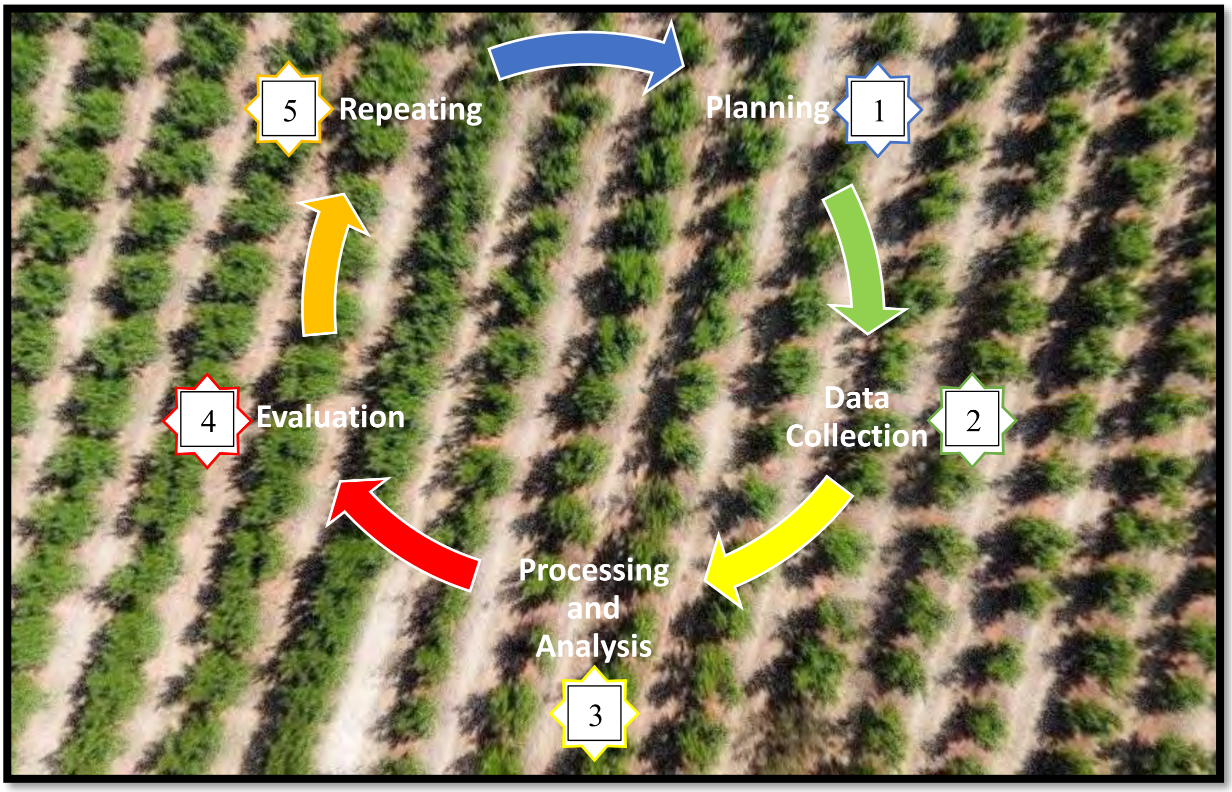


Figure 34: The cycle of adopting precision agriculture through geospatial technologies at farm level

Figure 34 above illustrates a five-step process for implementing geospatial technologies, more specifically, remote sensing techniques at farm level to enhance data driven farm management strategies. Planning is the first step of this process, and it involves determining what data to collect, why it should be collected, where, and when it should be collected. In this research, planning related to site selection through the identification of problem areas – that being the orchard that showed signs of stress as pointed out by the farmer. This informed the spatial extent, choice of aerial imagery, and type of sensors/platforms to be used, as well as the choice of VI's required to extract actionable data to help inform the *Phytophthora* spp infestation plaguing the orchard. From a point of view on executing UAV based data collection – this stage also informs flight plan creation and includes other aspects such as flight operations manual requests (FOM), equipment, safety, and weather checks, as they pertain to local regulations around commercial UAV flights. A farmer's knowledge of their cultivated environments, and experience they have in determining the likelihood of certain issues arising throughout a growing season are also essential to the planning and evaluation stages of these guidelines.

The second step is to deploy the desired platform to collect the data required to gain insights on a particular metric or application. This could include pest or disease identification and pressure, elevation, stand counts or a yield estimation, to name a few examples. In this research, this step related to the execution of the UAV flights and requesting tasks for deployment for the two satellite platforms, to obtain the required imagery.

Steps three and four involve processing and analysing the data collected at step two, that would allow for the extraction and reporting of relevant and meaningful data to inform decision making. Data processing requires a minimum of one working day, with one or two people that are skilled in geomatics and image processing to collect, extract, process, and report on this data (Modica *et al*. 2020). The pre-processing and processing phases used this research, depicted in Figure 26, illustrate the type of processes that take place at this stage including aspects such as the derivation of multi-band image composites, rendering, segmentation, image classification, and computing the outputs required for reporting and evaluation, such as the VI maps and accuracy assessment. The reports provided in the evaluation stage may typically be in written form, and usually contain visual interpretations or observations, annotated or prescription maps, statistics and figures on various metrics, and recommendations that provide growers with the necessary insights to help guide them in their decisions for remedying any issues that are noted (Jupp, 2018).

The fifth and final step is repeating, a stage that can often be overlooked, but can be critical for optimising short to long term improvements in farm management. By collecting multiple sets of data over the same areas, not only over a single season, but multiple seasons, can reveal patterns or variations when compared, allowing growers to measure performance over time, and make informed decisions for the following season (Jupp, 2018). Considering this research, the three UAV flights repeatedly performed over the section of interest aided in the identification and clear progression of the *Phytophthora* spp infestation plaguing this orchard over the duration the UAV flights were performed, thereby illustrating the benefits of repeated data collection. The types of insights a grower can obtain through output generated from remote sensing, and the important considerations such as data acquisition and suitability, that should be factored into each of the steps mentioned above, will be discussed further below.

5.2.1. Insights and important considerations when implementing remote sensing techniques.

5.2.1.1. Insights

The true value of the data that can be collected, particularly from that of UAVs, comes from the specialist imaging sensors that can be mounted onboard these aircraft. These range from standard cameras to multispectral, thermal, light detection and ranging (LiDAR), and hyperspectral sensors (Jupp, 2018). These sensors differ in terms of the spatial, spectral, radiometric, and temporal resolutions they offer (Sishodia *et al.* 2020). Several commercial satellites also offer high spatial and temporal resolutions and provide important metrics for PA purposes, such as soil moisture, soil organic carbon, leaf area index (LAI), groundwater and rainfall. However, due to their lower spatio-temporal resolution, satellite products are often insufficient for some PA applications as they lack the centimetre scale information required for field level PA applications (Sishodia *et al.* 2020).

In terms of PA, multispectral sensors feature more prominently, and they provide a wide range of VI. Providing growers with maps of these indices aids them in understanding spatio-temporal crop condition variability, within and between their fields. Having this understanding could allow growers, for example, to achieve uniform growth and yields through variable rate application of pesticides and water for irrigation derived from VI in the form of prescription maps. Access to high-level information like this, would allow growers to be more informed, and could help alleviate some of the pressures they face which stems from the three core problems mentioned earlier in this chapter. Some of the more common VI used in PA include:

- NDVI
- NDRE
- LAI
- SAVI (soil adjusted vegetation index)
- GNDVI (green NDVI)
- ARVI (atmospherically resistant vegetation index)
- WDRVI (wide dynamic range vegetation index)
- CVI (chlorophyll vegetation index)

The applications that these VI can be applied to include phenotyping, irrigation water management, water stress, soil moisture, crop management, yield estimation, and nutrient, weed, and disease management and mapping (Sishodia *et al.* 2020). In this research, NDVI and

NDRE were the two vegetation indices used to help identify any stress present in the clementine orchard. Both indices are used as a means of estimating plant biomass and vigour, with the NDRE being a slightly better indicator of this, as light in the 'red-edge' wavelength is more sensitive to medium-high levels of chlorophyll content than light in the 'red' wavelength, used in the NDVI equation (MicaSense, 2022). For this reason, the NDRE gave a better indication and earlier detection of stressed trees from one flight to the next, which subsequently became visible in the NDVI image sets in flights that followed.

5.2.1.2. Considerations:

There are several important considerations to make when acquiring remotely sensed data as well as the suitability of the data for certain applications, some of which were derived from the limitations noted in chapter four of this research. These include factors such as crop phenology and the time of day, and season for data collection for a given crop (Modica *et al.* 2020; Johannsen *et al*. 2020), such as assessing germination shortly after planting, or estimating yields shortly before harvesting (Jupp, 2018). A follow up to crop phenology and flight timing would be to factor in the spectral characteristics of different citrus cultivars at different phenological stages, as a variety of biotic and abiotic factors, such as weather, pests and diseases affect plant physiological processes, and lead to changes in leaf reflectance and photosynthesis (Johansen *et al.* 2020; Jaouad *et al.* 2020). It is also important to note that crop phenology may also change over time in response to management practices which may cause differences in phenotypes at local spatial scales (Johansen *et al.* 2020) Another factor to consider is that of spatio-temporal resolution, as the appropriate scale for this depends on aspects such as field size, management objectives and equipment application rates (Sishodia *et al.* 2020).

The decision to use a particular VI, or combinations thereof, is another important consideration, as some VI are better suited to certain metrics or applications than others. For example, NDRE typically performs better than NDVI at estimating nutrient status, biomass, and LAI at later growth stages (MicaSense, 2017; Sishodia *et al*. 2020). Given the wide array of composites and indices that can be derived from different imaging sensors, a final selection on what type of data should be collected will depend largely on the time of day, the season, survey timing, the target crop and how they have been planted (Jupp, 2018). This is due to the sensitivity of these datasets to these factors and the algorithms used to derive them.

Vegetation indices are not wholly prescriptive, that is, they do not pinpoint the exact type of pest or disease present in a field (Jupp, 2018). Verification by physical inspection must still occur to make the necessary recommendations required to address them. Though these indices do not pinpoint an exact issue alone, they remain a powerful tool, and repeated data collection flights over a season, or multiple seasons, will likely highlight certain trends, allowing growers to be even more informed on a variety of observations that may be taking place (Jupp, 2018).

Information pertaining to certain costs for implementing remote sensing techniques as well as other available applications for PA were presented in chapter's three and four and provide growers with several considerations to factor into their given choice of aerial platform. For growers who would not be willing to make use remote sensing techniques and technologies for PA, or may find them cost prohibitive, there are other useful alternatives to make use of that would allow them to implement simple yet effective means for farm management. Aeroview and FieldMargin were two alternatives mentioned in chapter three, that provide growers with added benefits and means of implementing PA techniques. Both applications provide means for mobile-based data collection, farm digitisation, task creation and sharing, and report generation. These applications essentially provide growers with useful ways to better manage their time and resources on their farms (Rubin, 2019; FieldMargin, n.d.). In terms of imagery, the Aeroview platform provides free access to Sentinel-2 satellite imagery and allows for tasking UAV imagery on-demand under their 'paid' service options at ZAR600 per hectare. FieldMargin at ZAR360 per month also provides growers with access to field health metrics via Sentinel-2 satellite imagery.

Spatial resolution should be a grower's main consideration when choosing imagery from the platforms available but would also need to decide if the intended benefits of acquiring either UAV or satellite imagery for PA would not outweigh the costs, not only concentrating on the cost of acquiring the data, but the cost of various farming inputs as seen in table 12 of chapter four. Though the satellite imagery may not have proved useful in this research, it still able to provide many actionable insights in agricultural practices, albeit at smaller scales (larger area) (Delavarpour *et al*. 2020).

The section of interest in this research was very small, which lent itself to a UAV assessment and allowed for adequate manual georeferencing of the UAV imagery. Another important consideration for conducting UAV surveys over larger areas would be to include the use of GCP's (ground control points) and calibrated reflectance panels (CRPS's) as they provide the grounds for improved repeatability of flights and processing thereof (Modica *et al*. 2020). Ground control points are physical points 'on the ground', with known coordinates, that are used specifically for geo-referencing aerial imagery (Johansen *et al*. 2020). For higher accuracy of GCP's a differential GPS should be used. However, it should be noted that this can be a complicated task and comes at a substantial extra cost (Modica *et al*. 2020).

Radiometric calibration panels are mostly used in conjunction with UAV imagery and are used to convert the imagery from digital numbers (DN) to at-surface reflectance. Digital numbers are the numerical values of individual image pixels that contain the record of electromagnetic energy intensity (AgEagle. 2020). In the absence of calibration, each pixel's value is relative to the condition it was captured in and is therefore not absolute. This is due to changes in light conditions, not only over the duration of a growing season, but during a flight as well. When detecting changes in canopy reflectance at different stages of a growing season, it is important to calibrate the imagery being used, as changes to lighting conditions can impact the detection of subtle changes in vegetation from flight to flight like pest, disease, and nutrient deficiencies, and therefore the accuracy of pixel values (AgEagle. 2020).

Should a grower's personal circumstance allow, one may decide to conduct UAV surveys themselves. This is not insurmountable, as many UAV and software providers are directly targeting farmers with their agriculture specific products (Jupp, 2018). Aside from the significant capital investment required to purchase UAV's, sensors, and software, they would need to contend with stringent local aviation regulations that may deter from their core business (Jupp, 2018). Stages three and four of the guidelines mentioned above can be a bottleneck in some respects for growers to take on themselves. Essentially, the determining factor will be if growers will solve their key issues and can reap the full benefits of UAV based surveys for PA, by going this route (Jupp, 2018). There are several local specialist companies that offer various types of services using UAVs that not only already have all these requirements in place, but have the technical knowhow to process, analyse and interpret this information, thus placing greater emphasis on making use of commercial UAV surveys instead. Making use of commercial UAV surveys does not eliminate the need for growers to make in-field assessments, but it allows them to be more productive, particularly with their time, by not having to traverse entire orchards as the data derived through UAV surveys will pinpoint problem areas for them (Jupp, 2018).

The level of detail really needed to help a farmer is only available from UAV based surveys, at a cost of roughly ZAR350 per hectare. The price point, higher resolution, and the 'on-demand' tasking for UAV imagery provide a good rationale for growers to implement these technologies, particularly on small-medium orchards. Other applications, like FieldMargin are more suited to the day-to-day tasks required to manage a farming operation. This research demonstrates that UAV based remote sensing techniques and technologies for use in PA practices, have the capability to identify horticultural issues in a citrus orchard, and by being informed through this technique - allows farmers to spend their time more productively, and focused on their farms, by not having to physically traverse their lands in search of problem areas, and to make timely, strategic, and cost-effective decisions (Jupp, 2018).

5.3. Recommendations for Future Research

Despite the increasing amount of new geospatial technologies available to farmers for PA, there are still several challenges and factors preventing widespread use of these technologies (Delavarpour *et al.* 2021). A major factor affecting this adoption is the derivation of meaningful and actionable insights from the complex data collected by the various remote sensing platforms, particularly for non-expert users. It also requires investment in terms of time, money, and interest in learning new skills. Clarity on the economic benefits of implementing geospatial technologies in PA are also required before adoption of these can take place (Delavarpour *et al.* 2021). Socioeconomic characteristics, physical farm attributes such as location, variable soil types and productivity, understanding and calculating the potential benefits from PA, data complexity and interpretation, a steep learning curve and the initial financial investment required, are also some of the technical factors that affect adoption of geospatial technology in PA. Additional efforts through the form of research, development and validation are required to make these technologies more available and user friendly, for different end users growing different crops. Particularly for UAVs, a fully automated pipeline that is simple yet reliable, and includes aspects such as flight preparation, flight execution and data processing with interpretation, is a further gap that requires further research in this field (Delavarpour *et al.* 2021; Sishodia *et al.* 2020).

In terms of the challenges faced in this research, particularly that of delineating individual tree crowns in the section of interest, an automated method to perform this would be beneficial, as well as examining the robustness of other deep, and machine learning techniques in response to various types of training data (Johansen *et al.* 2020). To acquire optimal UAV data, remotely sensed imagery must be atmospheric, geometric, and radiometrically corrected to ensure its accuracy and reliability (Delavarpour *et al*. 2021). For example, when measuring aspects such as stress detection using vegetation indices, change detection methods and time series analyses require absolute canopy reflectance values be derived, which takes place through comprehensive testing, calibration, and processing methods. In chapter three, UAV and satellite imagery were deemed to be complementary, rather than opposing sources of information for farmers, as they are used in similar ways (Micasense, 2020c). One area of future research that alludes to this, would be the use of historical satellite imagery, coupled with real time UAV imagery and other auxiliary data such as soil and weather data, to identify management zones within and between fields where inputs from PA can be implemented (Sishodia *et* al. 2020; Mulla, 2012).

The satellite imagery spaced has transformed in recent years, with improvements in quality and accessibility in many different sectors, yet analysts still grapple with access and interpretation issues even with the highest resolution imagery available (Cornebise *et* al. 2022; Buczkowski, 2023). "Even setting cost aside, and assuming, as some hope, that the thunderous technological advances in launch technologies unlock a deluge of high-resolution imagery at a smaller price point, the key material for Machine Learning is still simply not there: carefully curated datasets to train on!" (Cornebise *et* al. 2022). Super resolution satellite imagery (SR), derived through algorithmic means, aims to increase image quality, without technically enhancing the actual image resolution (Buczkowski, 2023; Muller *et al*. 2020). It essentially upscales low resolution imagery to high resolution imagery by deriving more pixels in an image without changing the GSD from the original (low resolution) image (Buczkowski, 2023). Super resolution imagery is enabling different sectors to apply this cost-effective machine learning technique in many different applications such as ecology, urban planning and agriculture using more historically accessible satellite imagery. Though this technology has seemingly endless benefits, there are several challenges that still need to be overcome, such as processing power and data storage costs, and the ethical and legal considerations that stem from privacy concerns and data usage restrictions (Buczkowski, 2023).

Modern remote sensing systems conduct frequent data collection often leading to issues around the efficiency of transmission, storage, and dissemination of imagery (Makarichev *et al*. 2022). This remains a major challenge for individual users and companies working with vast quantities of remotely sensed data. Lossless and lossy compression are the two methods used to aid in data size reduction of remotely sensed imagery among other data types (Makarichev *et al*. 2022). Near lossless methods for data compression typically produce undistorted data after decompression which aids image classification as any distortions that arise are controlled or restricted, but the compression ratio is often insufficient for data size reduction. Lossy compression, however, can produce much greater compression ratios but introduces greater distortion in decompressed imagery (Makarichev *et al*. 2022). One might question what a reasonable trade-off would be between compression ratios and the level of distortion that arises, for which several factors would need to be considered. Firstly, what are the level of restrictions that can be imposed when compressing data? Secondly, what criteria should the compressed image quality have in terms of its suitability for a given task? Thirdly, what are the properties and characteristics of the imagery being analysed? Lastly, what are the available computational resources that can be used as a threshold to justify a certain level of compression? There is research taking place in this space, but ultimately is up to the user to decide how, and to what extent their datasets need to be compressed based on the factors mentioned above.

5.4. Conclusion

Citrus cultivation in South Africa has grown over the last decade, and in the 2021/22 growing season, the area under citrus cultivation stood just under 100,000 hectares, driven largely by recurring investments and high export market earnings (CGA, 2023a). The net result being 2.13 million tons of citrus exports for the 2021/22 season. Despite challenges such as market headwinds, strict phytosanitary requirements, a high cost of production, increased competition, and water scarcity, production and exports continue to increase, fighting to meet the growing rise in global demand for citrus (Genis, 2018). Growers are continuously in search of anything that may provide them with the 'edge' or an advantage to overcoming some of these challenges (Jupp, 2018). Precision agriculture, particularly that of commercial, UAV based PA, provides growers with solutions to a variety of on-farm issues in the form of high quality, near real-time data, and provides access and benefits from technology driven agriculture to growers at all levels (Sishodia *et al*. 2020). The results from chapter four presented the application of selected remote sensing techniques to mapping and classifying a citrus farm in the Eastern Cape. The acquired imagery accurately aided the identification of *Phytophthora* spp in the section of interest and implies that remotely sensed data can be used to detect changes in citrus health. Some of the available imaging platforms come at a high cost and may be cost prohibitive for some users to implement, but there are cheaper or free alternative applications for growers to make use of. However, the level of detail really needed to help farmers make timely, strategic, and cost-effective decisions, is only available from high-resolution imagery obtained from UAV based surveys. A driving factor behind implementing remote sensing technologies in agriculture, is the time that can potentially be saved through the automation of crop monitoring, making the technology cost effective, objective, and practical for growers to implement (lost Filho et al. 2020). Guidelines for applying geospatial technologies at farm level were developed to provide a framework for enabling growers to enhance data driven farm management strategies.

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