The use of technology to improve current precision viticulture practices: predicting vineyard performance

by

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DECLARATION

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SUMMARY

Producing high quality grapes is difficult due to intra-vineyard spatial variability in vineyards. Variability leads to differences in grape quality and quantity. This poses a problem for producers, as homogeneous growth is nearly non-existent in vineyards. Remote sensing provides information of vineyard variability resulting in better knowledge of the distribution and occurrence thereof, leading to improved management practices. Remote sensing has been studied and implemented in several fields of research and industry, such as monitoring forest growth, pollution, population growth, etc. The potential to implement remote sensing technology is endless. Generating variability maps introduces the possibility of plant specific management practices, to alleviate problems occurring from variability. Aerial and satellite remote sensing provide new methods of variability monitoring, through spatial variability mapping of soil and plant biomass. Advances in geo-referencing and geolocations provide high accuracy precision tools for producers and researchers. New technology introduces possible means of vigour classification and stress monitoring on a plant scale, relieving the uncertainty caused by the distribution and extent of variability in vineyards. Vineyards are more difficult to analyse with remote sensing technology, due to the discontinuous canopies resulting in objects, other than plant biomass, to be monitored with the plant biomass. These objects can be soil and inter-row plant growth, along with trees close to or adjacent to the vineyards. This provides a dilemma through diluting biomass estimations and resulting in misinterpretation of the vineyard variability. These problems could be solved with the use of high-resolution multispectral imaging, providing clear classification and information of plant growth and health status. These sensing technologies have only been studied in some industries and have yet to be implemented to provide plant specific information. Introducing high accuracy plant specific information along with geolocation information will provide the producer with enough information to implement specific management practices alleviating heterogeneous plant growth and promoting homogeneous growth and yield, resulting in improved economic status through limiting input costs and environmental impact, providing better living conditions for plants along with increased plant longevity.

The aim of the study was to evaluate the accuracy of leaf area index (LAI) estimations from selected remote sensing technologies with three different sensor resolutions. Imaging of the experimental site with natural variability were taken with the remote sensors. Targeted vines in the vineyard were selected as ground control points for ground truth measurements. The data acquired from the ground truth measurements were compared to the normalised difference vegetation index (NDVI) values generated from the remote sensing technologies. Grid analysis was performed on the unmanned aerial vehicle (UAV) multispectral images, mapping the LAI of individual plants. Significant differences in LAI predictions were obtained with good correlations between the ground truth data and the UAV multispectral image NDVI, $r^2 = 0.69$. Climatic conditions proved problematic for the satellite images, where resolution also posed a problem.

Variability is often caused by environmental factors, although management practices influence variability of vineyards. Management practices can be beneficial to plant growth, such as tillage promotes soil aeration and biodiversity through mixing the soil layers and providing more homogeneous soil conditions in the vineyard, or detrimental, for example saline irrigation water can lead to toxic saline concentrations in the soil and result in plant degradation over time as the symptoms are only visual when toxicity has occurred. Salinity also provides improved soil moisture conditions through reducing the rate of soil drying. Other factors result in zonal variability, such as patchy growth from nutrient deficiencies or irregular growth patterns from pests or diseases. Remote sensing technology provides several sensing methods to determine the extent and distribution of variability. These methods involve various sensors, such as multispectral, light distance and ranging (LiDAR), etc., providing enough information to make informed decisions on management practices to limit variability or improve the extent thereof. These sensors are attached to aerial, satellite or ground platforms depending on the resolution needed and the extent of the study site.

Field measurements of the selected ground truth sampling points showed the presence of natural variability and the distribution thereof in the vineyard. Analysis of the UAV multispectral images revealed a good correlation between the ground truth data and the NDVI values. Soil and other objects were removed from the multispectral images, resulting in increased accuracy of biomass estimations and limited the NDVI blending effect observed in low-resolution images. Pixel based NDVI values of each plant, generated from the UAV multispectral device, were averaged to provide the NDVI per plant. Satellite images generated resolution-based area averages and blended pixel values of the soil and other objects adjacent to the vines limiting the plant-based information. Satellite images were affected by climatic conditions, especially cloud cover, along with limited image acquisitions revealed restricted image usability. UAV multispectral images provided plant-based LAI maps based on information generated through grid analysis, revealing the distribution of variability with accurate vine locations.

This study provided methods of autonomous image analysis for high- and low-resolution remote sensing technology. Models with accurate plant-based estimations to monitor and evaluate management practices will improve grape production and optimise quality resulting in improved wine quality. Selective harvesting and management practices will lead to optimised yield quality for targeted wine production, feeding the consumer driven industry. This study paved the way for future research in variability estimations from remote sensing technology with emphasis on the causes of within-vineyard variability.

OPSOMMING

Die vervaardiging van hoë gehalte druiwe is ingewikkeld as gevolg van variasie in wingerde. Variasie lei tot verskille in druiwe kwaliteit en kwantiteit. Dit hou 'n probleem in vir produsente, deur homogene groei wat byna nie in wingerde bestaan nie. Afstandswaarnemingstegnologie verskaf inligting oor wingerd variasie wat lei tot 'n beter kennis van die verspreiding en voorkoms daarvan en dus verbeterde bestuurspraktyke. Afstandswaarneming is ondersoek en geïmplementeer in verskeie navorsings- en nywerheidsvelde, soos die monitering van oerwoudgroei, besoedeling, bevolkingsgroei, ens. Die implementeringspotensiaal van afstandswaarnemingstegnologie is eindeloos. Deur variasiekaarte saam te stel, kan plantspesifieke bestuurspraktykte geïmplementeer word, wat probleme wat die voorkoms van variasie veroorsaak, kan verlig. Lugfoto's en satelliet afstandswaarnemingstegnologie bied nuwe metodes van variasie monitering deur die kartering van grond- en plantbiomassa ruimtelike variasie. Vooruitgang in geo-verwysings en geo-ligging bied 'n hoë akkuraatheid presisie instrumente vir produsente en navorsers. Nuwe tegnologie stel moontlike maniere van groeikrag klassifikasie en stresmonitering op 'n plantvlak voor, dus verligting van onsekerheid wat veroorsaak word deur die verspreiding en omvang van variasie in wingerde. Wingerde is moeiliker om met afstandswaarneming tegnologie te ontleed, te danke aan die diskontinue lower wat lei tot monitering van voorwerpe, anders as plantbiomassa. Hierdie voorwerpe kan grond en tussen-ry plant groei wees, saam met bome wat naby of aangrensend aan die wingerd is. Dit bied 'n dilemma deur verdunde biomassa skattings en lei tot waninterpretasie van wingerdvariasie. Hierdie probleme kan opgelos word met die gebruik van 'n hoë-resolusie multispektrale kamera, deur duidelike klassifikasie en inligting van plantegroei en gesondheidstatus te verskaf. Hierdie afstandswaarnemingstegnologie is slegs in sommige nywerhede bestudeer en is nog nie gebruik om plantspesifieke inligting te verskaf nie. Die bekendstelling van hoë akkuraatheid plantspesifieke inligting saam met ligginggewing inligting sal aan die produsent genoegsame inligting verskaf om spesifieke bestuurspraktyke daar te stel ter verligting van heterogene plantegroei en die bevordering van homogene groei en opbrengs, wat lei tot verbeterde ekonomiese status deur die beperking van insetkoste en omgewingsimpak, dus beter lewensomstandighede vir plante te verskaf tesame met 'n verlengde plant lewensverwagting.

Die doel van die studie was om blaaroppervlakte indeks (LAI) skattings van geselekteerde afstandswaarnemingstegnologieë met verskillende resolusies te evalueer. Lugfoto's is van die eksperimentele terrein, wat natuurlike variasie toon, geneem met die afstandswaarnemingstegnologie. Geteikende stokke in die wingerd is gekies as grondkontrolepunte vir grond waarheidsmetings. Data verkry uit die grond waarheidsmetings is vergelyk met die genormaliseerde verskil plantegroei indeks (NDVI) metings verkry van die afstandswaarnemingstegnologieë. Matriks analise is uitgevoer op die onbemande vliegtuig (UAV)

multispektrale beelde wat tot kartering van die individuele plante se LAI gelei het. Beduidende verskille in LAI voorspellings is verkry deur 'n goeie korrelasie tussen die grond waarheid data en die NDVI van die UAV multispektrale beelde. Klimaatstoestande het probleme vir die satellietbeelde aangedui, waar resolusie ook 'n probleem was.

Veranderlikheid is dikwels veroorsaak deur omgewingsfaktore, hoewel bestuurspraktyke variasie van wingerde beïnvloed. Bestuurspraktyke kan voordelig wees vir die groei van plante, bv. grondbewerking wat deurlugting en biodiversiteit bevorder deur die vermenging van grondlae en meer homogene grondtoestande te verskaf in die wingerd, of nadelig, bv. sout besproeiingswater kan lei tot giftige sout konsentrasies in die grond en met verloop van tyd lei na plant agteruitgang waar visuele simptome slegs toon nadat toksisiteit plaasgevind het. Soutgehalte bied ook verbeterde grondvog toestande aan deur die tempo van grond droging te verlaag. Ander faktore lei tot sonale variasie, soos onewe groei deur voedingstekorte of onreëlmatige groeipatrone van peste of siektes. Afstandswaarnemingstegnologie bied verskeie waarnemingsmetodes aan om die omvang en verspreiding van variasie te bepaal. Hierdie metodes behels verskeie sensors, soos multispektrale kameras, "light distance and ranging" (LiDAR), ens, wat genoeg inligting verskaf om ingeligte besluite oor bestuurspraktyke te neem om variasie te beperk of verbeter. Hierdie sensors is aan lug-, satelliet- of grondplatforms geheg, afhangende van die resolusie wat nodig is en die omvang van die studie area.

Veldmetings van die gekose grond waarheid monsternemingspunte het die teenwoordigheid van natuurlike variasie en die verspreiding daarvan in die wingerd. Ontleding van die UAV multispektrale beelde het 'n goeie korrelasie tussen die grond waarheid data en die NDVI waardes geopenbaar. Deur grond en ander voorwerpe uit die multispektrale beelde te verwyder, word verhoogde akkuraatheid van biomassa skattings verkry en die NDVI vermenging effek waargeneem in 'n lae-resolusie beelde beperk. Gemiddelde pixel gebaseerde NDVI waardes van elke plant, wat uit die UAV multispektrale toestel verkry is, het die totale NDVI van elke plant opgemaak. Satellietbeelde het resolusie-gebaseerde area gemiddeldes met gemengde pixelwaardes van die grond en ander voorwerpe langs die wingerd gegenereer en tot beperking van plant-gebaseerde inligting gelei. Satellietbeelde is deur klimaatstoestande beïnvloed, veral wolkbedekking, wat saam met beperkte beeld aanwinste die bruikbaarheid van die beelde verlaag. UAV multispektrale beelde, wat gebaseer is op inligting gegenereer deur matriks analise, verskaf plant-gebaseerde LAI kaarte, wat lei tot die onthulling van die verspreiding van variasie met akkurate wingerdstok posisies.

Hierdie studie verskaf metodes van outomatiese beeld analise vir hoë- en lae-resolusie afstandswaarnemingstegnologieë. Modelle met akkurate plant-gebaseerde skattings wat monitering en evaluasie van bestuurspraktyke tot gevolg het, sal druiwe produksie verbeter en druiwe kwaliteit optimaliseer wat sal bydra tot verbeterde wyngehalte. Selektiewe oes- en

bestuurspraktyke sal lei tot optimale opbrengsgehalte vir geteikende wynproduksie uitkomste, wat die verbruiker-gedrewe bedryf sal voed. Hierdie studie het die weg gebaan vir toekomstige navorsing in variasie skattings met afstandswaarneming tegnologie met klem op die oorsake van in-wingerd variasie.

This thesis is dedicated to my family and friends for their support and encouragement

BIOGRAPHICAL SKETCH

Yolandi Barnard was born in Pretoria on 20 April 1993. She matriculated at Stellenberg High School in 2011. Yolandi enrolled at Stellenbosch University in 2012 and obtained the degree BScAgric in Viticulture and Oenology in December 2016. She then enrolled for the MScAgric in Viticulture degree in 2017 at Stellenbosch University.

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PREFACE

This thesis is presented as a compilation of four chapters. Each chapter is introduced separately and is written according to the style of the South African Journal of Enology and Viticulture, except Chapter 3, which is a draft article for publication in Sensors Journal.

Chapter I   **General introduction and project aims**

Chapter II   **Literature review**
Causes of variability in vigour and variability assessment using remote sensing technologies

Chapter III   **Research results**
Chapter 3. Evaluation of intra-vineyard spatial and temporal variability of Leaf Area Index using multispectral images obtained by satellite (Landsat 8, Sentinel-2) and unmanned aerial vehicle platforms.

Chapter IV   **General conclusion and perspectives**

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Chapter 1

General introduction and project aims

CHAPTER 1: GENERAL INTRODUCTION AND PROJECT AIMS

1.1 Introduction

Vineyard spatial variability is a natural occurring phenomenon that can be generalised as the growth and responses of plants in an environment. These responses can be beneficial to the plant, promoting health and disease resistance, or detrimental where in severe cases plant death can occur. Variability can occur between adjacent vines (Hunter et al., 2010), vineyards situated close to each other (Bramley, 2004), or even in a given region (Blanco-Ward et al., 2007), e.g. Stellenbosch.
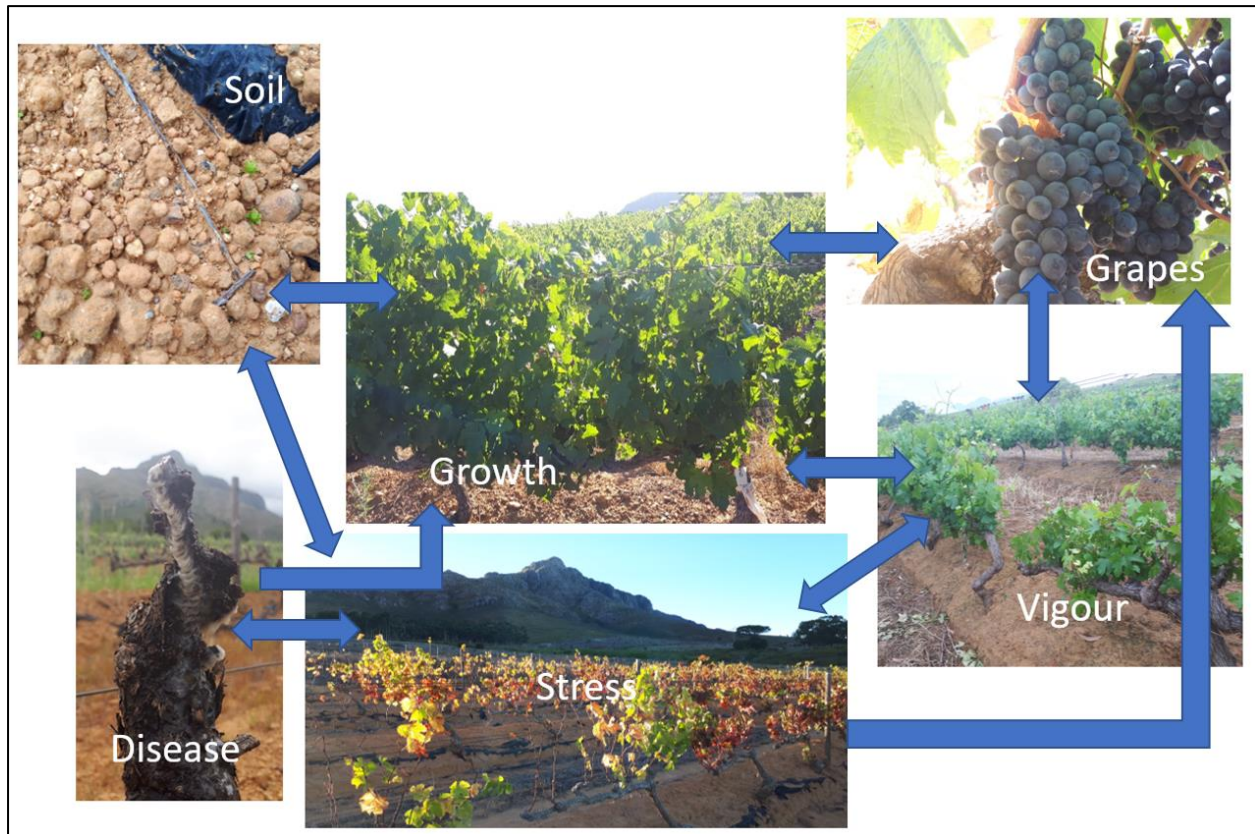
Viticultural practices currently in use, i.e. general management, do not generally account for the spatial variability in the vineyard and may therefore result in more stressed vines due to misrepresentation of the vineyard status. Strategies, especially irrigation, are implemented through the measurement of a few selected vines, which may not be representative of the whole block. The latter strategy may introduce larger problems in the vineyard, as over irrigation leads to waterlogged conditions that increase the occurrence of root rot and even vine death. Bramley & Hamilton (2004) stated that the strategies used to monitor and estimate variation are inaccurate due to the lack in methods to observe and monitor variation, therefore the variability of the vineyards are regarded as non-existing resulting in the implementation of general viticulture practices. Irrigation strategies, such as partial root drying, or deficit irrigation can be selectively implemented to increase the balance of vineyard growth (Zsófi et al., 2009), resulting in a decreased occurrence of variability.

To optimise the production, quality and health of vines, research on developing technology (Mack et al., 2017; Llorens et al., 2011) and remote sensing (Matese and Di Gennaro, 2015; Moran et al., 1997) have provided beneficial alternatives to improve management practices. These technologies along with the use of field measurements and historical records are beneficial to improve future management practices. The previously mentioned strategy is regarded as Precision viticulture.

Precision viticulture is regarded as a high priority in viticulture, due to the improvement of environmental impact and the consequent profitability (Whelan and McBratney, 2000). Remote sensing forms part of Precision viticulture, i.e. by using unmanned aerial vehicles (UAV's) mounted with sensors, such as multispectral, thermal and high-resolution cameras. Satellite image analysis has formed part of crop characterisation research and has proven to be beneficial for crops with continuous canopies, e.g. wheat and corn, rather than those with discontinuous canopies, e.g. vineyards. The use of these technologies has grown exponentially throughout the agriculture industry.

The continuous development of new technology provides the possibility of increased accuracy for estimations and evaluations of current and past management practices (Moran et al.,1997; Bellvert et al., 2014). These technologies are increasingly difficult to use and to interpret

data, due to the complex methodology and abundance of data. In the research field, creating automated and easy-to-use models are of great importance. Challenges arise to ensure the models are easily accessible and user friendly, creating usable on-the-go methods to determine vine health and production. The completion of the previously mentioned could provide models that can link vineyard variability parameters (Figure 1) to improve fast implementation for preventative or aiding management practices.

Figure 1: Relationships between parameters influencing growth and development that can be monitored or prevented with technology.

The goal of this study is to improve current analysis methods of various resolution satellite and UAV multispectral imaging technology and the influence of resolution parameters in the estimation of vigour (leaf area index; LAI), resulting in adequate knowledge of the status of the vines and where/when problem areas arise. This project received industry funding to study the possible role of imaging technologies to make timely decisions for optimal vineyard management and decreased inputs via costs and labour. Problems in the wine industry were identified and provided this study with relevant information to introduce objectives to address current problems. This project mainly focussed on *Vitis vinifera L.* cv. Pinotage in Stellenbosch (South Africa). This study was conducted to improve the understanding of variability in the vineyard. The project focussed on satellite and UAV multispectral imaging technology, and the improvement of the data analysis to make it more readily available for commercial farmers. Imaging technologies, therefore, formed the backbone of this study.

1.2   Specific Project Aims

To achieve these goals, a field trial was designed to incorporate random variability, leading to the following aims and objectives:

i)   Identify and characterise variability in the vineyard and the possible causes of vigour variability using UAV multispectral imaging

      a. Perform imaging at various stages during the growing season

      b. Analyse unmanned aerial vehicle (UAV) multispectral images to characterise vigour variability (temporal and spatial)

      c. To compare the relationship between field measurements and remote sensing UAV images in relation to temporal and spatial variability

ii)   Assess the accuracy of high-resolution UAV multispectral images regarding LAI estimation in comparison to low-resolution satellite imaging technology

      a. Provide an easy-to-use method of extracting normalized difference vegetation index (NDVI) values from UAV multispectral and satellite images

      b. Use extracted NDVI values to investigate the interference of inter-row soil reflectance

      c. Determine the optimal resolution needed for LAI estimation at plant level

The field experiment considered the natural variability of the vineyard block, enabling the satellite and UAV multispectral imaging technology currently available to cover the complete vineyard for preliminary field characterisation, classification and zoning. Vineyard zoning practices enable producers to select specified vines with pre-determined grape compositions or vigour, in theory, for selective vineyard management practices and winemaking. Allowing producers to identify the optimal vines for special wines, e.g. limited release, and limiting production costs and losses to ensure sustainable farming practices.

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Chapter 2

Literature review

Causes of variability in vigour and variability assessment using remote sensing technologies.

LITERATURE REVIEW

2.1   Introduction

Traditional management practices for viticulture are under immense pressure to provide accurate information for real-time implementation. As a result, continuous research is done on the improvement and validation of these methods, included under the collective name "Precision Viticulture" (PV) (Schieffer and Dillon, 2014; Matese and Di Gennaro, 2015; Rey-Caramés et al., 2015). The ever-changing vineyard environment promotes the implementation of PV practices to develop satisfactory and well-planned management strategies, including the use of emerging sensing technologies.

Terroir is classified as the interaction of an ecosystem, including human intervention (Seguin, 1986; 1988). These factors give rise to variation in soil patterns, variability in vine growth and health and can be attributed to differences in soil, aspect, altitude, effective soil depth, water supply, etc. Variability is present in all vineyards. Several factors attribute to the occurrence, effect and distribution of variability. These factors include, amongst others, the topography (i.e. height above sea level, aspect, slope and latitude) and geology (i.e. soil factors such as composition, water holding capacity, texture and structure) of the vineyard. The manipulation of these factors is considered close to impossible (Carey et al., 2002). Variability can be classified as either spatial or temporal, where the latter is regarded as the most important (McBratney et al., 1997). Nonetheless, management strategies can contribute to a delay in onset of variation.

Several studies have investigated the influence of spatial variability in vineyards, i.e. yield (Taylor et al., 2005), quality (Bramley, 2004), vigour (Bramley et al., 2011), soil moisture (Zucco et al., 2014; Ramos and Martínez-Casasnovas, 2006; Molina et al., 2014), soil properties (Vasu et al., 2017), and grapevine water status (Taylor et al., 2010). Temporal variability is regarded as variability over time. This includes climatic conditions (i.e. rainfall, temperature and wine) and annual vineyard manipulations. These factors change annually due to vineyard requirements and climate change. Temporal variability is regarded as the most important, as it is regarded as unstable (Krstic et al., 1998).

PV is regarded as a high priority in viticulture, due to the improvement of environmental impact and possible increased profitability arising from its use (Whelan and McBratney, 2000). It includes the spatial variability arising in a plot along with differential management focused on subareas of the plot to ensure that the grape quality and lifespan of the vines in the subarea are optimal. This approach allows for little loss due to variability, i.e. of water content resulting in over-irrigation of some subareas and under-irrigation in others. PV achieves reductions in environmental impact (Schieffer and Dillon, 2014), due to the restriction in application of

pesticides, herbicides, fertilizers and other chemicals to desired areas. Factors such as labour, machinery costs and time limitations also decrease as part of PV management.

Alternative monitoring for vineyard management practices includes the use of developing technologies, such as sensors and imaging. Studies have shown that the use of sensors increase the efficiency of monitoring through the availability of real-time data (Santesteban et al., 2016). Sensors can be used to classify and characterise the growth and health of fruit bearing plants, regardless of species (Gongal et al., 2015).

Satellite imaging has been used to classify and monitor vineyards (Yandún Narváez et al., 2016). The sensors mounted in the satellites use wavelengths of both short- and long-wave solar radiation bands (Unninayar and Olsen, 2008). Satellites, such as Landsat, Sentinel, MODIS (Moderate resolution imaging spectroradiometer), HJ (Huanjing satellite), GF-1 (Gaofen satellite no. 1), image the Earth continually (Wu et al., 2015). Passive or active instruments are attached to the satellites (Table 1). The former collects radiation in the form of reflection, refraction or emission from the atmosphere or Earth's surface. The latter generates and transmits electromagnetic signals, form instruments such as LiDAR and radar, to the Earth's surface (Unninayar and Olsen, 2008).

The goal of this study is to determine causes of variability in vigour, focusing on leaf area index, to assess the distribution and occurrence of variability using remote sensing technologies, such as satellites and UAV imaging.

2.2 Leaf Area Index (LAI)

Vine leaf area (LA) is defined as the total leaf surface covering the growing shoots per vine. Winter canes are lignified vine shoots that grew during the growing season. Pruning mass and shoot length indicate the growth and vigour of the vine. This is commonly used as a vegetation index for vine growth (Edwards and Clingeleffer, 2013). LA develops inter-annually and is dependent on current environmental effects (Soar et al., 2006). Larger leaf areas relate to larger exposed leaf surface and in turn higher evapotranspiration. High vigour vines with large leaf areas have higher evapotranspiration rates than low vigour vines, therefore have a larger water requirement (Rossouw, 2010). In grapevines, Stem Water Potential (SWP) is an indicator to the water status of the plant. This method is time consuming and the implementation thereof is limited, as this method is destructive, and the removal of leaves can affect the crop adversely. Large negative SWP induces restricted shoot growth and leaf area resulting in a decreased LAI. Grapevines respond to deficit soil water potential in various ways, i.e. internode extension, leaf expansion and tendril elongation (Pellegrino et al., 2005), influencing the LA.

LAI has several definitions, including total, green and effective LAI (Further reading: Fang and Liang, 2008). These definitions differ slightly, where total LAI is mostly used in measuring the total outside LA per soil area (Equation 1).

$$Total\ LAI = \frac{Total\ outside\ leaf\ area}{Soil\ area} \qquad \dots\dots (1)$$

Direct methods used to determine LAI require leaf harvesting, sampling of adequate size, along with field or laboratory area determination and are generally used for the calibration of indirect methods (Fang and Liang, 2008). Leaf removal is an accurate, destructive and time consuming direct LA measurement method (Johnson et al., 2003). Canopy dimensions, height and width, are used to estimate the canopy volume (Llorens et al., 2011). Canopy volume is used as an indication to the vigour and health of vines.

The measurement of pruning mass, shoot length and the number of shoots are indirect methods of LA estimation (Johnson et al., 2003). The optimal bud load can be determined by the length of the shoots or pruning mass, indicating the vigour of the vine. Several factors influence shoot growth. These factors can be natural (biotic, abiotic) or due to intervention (management practices). Strever (2003) stated that the implementation of management practices such as tipping or topping influences the pruning mass. Soar et al. (2006) found that the pruning mass decreased noticeably during high stress conditions. Regulated deficit and prolonged deficit irrigation resulted in decreased pruning mass where the latter irrigation strategy yielded the lowest pruning mass (Edward et al., 2013). Soil can influence the growth of vines, through restricting root growth that results in less vegetative growth.

Indirect optical and contact methods are faster and more convenient than direct methods of LAI estimation (Fang and Liang, 2008). Indirect contact methods include the point quadrants method (King et al., 2014), which is a 1.2 m sharpened rod used to pierce the canopy in the fruit zone and determine the number of leaves intercepted, resulting in leaf layer or canopy density measurements (Dokoozlian and Kliewer 1995). On the other hand, indirect optical methods include ceptometers, hemispherical canopy photography (fisheye lens), TRAC instrument (radiation tracer) and LAI-2000 (gap fraction) (Fang and Liang, 2008).

Comas et al. (2010) stated that minimal and spur pruning produces comparable final canopy density. With minimal pruning, earlier canopy development is observed due to the increased bud load per shoot resulting in an initial higher leaf area. Soar et al. (2006) stated that rootstock choice influenced the leaf area, where own rooted Shiraz produced larger LA in optimal conditions and lower LA in stressed conditions compared to the grafted vines. LA development is influenced by the water availability in the soil. Water deficits result in decreased LA development, i.e. amount, thickness, composition, orientation (exposure) and size, due to the decrease in transpirable water (Rossouw, 2010). Senescence of old leaves occur during water deficit conditions (Serra Stepke,

2014). Vine phenological development decreased duration of growing season and leaf senescence, is influenced by irrigation strategies (Strever et al. 2012). Therefore, the influence of irrigation strategies can be assessed through LA.

The vigour of the vine plays an important role in the pruning mass. Vigorous vines tend to have long and thick shoots where vines with weak vigour have short and thin shoots. Pruning mass can, therefore, indicate vine growth, balanced or irregular (Rossouw, 2010), and define the capability of the soil to sustain growth. Soar et al. (2006) stated that own-rooted Shiraz produced the largest pruning mass compared to the grafted vines. This was the opposite when stress conditions were introduced.

LA is largely influenced by plant spacing, i.e.1.3 m^2/vine for a spacing of 1.5 m by 0.5 m compared to 6.3 m^2/vine for a spacing of 3 m by 3 m (Jackson, 2014b). Internode length determines the number of nodes on a shoot. This is due to the decreased area for leaf attachment with elongated internodes or overcrowding in the case of dwarfed internode lengths. Shorter internodes are observed when the transpiration rate exceeds the leaf water supply, resulting in stomatal closure (Archer and Strauss 1989). Several factors, such as leaf removal, tipping, topping, shoot removal and cover crops, are regarded as LA management practices (Johnson et al., 2003). Shoot removal increases secondary shoot growth, whereby the removed LA is re-established (Strever et al. 2012).

The choice in pruning system effects the growth and consecutive pruning mass derived from the vine growth. Pruning systems include cane and spur pruning, amongst others. Cane pruning allows for more bearing wood to remain on the vine, resulting in a larger bud load and reduced pruning mass (May, 1972), compared to spur pruning. Uneven shoot development can be attributed from the length of the bearing wood, in the case of apical dominance (Keller, 2010b). Rapid shoot growth induces cytokinin delivery that stimulates secondary shoot growth, resulting in an increased pruning mass (Strever et al. 2012).

Strong winds with prevailing directions can influence the growth of vines (Eugster, 2008). This is due to the wind damaging young shoots, resulting in the secondary bud breaking, or breaking older shoots, leading to lateral shoot growth. Secondary buds are less fertile than primary buds with tertiary buds being mostly infertile (Keller, 2010b). This phenomenon leads to decreased yield with increased LA per vine.

2.3 Causes of vigour variability

Vineyards are subject to several factors that promote or hinder the occurrence of variability. Temperature, nutrient status, pruning, vine age, soil moisture and genetic plant characteristics influence shoot growth and the development of vines (Keller, 2010a), giving rise to variability. De

Clercq (1999) stated that the geometric features of canopies are difficult to study due to spatial and temporal variability.

2.3.1 Management practices

Management practices are in general the most effective manner of improving the occurrence of variability, due to the interaction of environmental factors that are not manipulatable. In the past, costly and labour-intensive conventional vineyard management practices were implemented to account for the variation in growth vigour (Strever, 2003). Nel (2005) concluded that natural cycles, e.g. carbon cycle, are negatively influenced through conventional management practice, due to the increase in off-farm inputs. Zapata et al. (2017) stated that the prediction of phenological stages, with little error in degree days, could lead to improved management practices.

Management practices, such as canopy manipulation, impacts the vine physiology and growth that could influence the grape and wine quality (Strever et al. 2012; Hunter et al. 2014). The timing is of absolute importance as the stage of vineyard development will result in a different plant response, i.e. plant water deficits leading to stomatal closure resulting in the inhibition of leaf and shoot development (Archer and Strauss 1989). Increased photosynthesis rates are observed in leaves when leaf thinning is applied, along with a delay in leaf senescence (Strever et al. 2012).

Soil nutrient management of macro nutrients are of great importance to the development of vines and sustaining crop productivity (Vasu et al. 2017), i.e. grape composition and ripening. Likar et al. (2015) concluded that soil and canopy management is detrimental to vine nutrition, affected by biotic and abiotic soil characteristics. Soil tillage improves the soil structure affecting the aeration, water availability and nutrient status of the soil resulting in improved growing conditions for vines (Jackson, 2014b). Farms managed organically have significantly larger earthworm populations than farms that use conventional management practices (Nel 2005). Higher mycorrhiza fungi populations and diversity are achieved by farming organically (Likar et al. 2015).

2.3.2 Soil

Vineyard growth and soil variability are correlated (Bramley and Hamilton, 2004), i.e. areas with low soil fertility with waterlogged soil conditions will have low vigour/dead vines, whereas areas with high fertility and good soil texture will result in healthy vigorous growing vines. King et al. (2014) stated that variability in important soil properties can occur over short distances. Conradie et al. (2002) found that the conditions of South African soils have large variation over small distances. Within vineyard differences in soil available water leads to vigour variability (Rossouw, 2010). The growth and development of fruitless shoots indicate increased sensitivity to deficit soil moisture content compared to shoots bearing fruit (Strever et al. 2012). Archer and Strauss (1989)

stated that shoot growth is sensitive to soil available water. Poor soil fertility and water content decreases yield and grape quality (Vasu et al. 2017).

Jackson (2014b) stated that heat absorption of soil is affected by colour and structure, relating to frost protection and fruit development. Slower soil drying can be attributed to soil salinity, with high salinity leading to reduced evapotranspiration (De Clercq 1999). The mineral composition of grapevines are affected by soil (Van Leeuwen and Seguin 2006), e.g. soil composition reflects environmental conditions. Soil characteristics, such as pH, Ca content, and partitioning, affect the soil mineral composition and vineyard growth conditions (Jackson 2014a).

2.3.3 Topography

The most noticeable cause of variability through topography is linked to the site, i.e. altitude and latitude. The resulting variability increases with an increased altitude and/or latitude. This is attributed to the changes in solar radiation, i.e. near-infrared and visible spectrum of light. Improved solar radiation is subject to optimal solar angle. Jackson (2014a) stated that the optimum slope for maximum solar radiation is directed toward the Earth's equator. Nonetheless, several local factors play an important role in site selection for optimal growing conditions for selected cultivars. The reflection of heat and radiation off water bodies and soil surfaces are limited with increased cloud cover conditions, resulting in reduced solar radiation and is most noticeable at low solar altitudes.

Row direction can decrease the effect of strong prevailing winds, that may cause damage to the vineyard growth. The row direction should be calculated to allow the wind to blow through the rows instead of through the vines (Jackson 2014a). This allows for improved air circulation to reduce the occurrence of rot or wind damage during the growing season. The airflow promotes decreased heat accumulation resulting in improved climate conditions for vines. This phenomenon leads to longer ripening periods and improved grape development (Strever et al. 2012), from a compound point of view, i.e. phenols.

2.3.4 Climate

Phenology is described as the initiation of new plant growth, through differentiation, and the impact of environmental factors on these processes (Coombe, 1995; Zapata et al., 2017). Slight changes in the localised atmospheric conditions could result in significant differences in the grapevine phenology (Lorenzo et al., 2013). Lorenzo et al. (2013) stated that grape composition is influenced by fluctuations in daily meteorological conditions.

Microclimate negatively influences soil properties, such as nutrient availability through leaching and erosion. This is also the case for water deficiency. The length and appearance of phenological stages are influenced by temperature (Caffarra and Eccel, 2010; Nendel, 2010). Holzapfel & Smith (2012) stated that carbohydrate mobilization and storage are more effected by seasonal climatic conditions than management practices. Warm temperature induces the

transport of cytokinin to auxiliary buds that stimulates secondary shoot growth (Strever et al. 2012).

De Clercq (1999) stated that increased crop stress is due to high temperatures, affecting the biochemical cycles in the leaves and increasing transpiration rates. Keller (2010b) suggested that low temperatures inhibit plant growth by lowering the production of proteins. Severe xylem cavitation occurs in vigorous vines during cold winter temperatures with dry soil conditions. Cavitation is irreversible and leads to abortion of plant structures.

2.3.5 Water stress

Grapevines are regularly produced under deficit irrigation (DI) strategies. Stress that occurs through the limitation of water has an impact on the development of berries. This could lead to misinterpretation of optimal ripeness as the biological ripeness and chemical ripeness of the berries fail to follow normal development when severe water stress is introduced.

Yield and grape quality are affected by the water status of the vine, in that severe water surplus increases the vegetative production of the vineyard and reduces the reproductive processes in the vine, resulting in limited production of grapes and a loss in grape quality (Pellegrino et al., 2005). Extreme water deficits can lead to canopy closure, reducing leaf area and exposing the fruit to environmental conditions (Pellegrino et al., 2005). There is, therefore, a need for the vineyard to have moderate water deficits, to ensure the vegetative growth is affected more than the reproductive growth and an increase in the quality of the fruit may be observed. Thus, there is a need for monitoring the water status of the vineyard throughout the ripening season of the grapes.

Vegetative growth and leaf area are restricted by salinity in irrigation water (De Clercq 1999), leading to stressed conditions. Plant water availability, indicated by leaf temperature, is an alternative method of determining plant response to stress conditions (Stoll et al., 2008). Water stress induces stomatal closure, leading to increased leaf temperature due to decreased transpiration (Sepúlveda-Reyes et al. 2016).

2.3.6 Other stress related factors

Vines grow in a diverse environment with numerous organisms influencing vine health, growth and development. Organisms present in the soil or above-round can be either neutral, beneficial or detrimental to vines. Brief explanations of some organisms will be covered in this section.

Neutral organisms do not damage grapes or vines, but rather use vines as shelter or as hunting grounds. Some of these organisms are incapable of breaching the defence system, such as yeast (Keller 2010b). Spiders and some birds use vines for hunting and reproduction purposes, along with shelter. These organisms do not influence grape development or vine growth.

Vines are dependent on beneficial organisms, e.g. bee's and birds for reproduction purposes. Bee's pollinate vine flowers whereas birds spread grape seeds. Grapevines are highly dependent on mycorrhizal bacteria, living around the root system and help break down important mineral bonds, making the minerals readily available for root uptake (Likar et al. 2015). Low mycorrhiza colonies in some over farmed soils are incapable of producing sufficient nitrogen (N) for plant growth, therefore N deficiencies occur in some vines, depending on soil structure and composition (Keller 2010b).

Phylloxera is a well know vineyard pest, feeding on vine roots and in some cases on the above-ground organs of vines (Keller 2010b). Jackson (2014a) stated that sandy soils prevent the movability of phylloxera and therefore less infestation is observed. Vines are usually grafted on phylloxera resistant rootstocks to prevent damage (Keller 2010b).

Cover crops determine the occurrence of pests, such as mealybug. Muscas et al. (2017) found that mealybugs performed better on vigorous vines with high nitrogen content. Mansour et al. (2012) found higher mealybug and ant populations in vineyards where no tillage was applied. Mealybugs influence grape composition and table grape quality (Daane et al., 2012), resulting in economic losses and vineyard variability due to variations in infestation and population. Virus transmission, promoting microorganism growth and feeding damage are some of the mealybug related damages (Jones et al., 2015).

Mealybugs are reported to be the vectors of some grapevine leafroll-associated viruses (GLRaVs). GLRaVs are recognised as the most important disease in grapevines (Jones et al., 2015), affecting vigour, yield and grape quality. This disease can only be prevented, as curative measures are non-existent. Infected vines of red cultivars show red discoloration, affecting photosynthesis rates, with an in-vineyard patchy appearance.

Botrytis cinerea is best known for causing mould on grapes, even though *B. cinerea* infects all green plant organs (Keller 2010b). Bunch rot, i.e. grey rot, influences the quality and quantity of grapes. Increased *B. cinerea* susceptibility is achieved through some cultivation practices that increase vigour, such as irrigation, excessive N fertilisation and vigorous rootstock scion combinations (Ferreira and Marais 1987).

2.3.7 Effect of variability on grape and wine quality

Wine quality can be influenced through spatial variability. Strever (2003) suggested that this can be due to external factors, such as genetic and physiological plant factors, management inputs and environmental factors. Grapevine physiology affects grape and wine quality and is affected by variability in vineyards (Rossouw, 2010), such as vigour and soil variability.

Reduced yield and berry size is achieved by deficit water conditions (Strever et al. 2012; Hunter et al. 2014). Strever et al. (2012) observed a reduction in berry mass from 140 to 160 days

after budburst and stated that the date of harvesting along with plant water status influenced berry mass. Decreased grape and wine quality is achieved by excessive leaf removal (Strever et al. 2012). Yield is reduced with early defoliation practices (Strever et al. 2012), though improving bunch compactness, berry size and the occurrence of rot (Johnson et al. 2003).

Decreased wine quality can be linked to unbalanced berry development through vineyard soil variability (Jackson, 2014b). Spatial and temporal changes in wine composition and quality are caused by variability in soil (King et al., 2014). The maintenance and management of soil nutrient status lead to increased grape and wine quality and production (Jackson, 2014b). Wine quality is associated with soil nitrogen status. Toxic ions inhibit vine growth and yield, with symptoms being initially dormant (De Clercq 1999).

The industry uses historical records along with climate and weather patterns to calculate yield. This is used in association with the samples taken in the field. This method is inaccurate as the performance of the vine along with the soil can differ each year, independent on the manipulations performed during the growing season, due to the small sample size compared to the spatial variability throughout the vineyard (Nuske et al., 2014).

Yield monitoring is critical to introduce a new approach to farming, enabling growers to monitor and observe the changes related to the variability in the vineyard. Bramley & Hamilton (2004) suggest that the implementation of an accurate yield determination method involves continuous observation of the viticultural changes that occur in the natural environment, interpretation and evaluation of the records and lastly the implementation of management to ensure the required results are obtained. This limits the impact that variation has on the determination and results in an increased accuracy of yield estimation, in the vineyard.

2.4 Assessing spatial variability using remote sensing technology

Computer systems are of great value, due to the non-contact and non-destructive techniques that are in use (Chherawala et al., 2006). Although these systems are beneficial to management practices, some problems arise with the use thereof. The risk of extracting unsatisfactory information, i.e. not enough or too much, is of great importance and therefore the research field of PV is highly active (Strever, 2003). Sawasawa (2003) stated that high quality spatial and temporal information is provided by remote sensing data.

Image analysis forms part of machine vision systems. These systems make analysis of data gathered in the field easier. Studies (Lamb 2001; Strever 2003; Matese and Di Gennaro 2015) have indicated that the use of image analysis for soil and vigour measurements should only be done at véraison and before harvest, rather than throughout the growing season. This is due to the lack of viable information generated through image analysis at early and late stages of vine canopy development (Tisseyre, Ojeda, and Taylor 2007).

2.4.1 Positioning/operational systems

Geolocation and time information are generated by a satellite-based radionavigation system (GPS), consisting of 30 satellites. The development of operational systems, such as global positioning systems (GPS) and geographical information systems (GIS), are highly pursued with the improved awareness of PV managements to improve grape quality (Strever, 2003). Sensors usually rely on Global Positioning Systems (GPS), which could present problems due to the interruption of data collection with the interference of canopies (Yandún Narváez et al., 2016).

The GPS satellite constellation generates accurate location information and in conjunction with computer-based GIS systems, generate spatial information maps (Hall et al. 2002) that enable monitoring and observation of the global environment (Unninayar and Olsen, 2008).

2.4.2 Sensors

Digital red, green and blue (RGB) images are images with three light beams, i.e. red, green and blue, that are combined in different intensities to produce the visible colour spectrum. RGB images are currently in use to determine gaps in the foliage, exposed leaf percentage and density of fruit (Rey-Caramés et al., 2015). Manzan et al. (2017) stated that RGB image segmentation produced good correlations between measured and imaged bunch weight (r^2 = 0.72) and bunch displacement (r^2=0.7). This was further improved through leaf removal resulting in better correlations between the measured and imaged vines, bunch weight (r^2 = 0.89) and bunch displacement (r^2=0.89). Diago et al. (2012) found a correlation between LA and leaf pixels (r^2=0.78) using RGB images.

Multispectral devices use 3 to 7 spectral bands, including RGB + NIR (Usha and Singh 2013). Multispectral imaging of vineyards have been obtained by numerous producers in the South African wine industry (Strever, 2003). These images are currently limited to vineyards with uniform requirements and have been used to estimate yield with great success (Nuske et al., 2014). Usha and Singh (2013) stated that multispectral imaging can distinguish between plant species using colour patterns exhibited by the plants. Baluja et al. (2012) studied Vegetation indexes (VI) obtained from the use of multispectral indexes. Table 1 illustrates the equation for some vegetation indexes that were used in their study. VI are calculated with multispectral imaging, such as the normalised difference VI (NDVI), Chlorophyll absorption ratio (CAR), green NDVI and the modified soil adjusted VI (MSAVI).

Table 1. Equations for vegetation index derived from the multispectral images. Modified from Baluja et al. (2012).

Index	Equation
NDVI	$$NDVI = \frac{NIR - Red}{NIR + Red}$$
Chlorophyll absorption ratio	$$CAR = \frac{[(RE - B) * 670 + Red + (G - ((RE - B) * 670) * 550)]}{\sqrt{((RE - B) * 670)^2}}$$ $$CAR1 = CAR\left(\frac{RE}{Red}\right)$$
Green NDVI	$$GNDVI = \frac{NIR - G}{NIR + G}$$
Modified soil adjusted VI	$$MSAVI = \frac{1}{2}\left(2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - Red)}\right)$$

NDVI = Normalised difference vegetation index, GNDVI = Green normalised difference vegetation index, MSAVI = Modified soil adjusted vegetation index, NIR = Near infrared, CAR = Chlorophyll absorption ratio, RE = Red edge, B = Blue, G = Green,

Hyperspectral images contain narrow spectral bands by the hundreds (Usha and Singh 2013). Possibilities of using narrow bands (350 – 2500nm) such as red-edge (680 – 750 nm), instead of red and NIR bands, arise with hyperspectral sensors, eliminating the saturation effect of NIR at high LAI levels (Mutanga and Skidmore 2004) and contain more information than multispectral images. Usha and Singh (2013) stated that conventional imaging techniques combined with spectroscopy give rise to hyperspectral sensors, resulting in spatial and spectral information of the object.

Temperature images (thermograms) are created by measuring IR light emitted from an object and scanned by infrared-detectors in thermal cameras (Ding et al. 2017). Thermal images of vineyards, using drones, have proved valuable in the determination of plant water status (Baluja et al., 2012). Thermal imaging have also been used to monitor plant responses to pathogen attack (Stoll et al., 2008). Sepúlveda-Reyes et al. (2016) concluded that grapevine water status can be monitored through aerial or ground based thermal imaging measurements depending on the canopy zone and methodology.

Light distance and ranging (LiDAR) devices are used to determine canopy characteristics, such as height and width, allowing three-dimensional scanning of objects (Manzan et al. 2017). Time of flight LiDAR sensors use laser pulse technology to determine the distance between the source and the object through measuring the time for a single laser pulse from emission to reach the target and back. Phase-shift LiDAR sensors measure the difference in phase of the reflected and emitted beams (Manzan et al. 2017). Vertical outlines of objects are represented by two-

dimensional LiDAR sensors. LiDAR sensors provide highly accurate and fast measurements. LiDAR sensors have been extensively used to estimate above-ground biomass (Koch 2010). Recently, Sanz et al. (2018) compared tree row LiDAR volume with measured vine LA and found a good correlation between the measurements (r^2=0.86). They found a strong correlation (r^2 = 0.80) between the projected tree row surface and LA, where they found correlations between LA and the frontal projection surfaces (r^2=0.85) along with the flat top projection surfaces (r^2=0.61).

Synthetic aperture radar (SAR) are relatively independent of weather conditions (Koch 2010). These sensors are widely used to assess biomass and forest cover. Radar is mostly used for insect movement monitoring and can be beneficial to vineyard management practices through tracking migratory patterns of beneficial insects (Usha and Singh 2013).

Depth sensors provide depth information of the targeted object. Depth sensors integrate information from various sensors, e.g. RGB, IR depth sensor, IR emitter and microphones. Manzan et al. (2017) used Kinect (depth sensor) to estimate vine yield and obtained significant correlations (r^2 = 0.85) between the measured bunch characteristics and the 3D model developed form Kinect measurements.

2.4.3 Platforms

Remote sensing cameras are attached to drones, satellites and robots for monitoring biomass of vegetation, such as forests and agricultural crops, or climate indexes, e.g. CO_2 emissions in the atmosphere and pollution. 2D LiDAR sensors are used to capture data from a points corresponding to aerial vehicles where positions are determined by GPS geo-referencing (Manzan et al. 2017). GPS and geo-referencing are done on all images, from ground scans using robots to aerial imaging.

Robots are ground based sensing devices, used for data acquisition from a vertical angle. Sensors attached to the device can be adjusted to the required specification of the trial, i.e. thermal or multispectral camera. Studies have shown good correlations between ground sensed NDVI and vegetation. Siebers et al. (2018) developed a vineyards robot, GRover, with a LiDAR scanner attachment to determine vineyard characteristics. Manzan et al. (2017) used a vineyard robot, Dassie mark II (CSIR, Pretoria, South Africa), with a LiDAR sensor attached, to determine vineyard yield obtaining a r^2 of 0.68 for bunch displacement and 0.69 for bunch weight.

Satellite imaging provides a fast and low-cost alternative to terrestrial data acquisition. Access to global spatial information is achieved through the development of satellite imaging, creating advances in crop monitoring (Sawasawa 2003). Satellite images provide monitoring and decision support to vineyard management (Usha and Singh 2013). Nonetheless, the resolution of the satellite imaging poses a great drawback in accurate monitoring of vineyards (Table 2). This sensor method has proved valuable to some producers, due to their ability to cover large

areas (Yandún Narváez et al., 2016), regardless of the lack in resolution. Johnson et al. (2003) concluded that canopy variability was sufficiently detected using IKONOS multispectral images with a 4 m spatial resolution (decommissioned in 2015). Wu et al. (2015) stated that reconstructed time series data, incorporating several imaging satellites, achieved higher NDVI crop mapping accuracy for cotton and wheat-corn. Sawasawa (2003) stated that NDVI combined with characteristics of land and management practices, compared to only using NDVI, improves the accuracy of rice yield estimation.

Table 2. Specifications of satellites (mentioned in introduction). Sourced form Wu et al., (2015) and Barnard et al. (2018) [Chapter 3].

Sensor	Band	Centre Wavelength (μm)	Resolution (m pixel^{-1})	Swath width (km)	Cycle (days)
Landsat 8	4 (Red) 5 (NIR)	0.655 0.865	30	185	16
Sentinel-2	4 (Red) 8 (NIR)	0.665 0.865	10	290	10
MODIS	1 (Red) 2 (NIR)	0.645 0.859	250	2330	2
HJ CCD	3 (Red) 4 (NIR)	0.660 0.830	30	700	2
GF – 1 WFV	3 (Red) 4 (NIR)	0.660 0.830	16	800	4
IKONOS	3 (Red) 4 (NIR)	0.665 0.805	4	13.8	3

Drones are classified as unmanned aerial vehicles (UAVs), having autonomously flying fixed or rotary wings (Matese and Di Gennaro 2015). UAVs are extensively used in different fields of interest (Gago et al. 2015), such as military, forestry, horticulture, risk management, etc. In food services, UAVs are used to monitor the growth and health of plants, along with yield estimations (Reynolds et al. 2017; Marciniak et al. 2017). Drones can carry different cameras, such as multispectral and high-resolution RGB cameras. This allows the surveyor to adjust the camera to fit the required measurements, i.e. NIR, IR or RGB. UAVs fitted with multispectral cameras are used to determine vegetative growth through NDVI measurements (Mathews and Jensen 2013). Increased resolution, compared to satellite images, is the main advantage of UAV imaging along with the temporal acquisition of images.

2.5 Conclusions

Numerous causes of variability are present in vineyards, where only some are deemed significant. The most important causes of spatial variability arise from climate and topography, where soil and management practices account for the temporal variability in vineyards. Spatial variability can be

manipulated using management practices, such as soil, irrigation or canopy management strategies, however, temporal variability is close to impossible to manipulate, therefore the better option is to implement PV to manage spatial variations to promote economic and sustainable vineyard growth. Automated and non-destructive methods can be used to monitor, estimate and limit variability patterns that influence grapevine growth and yield. Variability is rarely accounted for in management practices. Improved methods of measuring and limiting variability are available through remote sensing technology.

Combining different remote sensing technologies, such as satellite and UAV imaging, provides large amounts of information related to plant characteristics. Algorithms selecting relevant information and reducing noise could increase the usability of these technologies. Limiting vineyard variability to promote homogenous growth and grape production is in high demand. Remote sensing technology could provide accurate selection and mapping of specified grape characteristics, such as phenolic compounds, or promote selective management practices, reducing input costs from fertilizing, sprays and irrigation. This will improve winemaking techniques though pre-determining, selective harvesting, the major phenolic compounds present in wine. The technology available for use in the vineyard is developing continuously. It will be of great value to the industry to harvest the technology available and use it to improve the current management strategies.

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Chapter 3

Evaluation of intra-vineyard spatial and temporal variability of Leaf Area Index using multispectral images obtained by satellite (Landsat 8, Sentinel-2) and unmanned aerial vehicle platforms.

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Article

Evaluation of intra-vineyard spatial and temporal variability of Leaf Area Index using multispectral images obtained by satellite (Landsat 8, Sentinel-2) and unmanned aerial vehicle platforms.

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Abstract: Estimation of vineyard leaf area is of great importance to producers. The tracking and monitoring thereof is difficult due to time constraints. Satellite and unmanned aerial vehicle (UAV) imaging have become a crucial monitoring method for vineyard leaf area. Low-resolution images are incapable of distinguishing between adjacent vines due to the large area covered in each pixel, this leads to misinterpretation or generalisation of vineyard information. This study focussed on the resolution of imaging technology needed to accurately estimate vineyard leaf area. The normalised difference vegetation index (*NDVI*) generated from UAV drone and satellite images of Landsat 8 and Sentinel-2 were compared to field measurements. The low-resolution images (Landsat 8 and Sentinel 2) are mixed biomass pixels forming a single pixel of a larger area, averaging biomass reflectance with other objects, such as soil and road reflectance. Therefore, leaf area index (LAI) estimations are not accurate. Problems with cloud cover was observed with satellite imaging. Grid analysis performed on the UAV multispectral imaging resulted in the LAI estimation on a plant-by-plant basis with a good agreement (r^2 values of 0.69 at véraison). The model provided sufficient information for LAI estimations on a plant level. The grid analysis on a plant-by-plant basis implemented using drone multispectral images provides future economic benefits to producers regarding selective management practices.

Keywords: Normalised difference vegetation index (NDVI), unmanned aerial vehicle (UAV), grid analysis, spatial variability.

1. Introduction

Leaf Area Index (LAI) is defined as one half of the total leaf developed area per unit of horizontal soil surface area (Watson, 1947; Kalisperakis et al. 2015; Orlando et al. 2016). Leaf area and canopy structure determine the evaporation, transpiration and photosynthetic rates of plants (Döring et al. 2014; Kalisperakis et al. 2015; Zhao et al. 2012), therefore, LAI is used by crop management practices to define plant health, nutrient status and growth (Döring et al. 2014). In practical terms, LAI is used for monitoring plant vigour and determining the optimal management strategies (Orlando et al. 2016). In vineyards, LAI estimation thereof is of great importance for Precision viticulture (PV) practices, i.e. irrigation scheduling and zonal vineyard management strategies. The implementation of vineyard management strategies influences the density of the canopy, which determines the interception of solar radiation (Dokoozlian and Kliewer, 1995), defining the microclimate in the canopy, effecting grape growth and development (Orlando et al. 2016; Haboudane et al. 2004; Kalisperakis et al. 2015; Winkler, 1957; Aquino et al. 2015; Smart, 1985), and in turn the quality and quantity of wine produced (Stamatiadis et al. 2010; Hunter et al. 2014).

LAI can be estimated either directly or indirectly. The direct methods are highly accurate, destructive, labour intensive and time consuming (Kalisperakis et al. 2015; López-Lozano and Casterad, 2013). These methods require the removal of foliage (Kalisperakis et al. 2015; Döring et al. 2014) and influence the plant health through limiting the productivity of the plant. Direct methods require large sample sizes to decrease error margins (Döring et al. 2014), due to the unsatisfactory

representation of canopies (Zhao et al. 2012) and are therefore frequently used to calibrate the indirect methods (Kalisperakis et al. 2015). Indirect methods used to determine LAI are fast and user friendly, i.e. optical devices. Indirect methods of measuring LAI are based on light penetration through the canopy in the photosynthetically active radiation (PAR) region of the plant (López-Lozano and Casterad, 2013). Ceptometers have been used to estimate LAI and are suitable to use under different illumination conditions (López-Lozano and Casterad, 2013). These optical devices include, but are not limited to, AccuPAR (Garrigues et al. 2008), LAI-2000 (Nackaerts et al. 2000; López-Lozano and Casterad, 2013), SUNSCAN Canopy Analysis Systems (Vojtech, Turnbull, and Hector, 2007), and digital hemispherical photography (DHP) (Demarez et al. 2008; Liu, Jin, and Qi, 2012). Additionally, recent studies show the application of smart-apps such as VitiCanopy (De Bei et al. 2016) and PocketLAI (Orlando et al. 2016), similar to DHP, cell phone images from below the canopy are used to estimate vine porosity and vigour.

Optical devices can effectively determine LAI, although it is not practical to use on a large scale. This is due to the large number of vines (sampling points) that are resent in a vineyard. These devices require homogenous canopies, due to the relationship between light interception and leaf area (López-Lozano and Casterad, 2013). Furthermore, optical devices provide inconsistent results with bias samples as the vineyards are vertically trained and dis-continuous (Orlando et al. 2016). PV practices are used to increase accuracy and will therefore not benefit from optical device measurements. Optical devices are used to calibrate other means of LAI estimations, such as images from satellites or drones, rather than estimate on a large scale.

The practice of PV induces the ability for spatial variability management, segmented harvest and planning due to the generation of vineyard canopy maps (Hall et al. 2008). These practices make use of technology to improve and evaluate viticulture manipulations and strategies. To achieve this, PV is combined with technological advances to improve the efficiency and availability of vineyard monitoring and maintenance. These strategies involve the use of field measurements to validate technology, i.e. *NDVI* and satellite imaging. In PV applications, *NDVI* images are commonly used in the determination of plant biomass through remote sensing (Johnson et al. 2003; Lamb et al. 2004), due to the reflectance of certain wavebands found in the electromagnetic spectrum (Hall et al. 2008). The use of *NDVI* has increased through the years with producers harvesting the outputs of the data to evaluate the management practices in use. *NDVI* is regarded as a cost-effective and readily available technology that can estimate biomass with two reflective bands, i.e. red and near-infrared (Hall et al. 2008).

Current *NDVI* images are generated using several technological devices, such as satellites, drones and fixed wing airplanes. From these platforms, drones are more accessible due to the availability of images at any given time where satellite images are less available due to the fixed circuit of images. Satellites such as Sentinel and Landsat have cycles from 5 to 7 days and 16 days, respectively (Roy et al. 2014). The information of satellite imaging technology is freely available and can serve as a standard interpretation of LAI. Satellite images are readily available and have proven to be of great advantage to vineyard producers. This is due to the vague interpretation of the vineyard biomass (e.g. LAI) that the producers use to their advantage in vineyard managing. Non-soil surfaces without *NIR* information generate distinctive spectral signatures, misinterpreted as the development of vegetation, with *NDVI* images (Houborg and McCabe, 2016) inducing confusion between normal images (RGB) and *NDVI* signals.

Several studies have investigated the use of satellite images in agriculture, i.e. non-photosynthetic vegetation (Li and Guo, 2018), aboveground forest biomass (Gonçalves et al. 2018), crop monitoring (Wu et al. 2015; Lessio et al. 2017), winter wheat and maize biomass estimation (Dong et al. 2017), greenhouse detection (Novelli et al. 2016). Roy et al. (2014) stated that Landsat 8 has a high capability of land surface characterization and monitoring at high spatial resolution. Landsat is capable of capturing crop growth through continuous imaging and enough spatial

resolution (Gitelson et al. 2012; Roy et al. 2014). One consistent restriction of Landsat data is the limited reliability of data due to cloud cover and the image cycles (Gitelson et al. 2012; Roy et al. 2014). Cloudless imaging data is of critical importance for monitoring the productivity of crop growth and effect *NDVI* predictions (Houborg and McCabe, 2016). The Multispectral Imager sensor (MIS) of Sentinel-2 creates the opportunity to extract crop types through object-based image analysis (OBIA) of temporal data (Belgiu and Csillik, 2018). Yan and Roy (2016) stated that the analysis of spatio-temporal data from Sentinel-2 to classify agricultural areas is limited with the implementation of object-based methods.

Satellite and UAV images have different ranges of resolutions available. UAV image technology uses resolutions of 1 to 10 cm. This allows image analysis to be done on a plant to plant basis resulting in the better characterisation of each plant. Satellite images have image resolutions of 10 m to 30 m for Sentinel and Landsat, respectively (Wu et al. 2015). The images generated from such a low resolution make it impossible to distinguish between plants, which has an effect in LAI determination. Therefore, our objective was to evaluate the effect of spatial resolution on the accuracy of LAI estimation using different spatial resolutions: Landsat8 (30 m), Sentinel-2 (10 m) and UAV Multispectral images (0.05 m).

2. Materials and Methods

2.1. Experimental site

The Pinotage vineyard is situated in Stellenbosch, at the Welgevallen experimental farm. The region is classified as having a Mediterranean climate with 320 mm annual rainfall. It is located 210 m above sea-level with the GPS co-ordinates of 33°57′8.86″ S, 18°52′26.49″ E. Pinotage (Vitis vinifera; Pinot noir and Cinsaut crossing) clone 48A, grafted on Richter 110 (Vitis berlanderi var. Rességuir no 2 and Vitis Rupestris var. Martin cross) is cultivated in this block. Planted in the year 1994 with an inter row spacing of 2.7 m and vine spacing of 1.4 m. The block (1.9 ha) has a North-South orientation and is planted on a West-South-West slope. The vines are trained on a seven-wire (moveable) hedge trellis, VSP (vertical shoot positioning) system. The block is cultivated under dryland conditions with a unilateral cordon, spur-pruned, allowing 12 nodes per linear meter/vine.

2.2. Leaf Area Index measurements

To develop an empirical LAI model, shoots from 32 vines were carefully removed from the trellising system, to ensure that all the leaves and lateral shoots stayed attached. The shoots were placed in plastic bags, for transport to the laboratory. The lateral shoots were removed from the main shoot and the leaves were removed from the shoots and counted, keeping the two shoot's leaves separate. The leaves were placed in small sealed bags and labelled. The number of nodes on the main shoot was counted. The shoot length (SL) was measured using a measuring tape and leaf area per shoot (LA$_{shoot}$) was measured using a leaf area meter (Delta T Devices Ltd, Cambridge, UK). With these data, an empirical regression model was fitted to estimate LA$_{shoot}$ using SL measurements. 20 ground calibration sites (GCS) were randomly selected to cover the entire block area. In each GCS the total leaf area per vine (LA$_{vine}$) was estimated using the empirical model, as the sum of the LA$_{shoot}$. Finally, the LAI per vine was calculated considering the distances between rows and vines.

2.3. Remote sensing data

Three sources of remote sensing data, with different spatial resolutions, were chosen for this study.

i) First, multispectral images acquired by a "Drone" multi-rotor unmanned aerial vehicle (UAV). The UAV was equipped with a MicaSense RedEdge-M multispectral camera (MicaSence Inc., Seattle, WA, USA). This multispectral camera uses spectral bands of Blue, Green, Red, Near-Infrared,

and Red Edge to capture different analytical layers. The multispectral images were mosaicked and geo-corrected using PhotoScan (version 1.2.5 Agisoft LLC, St Petersburg, Russia). The *NDVI* was calculated from the NIR and red colour channels using the standard equation proposed by Tucker (1979):

$$NDVI = \frac{NIR-Red}{NIR+Red} \qquad (1)$$

The spatial resolution on the resulting *NDVI* images was 0.052 m pixel^{-1} (Table1). Following this, mean *NDVI* values were calculated over a polygon grid corresponding with the space assigned to each vine (Figure 1).

The relationships between *NDVI* and LAI was determined by regression analysis using the 20 GCS and the corresponding grid cells. The resulting model was used for estimating LAI, using the mean *NDVI* values for every grid cell, using this procedure, *LAI$_{UAV}$* on a plant basis was estimated (Figure 1).

ii) Second, images from Landsat 8 and Sentinel-2A were used to extract *NDVI* values from the experimental site. In this study, bands 4 (*Red*) and 8 (*NIR*) from the Sentinel-2A Multi-Spectral Instrument, with a spatial resolution of 10 m pixel^{-1} and bands 4 (*Red*) and 5 (*NIR*) from the Landsat 8 Operational Land Imager, with a spatial resolution of 30 m pixel^{-1} were used to calculate *NDVI* in the experimental block (Table 1).

Table 1. The wavelength bands used for the estimation of *NDVI* from multispectral images. The wavebands represent the red and near-infrared (NIR) regions of the spectrum.

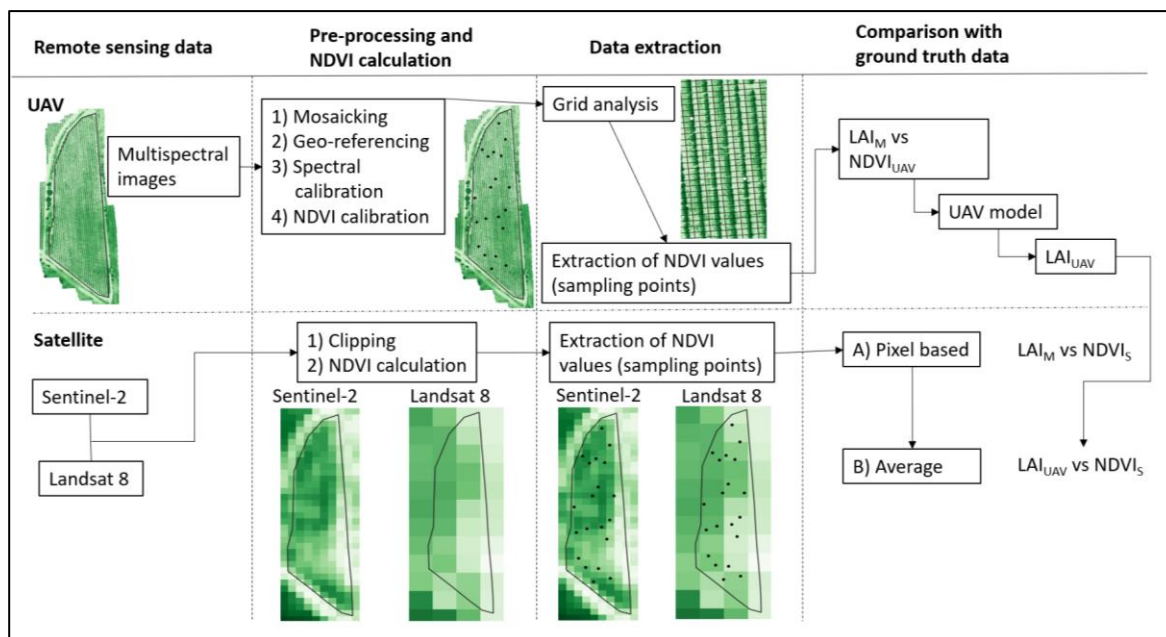| Sensor	Band	Centre Wavelength (μm)	Resolution (m pixel^{-1})	Swath width (km)	Cycle (days)
Landsat 8	4 (*Red*)	0.655	30	185	16
	5 (*NIR*)	0.865			
Sentinel-2	4 (*Red*)	0.665	10	290	10
	8 (*NIR*)	0.865			
Multispectral*	3 (*Red*)	0.668	0.052	-	User defined
	4 (*NIR*)	0.840			

* MicaSense RedEdge-M multispectral camera.

Table 2. Measurement dates used for the calculation of *NDVI* from the SL measurements (LAI) and images generated from UAV, Landsat-8 and Sentinel-2, accompanied by a modified EL code to indicate to progression of growth.

Location	LAI	UAV	Sentinel-2	Landsat 8	*EL
Stellenbosch	09 Nov 2017	09 Nov 2017	12 Nov 2017	11 Nov 2017	23
	26 Nov 2017	27 Nov 2017	27 Nov 2017	27 Nov 2017	27
	11 Dec 2017	12 Dec 2017	12 Dec 2017	13 Dec 2017	31
	20 Dec 2017	27 Dec 2017	27 Dec 2017	29 Dec 2017	35
	18 Jan 2018	31 Jan 2018	31 Jan 2018	30 Jan 2018	37

*Modified Eichhorn-Lorenz code.

Five dates were selected in this study, Table 2 shows the dates of measurements for the instruments used. The LAI column indicates the date when the SL measurements were conducted. From the numerous SL measurements and UAV imaging flights, only the dates that correspond with the satellite images of Landsat 8 were selected. These dates were then further filtered along with the Sentinel-2A dates to provide a single date, as close as possible to each other. These dates were chosen to ensure that the *NDVI* measurements could be correlated as close as possible to the different resolution devices. The Modified Eichhorn-Lorenz (EL) code (Chuine et al. 2013; Zapata et al. 2017) was used to indicate the phenological stage of the vines. The relationships between the mean pixel values of *LAI$_{UAV}$* and *NDVI* were investigated, though a simple linear regression analysis.

Figure 1. Methodology for the image analysis of the UAV multispectral and satellite images, resulting in the LAI estimation from the *NDVI* values.

3. Results

3.1. Descriptive analysis of leaf area index measurements

The descriptive analysis for LAI values in the 20 GCS, non-destructive SL measurements obtained during the field trail, is shown in Table 3. The average growth increased throughout the growth periods with a slight decrease at EL 35. The minimum LAI value of 0.516 m².m⁻² at EL 31, declined to 0.506 m².m⁻² at EL 35. The maximum LAI values of the different phenological stages indicate a steady increase in growth, from 0.638 to 0.838 m².m⁻². The LAI range for EL 23 is 0.348 m². m⁻², EL 27 is 0.256 m².m⁻², EL 31 is 0.253 m².m⁻², EL 35 is 0.293 m².m⁻² and EL 37 is 0.324 m².m⁻², which is less than the average for every phenological stage. This indicates that the dispersal of the data is closer to the maximum LAI values, rather than the minimum values. Therefore, more long shoots are present in the study area than short shoots, indicating a possibility of increased vine vigour for some vines.

Table 3. Descriptive analysis of LAI measurements at the various phenological growth stages (EL code) from flowering (EL23) to harvest (EL 37) in m².m⁻² for the experimental site.

EL	n	Average	Min	Max	SD	CV
23	20	0.460	0.290	0.638	0.010	2.09
27	20	0.583	0.462	0.718	0.068	11.7
31	20	0.656	0.516	0.769	0.070	10.7
35	20	0.651	0.506	0.799	0.081	12.4
37	20	0.671	0.514	0.838	0.089	13.4

EL = Modified Eichhorn-Lorenz code; n = number of sampling points; SD = Standard Deviation; CV = Coefficient of Variance; Max = Maximum; Min = Minimum

The SD of the GCS SL measurements was below 0.09 at the various EL stages. The Coefficient of Variance (CV) of the different phenological stages is below 13.5%, indicating that the dispersal of LAI from the average is moderate and very low at the flowering stage (EL 23), 2.09 %. This is due to

the limited number of sample points resulting in little dispersion along with a good range of measurements.

Table 4. Descriptive analysis of pixel NDVI values inside of the study block.

Platform	nP	EL	Average	Max	Min	S.D.	C.V
Multispectral	20886144	23	0.122	0.834	-0.225	0.175	143.44
		27	0.191	0.804	-0.077	0.160	83.77
		31	0.205	0.829	-0.142	0.186	90.73
		35	0.215	0.903	-0.185	0.159	73.95
		37	0.190	0.833	-0.196	0.170	89.47
Sentinel	180	23	0.048	0.058	0.033	0.005	10.42
		27	0.244	0.290	0.182	0.021	8.61
		31	0.260	0.317	0.184	0.031	11.92
		35	0.250	0.295	0.172	0.027	10.80
		37	0.103	0.197	0.048	0.039	37.86
Landsat	19	23	0.313	0.352	0.267	0.021	6.71
		27	0.307	0.325	0.247	0.019	6.19
		31	0.009	0.010	0.007	0.001	11.11
		35	0.309	0.341	0.272	0.023	7.44
		37	0.313	0.359	0.271	0.027	8.63

nP = Number of pixels; EL = Modified Eichhorn-Lorenz code; SD = Standard Deviation; CV = Coefficient of variance; Max = Maximum; Min = Minimum.

Descriptive analysis of vineyard block based *NDVI* for the Landsat 8, Sentinel-2 and UAV multispectral images is depicted in Table 4. The multispectral image has the highest quantity of pixels in the image, 20886144 pixels, with Landsat having the lowest, only 19 pixels. The average *NDVI* values of the multispectral and Sentinel images indicate an increase in vegetation from flowering to véraison (EL35) with a sudden decrease at harvest (EL 37), from 0.25 to 0.103 and 0.215 to 0.190, respectively. The average Landsat 8 *NDVI* values indicate inconsistency throughout the growing season with 0.313 at EL23 dropping to 0.307 at EL 27 with a further drop to 0.009 at EL 31. The latter phenomenon, observed at EL31, can be seen throughout the analysis, i.e. maximum of 0.010, minimum of 0.007 and SD of 0.001. Landsat 8 images the Earth every 16 days, resulting in problems arising from cloud cover. Cloud cover blocks satellite observations, resulting in lower NDVI values due to the reflection of visible light and absorption of NIR (Tang and Oki, 2007). These problems are mostly avoided with increased imaging, in the case of Sentinel-2. Cloud cover influences satellite images and the *NDVI* values extracted from the images. Cloud cover was present during the Landsat image acquisition during EL 31, 95.31% land cover and 84.9% scene cover, resulting in the discrepancy of NDVI values. Sentinel-2 also experienced cloud cover at EL 23, with 58.29% land cover and 19.61% scene cover, and EL 37, with 75.30% land cover and 0.054% scene cover.

The C.V of the multispectral image analysis was the highest at EL 23, with 143.44%. and the lowest at EL 35 with 73.95%. The Landsat 8 images had the lowest C.V with 6.19% at EL 27. The highest C.V of the Landsat images was observed at EL 31 with 11.11%. The lowest C.V for Sentinel-2 was achieved at EL 27 with 8.61% with the highest at EL 37 with 37.86%. The average C.V for the UAV multispectral, Sentinel-2 and Landsat 8 imaging technologies during the growing season was 96.27%, 15.92% and 8.02%, respectively. The minimum *NDVI* of UAV multispectral images indicates a negative value, i.e. -0.225 at EL 23. This is due to the high-resolution image incorporating soil reflectance values into the block based *NDVI* analysis. The average *NDVI* of the UAV multispectral images indicates progression of *LAI*, where Landsat 8 does not indicate any progression and Sentinel-2 indicates partial progression. The average *NDVI* values of Landsat 8 are identical at EL 23 and EL

37, i.e. 0.313, and similar at EL 27 and EL 31, i.e. 0.307 and 0.309, respectively. Satellite images proved to have problems to detect low leaf area (LA) values during the early stages of shoot development, showing high *NDVI* values similar to those registered at late growing stages.
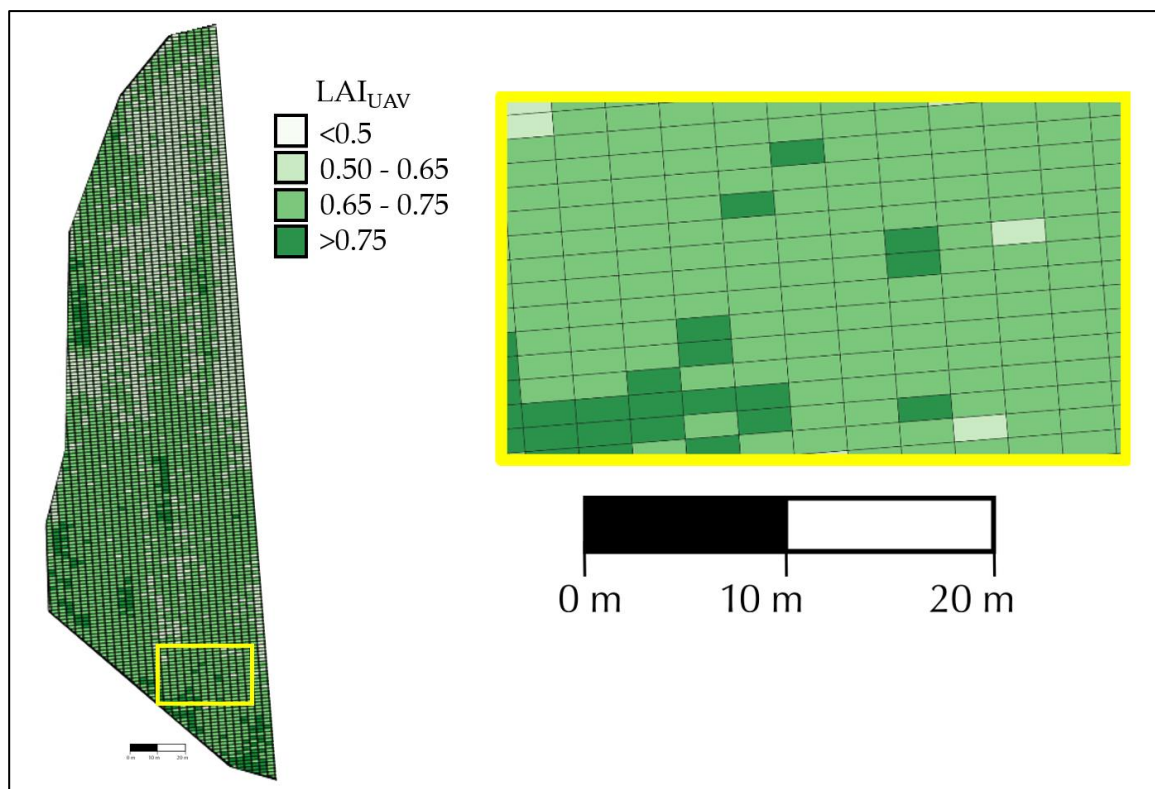
Table 5. LAI-NDVI relationship (pixel based) and average (Sentinel and Landsat).

	UAV		Sentinel-2				Landsat-8			
EL	r^2_{PB}	$RMSE_{PB}$	r^2_{PB}	r^2_{AVG}	$RMSE_{PB}$	$RMSE_{AVG}$	r^2_{PB}	r^2_{AVG}	$RMSE_{PB}$	$RMSE_{AVG}$
23	0.35*	0.070	0.019	0.023*	0.086	0.051	0.011	0.047	0.086	0.039
27	0.51*	0.060	0.20	0.450*	0.078	0.052	0.057	0.020	0.084	0.048
31	0.69*	0.048	0.15	0.390*	0.080	0.051	0.037	0.006	0.085	0.039
35	0.42*	0.060	0.15	0.290*	0.080	0.052	0.05	0.220*	0.085	0.051
37	0.56*	0.057	0.054	0.003	0.085	0.058	0.03	0.100	0.086	0.048

EL = Modified Eichhorn-Lorenz code; r^2 = Coefficient of determination; RMSE = Root mean square error; PB = pixel based; AVG = average. * indicates a significant linear regression (p-values < 0.05).

The *LAI-NDVI* relationship on a pixel base and by average pixels, the latter for satellite images only, is shown in Table 5. The r^2_{AVG} of Sentinel ranged between 0.003 and 0.450, compared to the r^2_{PB} values that ranged between 0.019 and 0.20. The r^2_{PB} of Landsat ranged from 0.011 to 0.057 and the r^2_{AVG} ranged from 0.006 to 0.22. The r^2_{PB} of the UAV multispectral ranges from 0.35 to 0.69 with EL 31 having the highest correlation between *LAI* and *NDVI*. The UAV multispectral image analysis had the second lowest $RMSE_{PB}$ of 0.048 at EL 31 with the $RMSE_{AVG}$ of Landsat being the lowest with 0.039 at EL 23. The $RMSE_{PB}$ of Sentinel ranged from 0.078 to 0.086 and $RMSE_{AVG}$ ranged from 0.051 to 0.058. The $RMSE_{PB}$ of Landsat ranged from 0.084 to 0.086 and the $RMSE_{AVG}$ ranged from 0.039 to 0.051.

The pseudo-colour index georeferenced *NDVI* vineyard map with clustered pixels (4 classes) is shown in Figure 2, indicating the grid developed from plant and row spacing allowing for average of pixels characterisation around the vine, represents differences in variability (Poblete-Echeverría et al. 2017). The UAV multispectral image at EL 37 provided a r^2 of 0.56 and together with the field measurements generated the grid *LAI* map for the vineyard block. The correlation between the *NDVI* of UAV multispectral images and measured *LAI* is indicated at Table 3. The maximum *LAI* value at EL 37 was 0.838, class 4, and the minimum *LAI* value was 0.514, class 2. The average *LAI* measurement was 0.671, class 3. With the SD being 0.089, it can be said that the minimum *LAI* value could be in class 1, referring to the dispersal of values (C.V = 13.4%). The map indicates the vigour variability present in the vineyard on a plant by plant basis. Plants with low vigour, *LAI* < 0.5 m².m⁻², are represented in the lightest blocks with high vigour plants, *LAI* > 0.75 m².m⁻², represented in the darkest blocks.

Figure 2. LAI map, plant basis, produced from the grid analysis of UAV multispectral images.

4. Discussion

This study compared the accuracy of LAI estimations with regard to different resolution devices such as UAV Multispectral, Sentinel-2 and Landsat 8 images using pixels as analysis units. Pixels contain the *NDVI* values of the area representative of the camera resolution, e.g. 10 m² area in a single Sentinel-2 pixel. Pixels represented the major entity being analysed due to the resolution differences in the imaging devices (Li and Roy 2017; Belgiu and Csillik 2018; Novelli et al. 2016).
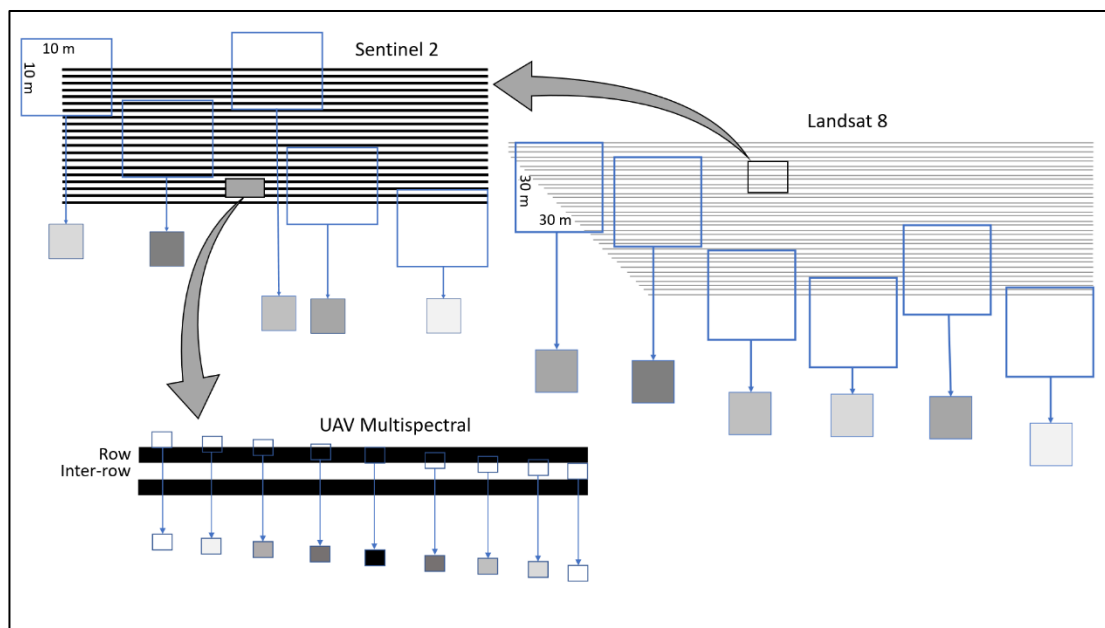
The decrease in LAI (Table 3) from véraison to harvest indicated in our results was due to wind and animal damage to the shoots that resulted in shoots breaking in half or completely off (Keller 2010). The average LAI increased without an impact from the minimum LAI, due to an overall increase in shoot length. This is also supplemented with the increased maximum LAI value during the growing period. The UAV multispectral images indicate a steady increase in LAI values during the growing season, with a decrease at EL37. This is due to leaf removal at harvest, resulting in less dense growth and a lower LAI value.

Low-resolution satellite imaging failed to express canopy characteristics due to large pixels sizes (Table 4). The progression of LAI with Landsat 8 imaging is almost non-existent, as the *NDVI* values during the growing season stay constant. This is almost true for that of Sentinel-2, where little changes in the *NDVI* values are observed. Ke et al. (2015) stated that Landsat 8 shows *NDVI* progression in forest sites with homogenous canopies. *LAI* progression of maize and soybean crops were obtained with Landsat images (Houborg et al. 2015). The previous mentioned studies focussed on crops with continuous canopies, where vineyards have discontinuous canopies due to missing plants, native vegetation, etc., resulting in a decreased performance for vineyard estimations and characterisation (Poblete-Echeverría et al. 2017).

The number of pixels represented in Table 4 correlates with the resolution differences in the remote sensing devices. Wassenaar et al. (2002) stated that the optimal resolution for vine and soil characterisation is 0.25 m x 0.25 m. Vineyard boundaries were successfully classified from 0.15 cm resolution that required manual window selection in the vineyard image (Da Costa et al. 2007). Hall

et al. (2008) studied the effect of low-resolution images mapping spatial variability rather than LAI. They stated that the *NDVI* for a grapevine starts at the value of 0.6 to eliminate the effect of the inter row space. Wassenaar et al. (2002) proposed a method for automated row width and orientation estimation from 25 cm resolution images on a per-field basis. Delenne et al. (2010) developed an automated vineyard detection model. The latter study succeeded in classifying and extracting vineyard rows from 50 cm resolution images resulting in 90% accuracy. These methods focussed on row classification, where this study focussed on vine classification. Poblete-Echeverría et al. (2017) stated that low-resolution images have mixed pixels that include other objects, such as soil, shadow and vegetation.

Figure 3. Scheme of row and inter-row (soil or cover crop) interaction based on pixel size (1 m, 10 m and 30 m) and pixel location using UAV multispectral, Sentinel and Landsat images.

NDVI values range from 1 to -1, with 1 being the highest possible value. Values of 0.1 or lower indicate no to low vegetation, with values higher than 0.6 indicating dense vegetative growth (Pettorelli et al. 2005). The nature of vine cultivation, discontinuous canopies, give rise to low soil cover that influences *NDVI* measurements (Johnson et al. 2003). *NDVI* is saturated at excessive LAI values, relating to the inability of *NDVI* to measure infrared wavebands (Wang et al. 2005). This is due to the high level of two-dimensional green growth relative to the image (Santin-Janin et al. 2009). Orlando et al. (2016) stated that a saturation effect was observed using PocketLAI for vine LAI measurements. Figure 3 represents the differences in *NDVI* from the resolution differences, with regard to the bleaching effect of the pixels. The discrepancy in the Landsat analysis (Table 4) is possibly due to natural factors such as cloud cover or solar radiation problems during the imaging period along with leaf removal at harvesting, therefore resolution affected Landsat 8 *NDVI* values moreover compared to the other devices. This is due to large pixels that cover large areas resulting in a bleaching effect of *NDVI*. Pea berry size (EL 31) depicts a sudden increase in *NDVI* values for the maximum values. This could be linked to differences in solar radiation or red wavelengths being refracted away from the source. Inter-row soil and cover crops reflect solar radiation that reduces the value of *NDVI*, especially with low resolution images due to the blending effect of the large pixel sizes. This was observed in the high-resolution UAV multispectral images, when applied to a vineyard scale, resulting in negative *NDVI* values during the growing season (Table 4). Hall et al. (2008) stated that the use of low resolution *NDVI* devices are best correlated with LAI during the mature phase of vine growth, i.e. véraison. Image resolution affected *NDVI* values, due to the pixel bleaching effect on a vineyard scale. *NDVI* values of 0.309 at véraison, resulted in higher LAI values

with the low resolution (30m) Landsat images, with better results obtained from the low resolution (10m) Sentinel images, 0.250 at véraison (Table 4). The harvest (EL37) period posed the largest problem for Sentinel regarding *NDVI* values. Landsat *NDVI* values proved to overestimate the growth at flowering (EL 23) with regard to the maximum and average LAI values. This is believed to be caused by the large pixel size allowing for external objects, such as inter-rows and roads, to be averaged along with the vegetation growth. Mixed pixels of soil and cover crops combined with canopy reflectance give rise to the variability in *NDVI* values of low-resolution images (Hall et al. 2008). This is due to the variability of the ratio of growth and inter-row space reflectance resulting in differences of measured canopy densities.

Johnson et al. (2003) observed a significant difference between ground and image based LA measurements at a block scale. Orlando et al. (2016) produced a *NDVI* map from field and PocketLAI measurements, where clear vigour classification was obtained on a block scale. Cola et al. (2014) developed a weather-based model for canopy LA and phenology prediction on a vineyard row basis with an excellent LA prediction capability. The most noticeable phenological stages are berry set (EL 27) and véraison (EL 35), with regard to overall imaging performance, as the devices slightly differ with *NDVI* values, predictable due to the differences in resolution (Table 4). The SD values of the UAV is higher than the two satellite imaging technologies. With the UAV multispectral having the most pixels, a higher SD is expected. Pettorelli et al. (2005) stated that low-resolution imaging has limited usefulness for detailed studies and is better suited for regional studies.

From Table 5 it is eminent that UAV is better suited to the model compared to the satellites, as the $r^2{}_{PB}$ for the UAV is greater than 0.3 for the growing season, where the $r^2{}_{PB}$ for Sentinel and Landsat is only greater than 0.05 and 0.01, respectively. Nonetheless, the $r^2{}_{PB}$ for UAV is lower than 0.7, indicating that the model can be significantly improved. The best phenological stage to implement the model for the UAV measurements is at pea berry size (EL 31) with a $r^2{}_{PB}$ of 0.69 and a $RMSE_{PB}$ of 0.048. For Sentinel, the best suited stage is at berry set (EL 27) with a $r^2{}_{AVG}$ of 0.45 and a $RMSE_{AVG}$ of 0.052. Landsat is best used at véraison (EL 35) with a $r^2{}_{AVG}$ of 0.22 and a $RMSE_{AVG}$ of 0.051. This was the case, using Sentinel and Landsat images when average *NDVI* values were compared to pixel based *NDVI* values. *NDVI* is generated from the transformation of pixels that are collected from remote sensing images (Johnson et al. 2003). Hall et al. (2008) stated that canopy descriptors, i.e. area and *NDVI*, have significant relationships with LAI. They further stated that the relationship between area and LAI has greater significance than that of LAI and *NDVI*. This is due to the lack of height perception in the *NDVI* calculation. We hypothesized that this phenomenon can be explained though comparing the *NDVI* of two vines, where the one vine has a height of 1 m and the second a height of 2 m. In this case, both vines have the same *NDVI* from a UAV image *NDVI* calculation, as the UAV images are unable to consider the differences in area. The first vine has a true LAI of 0.6 m²m⁻² and the second a true *LAI* of 1.2 m²m⁻². The vines are perceived as the same with UAV and different with other ground devices, i.e. LiDAR, PocketLAI (Orlando et al. 2016), LAI-2000, Crop Circle ACR-210 (King et al. 2014).

The grid analysis used in this study was based on plant by plant and the relevant single pixels in the grid area corresponding to the vine canopy. Grid area was fixed with the plant spacing, allowing only the characteristics of the vine to be extracted. In contrast, Lamb et al. (2008) stated that the correlation between *NDVI* and grape colour along with *NDVI* and the total phenolics measured increases when pixel values are averaged around the centre of the sampling point, instead of using single pixel values. Vasu et al. (2017) stated site specific soil nutrient management and accurate spatial interpolation depend on optimal fixed grid interval distances. Grid analysis reduces the amount of information to provide accurate extraction values for every plant in the experimental plot. These values integrate the mixture between pixels corresponding to plant and soil. The implementation of the grid analysis allows the *LAI* per vine to be calculated from the pixels that correspond to the area assigned to each vine (Figure 2).

5. Conclusion

Our objective was to evaluate the effect of spatial resolution on the accuracy of LAI estimation using ground truth measurements and different platforms (UAV, Sentinel-2 and Landsat 8). Results obtained from low-resolution satellite images compared to other studies, whereas new information was obtained on in-vineyard variability mapping using the grid analysis on a plant-by-plant basis. The UAV multispectral images obtained the best agreement with the field LAI measurements, due to the high resolution. It is clear with the results obtained that UAV imaging is the most relevant and accurate monitoring technology, with a 0.052 m resolution. Furthermore, vineyard maps with plant-by-plant characterisation is more valuable to producers in terms of PV implementation purposes. This study further compared the required resolution to estimate LAI on a plant scale. The image resolution of Landsat 8 and Sentinel-2 was not high enough to differentiate between adjacent groups of vines. Nonetheless, the high-resolution images of the UAV multispectral camera succeeded in providing enough plant information to estimate LA per plant. The benefits that can rise from automated LAI measurements acquired from satellite images along with UAV multispectral images are immense. Quantitative LA maps can serve as decision support regarding management practices. Value can be added through the incorporation of other variables, such as yield, grape composition, ripeness monitoring, etc. to provide quantifiable vineyard maps for classification and precision viticulture implementations.

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Chapter 4

General conclusions and perspectives

CHAPTER 4: GENERAL CONCLUSIONS AND PERSPECTIVES

4.1   General conclusions and perspectives

Precision viticulture practices can be immensely improved through remote sensing technology through predicting and differentiating vineyard performance. Vineyard variability provides a great deal of uncertainty for producers. This is due to the lack in knowledge of the location and cause of variability in the vineyard. Understanding variability and the causes thereof is the first step in precision viticulture practices. This can be done through aerial or ground based remote sensing, providing a better indication of plant vigour and variability dispersal. This will allow the producer to make timely decisions regarding the current management practices and facilitate new strategies to combat variability, decrease the severity and spread thereof.

In theory, producers should be able to track and keep records of their fruit quality parameters through using remote sensing technology, to generate maps for selected parameters. These maps are high in accuracy, therefore selective harvesting and selective management practices can be implemented, resulting in improved economic growth. Remote sensing technology does not provide the solutions to in-vineyard variability, yet it can increase variability efficiency and tracking to determine the causes of localised vigour variability resulting in improved management strategies and grape quality therefore, wine quality will increase.

Remote sensing technologies have provided knowledge of spatial and temporal variability, resulting in an increased understanding of variability and the factors influencing it. Nonetheless, the implementation of selective management practices is yet to be considered because of misinterpretation or low-resolution imaging, resulting in the generalisation of observations. Higher resolution could provide increased information regarding the location and severity of variability, along with disease, pest and virus indications.

This study aimed to analyse the performance of three remote sensing technologies, which considered both high and low-resolution cameras, in vineyard vigour estimations. Conventional ground measurements of LAI were used to compare the NDVI measurements from the remote sensing cameras. Analysis of imaging pixels was done to determine LAI of the selected ground control sampling point.

Field experiments in a naturally variable vineyard was conducted to estimate the accuracy of vigour estimations. The aim of this project was to promote remote sensing technologies for improved vineyard management, ideally to limit unknown variability through selective management strategies, such as irrigation, fertilisation and sprays. Remote sensing introduces vineyard classification, zoning and characterisation through image technology obtained from sensors gathering NDVI and other spectral information.

Vineyard variability is brought on by many factors. These factors include but are not limited to topography, soil content and composition, climate, management practices, water stress, diseases and pests. From these factors, some can be manipulated to provide improved living conditions for vines. Improved soil and management practices lead to an increase in vine vigour and balance, resulting in better grape and wine quality. Climatic conditions cannot be manipulated, therefore decisions on planting site should be taken with extreme care along with choice of planting material. Vineyard variability can be detected with remote sensing, relieving pressure from field measurements and labour. Remote sensing is widely researched and provides a low cost and timely management strategy. Remote sensing images are used to produce vigour maps along with soil and other variabilities. These maps can introduce selective management practices on a plant-by-plant level to limit the occurrence and spread of variability in the vineyard.

Multispectral imaging from the remote sensing devices provided NDVI information. The camera resolution of the satellite images, Landsat 8 and Sentinel-2, provided vague information with uncertainties regarding accuracy of LAI estimations resulting from blended information from the pixel area. Soil reflectance was excluded from the UAV multispectral images, where satellite images contained the reflectance of soil and other objects. Differences in pixel sizes related to the resolution effects on NDVI, where compared to ground truth data. Autonomous grid analysis was performed on the UAV multispectral images, where significant relationships between vine LAI and UAV multispectral NDVI were observed (r^2=0.69). Grid analysis proved to enable plant-by-plant vigour classification, with selected vigour categories, and generated vigour maps. These maps include spatial and temporal information. Vineyard vigour progression was obtained from the different remote sensing technologies, where the Landsat 8 images were incapable of providing information on the vigour progression.

Temporal variability is mostly induced by climate, whereas spatial variability is generally influenced by different management practices. Therefore, temporal variability is close to impossible to manipulate, yet some management practices can hinder or combat the development thereof. Remote sensing technology allows producers to follow the development of variability, therefore timely decisions to hinder the development and dispersal of vineyard variability can be made.

The author of this study is confident that autonomous grid analysis of high-resolution multispectral images can show variability differences in close to homogeneous vineyards and identify problem plants or areas with high accuracy. Extensive research on the causes of variability without vast amounts of ground truth information is still needed. Merging the information acquired from satellite and UAV image acquisition could provide easier classification of variability and ease the process of data acquisition and interpretation from an automated classification model, such as the grid analysis model used in this study.