Hyperspectral Imaging of Hill Country Farms

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Thomas Anthony Cushnahan
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Abstract

This thesis uses hyperspectral aerial imagery, processed and classified using a Support Vector Machine (SVM) approach applied to categorise the New Zealand hill farming environment. The analysis of hyperspectral imagery presented in this thesis provides information on land use and land cover that can assist land management decision-making for hill country farming. The ability of the approach to provide a mechanism to examine complex and inaccessible environments and capture information in fine detail makes it relevant to the management of other heterogeneous environments and marginal farming systems worldwide.

Precision farming techniques, used regularly in other farming sectors, hold the promise to better understand the hill farming landscape and therefore improve strategic management decisions. Pasture is the primary resource on the farm but due to the heterogenous nature of the hill farm landscape, the pasture area is currently only estimated. Aerially applied fertiliser applications represent the largest single input for these farms and are also a major source of nutrient contamination in waterways so finding ways to reduce costs and environmental damage are important.

The definition of the area and various pasture groups is critical information needed to improve fertiliser efficiency via use of Variable Rate Application Technology systems. This research was able to classify pasture area to 99.59% (Kappa 0.991).

Accurate base landscape information can improve management decisions, the accuracy of valuations, income expectations from lending organisations and the overall prosperity of the hill farming sector. Currently farmers and external groups must make major financial and strategic decisions with local expert opinion which is difficult to validate or question. Therefore, information derived from the hyperspectral classification is also shown to have benefits for strategic farm management decision-making and the wider farming community. This research was able to classify a number of economically valuable resources to high accuracies including;

water bodies (99.97%), Thistle (98.51%), Pine (99.44%), Kanuka (89.03%) and Manuka (97.71%).

By applying SVM to hyperspectral imagery the classification of pasture could be enhanced by the use of plant functional groups. The classes of High Fertility Responsive (HFR) represented sown rye varieties and had a classification accuracy of 89.06%. Low Fertility Tolerant (LFT) represented mixed swards dominated by browntop with a classification accuracy of 89.81%. The highest accuracy achieved for the legume class was 99.81%. The findings from this study represent a notable advance in our understanding of hill country farm and remote sensing research relevant to hill country farming. This is the first study to classify several key landscape components that are economically or environmentally important to the hill country farming community and this study created the most detailed map of hill farm pasture quality using plant functional groups so far. The ability to use a single hyperspectral aerial survey, to provide such a wide variety of information, useful to many industry actors, improves the potential return on investment and viability of the survey operation.

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https://www.mpi.govt.nz/funding-and-programmes/primary-growth-partnership/primary-growth-partnership-programmes/pioneering-to-precision-application-of-fertiliser-in-hill-country/

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"Ar scáth a chéile a mhaireann na daoine"

Old Irish Proverb (Under the shelter of each other, people survive)

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Chapter 1 : Introduction

This chapter provides an overview and scope of the thesis. It provides context by introducing hill farming and examines political and environmental factors that have influenced its development in New Zealand. This chapter also presents the aims and objectives of the thesis, and a brief outline of each chapter.

1.1 Project Background

This project was a small part of a Primary Growth Partnership (PGP) project entitled 'Pioneering to Precision'. The stated aim of the PGP project was to improve fertiliser placement and response on hill country farms (M.P.I., 2017d). To understand the importance of the overall project and the contribution of this thesis, it is necessary to first define the environmental and socio-economic conditions influencing the evolution of New Zealand's hill farming sector.

1.2 General Sector Statistics

The total area of New Zealand is 26.8 million hectares, divided among two main and 31 minor islands (Statistics, 2013). Approximately three-quarters of the country is 200m or more above sea level and 14.4 million hectares (53%) of the total land area is dedicated to farming (Statistics, 2013). In New Zealand, hill country farms are commonly associated with sheep and beef production, and steep, inaccessible terrain. There are a number of categories of hill farming that vary in topographic severity and therefore productivity. This thesis combines all those categories under the well-known local term of hill country farm for simplicity and because the technologies employed in this research are not limited by terrain.

The production choices on New Zealand's hill country farms are limited by the access and topographical extremes, which mean intensification though innovations such as irrigation are not feasible. Sheep and beef farms comprise 44% of the 55,473 farms in New Zealand, and 93% are owner-operated (BLNZ., 2018a). In 2016, the single largest expense on these farms was fertiliser, lime and seed application which averaged around $65,000 (25%) of total working expenses (BLNZ., 2018a). Before-tax farm profits were about $70,000, so fertiliser applications are vital decisions that can dramatically impact farm profitability. This farming sector, however was not always so lean; a changing political landscape in New Zealand brought great turmoil in the 1980's.

1.3 Political Background

The 1984 New Zealand budget began a series of government reforms aimed at removing economic farming subsidies (Ballingall & Lattimore, 2004). This was in stark contrast to the previous approach where government encouraged pastoral expansion by conversion of unimproved land with development grants such as the Supplementary Minimum Price (SMP) scheme (Gouin, 2006). The rapid expansion, enabled by such schemes, into unimproved hill country land, was led by the sheep and beef sector as other production opportunities were limited by the terrain. Various fertiliser subsidies supported and sustained the expansion of hill country farmers, initially with fertiliser transport subsidies (available since the 1930's) and other fertiliser subsidies introduced in the 1970's (Lattimore, 1985). However, the expansion into marginal land and reliance on subsidies left the industry vulnerable and unsurprisingly the sheep sector suffered greatly from the economic reforms that cut incomes by up to 40% almost overnight (Ballingall & Lattimore, 2004). The cessation of subsidy payments, combined with rapidly rising interest rates at the time, caused massive hardship for New Zealand farmers with large numbers sent to bankruptcy. The reforms in the 1980's led to a decline in farm numbers and in living conditions for those farmers who had difficulty keeping their businesses solvent in the new economic conditions (Gouin *et al.*, 1994; Gouin, 2006).

New Zealand's agriculture sector has seen a slow, steady recovery since the 1980s. The recovery is largely attributed to productivity gains from research, technology and from diversification into other products or crops (Ballingall & Lattimore, 2004). The sheep industry however was hit hardest by the reforms (Gouin *et al.*, 1994) and its recovery has been slower than other sectors, having been impacted by continued falling wool prices. Sheep numbers dropped by 40% between 1982 and 2003 with beef cattle numbers also dropping by 10% from 1994 to 2003 (Ballingall & Lattimore, 2004; Gouin, 2006). Market forces have driven the decline in sheep numbers as farmers moved from sheep, which previously attracted subsidies, to meat production. Hence, the drop in sheep numbers has been partly replaced by beef, deer and goats since the 1980s (Gouin *et al.*, 1994).

1.4 Farming Pressures

Today, other factors also strongly influence the farming sector. Water quality, greenhouse gas production (Leslie *et al.*, 2008), carbon sequestration (Hollinger *et al.*, 1993) and reduced native biodiversity (Craig *et al.*, 2000) are increasingly important in farm management decision-making. Consumer awareness and public perceptions are pressuring the sector to improve sustainability measures (Dodd *et al.*, 2008). For individual farmers however, financial considerations remain paramount and fertiliser is the largest single component in farm accounting (Gouin *et al.*, 1994).

1.4.1 Fertiliser Decision-Making

Fertiliser applications, applied annually or biennially, are often set for large areas or the entire farm based on soil tests from sampling transects. Despite advances in the accuracy of sampling methods (Morton *et al.*, 2000), these blanket fertiliser applications cannot possibly account for the highly variable nature of the topography, soils and micro-climates (Murray, 2007). Thus, the current approach means there is a large component of waste in the system. The diversity of the hill country farm environment creates many logistical and financial challenges, including:

- The steep terrain means inputs such as fertiliser must be applied by air rather than more cost-effective and accurate ground application methods (Grafton, 2010).
- The steep slopes make sward improvement by cultivation and reseeding difficult as equipment cannot safely navigate the steep terrain. Establishment is particularly difficult due to the variability in moisture content on steep slopes.

- Hill country farms are generally large which increases fertiliser application costs as the aircraft must return to the same landing strip to reload (Grafton, 2010).

Fertiliser subsidies were available before the 1980s reforms which encouraged farmers to maintain higher stocking levels. Following the removal of subsidies, the fertiliser applied per stock unit immediately dropped by 50%. This led to a decline in soil fertility as farmers, unable to afford the fertiliser applications, effectively 'mined' nutrients from the land. Fertiliser inputs have since recovered to cover maintenance needs (Gouin, 2006). However where base soil fertility was drained to low levels, these applications may be insufficient to correct the base fertility. Furthermore, large fertiliser inputs are now at odds with environmental pressures, so base nutrient levels must be corrected gradually and in accordance with regulatory requirements.

1.4.2 Fertiliser Application Methods

Existing aerial fertiliser application technologies are rather primitive with the pilot manually opening a door with a lever to control output. Given the coefficient of variance for aerial application is 70%, there is much room for improvement (Grafton, 2010). Furthermore, the 40% coefficient for ground-based applications (Lawrence & Yule, 2007) limited to moderate slopes also leads to unnecessary waste. The cost of this inherent waste in the system is twofold; first, the cost of the misplaced fertiliser, and second, the opportunity cost of fertiliser that could have improved productivity elsewhere.

Synge (2013) states the need for application technologies and practices that focus on accurate, targeted placement of fertilisers in the correct quantities where most needed. Variable rate application technologies exist that can address much of the inconsistency of the current systems by placing inputs more accurately and avoiding environmentally sensitive areas completely (Chok, Grafton, Yule, & Manning, 2016). To make real progress however, a system is needed that identifies and allocates fertiliser more efficiently than the current soil testing approaches (Min & Lee, 2005; Maleki *et al.*, 2007; Murray, 2007), and identifies areas where fertiliser should be excluded entirely.

1.4.3 Precision Farming

Precision farming is a term coined to describe the use of data, often collected on-farm, to target interventions that improve farm returns. Historically, farming and related industries rely heavily on expert judgement in decision-making processes. Precision farming offers the possibility to generate mechanical knowledge that has replicable objectivity. Many precision farming technologies rely on data collected during routine operations such as harvesting. However until now hill country farms have not widely benefited from their use. Emerging remote sensing technologies hold the promise of detailed mapping in the hill country setting, which could be used to inform management decisions and inputs such as fertiliser through variable rate application technologies. Given that sheep and beef farms operate on slender margins (Gouin *et al.*, 1994), even small productivity increases could profoundly impact farmers and the wider sector. However, the precision farming trend has left hill country farms behind. Even basic data, such as effective farming area, that is taken for granted in other farming sectors, can be missing or inaccurate. This is because direct measurement is expensive and often impracticable to collect in the hill country context due to farming systems limitations and terrain constraints. Thus, farmers mostly rely on a combination of expert knowledge and estimation for many critical decisions such as stocking rates. This situation is because of the low profitability system with limited funds available for research, and of the remote and extreme nature of hill country farms. Furthermore, despite progress in other agricultural sectors such as arable farming, there is a paucity of knowledge relating to the use of remote sensing in hill farm environments. As will be shown throughout this thesis, until now, most remote sensing work in this context has not been at a scale usable by or of benefit to farmers.

1.5 Research Aims and Objectives

The overarching aim of this study is to demonstrate that hyperspectral imagery can be used effectively to improve outcomes (business and environmental) for hill country farmers. The goal is to utilise currently available remote sensing tools to inform and improve decision-making processes on and off farm. Another objective is to better define hill farm landscape components, with a focus on filling an important knowledge gap by better understanding the vegetative landscape, especially pasture.

This thesis provides a robust response to the key objectives, which are to:

1. Investigate the variability of turf and pasture species reflectance, to develop understanding for pastoral remote sensing and provide insight into its use for species identification and pastoral breeding programmes.
2. Develop a method that accurately defines pasture area as input for variable rate aerial fertiliser application.
3. Categorise landscape components to inform strategic decisions related to agribusiness and possible diversification.
4. Map pasture quality to improve and inform decisions for aerial fertiliser application and to aid farm strategic decision-making.

1.6 Limitations

This research focuses on the novel application of existing remote sensing methods and techniques to the hill farm environment. Commercial software using pre-programmed processes and algorithms were employed in this research. This work does not seek to develop new remote sensing tools or techniques, rather it aims to provide novel applications for these technologies in challenging new environments. This work mainly uses data from the AisaFENIX© hyperspectral imager, although some proximal sensing data were also used. The sensor selection, choice of participating farms and the development of the farm survey methodology were predetermined by the data collection needs of a larger study, of which this study is a small component. The advantages and disadvantages to this arrangement are discussed in various locations throughout the text.

1.7 Research Contribution

This research provides the research funding body (Ravensdown Fertiliser Co-operative) with remote sensing techniques to elicit commercially-useful information from hyperspectral imagery of hill farm environments. Each chapter investigates a different aspect or application of the technology, which combine to form spatially referenced vegetation maps of hill country landscapes in unprecedented detail. These unique maps are generated from remotely sensed data, rather than extrapolated models, and are novel in this environment and farm type. This research has wider implications than the New Zealand hill farming community. Although the farming system is unique, the terrain and environment are comparable to some sheep producing regions such as the Scottish Highlands. The low economic returns of the farming system also have similarities to smallholder enterprises globally, particularly in the developing nations. This research represents a practical tool to improve information used in farm management and agribusiness related decisions.

1.8 Chapter Outlines

Chapter One has introduced the farming sector and the motivation for this work outlining the topographic difficulties associated with farming in these environments as well as some historical context. It has also identified fertiliser as the largest expense associated with running a hill farm business and discussed its inadequacies. It has also outlined how this research hopes to provide a step-change in the knowledge, and outcomes for farmers operating in the hill country setting.

Chapter Two provides further context for this research with a review of pertinent literature on New Zealand hill farming, remote sensing, remote sensing advancements, precision agriculture and species discrimination using remote sensing techniques.

Chapter Three investigates the use of a proximal (hand-held) spectrometer to identify spectral variability between pasture type species and add to the remote sensing knowledgebase for pasture species. It examines the potential of hyperspectral sensors to discriminate between turf and pasture type species and cultivars to reveal practical limitations. This work was a form of pilot to ascertain the ability of hyperspectral sensors to define differences in pasture type species. The investigation and discussion are couched within the overall pasture environment and specifically at how the use of the technology might aid breeding programmes that seek to introduce new pasture species or cultivars.

Chapter Four introduces and discusses the methods employed in the balance of the research carried out using hyperspectral aerial imagery. It describes the iterative testing employed to select a method suitable for pasture and species classification. Several hurdles encountered during the methodological search are also described, and an explanation of how they were overcome provided.

Chapter Five introduces an original method that defines the effective pasture area for environmentally diverse hill country farms. This simple, easily replicated method maps pasture to very high accuracies. It is neither spatially nor temporally restricted by replication on farms from various locations or surveys conducted at different times of year. The mapping utility is discussed in terms of usefulness to farmers and ancillary industries, such as the fertiliser and rural valuation sectors.

Chapter Six presents a method for mapping other key landscape components. These include manuka, a resource that is currently achieving superior returns to sheep, but one that needs good information to be managed effectively. This chapter reveals that mapping individual elements provides useful information for farmers, and importantly, that one survey can identify multiple components to increase the return on the investment associated with the survey work.

Chapter Seven expands on the previous chapters by adding a quality metric to the pasture areas defined using methods developed in chapter five. The separation of the pasture into high and low value pasture is based on the plant species growing within it. This information provides another metric to define or fine-tune fertiliser application rates and other management decisions from the single data collection event.

Chapter Eight examines the success of the study to meet the research objectives. It discusses the wider implications of the research project, combining the various elements within the hill farming sector context. It examines the efficacy of remote sensing in this challenging landscape and explores the practicalities of upscaling this approach to facilitate the implementation of this research on more of the estimated 24,000 hill country farms in New Zealand. This chapter also presents conclusions from the research, in terms of New Zealand hill farming, and from the remote sensing perspective. Future research that would support or enhance this study is identified which may support the confidence of the farming community in the technology and identify the economic benefits of employing the technology in different situations.

Chapter 2 : Background, New Zealand Hill Farming and Remote Sensing

Pastoral agriculture focuses on producing herbage for grazing animals. The productive capacity of any given area, whether measured in animal weight gain or milk production, is directly linked to the herbage accumulation rate (HAR) (Lambert *et al.*, 1986).

The purpose of this chapter is twofold; first, to provide context for research by introducing the various dynamics that characterise current New Zealand hill farming systems, and second to situate this research by reviewing key literature related to remote sensing of vegetation and discuss its relevance to pastoral farming.

2.1 A Brief History of New Zealand Agriculture

The first Māori arrived in New Zealand in or around the 1300's followed by European settlers in the early 1800's who traded with one another in pigs and potatoes (Te Ahukaramū Charles Royal, 2005). Deforestation accelerated on the arrival of European settlers who hand-felled and converted land to pasture (Blaschke *et al.*, 1992). New Zealand's climate ranges from sub-tropical in the north to temperate in the south. Mild winters across much of the country allow pasture growth for much of the year. By the 1920s agricultural products represented 93% of New Zealand's export income (MAF, 2006). Since then, New Zealand's agriculture sector has experienced a series of setbacks and reinventions that are intertwined with local and world events. Table 1 describes the key phases and influences of the industry since Europeans arrived on these shores.

Table 2.1: Factors and timing for key phases of New Zealand Agriculture (1845 – present). Adapted from (MAF, 2006) unless otherwise noted.

Phase description	Time frame/ Sheep population	Factors driving the changes
Experimentation	1845 – 1882 9 Million (1865)	Wool production overtakes wheat as the major product driven by colonial expansion and conversion of vast areas of native bush and tussock to grass.
1st Grasslands Revolution	1882 - 1920	Introduction of refrigeration facilitating exports of agricultural products to Britain, where higher living standards increased demand. Creation of the Department of Agriculture, cheap government loans to settlers, subdivision of large estates into family farms and conversion of 18 million acres to ryegrass, cocksfoot and clover pasture firmly established farming as the primary industry of New Zealand. During this time, in 1878, Lincoln agricultural college was also founded.
2nd Grasslands Revolution	1920 – 1950 32 million (1949)	Imported phosphate from Nauru delivers a cheap process to replenish declining soil nutrition. Britain's reliance on colonial support during the First World War provided an incentive to support New Zealand farming. Despite these advances and the improved productivity from the creation of the Department of Scientific and Industrial Research (1926) and Massey Agricultural College (1927), farmers struggled to cope with price drops of the 1920's and 30's. Many World War 1 returned servicemen became settlers, but around a third of these farms eventually failed. The Labour Government of the 1940's gave more assistance to farming but during the Second World War the industry became run down, especially hill country farms. Aviators, returning from war, changed this with the introduction of aerial fertiliser applications.
3rd Grasslands Revolution	1950 – 1984 70 million (1980)	The Korean War resulted in high prices for wool but Britain's deals with its European neighbours in 1967 saw a commodity price drop. Efforts to diversify into sectors such as forestry and venison first appeared in the 1960's.
Neo-liberal reforms	1984 – 2000 50 Million	The swift removal of all agricultural subsidies was expected to end stock farming described as a "Sunset industry". Despite this change and falling commodity prices, the industry survived
Dairy boom	1995 – present 27 Million (2016) split 50/50 north and south islands (BLNZ., 2018a).	Alongside a resurgence in sheep farming, dairy farming has undergone a boom driven by high commodity prices and advances in irrigation. New challenges of water quality, high fuel costs and fertiliser inputs have come to the fore. Sustainable farming methods are the new ambition of the sector as sought by the Resource Management Act.

Agriculture remains a dominant force in the New Zealand economy despite being described in the 1980's as a "sunset industry" by the then Prime Minister, David Lange (Woodfield, 2015). Agriculture represented 62% of New Zealand exports in 2017, between 2016 and 2017 agricultural export revenues increased by 13.7%, while non-agricultural exports rose by 5.8% (Stats NZ, 2018). As a burgeoning global population drives demand for food and other agricultural products, improving agricultural efficiency is as relevant now as it was in past agricultural phases. It is arguably even more so for hill farms that are economically marginal (Gouin, 2006).

Hill farms are typically diverse environments with significant variation within and between farms. Researchers have defined eight classes of farm that vary by location, terrain and production; this study chiefly focuses on farms rated as Class 3. For comparison, descriptions of classes 3, 4 and 5 are defined in Table 2. Information on the other classes can be found in (BLNZ., 2016).

Table 2.2: Farm classes and descriptions, Adapted from (BLNZ., 2016).

Class and Name	Farm numbers	Description	Carrying Capacity (Stock Units/Hectare)	Market
Class 3: North Island Hard Hill Country	1,065	Steep or low fertility soils	6 to 9	Mainly breeding properties
Class 4: North Island Hill Country	3,640	Easier hills or higher fertility soils than class 3	8 to 13	Forward store or prime condition animals
Class 5: North Island Intensive Finishing	1,275	Easy contours with potential for high production. Tend to be smaller in size.	10 to 14	Focused on high production per hectare

According to Beef and Lamb New Zealand, in 2017 the average hill country farm carried 3,977 (mixed cattle and sheep) stock units on 252 ha. The average before tax profit was $90,600 ($359 per hectare), which notably has tripled since 2007(BLNZ., 2018a). Class 3 farms vary from these averages, see Table 2.3.

Table 2.3: Category averages for Class 3 compared to averages of all farm classes, adapted from (BLNZ., 2018a) and (BLNZ., 2018b).

Category Averages (2016)	Class 3 Farms (BLNZ., 2018b)	Average, All Sheep and Beef Farms (BLNZ., 2018a)
Effective area	917	252
Stock Units per hectare	8.1	15.78
Stock units per farm	7427	3977
Fertiliser, lime and seed expenditure as percentage of total expenses	21.29%	24.28%
Before tax profits	$101,675	$90,600
Before tax profit per hectare	$110.87	$359.52
Before tax profit per Stock Unit	$13.61	$22.78

A cursory examination of farm revenues from Table 2.3 may suggest that Class 3 farms do slightly better than the average until examined with average effective area and stocking rates per hectare. Class 3 farms generate less than a third of the before tax profit per hectare than the average sheep and beef farm. Class 3 is defined by the steep terrain and low fertility so it is unsurprising that they have lower productivity. The lower profit margins per hectare realised by many of these hill country farms naturally effects their overall value. According to the Real Estate Institute of New Zealand (REINZ) in the 3 months ending December 2018, 152 finishing farms sold with a median per hectare price of $31,169. In the same period, 128 grazing properties sold with a median per hectare price of $10,192 (REINZ, 2019). There is no breakdown by farm class but based on the descriptions given of finishing farms and grazing farms they would align with Class 4 and Class 3 respectively. This project is centred around the use of remote sensing to better define these difficult farming landscapes and improve management decision-making information. The lower incomes and values associated with these farms are an important condition to bear in mind when assessing the significance of any stratagem for improvement.

2.2 Understanding Hill Country Farming

Pastural management and improvement has been the subject of research for many years (Linsley & Bauer, 1929; Suckling, 1959; Caradus, 2006; Casler, 2006; MAF, 2006; P. Kemp & Lopez, 2016). New Zealand sheep and beef farms are primarily located on terrain that is less (or un-) suitable for other farming enterprises. A crucial factor influencing pasture quality is botanical composition (Lambert & Litherland, 2000). The two main grasses associated with pasture in New Zealand are perennial ryegrass (Lolium perenne) and browntop (Agrostis capillaris), which are quite different in chemical composition and feed values (Lancashire & Ulyatt, 1974). Hill country farm environments are heterogeneous, that is, they often have a wide range of macro and micro relief (Lambert *et al.*, 1983) which contributes to variation in pasture species present (Grant & Brock, 1974; Luscombe *et al.*, 1981; López *et al.*, 2006). Soil characteristics and fertility have also been shown to vary within and between hill farm slopes (Lambert *et al.*, 1983). Steep slopes, variable soils and variable pasture makes the pasture management more difficult in hill country than in flat or more gentle terrain. Figure 2.1 presents a view of some hill farm pasture in the Manawatu region, about 2 hours north of Wellington to demonstrate some of this variability.

Figure 2.1: A view of hill country farm pasture on the western slopes of the Tararua ranges about 2 hours north of Wellington City, New Zealand.

Management of pasture quality was identified as the best opportunity to improve the financial returns of hill country farms (Lambert *et al.*, 2000). Fertiliser application, within limits, can strongly influence pasture growth, especially where fertility is below optimal (Lambert *et al.*, 2004) with production increases of 200% possible (Luscombe *et al.*, 1981). However, other than the animal health improvements from certain elements, fertiliser application has only a minor impact on pasture quality (Lambert & Litherland, 2000). Fertiliser application has its greatest influence on feed quality via its potential to change the species composition of pasture through competitive exclusion of browntop by ryegrass and clover (Luscombe *et al.*, 1981; Lambert & Litherland, 2000). In New Zealand hill farms, aerial top dressing with a phosphate fertiliser is the most common approach to encourage the legume content of the sward and subsequently ryegrass (Lambert *et al.*, 1986).

Combinations of fertility improvement, grazing management and over-seeding have been used to improve hill farm pasture with varying degrees of success (Lambert *et al.*, 2004). The key variables for hill farm pasture production have been well documented (Lambert *et al.*, 2004; López *et al.*, 2006). Winter is wet but temperatures are low, so the best growth is usually in spring when soil moisture is still high and temperatures rise. Rainfall is the primary limiting factor to pasture production in these landscapes (Rickard *et al.*, 1986), especially rainfall in spring (B. Zhang *et al.*, 2005). Slope was shown by B. Zhang *et al.* (2005) to be the next most important factor. The severity and aspect of slopes also have measurable influence on seasonal and yearly pasture production (Gillingham *et al.*, 1998). Increased slope angle is associated with reduced soil moisture availability, reduced fertility and reduced herbage production. An increase in slope is also linked to an increase in pasture species diversity (Lambert *et al.*, 1986).

2.3 Wider Farming Community Issues

The difficulties posed by this terrain for farming, and associated low incomes (BLNZ., 2018a), means that farmers are open to other opportunities. Scrub species, including manuka (Leptospermum scoparium), will colonise land that is not well managed and has been considered a weed in the past (Lambert *et al.*, 1986). In more recent years manuka has had its status lifted as the price of manuka flower honey has soared. Manuka honey exports in 2017 were valued at NZ$329 million (M.P.I., 2017a). This was driven by its proven antibacterial activity (Blair *et al.*, 2009) that is effective even against antibiotic resistant variants (Kwakman *et al.*, 2011). The lucrative income source is a welcome addition in a sector that had previously been fighting the plant’s spread. The value of a business is directly related the income potential; for farming this is also linked to the land and its value with more productive land valued higher (REINZ, 2019).

2.3.1 Rural Valuation

Rural real estate valuation is a key component of the New Zealand rural economy and is of national interest. All real estate is regularly valued for rating purposes and ratings valuation rules require rural valuers to record areas of land, contour and cover (2010).

2.3.1.1 Market Approach

The market approach has been historically accepted as the preferred method to assess the market value of rural land. The income capitalisation method is proposed as a useful check method (Eves, 2005; Hargreaves & McCarthy, 2010). The market approach compares like with like, therefore accurate land classification of comparable properties is imperative to ensure accurate valuation of the subject property. This approach is problematic when comparable properties have not been recently tested on the market. The income approach requires the productive potential of the land to be estimated; this can only be performed with accurate, detailed physical property information. At present, the process of acquiring base information for a valuation varies between valuers (Pete Loveridge, Personal Communication). This can create variation in valuation and presents the valuer with potential conflict of interest when balancing the requirements of the law and needs of their client. What is missing is a process where essential base data is generated in a consistent manner so bias can be reduced or eliminated.

2.3.2 Environmental Pressures

The public, and therefore governments, are becoming increasingly aware of the pressures that human activity, including farming, is having on the environment (Quinn *et al.*, 1997; Dodd *et al.*, 2008; Oliver, 2013). High amongst these concerns is the topic of water quality which, depending on metric used, is different between streams of native forest and pastures (Quinn *et al.*, 1997). This should not be a surprise to anyone as the removal of trees essentially creates a different habitat that will have a different range of flora and fauna adapted to it (Grime, 1979). According to Quinn *et al.* (1997) total species richness increases in streams running through pasture but the reduction of shade increases maximum water temperature and changes the species present. Because fertiliser is currently applied to hill farms in large (often yearly) events there is potential for over-application which can lead to negative environmental outcomes (Grafton *et al.*, 2010). However, most applications of fertiliser to hill farms are with single superphosphate (SSP) (Grafton *et al.*, 2012) rather than nitrogen but according to Quinn *et al.* (1997) there was no change in in dissolved phosphates between grassland and native forest streams. However, the phosphate on pasture is utilised by legumes which create nitrogen and consequently nitrogen levels were higher in streams running through pasture (Quinn *et al.*, 1997). Environmental sustainability is not just about water quality, as environmental issues have global implications.

Globalised environmental pressures are likely to play a role in future farming sustainability. New Zealand hill farming is already at risk from regular erosion events (Blaschke *et al.*, 1992) and is equally exposed to the increased global variability of climatic conditions (Gouin, 2006). Land where slips occur take around 20 years to recover around 80% of the previous productive capacity, but importantly it does not improve beyond that 80% level (Blaschke *et al.*, 1992). Although Blaschke *et al.* (1992) suggest that land with slopes over 32° is not suitable for pasture, other evidence that the land is also uneconomic as pasture, might aid decision-making towards diversification or land retirement. Some work on improved sustainable management was carried out by Dodd *et al.* (2008) but along with some success they reported that their process was cost prohibitive. Regardless of the approach a better understanding of the environment and vegetation within it, will help efforts for its protection and sustainable use.

2.3.3 Farm Diversification

Hill country farmers have been generally receptive to innovation or diversifications that can help their economic position, especially towards other pastoral production such as goats or deer. (Gouin, 2006). The rise of the manuka honey industry is another example of farmer's awareness and openness to innovation. Of course, the 23% per annum rise in export prices over the 10 years to 2015 did not go unnoticed (Bagrie *et al.*, 2015). The government too has noticed the opportunity and are investing in the sector to lift the export revenue from $75 million to $1.2 billion by 2028 (M.P.I., 2018c). One of the eight items identified by Bagrie *et al.* (2015) as requiring more work in the manuka sector is that of improved commercial arrangements with landowners. As with rural valuation there is little base information to start real dialogue on this topic. It is difficult to have a unified or fair contract system without clear definition of the quantity, and quality, of the resources being traded. That provided the impetus to use remote sensing data to investigate the categorisation of other landscape components in objective 3.

2.4 Precision Agriculture

The highly varied terrain of hill country farms and the myriad of micro-climates it produces make effective pasture management difficult. This is true of all farmland (Oliver, 2013). What works well in one area may not work in another (Gillingham *et al.*, 1998). Definition of these different areas has previously been limited to general slope categories and orientations (Gillingham *et al.*, 1998; López *et al.*, 2006). The introduction of geographic information systems (GIS) for localised studies in combination with modelling has brought added insight and accuracy (Wan *et al.*, 2009) but methods still focus on the traditional collection of physical samples. In these landscapes normal field sample collection is costly, time-consuming and can easily miss important data if the sample size is not large enough. Designing intelligent systems to improve agricultural yield is recognised as an important focus as world populations rise (Reynolds *et al.*, 2018). Other farming sectors have benefited from the adoption and integration of technology into their management structure (Oliver, 2013). Until now these modern Precision Agriculture (PA) techniques had not been adapted for the hill farming community.

2.4.1 Precision Agriculture Data and Approaches

Field variability has long been known about (Oliver, 2013). It was in part the need to address field variability in small plot experiments that led to the development of modern methods of research design (Yates, 1964). The variability of the soils has long been focused on fertility as a definition of productive capability. In response, methods for intensive field sampling to address the variability were developed (Linsley & Bauer, 1929). In the 1920's spreading of fertilisers was carried out manually from flatbed wagons or trucks after first being shovelled from a train, so the intensive sampling was considered labour-saving. The advent of mechanical spreaders reversed this (Franzen & Mulla, 2015) and has resulted in modern soil sampling protocols that combine a series of samples taken from 'representative' locations (transact) (Morton *et al.*, 2000).

Statistical approaches developed in the mining industry have been adapted to account for some of the field variability using fewer samples (Matheron, 1963). These approaches still leave the vast majority of the true conditions unknown, as only the sample is actually tested with the remainder interpolated from those results (Morton *et al.*, 2000; Franzen & Mulla, 2015). Identifying the variability of soil nutrients patterns became more important with the advent of variable rate spreaders in the 1980s. Subsequent experiments defined a sampling interval of 0.4 ha as optimal to make variable rate applications of fertiliser financially viable (Franzen & Mulla, 2015). However, the application of fertiliser to the correct location was still difficult. The release of the GPS satellite network for non-military use in 1993 vastly improved the precision of geolocation in agriculture (Oliver, 2013; Franzen & Mulla, 2015). Differential GPS allows samples to be associated with an exact location and that location associated with the application rate required. Precision farming tries to optimise farm revenues by applying inputs only when and where necessary, and in doing so reduces negative environmental effects (Oliver, 2013).

The aerial topdressing industry is only now arriving at the point that terrestrial application reached in the late 1980s with the introduction of variable rate application. Just as then, methods to determine application rates have not kept pace with the application technology. Oliver (2013) asserted that widespread adoption of precision farming is hampered by a lack of soil and crop information.

Another problem with the current aerial application technique is the inherent variability in the system. A pilot must fly at an optimal height regardless of terrain (contour flying) and manually open the hopper door in the correct place to apply the correct rate. The variation in application speed alone, as the pilot tries to maintain altitude into valleys and over ridges, makes it unlikely the correct rate is applied let alone applied only where it is needed (Grafton *et al.*, 2012). Variable Rate Application Technologies (VRAT) (Grafton *et al.*, 2012; Chok, Grafton, Yule, & White, 2016) hold the promise of improving the outcomes for the environment and farmers as well as the likely safety advantages achieved with the pilot focused on the task of flying.

The methods discussed thus far focus on the collection and use of physical samples for setting rates. Physical sampling is difficult, expensive and even dangerous in some hill farm locations.

Another technology, remote sensing, not only overcomes those issues but can vastly increase the sample interval at the same time.

2.5 Remote Sensing

Remote sensing is often defined as the collection of data or information without making physical contact and was practiced before the terminology was developed (Cracknell, 2007). When we combine remote sensing with verified ground data, the remote sensing acts as a scaling tool (Edward *et al.*, 2008). This means the properties identified from the ground data can be extrapolated to locations where ground data were not collected. The primary goal of remote sensing is to characterise the target in terms of quantity, condition and distribution (Jackson & Huete, 1991). The target in agriculture is usually vegetation, however soils and water bodies are also of interest.

This section presents a brief history of remote sensing focusing on research that has implications for this thesis. The characteristics of plants that may change or influence their spectral signature are then described. Next, the efforts to overcome research challenges are explored before the chapter closes with a discussion on species identification and the use of hyperspectral sensors.

2.5.1 The Quality of Light

Early photoelectric cells were developed in the 1930's by using a combination of glass filters. Coombe (1957) investigated the spectral composition of transmitted light (which he called shade light) in woodlands between 365nm and 730nm wavelengths. Federer and Tanner (1966) later concluded that light of wavelengths of 400, 450, 500, 550 675 and 750nm were enough to define the spectral distribution of shade light under such vegetation. The researchers studied various canopies and consistently found a low level of transmission in the 670nm range, where chlorophyll is active in light absorption, and a steep increase in energy above 700nm as a result of the reduced absorption.

The idea that some form of quantitative measure could be given to vegetation from the quantity and quality of light was first suggested by Jordan (1969). He theorised the ratio of light between 675nm and 800nm reaching the canopy floor could be used to quickly and accurately measure the leaf area index of the canopy. In determining the index, he also realised that as the sun angle changes, thus also the distance light must travel through the canopy, which could increase the biomass reading. To compensate for this, he added a correction for the angle of the sun for the time of year and suggested extra on-site measurements to allow for passage of time throughout the day. These practices have been refined over the intervening years.

When discussing remote sensing there are three categories of light and its interactions with objects. Transmitted light has passed through the object, absorbed light has been captured by the object and reflected light has been reflected by the object. Where Coombe (1957) used transmitted light modern sensors switched to the more practical reflected light as a means of measurement.

In 1972 NASA launched ERTS-1 (later renamed Landsat-1). In 1974 a group of researchers at Texas A&M University investigated the possibility of using the satellite to measure light reflected from vegetation and use it as a quantitative measure of vegetation condition over large areas (Rouse Jr *et al.*, 1974). The result, the Normalised Difference Vegetation Index (NDVI), was resistant to image variability and has been the workhorse of the remote sensing community since (Gamon *et al.*, 1992; Cho *et al.*, 2007; Grace *et al.*, 2007; Mahajan *et al.*, 2014).

2.5.2 Vegetation Indices

The light reflected from a surface is a function of the reflectance properties of the surface. However, because there are variations in atmospheric conditions such as nebulosity, sun angle and atmospheric water content it is not enough to simply measure reflectance. The atmospheric conditions would need to be matched exactly to compare results. The combination of two or more spectral bands to form Vegetation Indices (VI) tries to lessen external influences such as sun angle enough that comparisons of sites can be made spatially and temporally (Baret & Guyot, 1991; Jackson & Huete, 1991; Gilabert *et al.*, 2002). It is essential that the variability of the atmosphere, sun angle and background be taken into consideration to comparably characterise the amount and condition of vegetation (Jackson & Huete, 1991).

Ratios and linear combinations define the two main classes of VI. Ratios can be sums, products, or differences of any number of bands such as NDVI. Linear combinations such as the Perpendicular Vegetation Index (PVI) (Richardson & Wiegand, 1977) are “orthogonal sets of n linear equations calculated using data from n spectral bands” (Jackson & Huete, 1991). Jackson (1983) wrote an excellent explanation of multidimensional indices.

Because of their utility and resilience, VI are now commonly used and indispensable tools. Common applications include drought monitoring, habitat loss, climate change, land-use change, global biomass estimations, crop production, plant stress, wildfire risk prediction and water use (Jackson & Huete, 1991; Penuelas *et al.*, 1997; Cho *et al.*, 2007; Edward *et al.*, 2008). Hyperspectral vegetation indexes have also been used for species discrimination (Cho *et al.*, 2008), one of the main objectives of this work, but that use is not widespread, even in the research context.

2.2.4 Hyperspectral Indices

Precision farming largely relies on technologies developed for other sectors, such as the military (e.g. GPS). It is not surprising then, that the development of VI mirrors advances of other areas of remote sensing, including sensors. With the advent of modern sensor equipment VI have been further refined from broadband (or multispectral) indices to the modern narrowband (or hyperspectral) indices. The arrival of hyperspectral sensors in precision farming research in the 1990s delivered superior accuracy and utility over the multispectral sensors (Adam *et al.*, 2010). Importantly, the narrowband sensors generate more detailed measurements and evaluations of the target surface or feature of interest. Narrowband VI have been used to produce better correlation between predicted values of biophysical or biochemical properties and the actual values of plants (Cho *et al.*, 2008).

Hyperspectral sensor data has been successfully used in studies on many topics in ecology (Aspinall *et al.*, 2002; Axelsson *et al.*, 2013), mapping (Bandos *et al.*, 2009; Adam *et al.*, 2010; Alonzo *et al.*, 2016) and agriculture (Calderón *et al.*, 2013; Y. Liu *et al.*, 2015).

2.6 Plant Reflectance Properties

Understanding of the target has allowed improvements to be made to various VI. To spectrally categorise plant species, we must consider the stresses and factors that can influence plant chemistry and thus the spectral reflectance. There are recognised relationships between remote sensing data and biophysical properties of plants (Grace *et al.*, 2007; Edward *et al.*, 2008). Unfortunately, the task of species identification is potentially made more difficult by the natural variation that occurs within species as a result of environmental factors such as water availability, light levels and temperature. These factors can mean that examples of the same species can look different and different species can look the same. Community density and water content were cited by Sha *et al.* (2008) as reasons for within class variation.

There are a number of plant similarities and differences that influence reflectance and therefore our ability to differentiate them with spectral data.

2.6.1 Photosynthesis

Photosynthesis is the process that fuels most life on earth. In simple terms plants use light energy to convert carbon dioxide (CO_2) and water (H_20) into glucose with spare oxygen (O_2) given off as a by-product. The Photosynthetic Reaction Centre (PRC) is the physical location where plants convert solar radiation into a usable form of chemical energy (Hillier & Babcock, 2001). As the driving force behind photosynthesis, light absorption and reflectance of non-utilised light components, can tell us a lot about what is going on within the plant (Curran, 1989).

The reflectance at 531 and 570nm was investigated as an indicator of photosynthetic radiation use efficacy. The Photosynthetic Reflectance Index (PRI) was supported as a broad means of assessing radiation use efficiency (Gamon *et al.*, 1997). PRI was found to be inversely related to photosynthetic efficiency (Penuelas *et al.*, 1994).

Penuelas *et al.* (1994) found a clear pattern in photosynthetic rates throughout the day with values increasing before and decreasing after midday. Visible reflectance was found to be negatively related to Chlorophyll content, nitrogen and net photosynthetic rates while NIR reflectance had positive correlations. Gitelson and Merzlyak (1997) developed a method to remotely estimate chlorophyll content of plant leaves.

2.6.2 Photosynthetic Damage

Damage to the photosynthetic reaction centre appears to be an inevitable part of photosynthesis (Y.-I. Park *et al.*, 1995) and occurs when there are excess levels of light. Excess light conditions arise when the light received exceeds what photosynthesis can use. This occurs on most sunny days when light levels are high or when photosynthetic reactions are slowed by other stresses such as drought or low temperatures (Demmig-Adams & Adams, 1992; Grace *et al.*, 2007; Darko *et al.*, 2011).

Excess light conditions increase the rate of damage to the PRC and this damage is further amplified when other stress factors are present. The repair process is slow so a permanent reduction in photosynthesis can occur when damage exceeds the repair rate (Horton *et al.*, 1996; Nath *et al.*, 2013).

Plants employ many mechanisms both physiological and molecular, to lessen photo-reactive damage. Adjustments to leaf angle or chloroplast movement can reduce light absorption (by increasing reflectance) while the downregulation of the light harvesting system and dissipation of unwanted energy as heat also protects the photosynthetic apparatus (Demmig-Adams & Adams, 1992; Darko *et al.*, 2011; Takahashi & Badger, 2011; Nath *et al.*, 2013). Downregulation is the process where cells reduce the quantity of protein components in response to external variables such as high light levels. The mechanism of protection of the photosynthetic apparatus is the de-epoxidation of violaxnthin to zeaxanthin known as the Xanthophyll Cycle (Gamon *et al.*, 1992). (De-epoxidation is the chemical removal of an oxygen ring from a compound, in this case violaxnthin). This is part of the process known as Nonphotochemical Quenching (NPQ) in which energy is diverted from chlorophyll (Grace *et al.*, 2007). The excess energy is dissipated as heat which prevents the PRC from becoming over-excited which would lead to damage (Takahashi & Badger, 2011). Non-photochemical quenching is employed by plants to dissipate excess light energy from rising light levels and was found to increase when plants are in drought stress (Massacci *et al.*, 2008).

2.6.3 NPQ and Associated Pigment Detection

The plant responses designed to reduce photosynthetic damage change the patterns of light that a plant reflects. The pigments of the Xanthophyll Cycle were detected by Gamon *et al.* (1990) and showed a strong correlation between concentrations and reflectance at 531nm. Later, Gamon *et al.* (1997) showed a greater resolution at 526nm with increasing light levels over 100 umol m-2 s-1. The study confirmed a link between declines in carboxylation, photosystem II (PSII) down-regulation and changes in the Physiological Reflectance Index (PRI). Furthermore, Penuelas *et al.* (1994) found the PRI delivers more useful information on xanthophyll pigments and photosynthetic rates than the widely adopted NDVI.

The bands from 490 to 510nm have been linked to carotenoid absorption by Merzlyak *et al.* (1998). Values predicted from VI were found to be closely associated with actual values of carotenoids, chlorophyll a and chlorophyll b (Chappelle *et al.*, 1992; Gitelson *et al.*, 2002).

In Antarctic mosses, the total content of carotenoids was found to be highly correlated to total chlorophyll content (Lovelock & Robinson, 2002). Researchers also found negative correlations between chlorophyll and the photoprotective pigments zeaxanthin and antheraxanthin. (Penuelas *et al.*, 1994; Lovelock & Robinson, 2002).

2.6.4 Water Content

Water is absorbed through plant roots before being transported through the plant and transpired through the stomata. A small amount of water is needed for photosynthesis, with the balance being lost to the atmosphere. Monitoring water content is useful as reduced levels have a negative effect on photosynthetic activity (P. R. Kemp & Williams III, 1980; Sharkey & Seemann, 1989; Penuelas *et al.*, 1994) and therefore growth. Water absorbs light in specific regions of the spectrum. This property masks some plant information, such as nitrogen content (Knox *et al.*, 2010).

The effect of plant drying on reflectance was investigated by Penuelas *et al.* (1997). They found that a trough in their spectral measurements caused by water shifted lower in the wavelength spectrum as drying progressed. The effect was less visible at the onset of drying but was more pronounced and obvious at later stages. (Penuelas *et al.*, 1994) also found that the PRI, which is inversely related to photosynthetic efficiency, decreased in water stressed sunflower leaves which also showed higher nitrogen and chlorophyll contents.

In another study, Knox *et al.* (2010) discovered that when wavelengths of importance in nitrogen prediction are selected using fresh material those wavelengths can predict levels of nitrogen in dry material but the converse is not true. They theorised this was related to the ‘noise’ present in fresh samples, including water, that are absent in the dried material. The same water absorption features were used by Fuentes *et al.* (2001) to improve forest vegetation mapping results. However Poulter *et al.* (2011) found that arid and dryland landscape conditions added to classification error, this was possibly influenced by other environmental factors such as salt levels.

2.6.5 Physiology

Leaf angles and chemical composition of plants can also alter their reflectance. Mutant maize plants with reduced light harvesting complex II and chlorophyll were found to have similar photosynthetic productivity as wild types on a leaf area basis (Jenkins *et al.*, 1989). The similar photosynthetic productivity according to (Baker, 1991) was attributed to “an increase in leaf reflectivity and canopy structure of the mutant which ensures the total radiation intercepted by the two crops will be similar". Discriminant analysis of several narrow band spectral indices was shown by (Penuelas *et al.*, 1994) to separate treatments into relevant groups and showed promise for identifying plant physiological state. Cordon and Lagorio (2007) found that reflectance for adaxial and abaxial faces of dicotyledon leaves had different characteristics. Monocotyledons however showed similar reflectance properties for both sides of the leaf. Differences in leaf architecture were thought to play a major role in the observed results.

Planophile canopies (mostly horizontal canopies) have a higher Fraction of Absorbed Photosynthetically Active Radiation (fPAR) and NDVI than erectophile (mostly erect or vertical leaves) (Myneni & Williams, 1994).

Knowledge of a target plant's leaf structure and growth habit may prove to be a valuable tool in discrimination of plant type and may even assist with species discrimination.

Shifts in the chemical composition of leaves have also been shown to be related to elevation and soil fertility (Asner *et al.*, 2014). Moss growing on a ridge instead of in a valley showed lower values for PRI and around half the chlorophyll content. Xanthophyll-cycle pigments were also significantly higher as were the portion of them in photoprotective forms (Lovelock & Robinson, 2002). Differences in reflectance between sites and topography were found by Lovelock and Robinson (2002) to be attributable to variations in pigment content.

This degree of variability will have to be accounted for when attempting to define species throughout a large variable site or on different sites.

2.6.6 Nitrogen Limitation

PRI values were found by Penuelas *et al.* (1994) to be higher in nitrogen limited plants especially towards the end of the day. NDVI could not track diurnal changes in light use efficiency. Limiting nitrogen had a marked effect on reflectance in older leaves and presented as a shift in the red edge to lower wavelengths (Penuelas *et al.*, 1994). Several researchers have succeeded in using remote sensing techniques to predict nitrogen content of pasture species (García-Ciudad *et al.*, 1999; D. Lamb *et al.*, 2002; Pullanagari *et al.*, 2016).

2.6.7 Seasonal Variation

Leaf ageing of sunflower exhibited as higher levels of reflectance across all wavelengths but was more obvious in nitrogen and water limited plants (Penuelas *et al.*, 1994). Zomer *et al.* (2009) found high biomass conditions in middle to late summer produced spectra with high near-infrared reflectance.

The seasonal differences in some grass species have been exploited to help attempts at identifying and mapping their distribution (Foody & Dash, 2007; Marcinkowska-Ochtyra *et al.*, 2018; Crabbe *et al.*, 2019).

2.7 Species Identification

The chemical balance of plants clearly fluctuates with respect to environmental stimuli. Accurate species identification from remotely sensed data has been a long-held ambition of researchers. This is no less true for pasture agronomists and part of the reason it is a key objective of this study. The question of whether the reflectance carries enough information for pasture species identification given its variability and heterogeneity will be investigated in later chapters.

A consequence of the absence of quality soil and pasture data means that important hill farm management decisions are often based on assumptions or estimations of the quality and composition of pasture swards. Fertiliser applications, grazing regimes and decisions to improve pasture are among the most prominent and financially important. Making an incorrect decision or failing to act at the appropriate time can have significant financial implications for these farming systems that operate on slim margins.

Several studies have looked at identification of species from hyperspectral reflectance readings (Vaiphasa *et al.*, 2007; Cho *et al.*, 2008; Zomer *et al.*, 2009; Cho *et al.*, 2010; Ghasemloo *et al.*, 2011; Prospere *et al.*, 2014), although most rely solely on proximal sensing data. The approaches taken to address the problem are as varied as the applications for which the information is intended. Ecology and agriculture have bodies of work that both relate to this study. Ecologists and biologists wish to monitor large areas where access is limited, the sites are too large to map manually or where wildlife makes the environment too hazardous for manual mapping (Zomer *et al.*, 2009). In general, agricultural applications for hyperspectral data relate to crop production. Although the areas of interest on farms are large, they are usually more easily accessed and have fewer dangerous animals to contend with. Native or wetland habitats more closely resemble hill farm situations as they are less easily accessed and contain heterogenous groups of species rather than the single species. Limited access reduces the feasibility of interventions such as pasture renewal. Therefore the mix of vegetation is more naturalised and thus more reminiscent of wild pastures than of other agricultural situations (López, 2000).

2.7.1 Difficulties in Discrimination

There are several problems associated with discriminating species using reflectance, such as the spectral similarity of some vegetation and the spectral variability within a species (Price, 1994; Roth *et al.*, 2012). The mixed nature of plant communities adds further complexity to the information contained within reflectance data.

Zomer *et al.* (2009) found there were discernible similarities in the spectral signatures for plants of the same species which indicated to them that species-level mapping could be carried out without a prior knowledge of the species composition. However, the wetland environment where this worked well was composed of mosaics of monotypic species. They found heterogeneous mixed communities were more difficult to delineate and required prior knowledge from field data and/or the use of spectral matching or unmixing.

Although they found good correlation between spectral classification and field observations for some wetland species (e.g. Salicornia) L. Li *et al.* (2005) found another species (Grindelia) was underestimated or missed. They attributed this error to the similarity of the spectral signatures between the green Grindelia and Salicornia and suggested sampling at another time of year when differences were more pronounced or using another mapping method. Selection of a seasonal point where species are most distinct (Laba *et al.*, 2005) or use of multitemporal data (Foody & Dash, 2007; Crabbe *et al.*, 2019) has been utilised by other researchers to improve discrimination.

2.7.2 Sample size

To solve some of the issues related to sample variability and create characterization models for soils Brown *et al.* (2006) suggest collection and cataloguing a spectral library in excess of 5.2 x 10^9 of carefully selected calibration samples. Zomer *et al.* (2009) also commented that large sets of sample reflectance spectra might be needed to resolve variability caused by changes in chlorophyll, biomass and chlorosis and the associated shifts in the spectral response. Clearly if such large sample sizes were required it would negate much of the utility gained from remote sensing.

2.7.3 Leaf versus Canopy Measurements

Methods for collecting spectra vary between studies. Some studies use spectra collected from leaves that were harvested or leaf spectra taken in situ, for example (M. I. Sobhan, 2007; Prospere *et al.*, 2014). Collecting canopy reflectance data can be difficult if the species of interest are tall or in precarious locations. Some studies mention the use of bucket trucks (cherry pickers) or cranes for collection of spectra. Banskota *et al.* (2011) collected canopy reflectance of pine, but they used immature specimens which would have reduced the complexity of the collection.

Cho *et al.* (2008) found that species were much more easily discriminated with canopy reflectance than leaf reflectance. This is encouraging as the principal utility of remote sensing is the ability to capture reflectance from vast areas using aerial or satellite-based equipment.

2.7.4 Band Reduction

Modern hyperspectral sensors can produce reliable indicators of various nutrient contents or even species composition (Bin *et al.*, 1999; Tarpley *et al.*, 2000; M. I. Sobhan, 2007). The problem with the vastly increased amount of data that hyperspectral sensors gather is the greater the number of dimensions in the data the more training samples are needed (Hughes, 1968).

This naturally leads to techniques to reduce the dimensionality. Use of various indices or selection of a limited number of important bands that carry the important information while reducing classification error has become the norm (Portigal *et al.*, 1997; Tarpley *et al.*, 2000; Pullanagari *et al.*, 2012).

2.7.5 Bands of Importance

Studies that select bands rather than use prescribed indices must determine which carry the most or most important information (M. I. Sobhan, 2007; Pullanagari *et al.*, 2012). There are several statistical techniques available for this task.

2.7.6 Image Classification

If we wish to examine a scene or large area, we can use data collected by aerial or satellite-based imaging spectrometers. These collect data in many spectral bands over large areas enabling classification and examination on a local, regional or planetary basis. Selecting pure or 'endmember' spectra for use with imaging spectrometer data is the first step to accurate classification of data within an image (Roth *et al.*, 2012). Endmembers must be both spectrally representative of a target and distinctive. L. Li *et al.* (2005) report that a high correlation between endmembers or non-representative endmembers, produce unreliable results. The definition of pure spectra will be research dependant but for species-level definition pure spectra would represent a single species of interest.

There are three main ways to define endmembers. First, they can be collected from leaf spectra either in-situ or from field samples (M. I. Sobhan, 2007; Vaiphasa *et al.*, 2007; Prospere *et al.*, 2014). Second, they can be defined from canopy reflectance measurements (Banskota *et al.*, 2011; Mahajan *et al.*, 2014; Manjunath *et al.*, 2014) or finally, they can be defined directly from the imagery (L. Li *et al.*, 2005; Ghasemloo *et al.*, 2011). Boundary pixels, those that have a mix of classes, are naturally more difficult to classify and can adversely affect classification accuracy (Townshend, 1981). The problem of image versus target scale is also a crucial consideration when selecting methods, targets and sensors.

2.7.7 Image Resolution

Strahler *et al.* (1986) described the scene as the real conditions that exist on the ground and the aerial image as a collection of spatially arranged measurements drawn from that scene. This intuitive insight imposes the inescapable limitation on the image that it will never fully describe the scene unless every conceivable measurement can be included. The details that are carried in the spatially arranged measurements (image) are 'the' determining factor with regard to the image utility. Both spatial and spectral resolutions are important and limitations to data utility are imposed when either is too low (Weng, 2011). Resolution in remote sensing imagery can be spectral, the width of each waveband, and/or spatial, the area of the ground represented by each pixel of the image.

2.7.7.1 The Relativity of Image Scale

We can better understand scale and resolution when we consider our own visual perception. From a distance a forest may appear substantially uniform and green. As we move closer, we may resolve that some leaves are dead and there are branches showing through in places. Rather than High and Low resolution Strahler *et al.* (1986) used the terms H-resolution and L-resolution to describe imagery in relation to objects of interest. H-resolution refers to situations where the object of interest is made up of a number of pixels and L-resolution where the pixel may contain a number of objects. They described how an understanding of this can predict and improve modelling performance. This then means that it is the target size in relation to the pixel size that determines if it is an H- or L-resolution image. When there is a choice of sensor, the spatial resolution can be selected to best suit the target and improve classification results (Woodcock & Strahler, 1987). For instance, when the targets for classification are forest vs agricultural land designations, a spatial resolution of 1m would potentially create so much variability within the classes that classification accuracy would be reduced. However, Townshend (1981) also concluded that as spatial resolution increases, the number of boundary pixels reduces, so improvements in classification accuracy can be expected. In other cases however, a reduction in spatial resolution was found to improve classification accuracy (Townshend, 1981;

Roth *et al.*, 2015). This increase in accuracy comes with a loss of fine-scale variability and the inability to map small targets (Roth *et al.*, 2015). Deciding scale must therefore be made with these compromises in mind.

2.8 Remote Sensing in PA

Remote sensing of vegetation in agriculture is concerned with quantity and quality of the vegetation. Remote sensing of vegetation quality relates to plant health (Bock *et al.*, 2010; Mahlein *et al.*, 2012; Mahlein, 2016) and plant nutrition (Filella *et al.*, 1995; Raun *et al.*, 2002; Khun *et al.*, 2016). Estimation of biomass quantity and crop yield are often associated with monoculture crops such as corn (Ferencz *et al.*, 2004) but are also becoming more important in pastoral agriculture (I. D. A. Sanches, 2009). The focus of objectives 2 and 4, to accurately define pasture area and to then provide a quality metric of species content follows the needs of the farmer to maximise production. Understanding both quality and quantity is important to optimise agricultural production in pastoral agriculture (Ramoelo *et al.*, 2015).

2.8.1 Towards PA in Hill Farming

Precision agriculture on the pasture of hill country sheep and beef farms will look different to that of flat terrain arable farming. Precision agriculture is tied to the spatial resolution of the equipment being used (D. W. Lamb & Brown, 2001). Hill farms must apply fertiliser over much of their steep terrain area using planes which have a 20m swath width (Grafton *et al.*, 2010). This limits the precision that is possible or necessary to this 20m scale. However, a higher resolution is expected to be necessary for accurate target identification and may have additional uses or benefits.

2.9 Species Identification and Classification

Previous sections of this chapter explored some of the hurdles to be overcome in vegetation species differentiation/classification and help explain why species mapping is still difficult. Some researchers have negotiated some of these problems using proximal sensors, Table 2.4 lists a few, but species mapping from imagery is still difficult and complex.

Table 2.4: Successful classification approaches using proximal sensors with the best classifier used and reported accuracies.

Author	Target	Data Used	Best Classifier	Accuracy Reported
(Vaiphasa *et al.*, 2007)	Mangrove species	Leaf spectra	Genetic Algorithm	~80%
(L. Wang & Sousa, 2009)	Mangrove species	Leaf spectra	Linear Discriminant Analysis	~85-100%
(Pu, 2009)	Broadleaf trees	Leaf/canopy spectra	Linear Discriminant Analysis	~87%
(Prospere *et al.*, 2014)	Tropical species	Leaf spectra	Random Forest	~92%

The purpose of collecting remote sensing imagery is to gain insight and meaningful information that informs decision-making (Richards & Jia, 2006). One of the ways to convert image products into meaningful information is with a classification (Lang *et al.*, 2015). Classification identifies similar components within an image that can then allow further analysis or interpretation. The process has been applied in many fields of study such as wetland ecology (Hirano *et al.*, 2003; Carol, 2015; Ralph, 2015), forest ecology (Asner *et al.*, 2008; Asner & Martin, 2008; Feret & Asner, 2013) and agriculture (Galvão *et al.*, 2005). The two main techniques used to classify image components are object-based and pixel-based. In hyperspectral imagery each pixel has its own spectral signature derived from the sum of its components. Pixel based classifiers allocate each pixel to a class based on that spectral signature (Kamal & Phinn, 2011). Object-based classifiers group pixels with similar attributes and recognises their relationship and similarity to nearby pixels (Lang *et al.*, 2015).

There are many different approaches to classification of species from hyperspectral imagery, with varied levels of success. Figure 2.5 lists some of the successes and shows the variation in data source and method used. Interestingly, many successful classification problems were 'H' resolution in nature.

Table 2.5: Some of the methods successfully used for image classification of Hyperspectral data.

Author	Target	Data Source	Best Classifier	Accuracy Reported
(Martin et al., 1998)	Forest species	Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)	Maximum Likelihood	75%
(Feret & Asner, 2013)	Tropical forest species	Carnegie Airborne Observatory (CAO)-Alpha	Linear Discriminant Analysis (LDA)	>70%
(M. L. Clark et al., 2005)	Tropical forest species	HYperspectral Digital Imagery Collection Experiment (HYDICE)	(LDA)	100%
(Banskota et al., 2011)	Pine species	(AVIRIS)	LDA with Wavelet Transformation	>74%
(Naidoo et al., 2012)	Savannah tree species	(CAO)-Alpha	Random forest	>87%

2.9.1 Remote Sensing of Pasture and Grassland Species

The body of remote sensing research examining the spectral properties of grassland and pasture is small compared with other fields, such as forestry or wetland ecology. An even smaller subset of research has tried to categorise species or groups of species in the agricultural setting. Perhaps because of the 'L' resolution nature of pasture remote sensing or because the usable scale for management is large, the research has focused on identification and mapping of functional groups. This approach overcomes the high variability of species communities in pasture especially natural grasslands. The organisation of groups of plants, with similar habitat needs, into functional types is a well-established practice in ecology (Grime et al., 1997; Hodgson et al., 1999), although this approach has also been used to describe species dynamics within pastures

(López et al., 2006; Möckel et al., 2014; Möckel, Dalmayne, et al., 2016; Möckel, Löfgren, et al., 2016). The combination of functional groups and remote sensing has proven a practical approach to the difficulties of species mapping (Ustin & Gamon, 2010). In grasses there are many functional groups, including the separation of C3 and C4 grass species which exploit different niches in the environment, store carbon at different rates and reach peak growth activity at different points in the season (P. R. Kemp & Williams III, 1980; Davidson & Csillag, 2001). The separation of these species groups has been the target of remote sensing, mostly exploiting seasonal ascendancy (Homolová et al., 2013), to help identify subtle changes in climate and help with carbon sequestration calculations. Table 2.6 lists some investigations on the classification or mapping of C3 and C4 grasses.

Table 2.6: Examples of research carried out on identification or separation of C3 and C4 grasses.

Author	Data Source	Target Area	Classifier	Accuracy Reported
(Foody & Dash, 2007)	MERIS Terrestrial Chlorophyll Index	US State of South Dakota.	Discriminant analysis	77.8%
(L. Liu & Cheng, 2011)	Operational Modular Imaging Spectrometer II (OMIS II)	285 ha of the Linze Oasis in Gansu Province, China	Simple decision tree	92%
(Guan et al., 2012)	TERRA Moderate Resolution Imaging Spectroradiometer (MODIS)	Xilinhot grasslands	Hierarchical decision tree	87.3%
(C. Wang et al., 2013)	(MODIS)	North American Great Plains	Decision-tree classification	>90%
(Shoko & Mutanga, 2017)	Sentinel 2 MSI	Not specified	Discriminant analysis	90.36%
(Crabbe et al., 2019)	Sentinel-1a	740 ha farm	Random forest	86%

A notable exception to the use of functional groups was recent work carried out by Marcinkowska-Ochtyra *et al.* (2018) that mapped two invasive grass species in Poland. However, because these species are aggressive, they dominate the ecosystem (Marcinkowska-Ochtyra et al., 2018) and effectively produce a monoculture. This feature allows the classification of plant communities that, because of their dominance, then becomes a ‘H’ resolution problem. Bradley and Mustard (2005) had previously used time series Advanced Very High-Resolution Radiometer (AVHRR) data to distinguish Cheatgrass communities across the Great Basin. To date, there has been little success creating a remote sensing product that can be widely accessed by New Zealand farmers to aid their decision-making processes. One attempt to make such information available to farmers was the Pastures from Space Consortium that among other things attempted to supply up-to-date information on available feed to Australian farmers (Edirisinghe et al., 2004; Smith et al., 2004; Stovold et al., 2009).

2.9.2 New Zealand Pasture Remote Sensing

Remote sensing work in New Zealand has taken a similar trajectory to the rest of the world with most work carried out using more cost-effective and readily available multispectral sensors and their data (Thompson et al., 2003; Dymond & Shepherd, 2004; Vescovo et al., 2009; Dymond et al., 2012; Weeks et al., 2013). More recently, specific work on pasture has been carried out with proximal hyperspectral sensors, mostly focusing on pasture quality components and biomass (Kawamura et al., 2009; I. D. A. Sanches, 2009; Pullanagari, 2011; Pullanagari et al., 2012).

I. D. A. Sanches (2009) tried to define pasture sward content in terms of percentage cover of grass, clover and weeds. She found that R^2 values for predictions of grass content increased with higher proportions of grass in the sward, but the weed content was not well accounted for in the model.

Since the inception of the parent project that this study is part of, there has been further progress in the definition of pasture nutrients with hyperspectral imagery (Pullanagari et al., 2016; White et al., 2017). The combination of nutrient values for pasture with spatial reference now opens the door for more precise management practices to be designed and implemented as part of the farms’ economic strategy (White et al., 2017).

2.10 Summary and Introduction to Research

New Zealand hill farm pastures represent a large geographic area of the country and remain a substantial component of the national economy. Ongoing research has improved the productivity and profitability of these areas, but the sector remains barely profitable in many instances. Farm diversification has contributed to impoving their economic position. There is a paucity of knowledge of the environmental status of these farms. In most instances, farm paddock boundaries, that have been GPS surveyed, are the only accurate physical information available. For the sector to grow to meet 21st century environmental, productivity and economic goals it will require more substantial factual information.

Remote sensing and the trend to precision farming hold promise of supplying the spatially referenced information that the sector requires. This information in conjunction with other technologies, such as Variable Rate Application Technologies, can help farmer decision-making, improve environmental outcomes and improve economic outcomes for the sector and wider farming community.

The increased accuracies obtained from, and ease of access to, modern hyperspectral sensors creates an opportunity to take the current research to new levels of detail. Much of the work on spectral and spatial interactions to date is at regional, national or planetary scales which is not useful for localised farm management decision-making. Also, many authors have used temporal information to disseminate their target but that may not be practical for use in farming that requires up to date information to aid decision-making. More information is needed to address practical problems in pastoral farming in a timely manner and at a scale that is usable.

The research presented in this thesis examines the potential to use hyperspectral data to improve knowledge of the New Zealand hill farming environment in unprecedented detail. This work is based on the following insights gleaned from reviewed research:

- A narrow range of work has been carried out on the differentiation of pasture type species using hyperspectral remote sensing.
- Existing studies on differentiation of pasture species shows promise, but the limits of the technology should be tested by applying the technology to a broader range of species and assessing the benefits.
- A considerable volume of remote sensing work has been performed at regional and planetary scales, but pasture can be highly heterogenous at smaller scales with scant work carried out to define that variabilities implications to remote sensing.
- A review of the available literature reveals a dearth of research on species classification carried out on the New Zealand hill farm environment; work that encompasses the mapping of multiple environmental components at the farm scale appears to be absent altogether.
- Hyperspectral sensors maximise the available spectral detail of the target, but spatial resolution appears to play a major role in accuracy, the limits of which warrants further exploration.
- Differentiation of plant functional groups (PFGs) within pasture has been successful with C3 versus C4 species. Information on separating PFGs within the C3 class appears to be absent, especially in uncontrolled environments such as hill farms.
- The emergence of Variable Rate Application Technology affords a timely opportunity to carry out research that will have a profound impact on the New Zealand farming community.

Chapter 3 : Differentiating Grass Species Using Hyperspectral Sensing

3.1 Introduction

Taking the lab to the field. Since the release of hyperspectral sensors into the public domain in the 1980s, most research has been performed in the laboratory setting, controlling as many variables as possible. The nature of the technology means that small changes in environmental conditions can dramatically affect results. Consequently, a key challenge with performing hyperspectral sensing research in the field is managing the huge number of variables, even when measuring homogeneous plant systems. Unfortunately, the hill country pastures that are the ultimate object of inquiry for this thesis are notoriously diverse. This chapter explores the use of hyperspectral sensing in a more controlled field setting to better understand the abilities and limitations of the technology to separate similar fine turf species and cultivars of the same species. These were used as a surrogate for pasture type species as they have many similarities. Most importantly, unlike agricultural breeding programs that tend to focus on Ryegrass cultivars, they were available in a diverse array of species. This work is an important step prior to the challenges undertaken in later chapters and is a precursor to the identification of species.

In this chapter differentiation and identification are not considered the same. Differentiation is considered the ability to predict the correct target from a confined group. This can be thought of as a multiple-choice type question. Identification would be the ability to identify a target without definition of a restricted list of possible targets and in any context. This task would require a comprehensive spectral library. Brown *et al.* (2006) suggested it would take in excess of 5.2×10^9 of carefully selected calibration samples, for each subject, to create such a library.

This research is necessary because of the limited amount of work carried out on pastoral type species and their spectral responses. Aerial imaging spectrometers, such as that used in the remainder of this thesis, are expensive both in terms of capital and operational cost, especially when compared to hand held (proximal) sensors. Proximal sensors also tend to have a higher spectral resolution when compared to aerial sensors. Proximal sensing is therefore a logical starting point to examine how spectral interactions can be utilised for pastoral study. In attempting to understand spectral interactions of pasture type species this research also examines a problem that grass breeders have in bringing new cultivars to market. Persistence is the ability of a sown species to compete with self-seeded species and weeds to remain within the sward after sowing. The measurement of this trait is currently a bottleneck in the system that limits throughput of cultivars to the marketplace. It is suggested that hyperspectral remote sensing technology may allow for unbiased mechanical measurements to assist with defining and measuring this trait.

Hyperspectral data were collected on a series of species and more closely related cultivars with the challenge of differentiating the species using the data. Closely related plants were expected to be more difficult to separate as was the case. This chapter explores species separation to help define the abilities and limitations of the technology from the pastoral perspective.

3.2 Background

There is a long history of grass selection and breeding for pastoral and recreational use that began with multifunctional grasses and has culminated in a wide range of specialised cultivars (Casler, 2006). Plant breeding programmes are becoming increasingly complex, targeting specific improvements in plant breeding without the loss of already gained traits such as yield. It can take at least nine generations for a new openly pollinated or hybrid cultivar to be released (Shimelis & Laing, 2012) which requires major investment and which can limit throughput. Phenomics is the study of plants and how their genes are expressed under various environmental conditions. In recent years, researchers have started to study remote sensing methods to increase throughput of phenotyping trials for agricultural crops at a lower cost (Furbank & Tester, 2011; Araus & Cairns, 2014; Mahlein, 2016; Wahabzada *et al.*, 2016). More recently, remote sensing techniques have been applied in the fields of forage and turf species breeding (Walter *et al.*, 2012; Lilienthal *et al.*, 2016). Selection and breeding of plants for desirable traits such as drought tolerance, disease resistance and pest resistance, are slow and expensive (Furbank & Tester, 2011). Contrary to the untrained eye, and unlike arable crops, turf and forage pastures are rarely a monoculture (or at least not so for long). So, the persistence of the new cultivar under field conditions must also be evaluated alongside or after the initial breeding. According to the New Zealand Plant Breeders and Research Association (NZPBRA) evaluating persistence is time-consuming and usually needs multiple experts to judge the quantity of the trial cultivar in comparison to non-sown species (weeds) after a set time. The process involves several experts each assessing and scoring a trial plot. The reliance on operator dependent pattern recognition leaves the task subject to intra- and inter-observer variability, which is typically mitigated by using multiple experts (Morrison, 2015). The need for multiple experts, and time needed to assess the trials, also creates logistical issues to find, coordinate and pay for the required number of experts to be on site at the same time. This limits the throughput of such trials as some grasses must be excluded earlier in the breeding process. Varieties that might have greater persistence might therefore be excluded and also means breeders cannot readily select for this trait. There is a probability that the cumulative benefits (yield) from more persistent species might outperform less persistent species that are otherwise superior.

Researchers already employ remote sensing and precision agriculture techniques in breeding and cultivar development (Walter *et al.*, 2012; Araus & Cairns, 2014; Lilienthal *et al.*, 2016) so it is possible these techniques may be of value in assessing persistence. Remote sensing techniques could allow breeders to test more cultivars, with more efficient data collection by fewer and less experienced personnel. Remote sensing could also enable cultivars that display good persistence to progress in trials when they would previously be eliminated from the process due to some other limitation.

The prerequisite step in the research is to verify the ability and effectiveness of remote sensing to distinguish amongst different pasture type species and even cultivars. Their high spectral resolution makes hyperspectral sensors the most suitable technology for this research.

Hyperspectral sensor data have already provided useful information on characteristics such as plant nutrient content and species in other situations (Bin *et al.*, 1999; Tarpley *et al.*, 2000; M. I. Sobhan, 2007). While precision agriculture and remote sensing techniques have become more popular in recent years (Cushnahan *et al.*, 2017), pasture and turfgrass species remain largely unresearched despite being an early target of remote sensing research (Tucker, 1978). This is probably due to the lower returns from pastoral systems and high variability of the target compared to arable cropping where precision agriculture is well established.

This study explores the capability of remote sensing techniques to differentiate a wide range of plants. The aim of the study is to assess if the technology can differentiate species in a pastoral setting. This is an important step in preparation for the work later in this thesis. The objectives are to identify and define limitations to species differentiation and to assess if cultivar separation was possible with the technology. The number of bands needed for species separation and seasonal variation in reflectance are also investigated.

Hyperspectral sensors collect light reflected from objects such as plants in narrow contiguous bands over a wide range of the electromagnetic spectrum, much of it outside the ability of our eyes to detect. Much of the data from hyperspectral sensors can be redundant (Bellinaso *et al.*, 2010; P. Thenkabail, S. *et al.*, 2011) as the same information is carried by different bands. Another challenge created by these sensors is the vast volume of data produced. Having too many dimensions in the data (that is more dimensions than the number of samples) can lessen rather than improve accuracy (Hughes, 1968; Bellinaso *et al.*, 2010). These problems naturally lead to exploration of techniques to reduce the dimensionality of the data. Using indices or selecting a limited number of important bands that carry the relevant information, while reducing classification error, is the norm (H. Liu & Motoda, 1998; Schmidt & Skidmore, 2003; Bellinaso *et al.*, 2010; P. Thenkabail, S. *et al.*, 2011). Studies that choose bands rather than use prescribed indices, must determine which bands carry the most or most important information (M. I. Sobhan, 2007; Pullanagari *et al.*, 2012). Both techniques are relevant, but this study follows band selection techniques as the use of bands does not need prior knowledge of the target.

Hyperspectral data has improved our understanding of how the reflectance varies with changes in plant chemistry (Curran, 1989; Filella *et al.*, 1995), pigment concentrations (Ustin *et al.*, 2009) and stress (Kuska *et al.*, 2015). Despite our growing understanding, problems associated with discriminating species using reflectance remain. These issues include the spectral similarity of some vegetation from evolutionary convergence (Ollinger, 2011), and the spectral variability within a species from physical or biotic stresses (Price, 1994; Roth *et al.*, 2012; Feilhauer *et al.*, 2017). Differentiation of similar plant cultivars is more difficult than separating species and requires determination of finer scale features. The mixed nature of many plant communities makes using reflectance data even more complex. Zomer *et al.* (2009) found diverse communities more difficult to delineate and needed prior knowledge from field data and/or the use of spectral matching or unmixing. One concern for species identification by means of remote sensing and its' application to pastoral problems, is that changes within the plant, through the season, could complicate species identification. In this study, sites with relatively pure species were used to control some of these complexities. This allowed the experiments to be taken out of the lab without undue complication.

The goal of persistence trials is to determine the quantity of the original sown variety that remains in the sward after a given time. For a remote sensing application to contribute to trials of persistence it must first be able to differentiate amongst species or cultivars. Secondly, the technique must be able to quantify the desired species in comparison to non-sown (weed) species. The aim of this study is to examine the first problem, to identify various species and cultivars using hyperspectral sensor data. This might later be applied to various pasture trials including persistence trials.

Reflectance data were collected from highly managed turf and analysed to determine the ability of the technology to differentiate species from the reflectance data. The analyses included the use of band reduction to improve classification accuracy. The turf species were used as surrogates for hill country grass species and conditions as agricultural pasture field trials are limited in their diversity and do not provide as great a range of species to test at a single location.

Hill country traits were better represented in the turf trials rather than pasture trials in the following ways:

- Growing height: Hill country farms have high proportions of sheep that keep pasture close to mown turf heights where pasture trials allow the grasses to grow longer for standardised yield measurements (N.Z.P.R.A., 2017).
- Species: Pasture trials often focus on ryegrass varieties which have proven production benefits (D. Stevens *et al.*, 2007) whereas hill farm pastures often have high proportions of less desirable grass species such as browntop (Wan *et al.*, 2009).

There is debate within the remote sensing community on the most effective bands and band regions for species discrimination. To add to the body of evidence on this question the chapter also explores band selection to improve prediction accuracies specifically focused on pasture type species.

This research uses a series of fine turf species to test the ability of the ASD hyperspectral sensor to differentiate between them. As such the focus was the equipment rather than the species although both are important for the research. The work took place in a controlled field environment to explore two other aspects of remote sensing in turf and pasture;

- Firstly, this work is a form of pilot for the later work carried out using the Asia FENIX hyperspectral aerial imager. There is little research on the separation of pasture species so this work is necessary to provide some assurance that such detail can be resolved using hyperspectral sensors.
- The additional challenge was to investigate what level of detail might be discernible from the data. There must be a limit to the technologies ability to identify variations either between species or perhaps cultivars of the same species. The equipment used for this research had a higher spectral resolution than the Asia FENIX so if limitations are present with this equipment then they are likely to be more pronounced in the lower resolution equipment.

3.3 Materials and Methods

3.3.1 Trial Location

The trial sites were located on the north island of New Zealand, 6 km south of the Palmerston North Central Business District at the New Zealand Sports Turf Institute (NZSTI) (Figure 3.1). The location was selected for its wide range of C3, C4 grass species and some broad-leafed species grown in homogenous, long-term trial plots. The terms C3 and C4 are derived from a difference in photosynthetic mechanisms of temperate and tropical plants that represent quite distinct differences in chemistry and anatomy. The sites were established for various research trials and as teaching aids for greenkeeper training. Although the wide range of species was key, the site is close to Massey University so trial costs were low and access was simple.

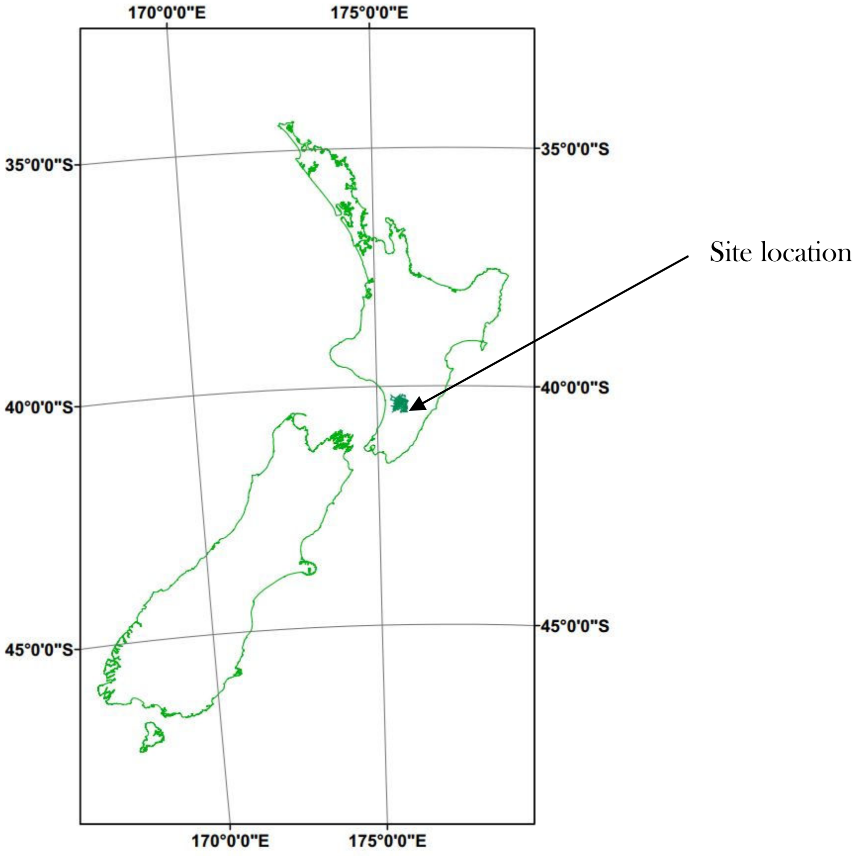


Figure 3.1: Coastline map of New Zealand showing the location of the study site near Palmerston North.

3.3.2 Site Description

For simplicity the various plants from each site are referred to as species in this chapter. Species from managed monoculture sites of turfgrass and broadleaf turf plants (Table 3.1) were used to standardise the experimental conditions and limit variability. Most sites had consistent management including mowing (25 mm cutting height), irrigation and fertiliser application to maintain healthy, uniform turf. Irrigation negated the seasonal drying and this, combined with mowing, prevented the grass from setting seed. Cotula (*Leptinella* sp.) is the primary species used on New Zealand bowling greens and was maintained at 5 mm. The sites were selected for their purity and to represent as wide a range as possible in taxonomic order, namely family, genus, species, variety and cultivar after (Sims & Gamon, 2002). It was assumed that it would be more difficult to distinguish plants with closer taxonomic associations, so having a wide range may offer insight into the technology's threshold for differentiation. Sites varied in size from 2 m^2 to 12 m^2 (averaging around 10m^2) and were positioned within a single 50 metre area on a series of terraces. The sites had been growing for at least two years so were well established and mature. The species used in the trial are listed in Table 3.1.

Table 3.1: Species, common and botanical names, chosen for inclusion in the trial.

	Common Name	*Latin Name*
1	Cotula	*Leptinella dioica* cv. Pahia
2	Couch	*Cynodon dactylon* cv. Agridark
3	Kikuyu	*Pennisetum clandestinum* cv. Regal Stay Green
4	Egmont	*Agrostis capillaris* var. Egmont
5	Browntop	*Agrostis capillaris* cv. Arrowtown
6	Ryegrass '4600'	*Lolium perenne* cv. 4600
7	Ryegrass 'Bizet'	*Lolium perenne* cv. Bizet
8	Ryegrass 'Premier 2'	*Lolium perenne* cv. Premier 2
9	Blue Fescue	*Festuca sp.*
10	Chewing's Fescue	*Festuca rubra subsp.* Commutata

3.3.3 Reflectance Data Collection

Data were collected from the fine turf sites using an ASD FieldSpec® 4 High Resolution (ASD Spectral devices, Boulder Colorado) with attached CAPP probe (I. D. A. Sanches, 2009). The device was used as it was already owned by Massey University and has a proven record as a field portable spectrometer. Consistent construction profiles and management regimes for the sites minimised variability between sites from factors such as nutrient availability and soil water content, thus limiting their potential impact on the spectral readings between sites. Plants on each site were closely mown and therefore had very high tiller densities (figure 3.3). The dense cover of vegetation was important to eliminate the penetration of light and minimise the influence of soil reflectance on the readings (Huete, 1988; Bausch, 1993). The high plant density also meant the sampling area under the spectrometer was collecting light from hundreds of plants in each scan. This substituted for the common remote sensing procedure of collecting spectral measurements from tens or hundreds of leaves to provide an approximation of an average spectra for a species (Sims & Gamon, 2002; Castro-Esau, 2006; M. I. Sobhan, 2007; Asner & Martin, 2008; Cho *et al.*, 2008; L. Wang & Sousa, 2009; Manjunath *et al.*, 2014).

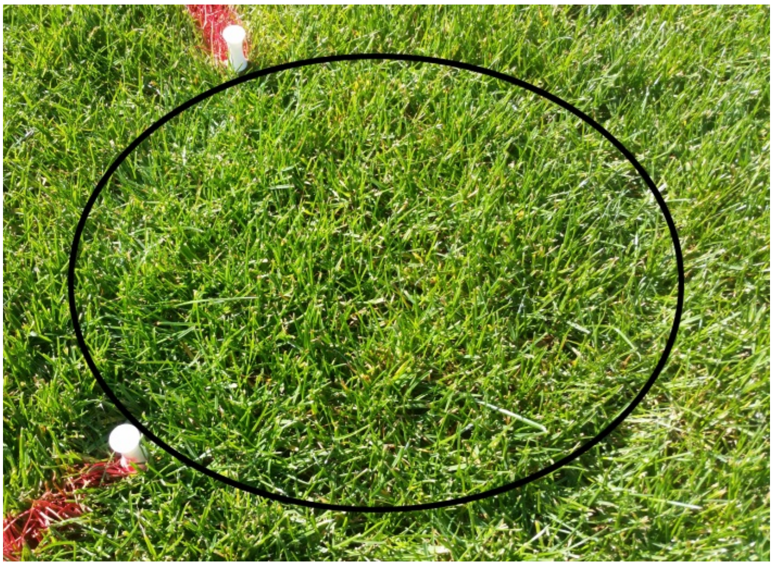


Figure 3.2. Ryegrass 'Bizet' plot showing locational pegs and a graphic (black line) how the CAPP probe was located within the pegs.

3.3.3.1 Analytical Spectral Devices (ASD) FieldSpec© 4 High Resolution

The ASD FieldSpec© 4 (henceforth ASD) is a field portable spectroradiometer from Analytical Spectral Devices Inc. (Boulder, Colorado). Weighing about 5.5 kilograms (plus backpack and additional equipment), the unit has a series of detectors that measure solar radiation collected through a bundle of fibre optic cables. The unit has three detectors; a Visible/Near Infrared (VNIR) (350 -1000 nm) 512 element silicon array and two Shortwave Infrared (SWIR) detectors. Shortwave Infrared 1 (1001 – 1800 nm) and SWIR 2 (1801 – 2500 nm), both use thermo-electrically (TE) cooled Indium Gallium Arsenide (InGaAs) detectors (ASD., 1999). Spectra acquired using RS3 software (Analytical Spectral Devices Inc., Boulder, CO, USA) had a spectral sampling resolution of 1 nm.

The VNIR sensor uses a fixed holographic reflectance grating that splits and disperses incoming light onto a fixed 512 element silicon array which measures the signal. As the detector has 512 channels the entire spectrum is scanned simultaneously so only needs around 17 ms for a complete scan (ASD., 1999).

Each SWIR sensor has an oscillating concave holographic reflectance grating and TE cooled (InGaAs) detector. The grating oscillates back and forth through 15 degrees and thus exposes the detector to different wavelengths of light. The grating takes 200 ms to scan forward and back, a single scan can be collected with each pass, forward or back, making 100 ms the minimum time needed to take SWIR readings. The SWIR sensors are the scanning bottleneck of the system so including SWIR in the data capture increases total signal acquisition time to at least 100 ms (ASD., 1999).

The digital numbers collected in each scan are meaningless without some form of reference. To determine percentage of reflectance, require definition of the lower and upper limits, or total darkness (dark current) and 100% light (white reference).

3.3.1.1 Dark Current (DC)

The instruments electrical components 'leak' electrons at a consistent rate which are collected by the detectors and added to the incoming signal. This background or 'Dark Current' (DC) would interfere with subsequent analysis and add unnecessary noise and error. It can be measured, and therefore removed from the signal, by blocking all incoming light. DC varies with temperature. The SWIR sensors measure and subtract DC from every scan but DC in the VNIR must be collected by the operator. When a DC reading is taken, a mechanical shutter can be heard to close of the VNIR entrance slit. This DC signal is automatically subtracted from each reading thereafter; the subtraction component is updated when a new DC signal is collected (ASD., 1999).

3.3.1.2 White Reference

Before we can calculate the percentage of light reflected from a specific target, a baseline standard (100% reflectance) must be defined. The raw digital number (DN) data collected by the ASD is influenced by the light qualities, instrument temperature and inclusion of any attachments and can also vary with wavelength. To compute the reflectance of an object it is necessary to compare it with a known 'reference standard' (ASD., 1999). A reference material with 100% reflectance across the entire spectrum is called a white reference. The target reflectance spectrum is the percentage of light, from each wavelength compared to the white reference. The absolute reflectance can be calculated by multiplying the measured reflectance by the calibrated reflectance of the white reference (ASD., 2002). Having all data converted to reflectance values in this way enables data collected at different times and different locations to be compared. Otherwise reflectance collected on a bright day would appear different to that collected on a dull day.

3.3.1.3 Canopy Pasture Probe (CAPP)

The CAPP probe was developed by I. D. A. Sanches (2009) to collect pasture reflectance data irrespective of the ambient light or atmospheric conditions. It is a 600mm tall round plastic enclosure with an ASD tungsten-quartz halogen bulb mounted inside. The fibre optic cable is mounted in a grip 11° of nadir with an 8° Field Of View (FOV) which creates a 100 mm diameter survey footprint. A matt white ceramic tile was used for the reference standard (I. D. A. Sanches, 2009). The CAPP has the advantage of reducing variations in light geometry and illumination between the unknown and reference spectra; this allows field spectra to be captured under semi-controlled conditions. Also, researchers can collect spectra where normal acquisition would be problematic, such as in low light.

3.3.1.4 Calibration

The RS3 software that accompanies the equipment semi-automates the calibration processes described as follows;

OPTIMISATION: Optimisation adjusts the sensitivity of the detectors to match the available light levels, keeping it within measurable limits. The process is automatic, once started (ASD., 2002). Incorrect optimisation or a change in conditions can oversaturate the detectors, causing the instrument to alarm. The alarm means that one or more channels are receiving light that is greater than that previously defined as 100%. This would make the data unusable. Under field conditions this step should be repeated regularly (ASD., 2002; MacArthur, 2007). This process was carried out with the CAPP lamp turned on and in place over the white reference tile. Optimisation was carried out regularly, but the controlled environment of the CAPP probe reduced the requirement.

WHITE REFERENCE: With the CAPP placed over the reference tile (as shown in Figure 3.2) and the lamp turned on, the white reference was taken. This process includes collection of the Dark Current signal for the VNIR sensor, identifiable by the accompanying click of the mechanical shutter closing. The white reference was taken prior to each group of samples and more often at the start of sampling to compensate for variability in the Dark Current (DC) as the sensors climb to a stable working temperature.

Figure 3.3: ASD FieldSpec© 4 with attached CAPP in operation (white reference standard being collected).

3.3.3.2 Collection of Data for Analysis of Collection Time (Diurnal Patterns)

Reflectance spectra were collected at 0800, 1000, 1200, 1400 and 1600 hours on the 3rd and 5th of September 2014 (Southern Hemisphere Spring) to discover if daily fluctuations in reflectance followed a predictable, detectable pattern.

Each site had a sample area marked with location pegs that remained in place for three days. The pegs were used to locate the CAPP probe so each subsequent sample could be collected from the same location (figure 3.3). The probe was rotated for each collected profile to allow for variations in leaf orientation while still maintaining positional accuracy over the target. Both days were bright and sunny with no cloud. Data collection began three days after mowing to allow the plants time to recover from mowing. The intention of the delay in data collection after mowing was to minimise any influence mechanical damage could have on the captured data.

3.3.3.3 Collection of Data for Analysis of 'Species' and Season

After the initial daily collection, spectral profiles were randomly collected from each site every 4 to 6 weeks (weather dependent) for one year. The edges of the sites were not clearly defined so data were taken from various points within the core of the sites to optimise the purity of samples. Unfortunately, the *Cynodon* site was removed towards the end of the trial period. Data collection for the other sites continued for the rest of the year.

3.3.4 Data handling

All spectra were corrected for variations in the internal sensors according to manufacturer specifications using the Viewspec software supplied with the instrument. The data were then exported to Matlab® and R statistical software packages via Excel. The first and last fifty bands (350 nm – 400 nm and 2400 nm – 2450 nm) were excised due to signal-to-noise problems (Pu, 2009), thought to be a result of natural light 'leaking' into the CAPP (Pullanagari, 2011), leaving 2050 bands from 400 nm to 2450 nm.

3.3.4.1 Primary Datasets

2,800 samples (280 per species) were collected over the one-year time frame. From this, three variations of the whole dataset were created;

1. **Diurnal Patterns:** The first dataset (n=2000) collated each species to investigate the ability of the equipment to discern fluctuations in diurnal reflectance of each 'species'. Forty samples were collated for each 'species' taken in each of the five time periods. Each sample was made up from the average of ten readings. The results were used to inform the exploration of the question; "Can the sensor data be used to predict the time of day a reflectance sample was collected"?

2. **Seasonal Variability:** The second dataset (n=2800) was created to investigate the ability of the equipment to differentiate collection season. Samples were split into four groups for each species. The results were used to answer the question; "Can the sensor data be used to predict the species and season a sample was taken"?

3. **Band Selection:** The final dataset (n=2800) collated all the data to investigate the separability of the various species and to look at reducing the dimensionality of the data via band selection. The results were used to answer the question; “What is the optimal number of bands in species identification”?

3.3.5 Research Path

Figure 3.4 represents an outline of the research steps and how they are interrelated.

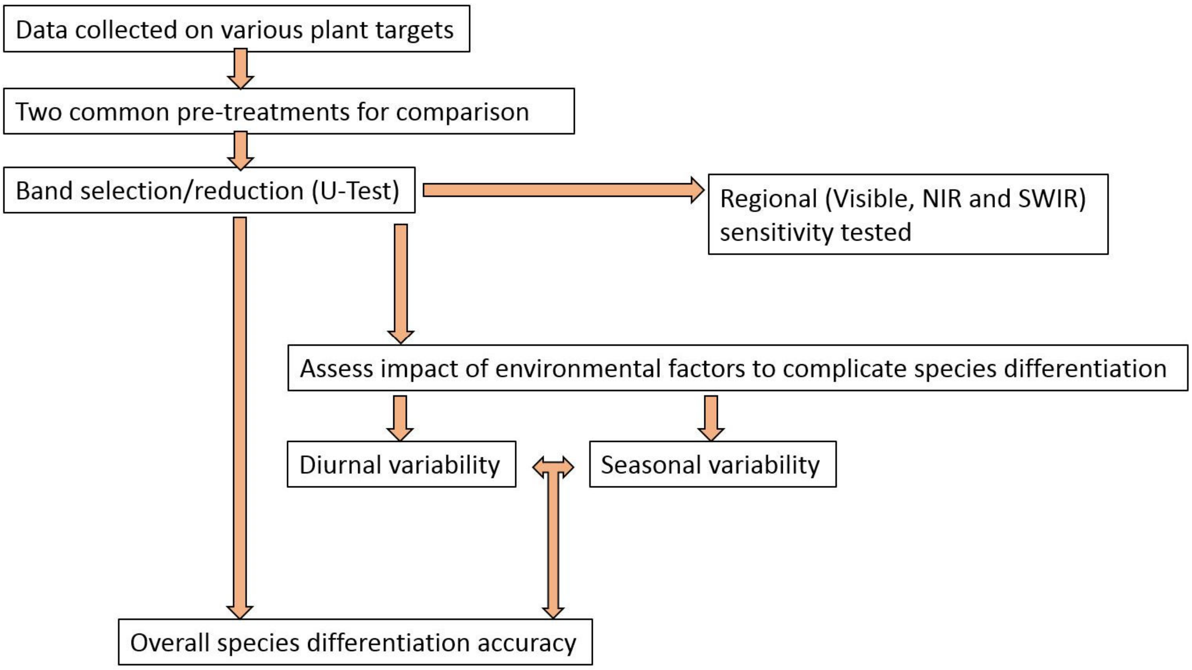


Figure 3.2: Flow chart showing how data were explored in multiple arenas to determine if known temporal variabilities within and between species significantly influence species differentiation.

3.3.6 Statistics and Analysis

3.3.6.1 Pre-Processing

Removal of unhelpful signal components (i.e. noise) and reduction of the highly correlated variables, that interfere with material analysis is a critical step for spectroscopic data (W. Wu *et al.*, 1996). The raw spectral data were transformed in two ways; Standard Normal Variate (SNV) transformation ((x)-Mean(x)/Std(x)) (Barnes *et al.*, 1989) and by conversion to 1st derivative.

SNV ((x)-Mean(x)/Std(x)) is a scatter correction method that lessens the within class variation (Barnes *et al.*, 1989; W. Wu *et al.*, 1996). Spectra transformed thus have a zero mean and variance equal to one (Dhanoa *et al.*, 1994).

The 1st derivative was calculated by application of the Gap-segment algorithm after filtering with a Savitzky-Golay filter (Savitzky & Golay, 1964). The filter with a window size of 11 followed by gap segment derivative with a segment size of 10 was carried out using the 'prospectr' package in 'R' (A. Stevens & Ramirez–Lopez, 2014).

The first derivative was calculated by application of the Gap-segment algorithm and smoothed with a Savitzky-Golay filter. Filter size requirements are considered to be data dependent but a minimum size of 5 points was reported as necessary by Tsai and Philpot (1998). The filter with a window size of 11 followed by gap segment derivative with a segment size of 10 was carried out using the 'prospectr' package in 'R' (A. Stevens & Ramirez–Lopez, 2014). The calculation of the derivative cannot be made for the first and last bands so the spectrum is shortened by the number of bands used in the filter (half from each end).

3.3.6.2 Spectral Band Reduction Analysis:

A Partial Least Squares Regression (PLSR) and Mann–Whitney U test (U-Test) were carried out in Matlab® to identify bands that were sensitive to species discrimination. PLSR is a multivariate regression technique that can be used to analyse data where the variables have a high degree of correlation, are highly noisy and may have missing components (Wold *et al.*, 2001).

A Mann–Whitney U-Test (U-Test) does not require a specific distribution (McKnight & Najab, 2010) so is more robust when normality cannot be confirmed (Lehmann & D'Abrera, 1975). Similar to the approach taken by (Schmidt & Skidmore, 2003; Prospere *et al.*, 2014), the U-Test was used to compare median values at each wavelength to determine if the between species variation was greater than the within species variation. Matlab® was used to rank bands that showed differences between samples and were therefore more likely to be useful to species discrimination. The process was systematically repeated for each wavelength and for every combination of species in turn. Forty-five iterations of the process were used for the ten species included in this trial. The output for each band combination was either a one (signifying a rejection of the null hypothesis at the 5% threshold) or zero and when collated by band were graphed to rank those bands where a difference was found most often.

The collated output of the U-Test was used to create a hierarchy of bands with greater potential to assist the task of species differentiation.

Knowledge of the bands most relevant for species separation has two main applications. First, the test accuracy can be maximised with a suitable number of bands. Second, using fewer of the most relevant bands can reduce computational load or later used to create a bespoke sensor to capture only wavelengths necessary for the chosen task.

Band ranking, U-Test:

The U-Test was used to rank all bands that might prove more useful for classification or prediction. A Linear Discriminant Analysis LDA was first carried out to train and predict the species using a small selection of the highest ranked bands. This approach was repeated for both standardised and derivative data. The test was repeated increasing numbers of bands by adding the next highest ranked bands. The result was a series of accuracies that could be graphed against the number of band variables used which can be used to identify the point where accuracy is maximised using the least possible bands.

Random band analysis:

The U-Test suggests that it can identify, and thus rank, wavelengths where the reflectance for different species varies enough to allow differentiation. This implies that the median value for a band can define if there is a difference between two samples. If that is not the case arbitrary band selection would yield equal or superior results to those derived from bands selected via the U-Test. This is especially true when fewer band variables were used as the probability of randomly selecting a ‘good’ band increases with the number of variables. To confirm the utility of the U-Test ranking, random bands were chosen, and the accuracy compared with those indicated by the U-Test.

Regional predictive strength analysis:

The analysis of the U-Test results suggested that different regions had different predictive power depending on how the data were transformed. An LDA analysis was carried out using all the bands from each spectral region (Visible, NIR and SWIR). The goal was to investigate the relative predictive strength of each region and explore if one form of data were better suited for use with the U-Test, producing more accurate or relevant results.

3.3.6.3 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a statistical technique based on Fisher’s linear discriminant (Welling, 2005) that is used for classification and pattern recognition. It tries to maintain the between-class variance to project a line that is orthogonal to the overall class variance and best separate the classes (Welling, 2005). The LDA decision boundary is determined by both the position of the class centroid and class distribution covariance (Hastie *et al.*, 2009). The approach is applicable with numerical data such as reflectance data and is a good approach for classification (Bhardwaj & Verma, 2015). LDA has been investigated for a wide variety of classification problems including cancer classification (Siqueira *et al.*, 2017), facial analysis (Juwei Lu *et al.*, 2003), complex pattern recognition (Dudoit *et al.*, 2002) and for analysis of spectroscopic data (W. Wu *et al.*, 1996). The use of LDA for classification of plant species as shown in table 3.2, perhaps because of its straightforward application (Bandos *et al.*, 2009). Penuelas *et al.* (1994) used discriminant analysis, and a suite of other tests, to study diurnal and seasonal changes in sunflower leaves and Pu (2009) found that its linear methodology had comparable results to the non-linear Artificial Neural Networks (ANN). Table 3.2 lists some of the studies that have used LDA as part of their investigations with the main classification target and their reported accuracies with the test.

Table 3.2: Other authors that have tested LDA for a range vegetation classification tasks using spectroscopic data.

Reference	Classification Target	Reported LDA Accuracy
(M. L. Clark *et al.*, 2005)	Rain forest tree species	89.9% (mean)
(Pu, 2009)	Broadleaf tree species	~86%
(Feret & Asner, 2013)	Tropical forest species	72%
(Prospere *et al.*, 2014)	Wetland Species	83-87%
(Acquah *et al.*, 2016)	Logging residue components	>96%

LDA is often coupled with a dimension reduction technique such as Principal Component Analysis (PCA) (Acquah *et al.*, 2016; Siqueira *et al.*, 2017) to overcome the problems associated with having many more variables than samples (Hughes, 1968). However, in this study the transformation of the variables into principal components is not desirable, because a further aim is to evaluate band selection as a method of dimension reduction.

3.3.6.4 Species Classification with LDA

It is important that an independent test dataset be set aside to measure the performance of the prediction to ensure the validation is robust and to prevent overfitting the model (Guyon & Elisseeff, 2003). Validating a model's performance with the same data that the model was built from violates the assumption of independence (Guyon & Elisseeff, 2003) needed for many statistical tests. Thus, the data used for this study was randomly separated into training and test datasets for model training and validation/prediction respectively.

The LDA for the species was first carried out using a selection of 12 of the most prominent bands that were predicted by the U test to be useful for species identification. The number of bands used was incrementally increased and the accuracy noted to identify the optimal number for highest accuracy. This approach was repeated for both standardised and derivative data. All analysis for band reduction, and regional predictive ability was tested using the LDA.

3.3.6.5 Stepwise LDA

Another method of feature selection is to include or exclude features based on improvements in model performance. Feature selection can be forward, adding features for improved results or backwards, removing features until there is no improvement. Forward feature selection is arguably less computationally intensive than backwards elimination in variable selection. However, in forward selection the importance of the chosen variables is not assessed in the context of all variables (Guyon & Elisseeff, 2003) so important interactions between bands may not be assessed.

Stepwise feature selection tries to combine the advantages of both. It begins with a single variable then adds variables to improve the model performance as in forward feature selection. However, after adding a variable one may be removed if it no longer adds to the model performance. The process continues until the minimum improvement threshold is reached (James *et al.*, 2013). Huberty (1984) stated that stepwise feature selection should only be used in certain circumstances for example when there are a large number of variables (>20). As the reflectance data in this work contained 2050 variables (bands) LDA, with stepwise feature selection, was used to overcome the sensitivity that LDA is known to have to the Hughes effect (Bandos *et al.*, 2009; Bioucas-Dias *et al.*, 2013).

The LDA model was created and refined with a 10-fold repeated cross validation in 'R' using the 'KLAR' package (Weihs *et al.*, 2005). In this study, the K-fold cross validation was used within the training data with repeated testing of each model (ten times) until the model was optimised. The model was then independently validated on the previously isolated test dataset.

Thus, a reduced number of variables were identified for the analysis of ‘season’ and collection ‘time’.

3.4 Results

The subtle variations of reflectance recovered from each of the species is illustrated in figures 3.5 and 3.6 showing the overall similarity yet subtle differences between species for the average vegetation spectra and first derivatives of the reflectance respectively. Visually there is similarity in the average spectra although there appears to be amplitude variation, notably in the SWIR, that might help separate species. Species appear to be more similar in the 1st derivative plot which suggests that the differences in figure 3.5 have a source other than species. Further, the distinct localised variation of the 1st derivative spectra at 1150, 1390 and 1875 nm may signal locations where variability could be exploited for species differentiation. The red-edge (~680 to ~730 nm) in particular exhibits the most distinct variations between species and even the three ryegrass cultivars were well separated at this location. The red-edge has been shown to be useful for physical characteristics such as leaf area index (Gupta *et al.*, 2003) and has been used for vegetation classification in conjunction with derivatives (Cochrane, 2000).

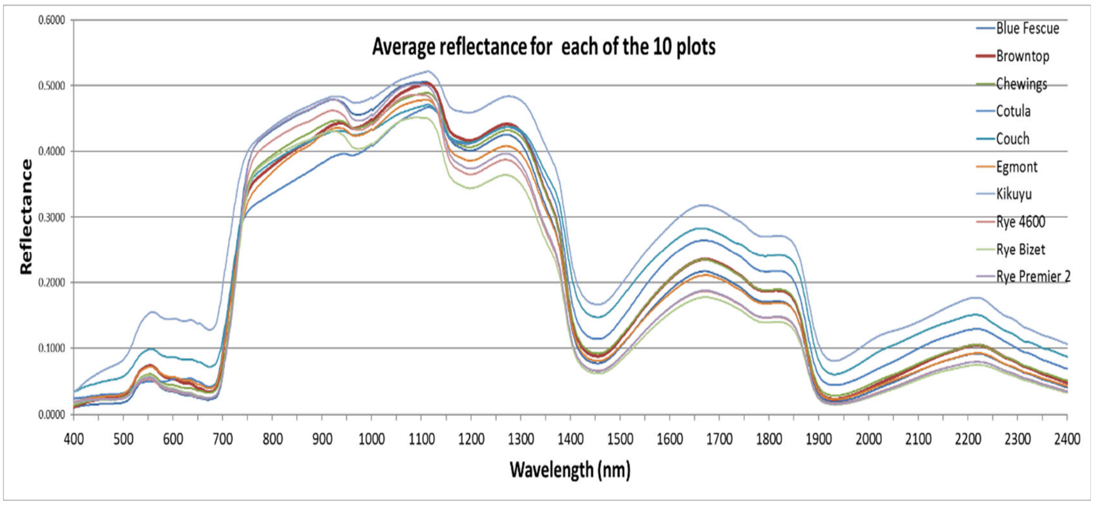


Figure 3.3: Graph of average reflectance for the 280 sample from each of the 10 plots.

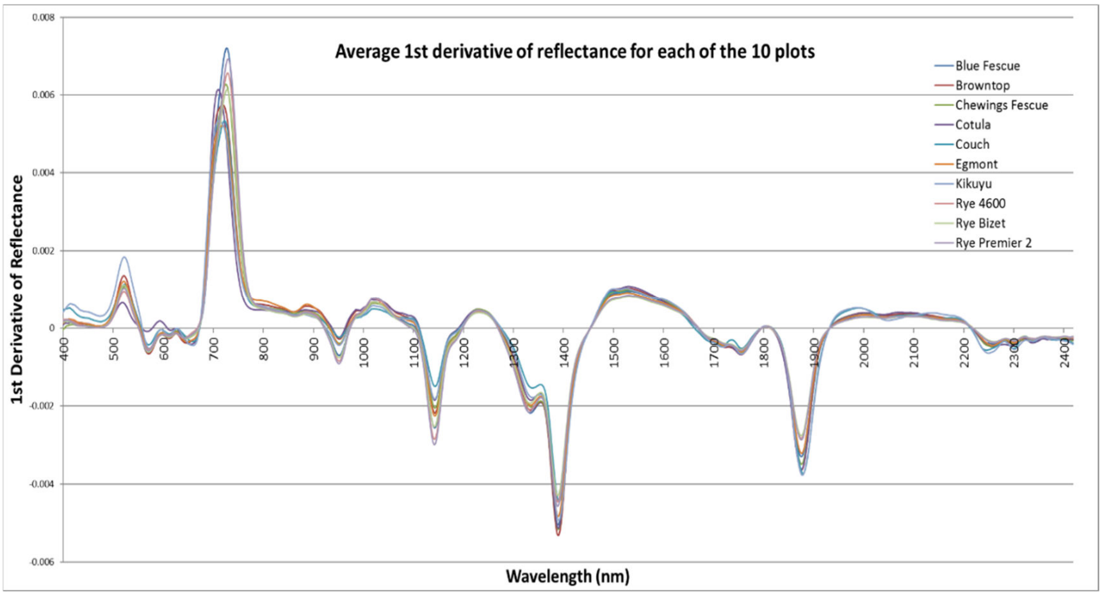


Figure 3.4: Average of 1st derivative of reflectance for the 280 samples.

3.4.1 Importance of Pre-processing

When a few bands from each pre-processing method are compared for species separability (Tables 3.3, 3.4 and 3.5) the first derivative transformation proved more able to separate species (overall accuracy 81.25%) than the SNV (overall accuracy 78.21%) and both transformations were better than unmodified (raw) spectra (overall accuracy 73.04%).

Table 3.3: Confusion matrix and basic statistics for LDA used to identify species. Analysis carried out on 17 bands of unmodified (raw) spectra.

		Reference Sample									
		Blue Fescue	Browntop	Chewings	Cotula	Couch	Egmont	Kikuyu	Rye 4600	Rye Bizet	Rye Premier 2
LDA Prediction	Blue Fescue	45	0	5	0	0	0	0	1	0	0
	Browntop	1	36	0	5	2	6	3	1	0	3
	Chewings Fescue	4	2	46	0	0	0	0	3	1	0
	Cotula	0	0	0	50	0	0	0	0	0	0
	Couch	0	2	2	1	43	1	0	2	2	1
	Egmont	0	3	0	0	9	38	0	0	4	2
	Kikuyu	0	0	0	0	2	0	53	0	0	0
	Rye 4600	4	0	3	0	0	0	0	37	1	24
	Rye Bizet	1	13	0	0	0	9	0	2	39	4
	Rye Premier 2	1	0	0	0	0	2	0	10	9	22

Overall Statistics	
Accuracy :	0.7304
95% Confidence Interval :	(0.6916, 0.7667)
No Information Rate :	0.1
P-Value [Acc > NIR] :	<2.2e-16
Kappa :	0.7004

Table 3.4: Confusion matrix and basic statistics for LDA used to identify species. Analysis carried out on 12 bands of SNV transformed spectra.

		Reference Sample									
		Blue Fescue	**Browntop**	**Chewings**	**Cotula**	**Couch**	**Egmont**	**Kikuyu**	**Rye 4600**	**Rye Bizet**	**Rye Premier 2**
LDA Prediction	Blue Fescue	50	2	7	4	0	2	3	0	0	0
	Browntop	0	44	2	5	2	2	0	0	0	0
	Chewings Fescue	0	3	34	0	0	1	0	0	1	0
	Cotula	0	1	2	46	0	0	0	0	0	0
	Couch	0	0	0	1	52	0	0	0	0	0
	Egmont	0	5	2	0	1	50	0	5	0	2
	Kikuyu	0	0	1	2	1	0	49	0	0	0
	Rye 4600	1	0	0	0	2	1	0	24	4	6
	Rye Bizet	5	0	8	2	0	0	4	7	50	9
	Rye Premier 2	0	1	0	1	0	0	0	20	1	39
Overall Statistics											
	Accuracy :			0.7821							
	95% Confidence Interval :			(0.7456, 0.8157)							
	No Information Rate :			0.1							
	P-Value [Acc > NIR] :			<2.2e-16							
	Kappa :			0.7579							

Table 3.5: Confusion matrix and basic statistics for LDA used to identify species. Analysis carried out on 11 bands of spectra transformed to 1st Derivative.

Reference Sample											
		Blue Fescue	Browntop	Chewings	Cotula	Couch	Egmont	Kikuyu	Rye 4600	Rye Bizet	Rye Premier 2
LDA Prediction	Blue Fescue	34	3	2	0	5	2	1	2	2	1
	Browntop	0	50	1	0	0	4	0	0	0	0
	Chewings Fescue	6	2	48	0	2	2	0	0	0	1
	Cotula	0	0	1	54	0	0	0	0	0	0
	Couch	5	0	2	0	46	0	0	2	6	2
	Egmont	0	0	0	0	1	47	0	0	0	0
	Kikuyu	0	0	0	0	0	0	54	0	0	0
	Rye 4600	0	1	0	0	0	1	0	43	1	3
	Rye Bizet	5	0	0	0	2	0	1	6	43	13
	Rye Premier 2	6	0	2	2	0	0	0	3	4	36
Overall Statistics											
	Accuracy :			0.8125							
	95% Confidence Interval :			(0.7777, 0.844)							
	No Information Rate :			0.1							
	P-Value [Acc > NIR] :			<2.2e-16							
	Kappa :			0.7917							

3.4.2 Band Reduction

3.4.2.1 Band Ranking: U-Test Results

After an initial favourable comparison with Partial Least Squares Regression (PLSR) (data not shown) the U test was used for band selection because of its simplicity and ease of application. The higher rank totals (figures 3.7 and 3.8) indicates bands that show differences between more species at that wavelength and might therefore be useful to discriminate between species.

Figures 3.7 and 3.8 also show that the distribution, over the spectrum, of important ranked bands from the U-Test changed markedly between the standardised and 1st derivative data. Results from the U-Test on raw spectra were almost identical to the SNV standardised data with a few very minor variations (data not shown).

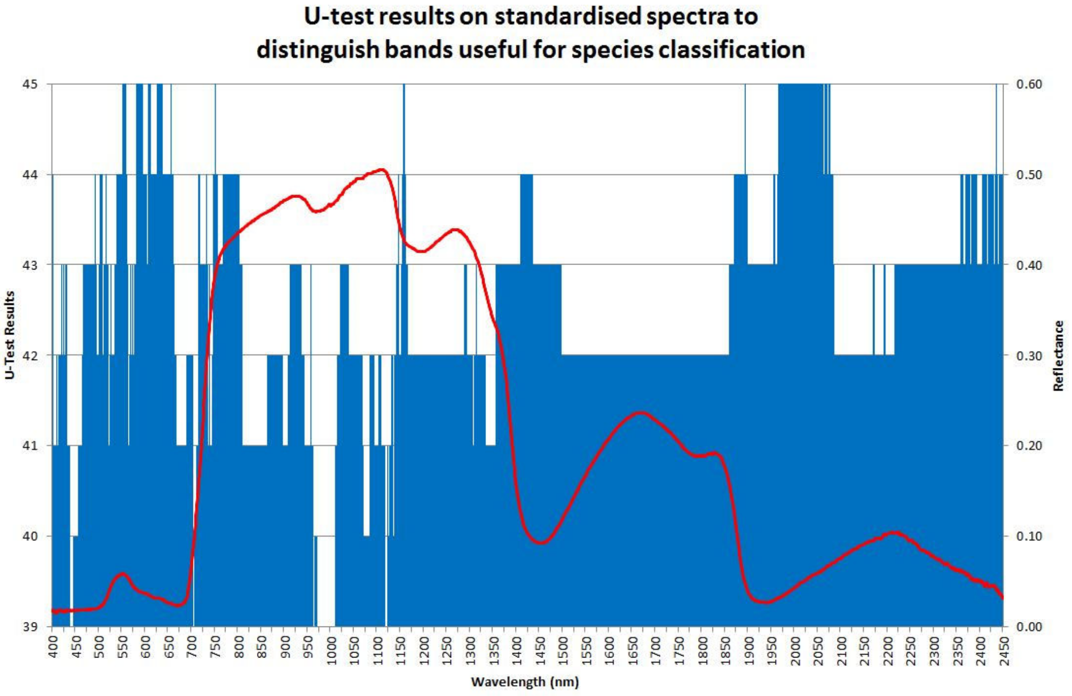


Figure 3.5: Frequency plot of U test results for standardised spectra with a significance level of 5% from standardised data. The reflectance curve of Blue Fescue is overlaid for visualisation of typical reflectance features. The y axis represents the cumulative total of positive results when each species is compared against every other species at a given wavelength.

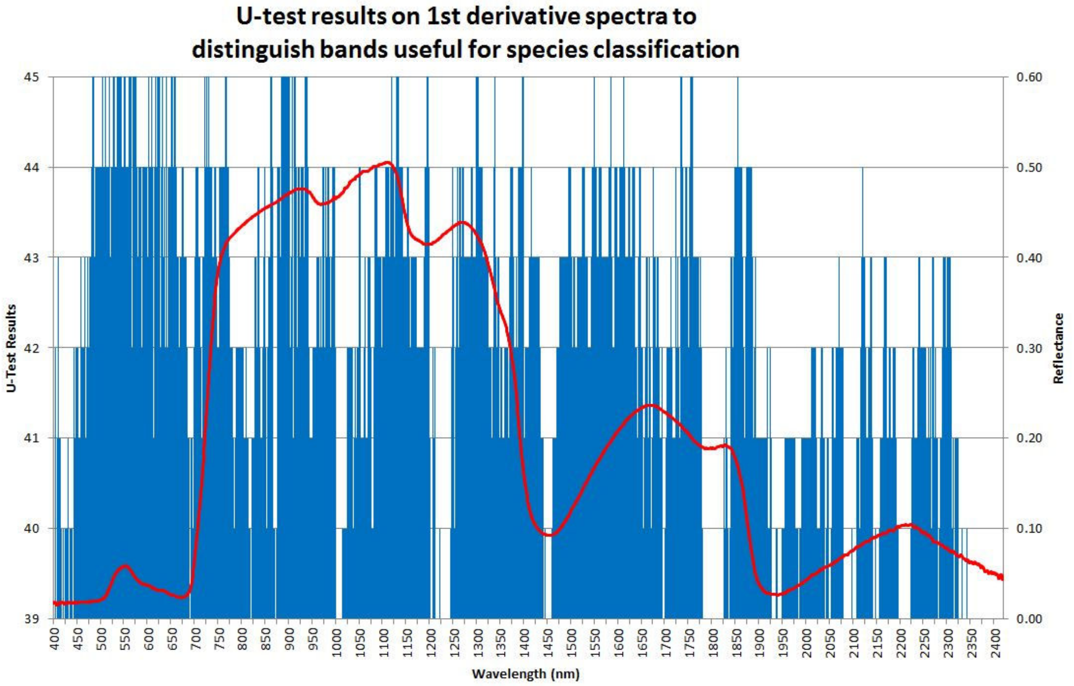


Figure 3.6: Frequency plot of U test results for 1st derivative spectra with a significance level of 5% from 1st derivative data. The reflectance curve of Blue Fescue is overlaid for visualisation of typical reflectance features. The y axis represents the cumulative total of positive results when each species is compared against every other species at a given wavelength.

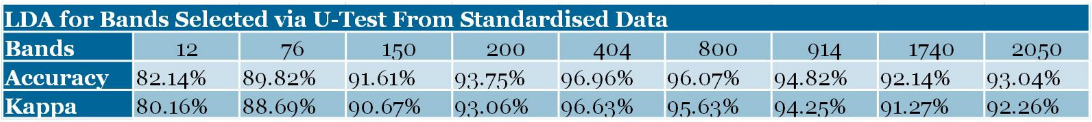
The U test from the derivative data indicated a higher importance of visible and NIR bands where the same test carried out on standardised data highlighted a greater importance of bands in the SWIR. Cho *et al.* (2010) did not include any bands from the SWIR region for their study on savannah tree species but suggested some bands in the SWIR might have improved their results. I. Sobhan *et al.* (2007) found important bands for discrimination in the visible part of the spectrum but noted a reduced number of bands in the NIR. They idenitified bands for species descrimination in several regions including the SWIR and suggest that bands within these regions 'share' information to descriminate species. Results from both data transformations indicated useful bands in the visible and in the red-edge. The red-edge position has proven useful in other studies of species (Cochrane, 2000; Lovelock & Robinson, 2002) and for leaf pigment concentrations (Sims & Gamon, 2002) which might be related to species variation.

The very different results from the same test with transformed data were unexpected as the data were collected using the CAPP probe which is designed to lessen sample variability (I. Sanches *et al.*, 2009). Band reduction is important to avoid overfitting and to reduce computational load for larger datasets. To effectively discriminate species with a lessened number of bands requires the use of those bands that carry the most relevant information. This result can be interpreted in two ways that one or other result is less accurate. The alternative is the transformations highlighted a different aspect of the data. The transformation to 1st derivative spectra highlighted the rate of change in the spectra rather than the amplitude. The question of which form of data is better suited to this form of analysis is partly answered later.

3.4.2.2 Bands: Optimum Number of Variables

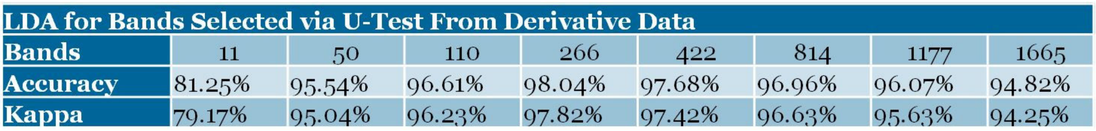
The number of variables (bands) needed to achieve the highest 'species' prediction accuracies was 404 and 266 for standardised (SNV) and first derivative data respectively (Tables 3.6 and 3.7). Both datasets performed well and showed an improved accuracy when a smaller portion of the available bands were used. This means that collinearity is an issue for this test confirming band reduction or feature selection techniques are important when using the LDA as found by Dudoit *et al.* (2002).

Table 3.6: LDA prediction accuracy results using standardised data with various numbers of bands chosen via the U-Test. Accuracy peaks at 404 bands.



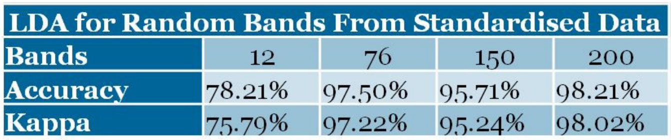
LDA for Bands Selected via U-Test From Standardised Data									
Bands	12	76	150	200	404	800	914	1740	2050
Accuracy	82.14%	89.82%	91.61%	93.75%	96.96%	96.07%	94.82%	92.14%	93.04%
Kappa	80.16%	88.69%	90.67%	93.06%	96.63%	95.63%	94.25%	91.27%	92.26%

Table 3.7: LDA prediction accuracy results using first derivative data with various numbers of bands chosen via the U-Test. Accuracy peaks at 266 bands.



LDA for Bands Selected via U-Test From Derivative Data								
Bands	11	50	110	266	422	814	1177	1665
Accuracy	81.25%	95.54%	96.61%	98.04%	97.68%	96.96%	96.07%	94.82%
Kappa	79.17%	95.04%	96.23%	97.82%	97.42%	96.63%	95.63%	94.25%

Table 3.8: LDA prediction accuracy using numbers of bands selected randomly from the entire spectrum of standardised data.



LDA for Random Bands From Standardised Data				
Bands	12	76	150	200
Accuracy	78.21%	97.50%	95.71%	98.21%
Kappa	75.79%	97.22%	95.24%	98.02%

Table 3.7 shows an increased accuracy with fewer bands when using the first derivative data. Where the standardised data improved gradually with increasing variables, the first derivative data peaked rather more quickly and reached 95.54% with just 50 bands. One possible reason is the first derivative data amplified variabilities in the spectra that allowed the U-Test to choose more important bands for species separation. The resolving of fine detail by first derivative

transformation was suggested by Demetriades-Shah *et al.* (1990) as reason for improved results. The steady increase in prediction accuracy from the standardised data and the greater number of bands needed for peak accuracy may result from only some of those bands used in the analysis, carrying pertinent information.

The number of bands needed for species discrimination varied with the pre-processing method although both datasets had similar prediction maxima. The implications are the transformation improved the result with fewer variables. Although J. Zhang *et al.* (2006) suggest first derivatives may not be suitable for species identification, this result supports the studies of reflectance data that have espoused the value of first derivatives to improve analytical results (Penuelas *et al.*, 1994; Cho & Skidmore, 2006).

3.4.2.3 Random Bands

Randomly selected bands (Table 3.8) proved just as useful and predictive, especially when larger numbers of bands were used. This corresponds with the other results (Table 3.6 and 3.7) that show better predictions with greater numbers of bands. The drawback with the random selection of bands is the potential variability of results and problems with replication.

3.4.2.4 Spectral Regions: Predictive Strength

A strength of reflectance data is that it can be repurposed to examine questions not considered in the initial trial setup. The regional sensitivity test was prompted by contradictive results from the U-Tests for band selection. The regional analysis, carried out on standardised data, supported the utility of bands from the visible and NIR regions. It showed a lesser predictive power of SWIR bands for species identification. The U-Test standardised reflectance data predicted bands in the visible and SWIR as primary to species identification which corresponds well with I. Sobhan *et al.* (2007). The U-Test on the first derivative data contradicted this by predicting less influence from the SWIR and more in the NIR.

Using the 350 bands from the visible region (400 nm -750 nm), the LDA predicted species with 97.68% accuracy. The 500 NIR bands (750-1250nm) had a prediction accuracy of 93.39% and the 1200 SWIR bands (1250-2450nm) an accuracy of 79.46%. Given that larger numbers of bands were included from the SWIR, the poor accuracy of prediction supports the view that SWIR is less important for species prediction. This may be partly explained by the lower signal-to-noise ratio from the SWIR (Curran, 1989). The result does not necessarily mean the SWIR is not useful as Vaiphasa *et al.* (2007) found that three of the 6 important spectral positions in their study came from the SWIR. However, their study did focus on mangrove species, which are very different from turf or pasture. The SWIR was less prominent in this study, reinforcing the value of preliminary investigations such as this. The first derivative processing has also improved or resolved the reflectance data, making the species-level information more obvious.

3.4.3 Results for prediction of Season:

The LDA predicted the ‘season’ and ‘species’ with an overall accuracy of 73.9%. Table 3.9 shows the confusion matrix produced including a cluster of erroneous predictions associated with the various ryegrass cultivars where the analysis was less able to tell them apart, this is unsurprising as they are more closely related to each other than any of the other subjects.

Table 3.9: Confusion matrix for predicted and season and species. The quantities in each group vary because the LDA training and test groups were randomly selected. Correct classifications are on the main diagonal (green) while classifications in error are highlighted in red.

Reference Prediction	Blue Fescue Autumn	Blue Fescue Spring	Blue Fescue Summer	Blue fescue Winter	Browntop Autumn	Browntop Spring	Browntop Summer	Browntop Winter	Chewing Fescue Summer	Chewings Autumn	Chewings Spring	Chewings Winter	Cotula Autumn	Cotula Spring	Cotula Summer	Cotula Winter	Egmont Autumn	Egmont Spring	Egmont Summer	Egmont Winter	Kikuyu Autumn	Kikuyu Spring	Kikuyu Summer	Kikuyu Winter	Rye '4600' Summer	Rye 'Bizet' Summer	Rye 'Premier 2' Summer	Rye 4600 Autumn	Rye 4600 Spring	Rye 4600 Winter	Rye bizet Autumn	Rye Bizet Spring	Rye Bizet Winter	Rye Premier 2 Spring	Rye Premier 2 Winter	Rye premier2 Autumn
Blue Fescue Autumn	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Blue Fescue Spring	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Blue Fescue Summer	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Blue fescue Winter	0	0	0	5	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Autumn	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Spring	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Summer	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Winter	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewing Fescue Summer	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Autumn	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Spring	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Winter	0	0	0	0	0	0	0	1	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Autumn	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Spring	1	0	0	0	0	0	0	0	0	0	0	0	0	16	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Winter	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Egmont Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Egmont Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Egmont Summer	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Egmont Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kikuyu Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kikuyu Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kikuyu Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Kikuyu Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0
Rye '4600' Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0
Rye 'Bizet' Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
Rye 'Premier 2' Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rye 4600 Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2
Rye 4600 Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	0	3	0	0
Rye 4600 Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	1	0
Rye bizet Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0
Rye Bizet Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	5	0	4	0	0
Rye Bizet Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	0	5	0	1	0
Rye Premier 2 Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	2	0	1	0	0
Rye Premier 2 Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0
Rye premier2 Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1

3.4.3.1 Results for 'season' prediction (single rye cultivar)

Two of the three ryegrass cultivars were isolated from the analysis to determine the impact of the interaction between ryegrass cultivars on overall prediction accuracy. The prediction accuracy for season collection with the single ryegrass improved to 95.49% (Table 3.10). Notably, there were consistently incorrect predictions in both tests, for example cotula in the Spring and Winter (Tables 3.9 and 3.10).

Table 3.10: Confusion matrix for predicted and actual season and species with a single ryegrass cultivar. Quantities in each group vary because the LDA training and test groups were randomly selected.

Reference Prediction	Blue Fescue Autumn	Blue Fescue Spring	Blue Fescue Summer	Blue fescue Winter	Browntop Autumn	Browntop Spring	Browntop Summer	Browntop Winter	Chewing Fescue Summer	Chewings Autumn	Chewings Spring	Chewings Winter	Cotula Autumn	Cotula Spring	Cotula Summer	Cotula Winter	Egmont Autumn	Egmont Spring	Egmont Summer	Egmont Winter	Kikuyu Autumn	Kikuyu Spring	Kikuyu Summer	Kikuyu Winter	Rye '4600' Summer	Rye 4600 Autumn	Rye 4600 Spring	Rye 4600 Winter
Blue Fescue Autumn	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Blue Fescue Spring	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Blue Fescue Summer	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Blue fescue Winter	0	0	0	5	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Autumn	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Spring	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Summer	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Winter	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewing Fescue Summer	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Autumn	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Spring	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Winter	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Autumn	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Winter	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0
Egmont Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
Egmont Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0
Egmont Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
Egmont Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0
Kikuyu Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0
Kikuyu Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0
Kikuyu Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Kikuyu Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0
Rye '4600' Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
Rye 4600 Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0
Rye 4600 Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0
Rye 4600 Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5

3.4.4 Results for Collection Time

The LDA was highly accurate (>92%) in predicting the time of day when data collection occurred for all species. Table 3.11 shows the accuracy associated with each species. Chewings fescue had the lowest overall accuracy at 92.14%.

Table 3.11: Prediction accuracy for collection time associated with each species.

'Species'	Accuracy	Kappa
Blue Fescue	97.86%	97.32%
Browntop	95.71%	94.64%
Chewings	92.14%	90.18%
Cotula	98.57%	98.21%
Couch	94.29%	92.86%
Egmont	96.43%	95.54%
Kikuyu	98.57%	98.21%
Rye '4600'	97.86%	97.32%
Rye 'Bizet'	94.29%	92.86%
Rye 'Premier 2'	100.00%	100.00%

Overall 0800 hrs was correctly predicted with 100% accuracy for all species. Later times showed some variability from one species to another with the last two collections 1400 hrs and 1600 hrs misclassified most. Chewings fescue had the poorest overall prediction accuracy, with ryegrass 'Premier 2' the highest. The plot of the first two linear discriminants for 'Premier 2' and Chewings fescue (Figure 3.9) show the separability of the early collection times and similarity of the later collection times as plotted in discriminant space.

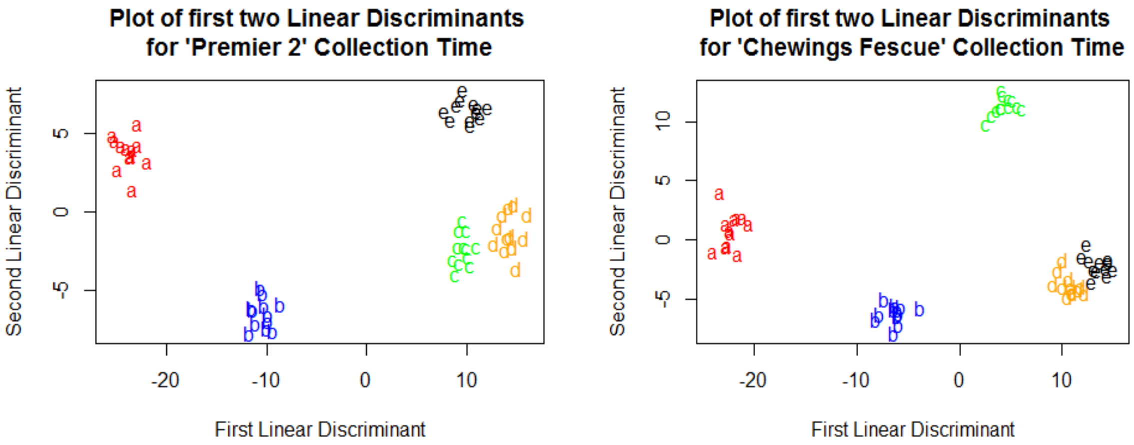


Figure 3.7: Plot of first two linear discriminants for 'Premier 2' and 'Chewings fescue' (n=200). a = 0800hrs, b = 1000hrs, c = 1200hrs, d = 1400hrs and e = 1600hrs.

In stark comparison to the season analysis, the bands chosen by the stepwise feature selection process heavily favoured bands in the SWIR region. Just five of the 25 bands selected were from outside the SWIR. These bands, known to be sensitive to protein, starch and nutrients in plants (Curran, 1989; Axelsson *et al.*, 2013), are thought to be enabling detection of subtle differences in plant chemistry that change systematically through the day, such as carbohydrates.

3.4.4.1 Analysis of All Samples Collated by Collection Time

The prediction accuracy for sample time fell to 68.36% (Kappa 60.45%) when all the data were combined and analysed regardless of species as shown in table 3.12. Within the total 68% prediction accuracy, 0800 hrs (a) and 1200 hrs (c) were most separable. 10.00 hrs (b) had a spread of predictions before and after the actual time as did 1400 hrs (d). As demonstrated by Table 3.12 and Figure 3.10, many samples were correctly classified even when all species were included in the analysis. However, the overall accuracy improved when each species was interrogated separately. The lower overall result suggests the factors that allow the time prediction to vary, or vary in concentrations, between species.

Table 3.12: The confusion matrix for collection 'time' prediction when using all data (n=2,000). a)08.00 b)10.00 c)12.00 d)14.00 e)16.00.

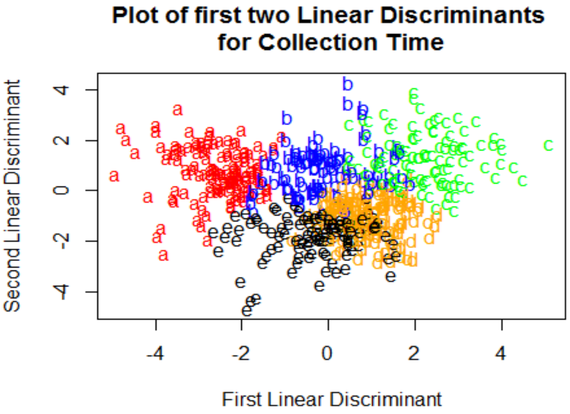


Figure 3.8: Plot of first two linear discriminants for prediction of collection time when all the data were collated and analysed together.

	Reference				
Prediction	a	b	c	d	e
a	257	71	0	2	6
b	8	158	28	18	2
c	0	24	225	9	8
d	1	20	25	172	119
e	14	7	2	79	145

3.5 Discussion

The Linear Discriminant Analysis used for this work achieved high accuracies in each task despite other authors such as Prospere *et al.* (2014) suggesting it is not the ideal solution. The classification results were improved with the use of first derivatives in the pre-processing stage. By carrying out band selection it was hoped that some definitive group of important bands might be identified relating to subtle variations in leaf chemistry or structure that might be exploited for species discrimination. Although the accuracy was improved in the process, there was no such clear or obvious markers. The ability to predict season was interesting in so much as it did not preclude species identification, but it was surprising that collection time could be predicted. Such predictions required that the equipment be able to detect tiny variations in reflectance within a time frame as short as two hours. It is believed the sensitivity of the sensor due to its high spectral resolution played a key role in the results attained.

3.5.1 Species Prediction and Band Selection from the U-test

The optimum number of bands necessary for species differentiation varied with the pre-processing method although both datasets ended up with similar maximum prediction accuracies. The U-test may have contributed to this, indeed Prospere *et al.* (2014) reported slightly lower classification accuracies from bands chosen by U-test that were consistent across the three methods they used for classification, including LDA. Despite this drawback, in this work, accuracies greater than 95% were achieved with 50 bands. The number of bands used in this study is high compared with other studies. For example, Schmidt and Skidmore (2003) used six, Prospere *et al.* (2014) around twenty and Vaiphasa *et al.* (2007) managed with just four. However, fifty bands represent only 2.5% of the two thousand total bands produced by the sensor and they produced high accuracies.

The U-Tests from the two types of data pre-processing produced very different results. Not only did the graphs look very different (figures 3.7 and 3.8) but the bands identified as important for species separation were different. These apparent contradictive results prompted the regional sensitivity test to help define which part of the spectrum had most influence. The analysis supported the use of bands selected from the first derivative data. This supports other studies of reflectance data that have promoted the value of first derivatives to improve analytical results (Penuelas *et al.*, 1994; Cho & Skidmore, 2006) but it does contrast with J. Zhang *et al.* (2006) who suggested they may not be suitable for species identification, although the later study was on tree canopies rather than pasture species.

The regional analysis implies a lesser predictive power of SWIR bands for species identification. There is some variation in the bands reported to be used for species discrimination. Prospere *et al.* (2014) reported a wide range of important bands that, interestingly, varied substantially between each of their selection methods. They also compared bands chosen in their study with some other authors which showed similarities without any real outright agreement. Adam and Mutanga (2009) reported having difficulty identifying important bands and note that other researchers have used various band selection techniques with inconsistent results. Further refinement of the smoothing and first derivative transformation may overcome the higher noise levels and elicit more information from the SWIR which may improve results.

The bands chosen from the U-Tests performed well, producing highly accurate species predictions. However, these wavelengths may not be the only bands that could generate a positive result (Huberty, 1984). The analyses of species revealed that different bands selected from the two pre-processing methods, yielded comparable results, as did some random bands. This suggests that the relevant information is widespread in the reflectance bands, supporting the findings of Asner (1998) who suggest that bands carrying the pertinent information will vary depending on the species. It is therefore unlikely, that a single analysis or group of bands will be usable for all species. For this reason and because the maximum accuracy was achieved with >50 bands it may be prudent to have a larger number of bands in an analysis than previous researchers aspired to use (Schmidt & Skidmore, 2003; Vaiphasa *et al.*, 2007; Prospere *et al.*, 2014). The number of bands used may require some consideration of the variability within the species being examined.

The techniques and data combined to produce high accuracies for species determination even though some of the subjects were closely related cultivars of the same species. This attempt to distinguish subjects as closely related as cultivars appears to be unique so comparison to other studies is not yet possible. This gives promise that the technology could be adapted for persistence trials if only as a tool to identify those plots which should be attended by experienced agronomists for further scrutiny.

Some studies have included grasses as part of their analysis e.g. Schmidt and Skidmore (2003) and others have sought to map species richness or diversity in grasslands (Carter *et al.*, 2005; Möckel, Dalmayne*, et al.*, 2016). Many of the attempts to differentiate grass species have focused on C3 vs C4 species as outlined in Table 2.5 of Chapter 2. In doing so most have taken advantage of the spectral variability that they exhibit at different times of year (Davidson & Csillag, 2003; C. Wang *et al.*, 2013). Although this is a step forward in our understanding the reality is that such a method requires data from two seasons to carry out such an analysis. L. Liu and Cheng (2011) have showed that it is possible to define C3 and C4 species within a single image. The challenge still exists to define different components within the C3 or C4 groups and even more importantly to do so from a single image. Greater insight into species variability at the proximal level may lead to mechanisms that can be exploited at farm, regional and planetary scales.

3.5.2 Prediction of collection season

The capability of the LDA to distinguish the added criteria of collection season was impressive although not altogether unexpected as the seasonal variability of plant physiology due to environmental factors is well known (Magney *et al.*, 2016). Seasonal fluctuations in plant reflectance allowed season prediction with an overall 73.9% classification accuracy while only using twenty bands selected via Stepwise feature selection. Including all three ryegrasses in the analysis negatively impacted the result. The accuracy increased to 95.49% when two ryegrass cultivars were excluded from the analysis. This classification may only have been possible due to the fact the species were managed, irrigated, fertilised and mown. Plant reflectance can change through the year (Asner, 1998) but the use of managed sites may have masked some seasonal effects.

3.5.3 Prediction of sample collection time

The LDA proved capable of predicting sample collection time of each species with the 80/20 (training/test) data split using 25 bands (data not shown). The positive result was initially suspected to be an error, so after checking that the test was correctly setup the training test split was progressively altered to find how little data were necessary for a good result. Although it is unusual to present results of a lower accuracy, the decision was taken to present the analysis of a 30/70 (training/test) split as it was more revealing of the limits of the analysis and therefore of the equipment. The reduced training set (30%) also resulted in a larger test set for validation. Successful prediction of collection 'time' with accuracy >92% was achieved but it was equally important to be able to see where, or when, separation difficulty was encountered. This information might provide insight for future work by this or other researchers.

This study investigating the diurnal fluctuations of plants as measured by reflectance appears to be unique so comparison with other study results is not possible. The nearest comparison was found to be (Gamon *et al.*, 1992) who created the Physiological Reflectance Index (PRI) to measure subtle diurnal fluctuation in photosynthetic efficiency. The goal of this analysis was quite different as it only sought to identify if it is possible to predict the 'time' of a sample collection and was not limited to a 2-band index. It was successful in this respect as collection time was accurately predicted so supporting the use of this equipment for such tasks.

The less accurate result returned when all 2,000 samples were analysed together for collection 'time' was appropriate. Plant species and communities are physiologically adapted to different environments, which enables each to compete in unique circumstances (Grime *et al.*, 1997). These environmental forces can pose difficulties in respect to species identification when different species adapt to the same environmental niche (evolutionary convergence) (Ollinger, 2011) but may also allow the variability inherent in plants adapted to different environments to be detected. The challenge the test encountered identifying the collection time with some species is interesting, because it consistently occurred at the end of the day. Not all the species exhibited this trait, which points to a possible divergence in physiology. Other than Kikuyu, the species that were more difficult to categorise later in the day are less adapted to high growth competition situations. This supports the premise that the criteria responsible for change in the spectra through the day may have reached an asymptote in some species. This is feasible given the high light conditions experienced during the trial. It is hypothesised that this could relate to a build-up of xanthophyll cycle pigments, carbohydrate storage or a combination of such biophysical properties. The samples were collected in early spring, which may help explain the inclusion of Kikuyu in this group, as the warm-season Kikuyu is less active at that time of year (Betteridge & Haynes, 1986). The results are based on limited data but raise intriguing questions around species competition strategies that hyperspectral data may help answer. Further tests on cloudy days with reduced light levels and on days where sunlight hours are longer (Summer) might be a good follow-up study.

The sensitivity of the test in detecting collection time suggests it may be possible to measure the components that enabled the detection to occur. It would be necessary to repeat the collection of spectral data and to carry out detailed leaf tissue analysis simultaneously for correlation. The possibility of a non-destructive method of measuring carbohydrate or other components could have valuable applications in plant breeding, especially for animal forage.

The bands used for the analysis of season and collection time varied from those identified for species. The influence of the SWIR increased from species to season and increased again in the diurnal analysis. The implication is that these bands, known to be sensitive to protein, starch and nutrients in plants (Curran, 1989; Axelsson *et al.*, 2013), enable the detection of subtle differences in plant chemistry that systematically change over a season or through the day.

3.5.4 Limitations

There were many limitations to this study, most notably there was only one site for each subject. This meant that there was a limited area to collect samples from. Although they were sown in homogeneous rootzone media small variations in soil conditions were not possible to be accounted for. However, in partial response to that limitation, the sensor had a ground footprint diameter of 100mm which equates to 0.03m^2. The sites ranged from 2m^2 to around 12m^2 so after the initial sampling stage was complete it was unlikely that collection at any location was repeated. If any of this work were to be repeated or progressed this limitation should be addressed. Added rigor would be introduced if trial locations could also be established in areas with a variety of soil and climate conditions.

3.6 Conclusion

This research confirms that highly detailed hyperspectral data can be used to differentiate pasture/fine turf species. This paves the way for the use of hyperspectral data to answer the remaining questions in this thesis.

Pasture and fine turf species inhabit a similar environmental niche of open land and their growth strategies are similar in that they have green vegetative, non-woody, low growing habits. Despite the similarity of their environmental adaptation their reflectance shows clearly identifiable variability. That means highly heterogeneous pasture is likely to have similar heterogeneity in its reflectance. That heterogeneity could be a problem for remote sensing of hill farm pasture. Later chapters of this study explore if it is possible to account for that diversity in hill country pastures.

This study clearly identified that, as planetary and regional scale studies have shown (Crabbe *et al.*, 2019), pasture has seasonal fluctuations in plant reflectance. These variabilities allowed this study to classify plant species and season with 92% classification accuracy. The seasonal variability of C3 and C4 species has already being exploited but this study suggests that perhaps there is within group C3 or C4 variability that might also be exploited to increase resolution of species mapping.

For species information to be of practical use for farm management, we need to develop techniques that can identify/map these species with a single survey. Importantly, the differences in plant reflectance both diurnally and seasonally did not restrict the capability of the LDA to identify the species from hyperspectral data. This supports the hypothesis that such techniques could be adapted to assist with forage trials and evaluation of new pasture species.

There is little doubt that species can be separated when sampled at similar points in time. The question of whether individual species can be identified from samples taken under different growth and stress conditions is yet to be fully answered. Price (1994) gave a concise list of reasons why it may be difficult or impossible to distinguish any given species from spectra alone and it has been suggested by others (M. I. Sobhan, 2007; Cole *et al.*, 2014) that identification may need to be defined by spectra taken at a particular time or growth period to be most effective. This research provides valuable insight into regions of the spectrum that might assist with species identification on a larger scale. The derivative transformed data proved superior in all tests. The comparative results of the Raw, SNV and Derivative data transformations proved useful and influenced much of the later work in this thesis.

This research confirms that hyperspectral data can be used to distinguish species which is the first condition for use in pastoral or turf breeding programs. The second requirement, for use in persistence trials, is the ability to define the percentage of the original species remaining after a set time. That question will require further research. To that end it may be possible to take reflectance data at establishment and subsequent time frames to determine the level of change or dilution. To achieve this may alternatively require the definition of the 'intruder' to determine comparative levels. These are questions that future research should consider.

Proximal sensing spectroscopy techniques, such as those used in this work, offer a detailed examination of a specific target, but without geospatial information (B. Park & Lu, 2015). As such these techniques have limited utility and require another method to relate their results to specific geographic targets. These techniques are also limited in scale so, although they might work well for trial plots, or other research applications at smaller scales, farm scale measurements would not be practical. Imaging spectroscopy however can resolve spectral detail with the added advantage of a spatial context which allows extrapolation of results into georeferenced maps. Their downside is that they have lower spectral and spatial resolution. The next chapters build on the findings in this section by focusing on the application of remote sensing techniques to hyperspectral imagery and the possible benefits for hill country farming.

Chapter 4 : Data Sources and Early Challenges

4.1 Introduction

Chapter three expanded on the themes that surfaced in the literature to establish a case that supports the notion that remote sensing can be used to discriminate similar pasture species. This chapter builds on this broad foundation to introduce the main methods adopted for the rest of this PhD study. It examines the challenges of relying on 'exhaust data' and explains and justifies some of the methodological decisions taken during the process. The chapter also discusses some of the critical influences and circumstances that have driven and guided the approaches adopted in this project. This chapter discusses the data, collection methods, processing protocols and classification method search, which are important contextual information relating to this work.

The main topics in this chapter are:

- Primary Growth Partnership (PGP)
- PGP data collection
- Data handling and processing
- Data mining; an Iterative methodological search
- Support Vector Machines (SVM) overview

4.2 Background

This study was a small part of a larger seven-year PGP project called *Pioneering to Precision*, which is funded by a Ravensdown Fertiliser Co-operative and the New Zealand Government. 'Exhaust data' from *Pioneering to Precision* is the primary data source for this thesis. The term exhaust data refers to collection or generation of information gathered during a project that is not necessary for that project (Kitchin, 2014). The data collection protocols for *Pioneering to Precision* were pre-determined to meet the project's goal. These protocols were designed to build an algorithm that would calibrate an airborne hyperspectral sensor as a proxy for measuring soil nutrient status on hill country farms (M.P.I., 2014a; Grafton & Yule, 2015). If successful, the new algorithm would replace expensive, laborious and time-consuming conventional data-collection to guide and inform fertiliser decision-making in hill country environments. The protocols were established for the main project before this study started and could not be changed. This is a strength of the PGP programme, as the data gathered from all the sampling events on the various farms can be compared. The scale of the larger study also had other advantages including having access to the type and volume of data that is ordinarily impractical and cost prohibitive for a single PhD study. The inability to influence data collection protocols proved to be a constraint for this study, as the work was limited to the data provided, with no control of how or when the data were captured. Consequently, this placed limitations on the study which are discussed in more detail later.

4.3 Primary Growth Partnership (PGP) 'Pioneering to Precision'

In 2009 the incumbent New Zealand government established Primary Growth Partnership (PGP) to fulfil its policy to increase export earnings from primary industries. Subsequently, the New Zealand Ministry for Primary Industries (MPI) funded a series of the PGPs including the *Pioneering to Precision* partnership led by Ravensdown Fertiliser Ltd. Its stated goals are to improve fertiliser practice on hill country sheep and beef farms by using remote sensing and variable rate precision fertiliser applications (M.P.I., 2016).

The project began in the last quarter of 2013 and was expected to take up to ten years. The *Pioneering to Precision* (hereafter referred to as the PGP) project represents a financial commitment between the parties totalling $10.3m (Office of the Auditor General, 2015). The PGP programme uses ground-based soil and pasture data which can then be correlated to proximal hyperspectral remote sensing data. Airborne data were also collected with an advanced airborne spectral imager. Protocols for data collection were developed and approved by the PGP's Science Steering Group in November 2013 (M.P.I., 2016). None of the protocols were defined by or for this study, so this chapter only includes a brief discussion of the main characteristics. A more detailed explanation of the protocols is available in Appendix 1.

4.2.1 PGP Data Collection

Figure 4.1 shows the locations of the eight farms selected for the *PGP* project, five in the North Island and three in the South Island. The farms were selected to provide a mix of climate, soil and vegetation types. Each farm was scheduled for at least two sampling events, however as Table 4.1 shows, some farms were sampled more often, with one sampled five times. For each farm, one sampling event was timed to match with spring peak growth and another scheduled for the autumn season. Data collected included information on site botanical composition, leaf tissue and soil nutrient analysis, proximal hyperspectral data and a hyperspectral aerial survey. The data collected with relevance to this study includes AisaFENIX hyperspectral imagery and botanical composition information. The materials and methods for the aerial survey mainly follow those of Pullanagari *et al.* (2016), although some relevant aspects are outlined here.

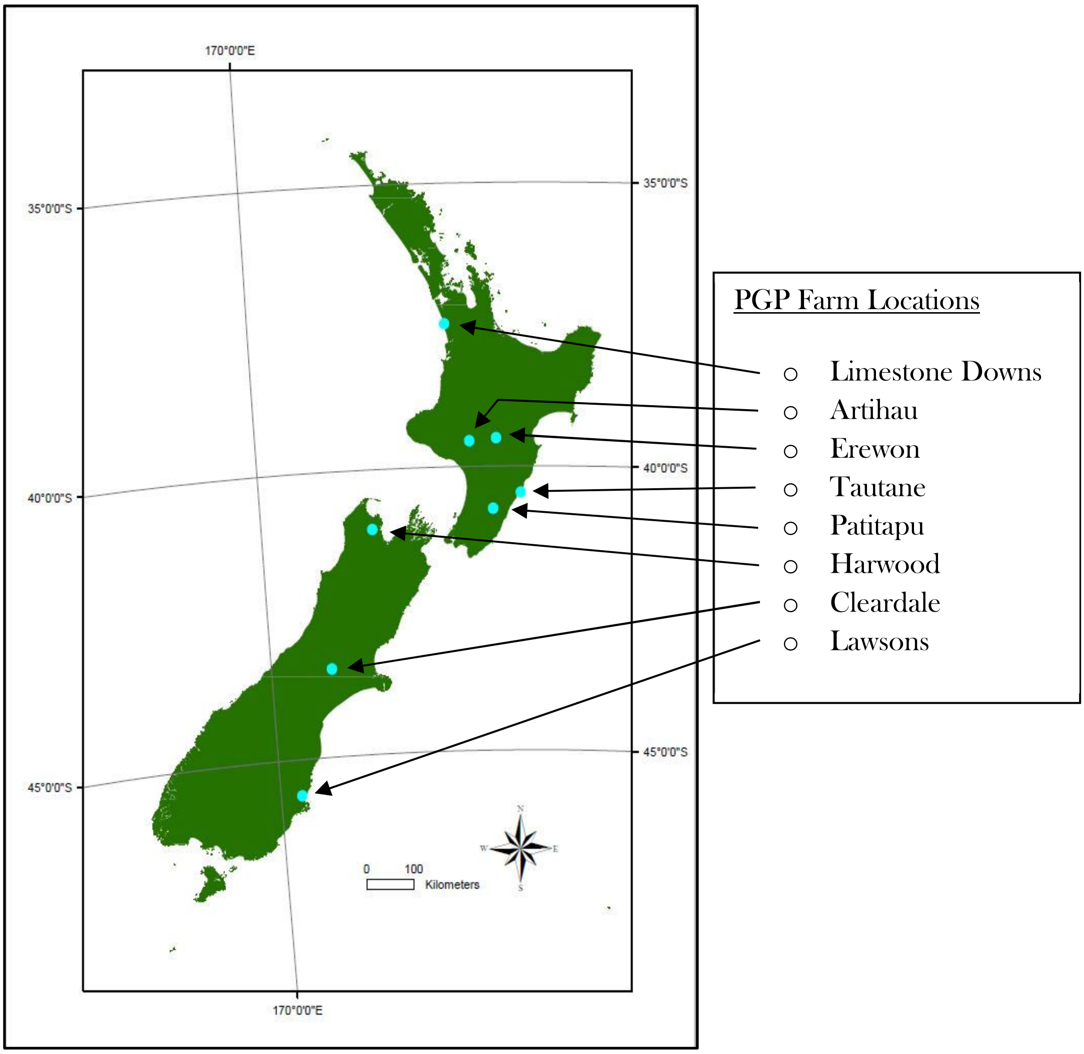


Figure 4.1: Locations for the 8 farms chosen to take part in the Pioneering to Precision PGP project.

Table 4.1: List of survey dates for sample collection on each of the eight selected farms in the Pioneering to Precision PGP project up to March 2017. Data from farms, marked with an asterisk, was used in this study.

Farm	Survey Dates	Total Surveys
Limestone Downs*	2013,Dec / 2014, Jan, May, July, Oct	5
Erewhon	2014, Dec / 2015, May	2
Atihau*	2014, April + Nov / 2015, May + Oct	4
Tautane	2014, Oct / 2015, April	2
Patitapu*	2015, Nov / 2016, April	2
Harwood	2015, Nov / 2016, April	2
Cleardale	2015, Nov / 2016, May	2
Lawson*	2015, Nov / 2017, March	2

4.2.2 PGP Ground Data Site Selection

Stratified random sampling based on slope, aspect and soil type was used to generate potential location points for 80 sites on each farm. Each site was located by the setup team and visually assessed to decide if it met the requirements originally designated for that position. Five pegs were located at each site within close proximity (roughly a 5m x 5m area) by the setup team as shown in Figure 4.2 for 400 peg locations. A 0.5m x 0.5m ($0.25m^2$) quadrat was used to collect ground reference data at each peg.

Figure 4.2: Site location photograph taken during ground data collection showing 4 of 5 site pegs with the 0.25m² quadrat and site photo board clearly visible.

During the setup phase it emerged the digital elevation model (DEM) was often inaccurate so some sample sites did not meet the design criteria. This was reportedly because the detailed DEM was interpolated from a regional survey. The issues around survey data accuracy and the remote sensing community's unquestioning reliance on them are a known issue (Foody, 2008). Unfortunately, despite the DEM's errors, there was no better alternative available, so where the ground location did not meet the sample design criteria, the site was relocated by the setup team. The new site location was placed in pasture on a slope that matched that of the original target site. Importantly, this new location was not necessarily in the same region of the farm, and sometimes was not in the same category as the original site. On the first farms great effort was made to keep the site as close as possible to the pre-determined location. On the later farms the pre-determined locations became more of a guide than a rule. The information of how many sites were moved was not made available. Each site had five sample locations designated by the setup team with wooden pegs. The pegs were placed in areas of pasture that did not have thistle or other weed infestations.

4.2.3 Botanical Species Composition

Information on volumetric percentages of dead matter, legumes, weeds, grass stem, grass leaf and bare ground was gathered by an expert agronomist for each sampling event (Grant Rene, Personal communication). The agronomist identified and recorded the first, second and third most abundant species present on each site. Importantly, the same agronomist performed most of the surveys to promote consistency between sampling events. The data were collated on a spreadsheet as Table 4.2.

Volumetric percentages work well for most forage-based trials that are often concerned with total available energy or biomass production. Remote sensing instruments collect data from light reflectance, so this form of information is less useful as no light is returned from the depths of dense vegetation. Consider the scenario of a trial plot with a quarter of the area covered in grass and three quarters covered in clover. The grass may be 300 mm tall and make up half of the total volume or biomass in the plot. Reflectance data however, would be dominated by the three quarters of the plot that was covered by legumes. Pasture growth and feed cycles (i.e. biomass) can impact the accuracy of results derived from reflectance data (Grafton *et al.*, 2016). This type of mismatch of data meant that the botanical data collected as part of the PGP was only of use as background information and could not be used for any form of regression analysis. Therefore, extra trials were needed to correlate to the aerial imagery.

Table 4.2: Example of output from pasture species analysis conducted by an experienced agronomist in the field for the Pioneering to Precision PGP project.

	Visual estimation										
Sample number	%Dead	%Legume	% Weed	% Grass Stem	%Grass Leaf	Percentage check	%Bare	Most abundant species#1	Most abundant species#2	Most abundant species#3	Comments
SLA8046	5	5	5	2	83	100	0	Sweet Vernal	White Clover	Browntop	
SLA8047	10	5	0	0	85	100	0	Sweet Vernal	Browntop	White Clover	

4.2.4 Hyperspectral Aerial Survey

Aerial imagery of the farms involved in the PGP project was gathered using an AisaFENIX hyperspectral sensor manufactured by Specim (Finland). The captured data were atmospherically corrected and mosaiced into a single geo-rectified image by the PGP team using the method outlined in Pullanagari et al. (2016). After the georectification process undertaken by the PGP team, all analyses, smoothing and transformations were carried out by me.

4.2.4.1 AisaFENIX© Specifications

The AisaFENIX (FENIX) is a, push-broom type, hyperspectral imager designed for collection of both aerial and laboratory based hyperspectral data (SPECIM, 2013). The push broom sensor has a series of detectors that capture the spectral information for an entire row of pixels perpendicular to the direction of travel (Richards & Jia, 2006). Individual detectors, for each pixel in the row, capture data for the whole row in the instantaneous field of view (IFOV), the sensor operation type is depicted in Figure 4.3.

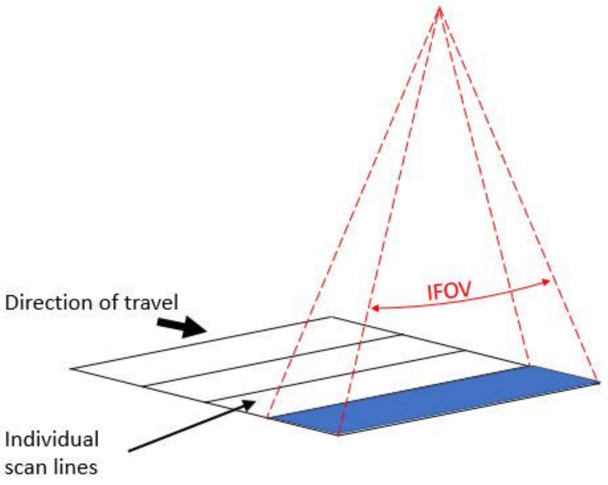


Figure 4.3: Push broom sensor operation diagram, adapted from *(Tempfli et al., 2009).*

The AisaFENIX has a spectral range from 380 to 2500 nm collected using a pair of push-broom cameras for VNIR (380 – 970 nm) and SWIR (970 – 2500 nm). Both cameras are focused through a single fore optics dispensing with the need for co-alignment of two separate optical systems with possible differences in image sharpness, distortion and field of view (FOV). The imager’s FOV is 32.3 degrees (SPECIM, 2013) which at an operating height of 800 metres altitude results in a ground pixel size of around 1 metre (Pullanagari et al., 2016). The instruments key specifications, as listed in the user manual, are shown in Table 4.3.

Table 4.3: AisaFENIX key optical and camera performance factory specifications (SPECIM, 2013).

Optical Characteristic	VNIR	SWIR
Spectral range	380 - 970 nm	970 - 2500 nm
Spectral resolution	≤ 3.5 nm (30 µm slit)	≤ 10 nm (30 µm slit)
Spatial resolution	RMS spot diameter <30 µm	RMS spot diameter < 31 µm
Image aberrations	Keystone <4 µm Smiling < 0.5 µm Distortion < 8.5 pixels	Keystone < 3.5 µm Smiling < 0.7 µ Distortion < 8.5 pixels
F – number	1.6	2.4
Magnification	0.667	1.0
Reciprocal dispersion	106.6 nm/mm	193.7 nm
Polarisation sensitivity	< 2.5 %	< 2 %
Stray light (with notch filter)	< 0.6 %	< 0.6 %
Field of view (FOV)	32.3 degrees	32.3 degrees
Hyperfocal distance	4 m	4 m
Focusing distance	1m to infinity	1m to infinity
Detector type	CMOS	MCT
Pixel size	16 x 16 um	24 x 24 um
# Spatial pixel	384	384
# Spectral pixels in range	370*	280
Spectral sampling/pixel	1.75 nm	6 nm
Detector area used for the specified spectral image	6.144 (spatial) mm x 5.920 (spectral) mm	9.212 (spatial) mm x 6.912 (spectral) mm
Quantum efficiency	50% (peak)	60%
Well capacity	360 ke$^-$	1000 ke$^-$
Read noise	120 e-	310 e-
Dark current	40 e-	200 e-
SNR @ maximum signal	500-1000:1*	900:1
Maximum frame rate	120	120
Integration time	0.1 ms – 100 ms	0.1 ms – 20 ms
# Bad pixels	< 0.1 %	< 2 %
Data interface	CL, 12 bits	CL, 16 bits
Camera control	CL	CL
Cooling	Camera and optics thermo-electrically temperature stabilised.	Stirling cooler, 160K

4.2.4.2 AisaFENIX Data Collection

This AisaFENIX sensor was mounted in a Cessna 206 aircraft. A single antenna RT Oxford Survey+ Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU) system was used to collect geospatial data for image registration and orthorectification. The swath width of 400-500 m and ground speed of 110 knots meant the system could collect data for around 1,000 hectares per hour. Spectral binning can be applied in the VNIR camera for coarser spectral sampling and higher signal-to-noise ratio (SNR). Spectral binning of the VNIR reduced the total spectral bands to 448 (380 nm to 2,500 nm). Flights were flown in a north south orientation and, where possible, carried out as close to solar noon as possible. The output created a series of image 'strips' that when mosaiced together formed a single image of the entire property.

4.2.4.3 AisaFENIX Data Preparation

For AisaFENIX data to be of use for any remote sensing application the raw Digital Number (DN) data must be temporally comparable and geometrically corrected (Moran et al., 1997). The raw DN data were converted to radiance values using CaliGeoPRO software using a flat terrain model. The georectification was carried out using an 8-metre resolution Digital Elevation Model. For atmospheric corrections, a physical based atmospheric model based on MODTRAN5 was used to process the radiance images in ATCOR 4. This procedure reduced unwanted noise from solar illumination and atmospheric effects ensuring the data could be directly compared with other atmospherically corrected spectra. The PGP team performed this process for their project before making the data available for this study.

4.3 Data Handling and Processing

The aerial imagery data were provided, after preparation, as a mosaiced georectified image with 448 bands. All subsequent pre-processing and classifications used ENVI image analysis software version 5.1 (Exelis Visual Information Solutions, Boulder, Colorado), which has a suite of built-in analytical algorithms.

The application of smoothing or data transformation procedures are generally carried out to improve signal-to-noise ratios or to improve correlation between the spectra and component of interest (Moran et al., 1997; Thulin, 2008). Noise is often random, unknown fluctuations in the signal that does not contain useful information, or which obscures meaningful information. Noise can be introduced to a sample from several sources including atmospheric effects, instrument error and multiplicative or additive scattering of light from the target (Dhanoa et al., 1994). The simplest way to reduce noise is to take repeated measurements which will decrease the noise by a factor of $\sqrt{n}$ (A. Stevens & Ramirez–Lopez, 2014). Doing so also allows a more definitive group mean to be established. Various mathematical techniques have been used to account for or remove the noise component of data including first and second derivatives and standard normal variate transformations (Asner, 1998; Thulin, 2008; Williams et al., 2012; Iqbal et al., 2014; Y. Liu et al., 2015).

This data were smoothed or transformed before data analysis or interpretation. The handling and application of transformations or smoothing of data are often common to numerical and image based hyperspectral data (Thulin, 2008). The smoothing and transformations used for various parts of the subsequent analysis described in later chapters are:

1. Savitzky-Golay smoothing
2. Transformation to 1st derivative
3. Continuum removal
4. Minimum Noise Fraction (MNF)

4.3.1 Savitzky-Golay Smoothing

Savitzky and Golay (1964) asserted the benefits of smoothing data to remove

“random errors which, regardless of their source, are characteristically described as noise”.

Data smoothing is needed to eliminate noise from the spectra, but this can also remove important information (Vaiphasa, 2006). The most widely used method for improving the signal-to-noise ratio (noise reduction) of remote sensing spectra is the Savitzky-Golay polynomial approximation procedure (Savitzky & Golay, 1964). This procedure takes a moving window of set size and fits a polynomial regression function by least squares and requires that wavelengths be equidistant. The implementation usually requires a window size of odd number (the smoothing occurs at the centre value) to which predefined coefficients are fitted. Derivative transformation can also be implemented during this smoothing process (Thulin, 2008; A. Stevens & Ramirez–Lopez, 2014).

4.3.2 Derivatives

The derivative of a spectrum is its rate of change with respect to the wavelength (Demetriades-Shah et al., 1990). The derivative can be calculated by dividing the difference of a signal at two wavelengths by the interval between the wavelengths. This produces the first derivative of the midpoint with higher order derivatives generated by repeating the process. Small gap differences in wavelength used for the calculation may produce derivatives which are small in comparison to the noise producing a noisy derivative spectrum. Alternatively, a larger gap may result in reduced noise but this approach compromises spectral detail (Demetriades-Shah et al., 1990). Using derivatives can assist with noise reduction if that noise is low frequency, such as soil background noise. Derivatives are also helpful when trying to resolve overlapping spectral features, allowing detection of detail ordinarily masked by nearby features (Demetriades-Shah et al., 1990; A. Stevens & Ramirez–Lopez, 2014; Jin & Wang, 2016).

4.3.3 Continuum Removal

Continuum removal (CR) is a mathematical process where the highest reflectance values are identified and connected by linear interpolation to form the continuum. The original reflectance value is then divided by the continuum value to produce the continuum removed values (R. N. Clark & Roush, 1984; A. Stevens & Ramirez–Lopez, 2014). Continuum removal can improve results when predicting macronutrient content of grasses (Mutanga et al., 2004) and for use in sugar cane identification (Galvão et al., 2005). However, while Schmidt and Skidmore (2003) found continuum removal a useful tool, it also removed species differences associated with canopy structure.

4.3.4 Minimum Noise Fraction

MNF is comparable to a principal component analysis in that the spectra are converted to new variables. They differ in that the MNF considers the noise in the data while the PCA identifies the variation of the data (Green *et al.*, 1988). The first variable (component) is the component that carries the greatest information with the least noise. The second is the component that carries the greatest information from the remaining information and so on. The MNF thus carries most of the useful information in the first few components and the noise in the latter components. The method applied in ENVI is modified from Green et al. (1988). The MNF can reduce computational load for subsequent analysis and improve the signal-to-noise ratio of the data (Keshava, 2003). MNF is often used to reduce the dimensionality of hyperspectral data (Rosso et al., 2005) and is often used as a precursor to other analysis such as spectral unmixing (Boardman et al., 1995; Keshava, 2003).

4.4 Data Mining; an Iterative Methodological Search

Knowledge is the goal of science. Pure science is the pursuit of reliable knowledge for knowledge sake, while applied science is the application of existing scientific knowledge in a useful way to fill a specific need (Bhatta, 2013). Data mining is an extension of data analysis that seeks to create new insight from data sets (Bhatta, 2013).

4.4.1 Hyperspectral Imagery

Hyperspectral imagers collect light with the added advantage of a geospatial reference (B. Park & Lu, 2015). They collect what is referred to as a ‘data hypercube’ which consists of two spatial dimensions and one spectral dimension, x, y and z respectively (Moran et al., 1997). The final image hypercube is best described as a stack of images where each page in the stack has the same spatial location but represents a different spectral wavelength. Humans’ ability to discern light is limited to the visible wavelengths, so we convert wavelengths outside this range to visible colours so they can be viewed and interpreted. Images created with non-visible wavelengths displayed in visible colours are commonly referred to as ‘false colour’ images (Jensen, 2000).

The origins of image analysis date to the arrival of photography (Jensen, 2000) and it could be argued that manual image interpretation is a basic form of data mining. Disadvantages of manual interpretation include being time-consuming, potentially biased, and analysts may be unable to view an entire scene at once (Richards & Jia, 2006; Bhatta, 2013). This is especially true when the sensor is producing many layers (bands) of information that cannot all be viewed together. While computers can process much more information than humans, they lack insight, so processes that combine human and computer interpretation in an iterative process are favoured (Bhatta, 2013). For example Dymond *et al.* (2012) first used automated classification to reduce the workload, followed by a manual validation of selected locations for forest changes.

The iterative nature of remote sensing modelling is frequently reported as a linear process, with only the successful method being reported including for the *Pioneering to Precision* project (Pullanagari et al., 2016). The format of this thesis affords the luxury of reporting the true nature of the scientific enquiry, with a view to informing future studies on the more realistic, true path of discovery. Hence, this chapter includes both information on the primary method used in the remainder of this work, and some discussion on how and why it was chosen.

4.4.2 Data familiarity

The first stage in understanding new information is to gain some familiarity with its properties. Human beings interpret visual cues many thousands of times a day throughout their whole lives (Jensen, 2000) and are therefore able to identify visual patterns. It was therefore a logical first step to simply view, examine and become familiar with the farm hyperspectral imagery prior to more complex procedures. This process was performed on a small 25 hectare (500m x 500m) image segment taken from a single survey strip. The process only used data from Limestone Downs, a farm that had been visited several times. The smaller area was selected to speed up the search as the whole image covered up to 4,000 hectares. The full images were around 60GB each in size. The large images also required that a 90GB swap file be allocated on the C: drive of the processing computer and took many hours to process. The smaller image segment was selected as it contained as many elements found in the entire image as possible such as roads, buildings, pasture, and trees. Another motive for using the particular image segment was that the area had been visited several times. This provided first-hand knowledge of the site, which proved useful as a guide when evaluating the early investigations.

The early analysis involved visualising various bands together. The search was initially random, but this soon advanced to a targeted search. Spectra from various target features were isolated and exported into Excel. The spectra were graphed and compared to find areas where variability might be exploited, much as NDVI utilises variations in reflected light from the red and near-infrared (Rouse Jr et al., 1974). This examination was carried out with spectra from various targets and focused on their differentiation. The goal of this work was to identify three bands that may allow the primary targets to be clearly defined. It was hoped that visualisation of the imagery using these bands would improve the selection of regions of interest for training of classifications.

Some results from this search appeared to have image distortions that manifested as lines in the imagery, especially when using wavelengths from the Shortwave Infrared (SWIR). Figure 4.4 shows one such example of this distortion. Initially this was not considered a problem. The image in Figure 4.4 (b) uses red, green and blue to visualise wavelengths of light that are beyond the human eyes ability to perceive, a so-called ‘false colour’ image.

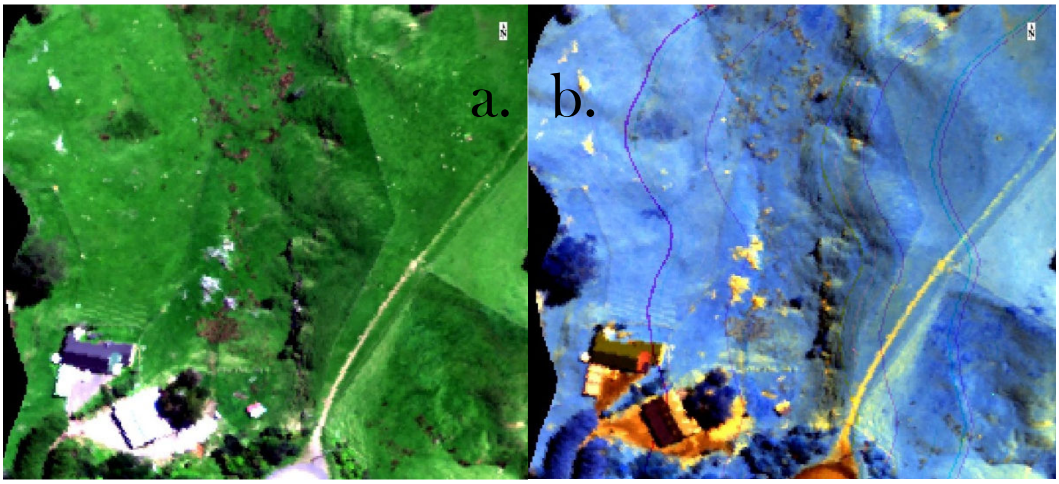


Figure 4.4: a.) Visualisation of the data using real colour wavelengths (red - 640nm, green – 550nm and blue 460nm). b) False colour image visualisation of three non-visible wavelengths (red - 2179nm, green – 1680nm and blue 956nm) with some linear distortion, running north-south.

4.4.3 Unsupervised Classification

Soon after the visual examination, an unsupervised K-means classification was performed to assist with defining the number of categories in the image. This technique is a basic starting point in image analysis tutorials. It uses image statistics and does not require definition of training data (Harris-Geospatial, 2018). The process categorises pixels that have spectral similarity without knowing what each represents. The classes can be combined or named after the classification is complete.

Although some patterns were visible, the unsupervised classification produced poor results that did not match with categories obvious to the observer. The high spatial resolution (and likely spectral resolution) produces great diversity within the image (Bhatta, 2013) and is the likely reason for the poor result. High spatial resolution data has been shown to be problematic to analysis in some cases (Khun et al., 2016).

4.4.4 Data Error

Two problems were encountered with the hyperspectral imagery over the course of this study. An error in the spatial registration was apparent early in the study, but was not properly defined until much later. The circumstances and nature of that error are best discussed in the context of the work that led to its definition so are not discussed in this section.

The other error, that became apparent in the early stages of the data mining process, also appeared during the basic unsupervised classification, though to a lesser extent. A spectral error was present in the aerial imagery. It manifested as a series of lines running vertically, in line with the survey flight, in the image. The error did not appear in the initial trial survey data. That data were collected with an identical, but different, sensor. The spectral error was originally deemed, by the primary research team, to be random noise (Ian Yule, personal communication), so effort was then directed towards selecting a test that would be less affected by the error rather than removing it. Spectral Angle Mapper (Yuhas et al., 1992) was one of the first classifications tested, but as Figure 4.5 shows it was quite prone to the error as were most of the other options available.

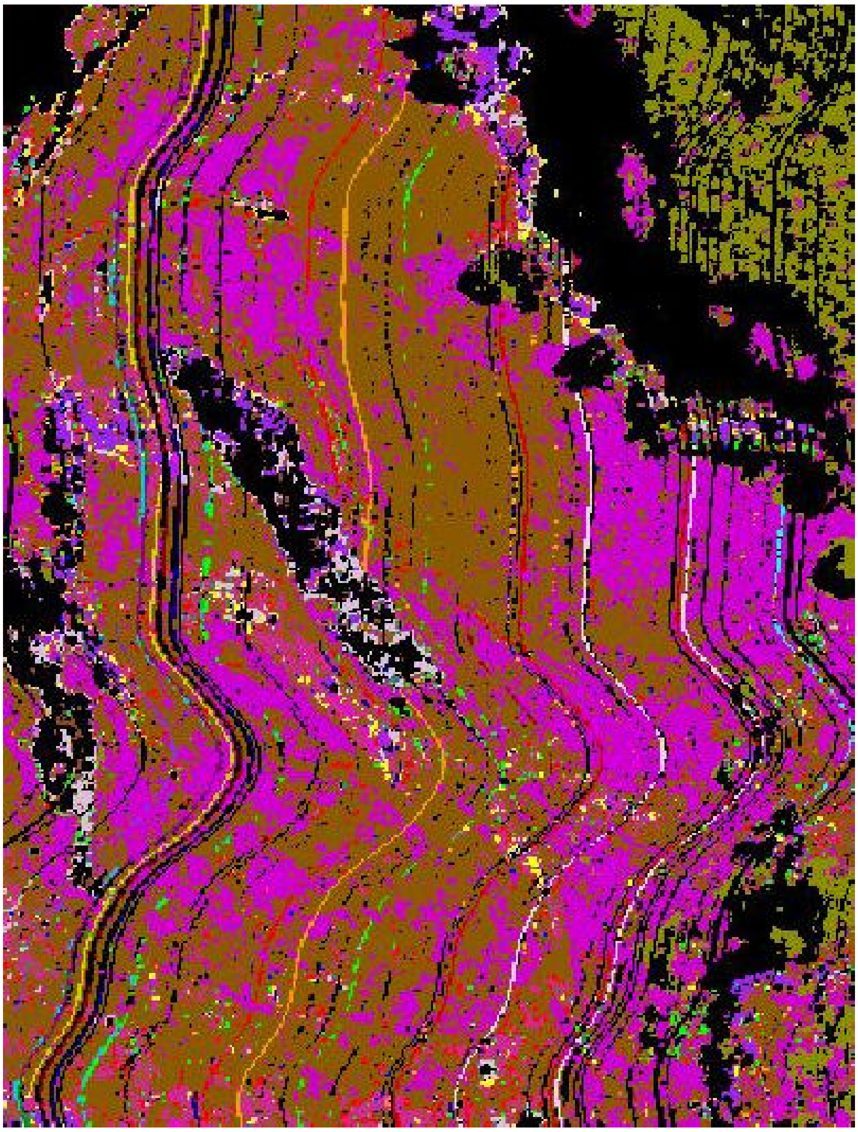


Figure 4.5: Results from the Spectral Angle Mapper classification from a portion of the Limestone Downs 2015 data acquisition showing a very distinctive error pattern.

An examination of the image error indicated the bands affected varied from one column of pixels to the next indicating it may have been a problem with the detectors. Push broom sensors are prone to stripes in the data if the detectors are not perfectly calibrated (Haris Geospatial, 2019). It is certainly the case that this sensor produced images that were greatly affected by the line features where a similar sensor, rented and used in the very first survey, did not produce any features of that kind.

An examination of a line of pixels across the image was carried out to better describe the problem. Fifty different bands, above 1,000 nm, were identified to have unusual errors present. Figure 4.6 shows how the spectral noise manifested, within the spectra of a single pixel. A single band has a data value that is a magnitude above neighbouring bands within the same pixel. The band could have been excised if it had been consistent across all pixels of the image, but that was not the case.

During these initial tests Support Vector Machines (SVMs) (Vapnik, 1995) with a linear kernel produced clearly superior results that almost always ignored the error in the data. Rather than spend time attempting to remove the problem and following the preliminary testing, the use of SVMs was considered the only viable option going forward. That decision allowed work to progress, albeit with fewer options for image classification and method comparison.

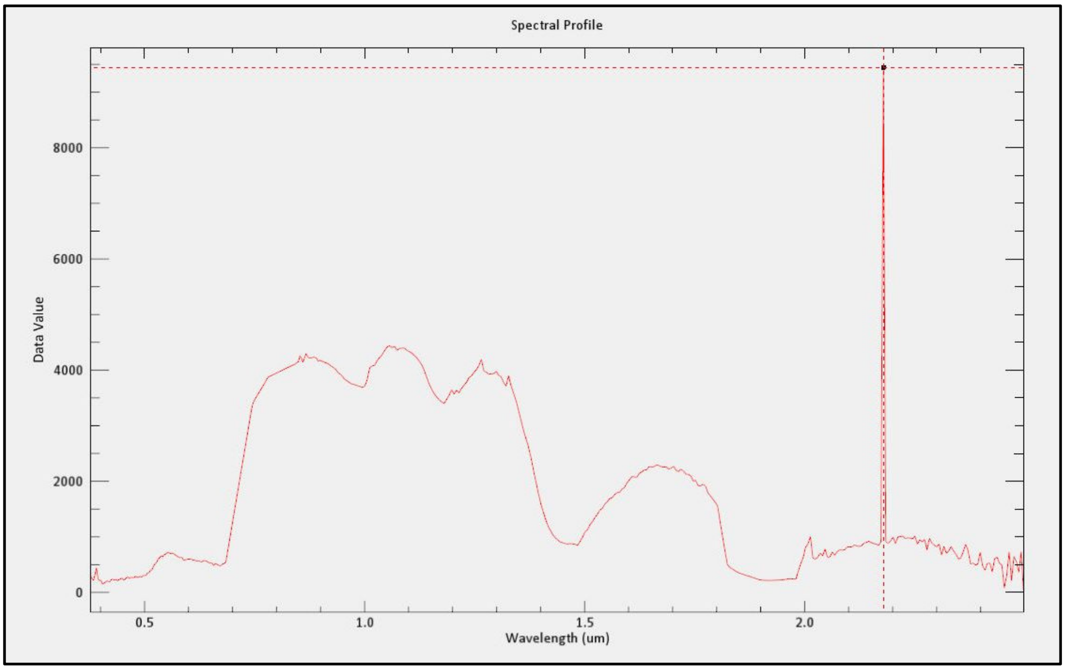


Figure 4.6: The spectral signature from a single pixel of the Patitapu 2017, image prior to smoothing or transformation displaying how the spectral noise in the image manifested. The point at the crosshairs is band 390 (2,178.9 nm). The data value at that point is 9,450, the bands either side of that point 389 and 391 have data values of 908 and 913 respectively.

4.5 Support Vector Machines (SVM) Overview

The aim of supervised classification is to accurately predict the target class of an unknown sample from a known example (Hsu et al., 2003). Support Vector Machines (SVM) are an adaptation of the maximal margin classifier developed by Boser et al. (1992). The maximal margin classifier selects a separating hyperplane that maximises the distance between the two classes. It was developed and intended for binary classification applications (Vapnik, 1995). It defines the optimal separating hyperplane that is furthest from the training observations. The margin is the distance between the hyperplane and the nearest training observations. The nearest training observations are the support vectors (Vapnik, 1995; James et al., 2013). The classifier only uses a subset of the training data, the support vectors (Boser et al., 1992). Data points further from the margin are not needed.

In the simplified example represented by Figure 4.7 two of the possible myriad of separating hyperplanes that could be used to divide the classes are displayed. Both the (a) and (b) hyperplanes correctly separate the data classes. However, the margin of hyperplane (b) is smaller than (a). The resulting classification for the unknown sample (X) would not be the same for these hyperplanes. In this crude example it would appear more probable, from its apparent proximity, that it belongs to Class 1. If it were known that sample (X) did belonged to Class 2 it is highly likely that it would become a new support vector for a redrawn hyperplane to describe the two classes. The three points along the margins of hyperplane (a) are the support vectors, if they are moved or removed the hyperplane would require recalculation. The same cannot be said for any of the other points whose presence or location do not affect the hyperplane and consequently their removal would not affect the hyperplane boundary.

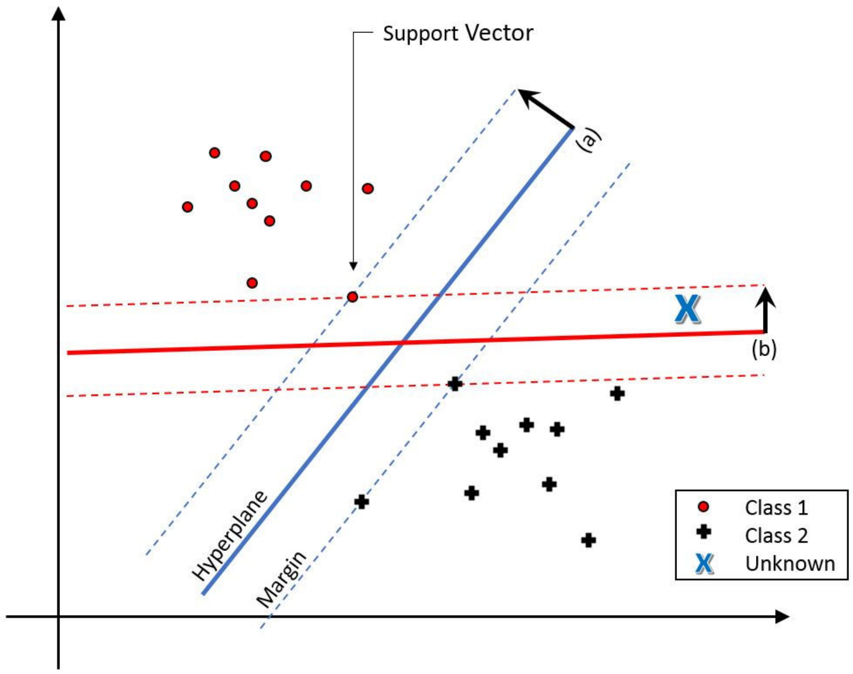


Figure 4.7: Simplified example of two possible classification hyperplanes for a maximal margin classifier adapted from (Hsu et al., 2003; Hastie et al., 2009; James et al., 2013). (See text for explanation)

SVMs are an adaptation of the maximal margin classifier that can cope with non-linear relationships via a non-linear decision boundary (Hsu et al., 2003; Hastie et al., 2009; James et al., 2013). With the introduction of a soft margin and kernel functions the SVM can be tuned to fit nonlinear relationships (Ben-Hur & Weston, 2010). As a means of fine tuning the SVM to non-linear relationships, a range of kernel functions are available. The following are listed by Hsu *et al.* (2003) as four basic kernels:

○ Linear	$K(x_i, x_j) = {x_i}^T x_j$
○ Polynomial	$K(x_i, x_j) = (\gamma {x_i}^T x_j + r)^d, \gamma > 0$
○ Radial Basis Function (RBF)	$K(x_i, x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right), \gamma > 0$
○ Sigmoid	$K(x_i, x_j) = \tanh\,(\gamma {x_i}^T x_j + r)$

With the linear SVM the only tuning parameter is the soft margin constant. Figure 4.8 shows a simplified example of how this affects the hyperplane projection.

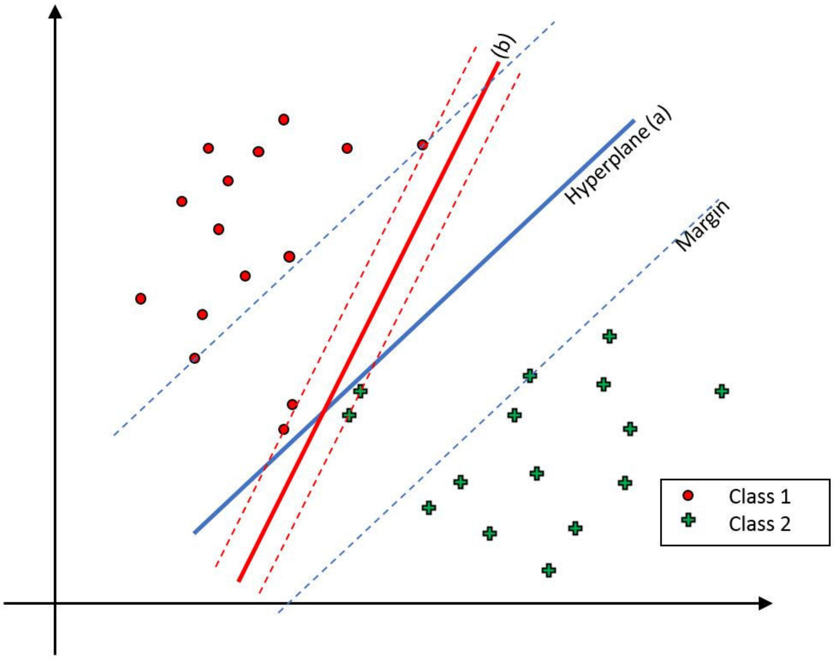


Figure 4.8: The effect of the soft margin constant on the hyperplane decision boundary. In this case a smaller penalty to (a) in comparison to (b) allows the margin to become larger by ignoring some points within the margin. Adapted from (Ben-Hur & Weston, 2010). (See text for explanation)

Polynomial and RBF kernels require that, as well as the soft margin constant, the degree of polynomial and gamma (γ) parameters must be defined. This is normally carried out with a two-dimensional grid search of accuracy (Hsu et al., 2003; Ben-Hur & Weston, 2010). It is possible to get similar accuracies with different combinations of tuning parameter but, since the linear kernel only has the soft margin to tune, it is less complicated (Ben-Hur & Weston, 2010). Additionally, in many instances the linear SVM has advantages of computational speed over RBF. Bazi and Melgani (2006) showed that a simple SVM had a lower computational burden compared to their more complicated variation. That computational saving however did not greatly diminish the overall accuracy of the classification as it outperformed some other more complicated variations (Bazi & Melgani, 2006).

Since data outside the margin is not necessary for the hyperplane formation SVMs can be applied with just a few well-chosen training samples (Foody & Mathur, 2006). That makes them ideal for classification applications where ground data collection is limited by financial or topographic constraints. They are also useful for applications where a fast turnaround is advantageous, a likely criterion for a commercial operation.

4.6 Conclusion

This chapter presented the circumstances around how the primary PGP data were collected, what problems were encountered in the early stages of the study in using that data and what solution allowed for those problems to be circumvented.

The first challenge encountered in the early stages of this study was related to the collection of ground reference data. There were several advantages to being part of the larger study including having access to a large volume of data that is ordinarily impossible for a single PhD study to collect. However, the inability to define data collection protocols meant the collection of ground data, particularly species composition, was not in a compatible format for use with remote sensing analysis. It resulted in much of the data collected by the program being of little use for this study. This meant a smaller scope of the research and a lost opportunity to validate the study across all the farms. However, the four farms used represent a larger dataset than previously available.

The other main challenge encountered in the early stages of the study was the presence of stripes or error in the hyperspectral imagery. Their prominence defied the use of all classification options, except SVMs. An iterative search eliminated other options and, in some ways, limited the scope of the research. The resulting shift in focus forced the research to be bolder and achieve more from single images rather than utilise multi-temporal techniques that had been used in other studies. The use of single images instead of multi-temporal data a great advantage for farming applications that are often time sensitive. The simple application of the SVM was shown by (Bazi & Melgani, 2006) to have benefits for processing without major implications for accuracy. The simple approach is also easier to implement in off-the-shelf programs so for ease of future widespread adoption, makes financial and logistical sense.

The challenges and limitations of the research had a major influence on the direction and outcomes of the research. Those already noted include;

- Closed research methodology – preventing the tailoring of the data collection
- Inappropriate or inaccurate ground reference data – which meant that a lot of the data that was collected was not suitable for use with remote sensing.
- Spectral error in the imagery – which added a level of 'noise' to the data that prevented the use of many standard remote sensing tools.
- Spatial error – that invalidated even more of the ground data collected as it could not be correlated to the imagery.

These challenges were accompanied by some others not yet discussed.

- The impact of distraction – Time spent finding solutions to the research and data related problems was time lost that might have been spent more productively. It might have allowed greater insight to be gleaned from alternative methodologies or more ground data to be collected.
- The impact of a closed team with limited domain expertise – The team involved in the PGP project were new to hyperspectral imagery acquisition and interpretation. This meant that there was no one available to assist with many of the mundane problems that arise, especially at the outset of the project when understanding of the topic was limited. Also, everyone on the project was under non-disclosure agreements (NDAs). This meant no one could discuss the project outside of the group which prevented peer

discussions that could constructively improve outcomes. One such issue was highlighted when discussing the potential of the research with the NZPBRA in the previous chapter.

This chapter also demonstrates that Support Vector Machines have been successfully implemented for many studies of vegetation in remote sensing. Their ability to operate effectively with small training datasets could be a very great advantage if this technology is to be implemented for the benefit of farmers. Smaller datasets would reduce collection time and resources necessary and therefore reduce implementation costs. The cost to implement will be a major factor in generating a return on investment which will determine the potential uptake of the technology.

The next three chapters build on the findings of this chapter to define how remote sensing techniques were utilised to discern pertinent landscape information for practical benefit to farmers and greater farming community.

Chapter 5 : Pasture Classification for Automated Variable Rate Fertiliser Application

5.1 Introduction

In Chapter 1 Synge (2013) cited a need for application technologies and practices that focus on accurate, targeted placement of fertilisers in the correct quantities where they are most needed. This chapter aims to address this knowledge gap by describing a novel method to define pasture for variable rate aerial fertiliser application on hill country pastures.

The stated goals of the PGP *Pioneering to Precision* focus on bringing Precision Agriculture (PA) techniques to New Zealand hill country sheep and beef farms. The objectives include improving fertiliser placement and utilisation with stated environmental and financial benefits. Central to realising these goals is the availability of accurate base information on farm maps (Grafton & Yule, 2015). Differential/Variable Rate Application Technology (VRAT) has been developed with improved accuracies over manual control methods (Chok, Grafton, Yule, & Manning, 2016). The application has been implemented with interpretation of the target areas and exclusion zones carried out through manual digitisation (White *et al.*, 2017). While manual image interpretation is still practiced in remote sensing, for example the manual removal of unrelated target pixels (Raab *et al.*, 2018), it is considered time-consuming and costly (White *et al.*, 2017). Currently the best digital input information that can be accessed for hill country farms are paddock and farm boundaries generated from GPS surveys. Although aerial photographs are often available, they require manual interpretation to designate non-productive or sensitive areas where fertiliser exclusion is preferred (White *et al.*, 2017). Manual interpretation however has the potential to introduce bias or error (Dymond *et al.*, 2012).

The implementation of precision agriculture techniques often utilises remote sensing technology, but is more often focused on arable crops or other high value enterprises. A considerable volume of research has occurred using remote sensing systems into fertility (Filella *et al.*, 1995; Y. Liu *et al.*, 2015), disease (West *et al.*, 2003; Oerke *et al.*, 2014) and crop yield estimation (Mariotto *et al.*, 2013). There are many likely reasons for the lack of progress with remote sensing technologies in the hill farming or other marginal pastoral environments. A key constraint, as mentioned in the introduction, is that the steep terrain of hill country farms restricts data collection and product application options. Most existing precision agriculture technologies rely on some degree of proximal data sampling, which is expensive and even unsafe in the hill farm environment. Also, hill farms are much less profitable and with lower available capital for investment into expensive new technology when compared to more productive arable farms. So far, there has been little investment in remote sensing research for hill farms. Until the recent introduction of variable rate fertiliser application technologies there has been no financial incentive to use or utilise remote sensing in these environments. The limited research undertaken in this sector has largely centred on management practices and plant and animal breeding efforts.

The PGP therefore represents a milestone, with significant investment focused on the application of remote sensing techniques in these environments. It is unsurprising that fertiliser is the focus of this work as it is the single largest expense for these farms (Burtt *et al.*, 2016) and therefore is the most likely application to provide a positive return on investment for both the research and implementation. Researchers in the past have successfully used remote sensing techniques to measure pasture fertility to help define the amount of fertiliser required in a set area (I. D. A. Sanches, 2009; Pullanagari *et al.*, 2016). However, no studies accurately delineate the fertiliser application area on hill country farms. This shortfall in information is pertinent given the recent advances in automated variable rate application technologies (VRAT) achieved by (Grafton *et al.*, 2012; Chok, Grafton, Yule, & Manning, 2016), and which are now commercially available to New Zealand farmers. VRAT technologies require accurate application maps in a fast, efficient manner and with minimal operator input to realise their potential. This innovative study helps address this knowledge gap by delivering a solution to delineate pasture areas in a fast, efficient manner and with minimal operator input.

5.1.1 Remote Sensing

The variability of hill country farms, particularly topographical variability, constrains every aspect of these farming systems. Importantly, the terrain also limits the use of conventional ground survey techniques. These constraints are not shared by aerially-acquired remote sensing techniques (Wachendorf *et al.*, 2018). Hyperspectral aerial imagery offers the possibility to gather a large amount of geo-referenced data in an economical manner that can be interpreted to differentiate species and create vegetation distribution maps (Irisarri *et al.*, 2009). While this technology has other potential applications in the hill country environment, for example slip monitoring, pasture is the only target of interest for this study.

5.1.2 Additional Mapping Benefits

Aside from the aforementioned fertiliser application benefit, there are other practical benefits of pasture distribution maps. Two stand out above the rest. First, from the farmer's perspective a classification map that lists the effective grassed area (EGA) of each paddock would be useful information when setting stocking rates. The farmers would subsequently gain additional benefit from knowledge of the quality of said paddocks to support management decisions. That understanding can come from expert local knowledge or further spectral analysis such as provided by Pullanagari *et al.* (2016). Knowing the correct stocking rate is a vital component of this farming system as too few animals underutilise the resource and too many deplete it too fast to be sustainable for that season. Either situation would result in financial losses for the business.

Second, the rural valuation sector would benefit from accurate, unbiased pasture mapping. Rural valuers currently employ a variety of ad hoc methods to determine their assessment of value. The value of rural property comes primarily from the productive capacity of the land (Baxter & Cohen, 2009); therefore, accurate estimation or measurement of various land classes within a rural property is essential to an accurate assessment of its value. In the hill farm environment, the primary class of value has traditionally been the pasture although that dynamic will be more fully explored in chapter 6.

5.1.3 Research Rationale

It is important that farmers and others utilising pasture mapping information have confidence in it so an accuracy of 95% or greater was set as a target. In this work, only pasture and non-pasture were defined targets for separation. This step was taken to account for the potential that introducing multiple components into a classification might be detrimental to accuracy (Joria & Jorgenson, 1996; Melgani & Bruzzone, 2004). Fast and accurate automated classification are important in this endeavour to keep costs low and reduce the potential for operator error.

To be commercially viable, the classification must:

- Be robust enough to be applicable to hyperspectral imagery collected across the varied landscapes of New Zealand.
- Be applicable to imagery collected at different times of year.
- Be straightforward to implement with limited operator input.
- Need limited ground data collection (preferably none).

These criteria are essential to allow a long window for data collection and allow a fast turnaround. Results will be discussed with these criteria in mind.

No farm scale classification currently exists for this environment, so there is no current standard with which to compare. However, the main farm in the study, Patitapu station, was the subject for a Horizons Regional Council report that included pasture area estimation. The methods suitability will therefore be judged by overall accuracy, which should be high (>95%), and in comparison to the information in that Horizons report. That will show the methods suitability as a substitute for manual photointerpretation.

This study aims to map the primary resource on hill farms, pasture, with no consideration for the composition of the 'non-pasture' class, which is discussed in more detail in chapter 6.

5.2 Materials and Methods

5.2.1 Trial Locations

The two farms included in this trial are Patitapu Station and Lawson's Farm (Figure 5.1).

Patitapu Station is a sheep and beef station located in the Wairarapa region of the North Island of New Zealand at about 40° latitude south. The 2,610 hectare property includes around 1,800 hectares of pasture that supports almost 17,000 stock units with a further 450 hectares of indigenous bush. The terrain ranges from 150 to 534 metres above mean sea level. Patitapu Station is situated in the Horizons Regional Council district and has been subject to detailed analysis and reports as part of their 'One Plan' (Horizons Regional Council, 2014). Patitapu was designated as a high priority area within the Horizons district. This is of benefit for this research because, unlike most hill country farms in New Zealand, significant analysis has been performed on the farm's assets as part of a Whole Farm Plan (WFP) (AgResearch, 2016). Their 2009 WFP (unpublished) includes a calculation of the farms grassed area at the paddock scale. This represents a benchmark to compare the output of this work with current methods. This information was not available for any other farm involved in the PGP project. The Horizons report lists paddocks by name - those names are also used in this study for identification.

Lawson's farm is a 2,312 hectare property 30 minutes north of Dunedin on the South Island of New Zealand at about 45° latitude south. Lawson's Farm was chosen as a comparison site as it was the most southerly of the eight farms included in the PGP project (Figure 5.1) so was the most different climatically.

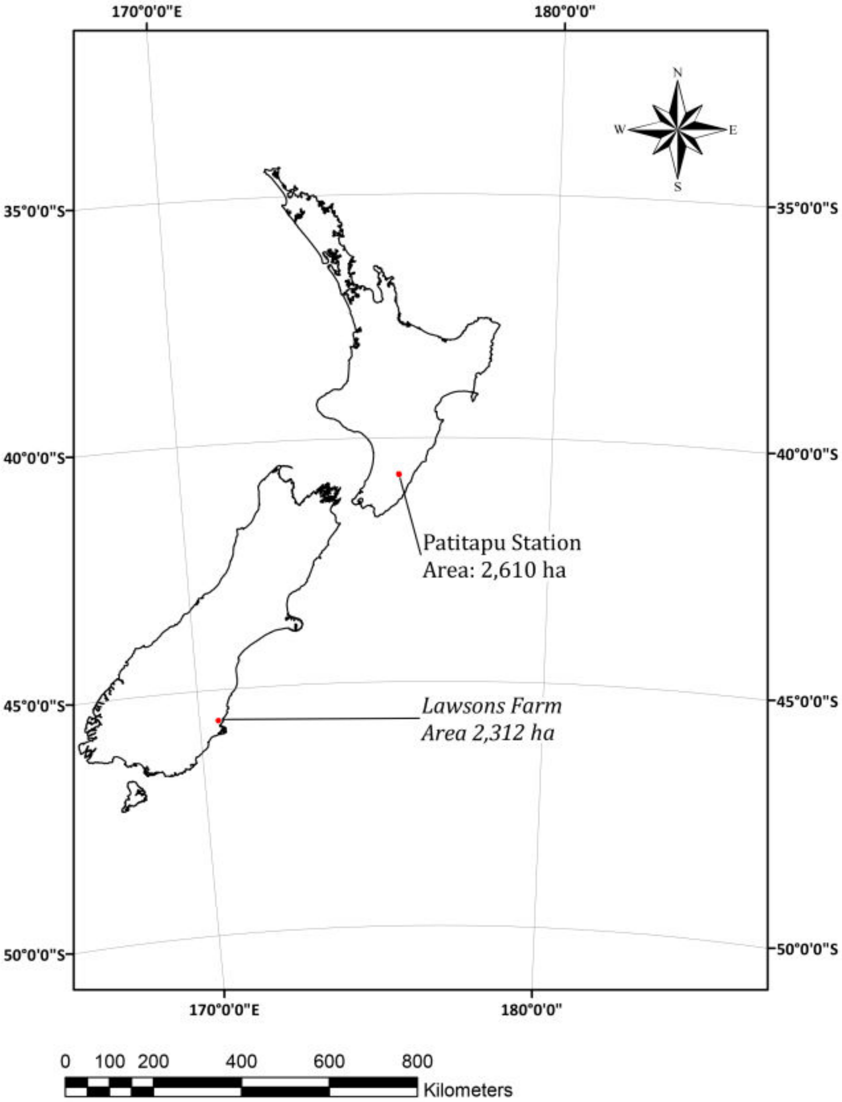


Figure 5.1: Locations of trial farms used in this study within New Zealand.

5.2.2 Hyperspectral Image Collection

An AisaFENIX hyperspectral sensor manufactured by Specim (Finland) was used to obtain imagery for two geographically and environmentally distinctive hill country farms in New Zealand (locations shown in Figure 5.1) at the times and dates detailed in Table 5.1. Methods for data collection, georectification and atmospheric correction were identical to those of Pullanagari *et al.* (2016). Image acquisition details are listed in Table 5.1.

Table 5.1: Hyperspectral image acquisition details for each survey. The autumn survey of Patitapu Station was collected in two parts due to cloud obscuring part of the site on the first day.

Image Acquisition Details		
Location	Date	Flight Start Time (local)
Patitapu (Spring)	30th October 2015	10:40
Patitapu (Autumn) (part1)	14th April 2015	10:58
Patitapu (Autumn) (part2)	15th April 2015	12:04
Lawson's (Spring)	12th November 2015	11:26
Patitapu (Autumn)	2nd March 2016	11.30

5.2.3 Band Reduction

The imagery was received after orthorectification and mosaicing had been carried out by a colleague working on the main PGP project. The data had 448 bands, that, combined with the area covered by the survey created some computational problems. At around 60 gigabytes, the data placed a growing strain on the storage capacity of the workstation carrying out the analysis. Critically, the temporary swap file used by the analytical program required >90 gigabytes of free hard drive space to perform the analysis. This swap file was restricted to the drive where the operating system was installed which was much smaller than the installed storage drives. Band reduction was therefore carried out for two main reasons:

1. To reduce file size for stored data.
2. To reduce the file size to a point where the computer could perform the analysis.

The original file came with 448 bands that represented the spectrum from 370 nm to 2497 nm. The spectral bands were reduced by removal of the first 15 (370 - 420nm) and last 98 bands (1963 nm – 2497 nm) leaving the final band range from 16 to 350 (428 nm to 1957 nm). Although this decision was made primarily for practical reasons, work discussed in an earlier chapter suggests the short-wave infrared bands are less critical for species identification. This is supported by other literature (Adam & Mutanga, 2009; P. S. Thenkabail *et al.*, 2013; Prospere *et al.*, 2014) which found very few bands above 2000 nm to be helpful for species separation. It was also necessary to remove bands most affected by the lines in the data already discussed in Chapter Four (section 4.4.4).

5.2.4 Data Pre-Processing

Four forms of pre-processing method were applied prior to classification, with each method being assessed for their effect on the classification result. These methods are:

1. Basic spectral smoothing
2. Continuum removal
3. Minimum Noise Fraction (MNF)
4. Transformation to 1^{st} derivative

Basic spectral smoothing was performed using a Savitzky-Golay filter with a width 5 and smoothing polynomial of 3.

5.2.3 Image Classification

A pixel-based classification attempts to assign each pixel of an image into a class regardless of its neighbour. Pixel based classification has a long history in remote sensing and was the first widely accepted and practiced method for classification (Goetz, 2009).

Support Vector Machines (SVM)

Support Vector Machines (SVM) were discussed in detail in the previous chapter. In brief, as the output from this classification is intended to be binary, for example pasture or non-pasture so SVM are well suited to the work (Melgani & Bruzzone, 2004). SVM classifiers also proved effective despite line error problems with this data and they are widely accessible.

The SVM was carried out in ENVI using a linear kernel setting, no pyramid levels, a penalty parameter of 100 and a classification probability threshold of zero that ensured all pixels were classified.

Mahalanobis Distance (MD)

The MD classifier uses statistics for each class to establish a group mean similar to the maximum likelihood classifier except that class covariances are equal which provides it the advantage of greater speed (Richards & Jia, 2006). Points that are closer to the centre of the group (nearest the mean) are more likely to belong to the group. Distance from the mean is measured in standard deviation units and used to define which group a new point (pixel) belongs to. The method has been used for various classification applications (South *et al.*, 2004; Krishnaswamy *et al.*, 2009; García-Santillán & Pajares, 2018). Where SVM defines a sample into a class by which side of a decision line it falls on, MD classifiers define class by which group mean the sample is most similar.

Where an SVM line might be defined by a small number of points and still produce a high accuracy the class mean might be more easily influenced by ill-defined training samples. It was thought that they would thus make an interesting comparison for the potential application of hyperspectral data in defining farm pasture area.

The classification was carried out in ENVI using the same training samples as the SVM and with no maximum distance error value set to force the classification of every pixel into the nearest class.

5.2.4 Region of Interest Collection

Regions of Interest (ROI) were defined to represent the two desired classes within the image; pasture and non-pasture. The non-pasture ROI included trees, bush, tracks, buildings, bare soil and water. The pasture class only contained grassed pasture.

The hyperspectral image included the visible wavelengths. When the true red, green and blue bands are viewed the image is recognisable as an aerial colour photograph. ROI for training the classification were collected directly from the true colour image by visual comparison of the image with field observations (Schmidt & Skidmore, 2001; Weeks *et al.*, 2013). Site visits, terrestrial photographs and very clearly defined targets in the true colour image provided high confidence in the accurate collection of this information (Gienko & Govorov, 2017). Samples were taken from across the farm to ensure that any variability in sensor drift or light level changes during the survey were accounted for in the training samples. By selecting from the true colour aerial survey any variability in georectification of the image was negated.

The 0.8 metre pixel size allowed the primary target classes to be identified with ease. The number of ROI collected for training the classification was small (as listed in Table 5.2) and carefully chosen to maximise the variation that existed in the class. For example, a variety of dry, and lush, grassed areas were included in the pasture ROI to ensure suitable support vectors were available to the SVM as suggested by Foody and Mathur (2006). These bands should also allow a good estimation of the class mean for the MD classifier analysis. Table 5.2 lists details of ROI collected from each image. As there was a greater range of components in the non-pasture class, such as trees, roads, buildings and water, a larger number of ROI were collected to define the class. Each data pre-treatment was classified using both a linear SVM and MD classifier. The training ROI were used as class definitions and were separate from those used for validation. The numbers of ROI collected are listed so the reader can understand how many were collected. ENVI uses the pixels within the ROI and its statistical output uses pixel counts to define accuracy so the pixel counts are also noted. This is also why discussion of the results must follow that format.

Table 5.2: ROI collection statistics for each image. ROI for classification training and accuracy testing were collected separately and are listed with ROI and pixel count. The pixel count is the total number of pixels collected within all the associated ROI. A larger number of ROI were collected for training the non-pasture class as it had a greater variety of components.

Patitapu (Spring)	Training (ROI)	Test (ROI)	Training (Pixels)	Test (Pixels)
Pasture	14	999	4,762	39,186
Non-pasture	24	789	3,631	31,981

Patitapu (Autumn)	Training (ROI)	Test (ROI)	Training (Pixels)	Test (Pixels)
Pasture	18	922	4,640	36,349
Non-pasture	22	766	2,972	31,545

Lawson's (Spring)	Training (ROI)	Test (ROI)	Training (Pixels)	Test (Pixels)
Pasture	13	106	3,432	23,106
Non-pasture	26	145	2,638	24,392

This experimental design differs slightly from the norm in that a deliberately small number of samples were used. This provides greater opportunity for error to occur or to confirm the functionality of the ROI chosen to train the classifiers (Pal & Foody, 2010). The ability of the classification to be carried out with a small number of defining points would also be a benefit to the economical implementation of the method for commercial purposes.

5.2.5 Accuracy Testing

The collection of adequate numbers of validation sites for accuracy testing is important for credibility of the results. Given the size of the property, and difficulty of access and limited funding, it is problematic to carry out this task on the ground. As such the methodology employed for accuracy testing of the New Zealand land cover database v3 (Landcare Research, 2019b) was adapted. This method supported collection of a much greater number of validation sites than physically possible on the ground. Unlike Landcare Research (2019b), the process was carried out before the classification and accuracy assessment.

Prior to the classification, regions of interest (1,500 locations) for accuracy testing were randomly generated across the image in ArcMap 10.5.1 (Harris Geospatial). These ROI locations were confined to the farm area by a property boundary to create a simple random sampling design with many samples to represent the two classes (Foody, 2002). The ROI locations were transferred to ENVI and a group of pixels collected from around each point and given a class (pasture on non-pasture) based on the visual interpretation of aerial and terrestrial photography and from site knowledge informed by numerous site visits (Gienko & Govorov, 2017).

Additional to the randomly chosen ROI locations another 288 ROI locations (16% of the 1,788 total) were added manually, close to the boundaries of classes. That is, ROI locations were added close to pasture and non-pasture interfaces. This was done to take greater account of any ‘bleeding’ of one class into the other. Although the proportion of boundary pixels reduces as image resolution increases, they often have a mix of classes which can reduce classification accuracy (Townshend, 1981; Woodcock & Strahler, 1987). The farm has a large area of grass and even small variations in accuracy can have quite large financial implications. These combined total 1,788 ROI were only used to validate the classification accuracy.

The validation of the Autumn Patitapu Station image followed the same procedure with fewer additional ROI selected on the interface of classes. ROI collected at each point on both Patitapu images were an average of about 40 pixels. It would have been easy to collect very large areas of pasture or bush as validation sites, but the extremely large areas might have skewed the accuracy results by masking relatively smaller classification errors, for example along class boundaries. It was decided that a larger number of ROI with relatively few pixels would provide a more robust measure of real accuracy and avoid some of the pitfalls of classification accuracy assessment (Foody, 2002). Fewer ROI were collected for the Lawson’s image but the number of pixels per ROI was larger at between 140 and 200 average for pasture and non-pasture respectively.

After both classification methods were compared on the Spring Patitapu image the SVM with 1st derivative method was chosen to classify additional images for both seasonal strength, by applying the method to an image of the same farm taken in Autumn, and locational strength, by applying the method to an image of a farm in a different area of the country. Table 5.2 lists the number of ROI collected for training and validation of the classifier was well as the total pixel count for each group on each farm or survey.

5.2.6 Seasonal Strength

The robustness of the classification methodology to handle data from a different time of year was tested with the analysis of data collected at Patitapu Station from Autumn 2016. This analysis was carried out using the SVM on data that had been transformed to first derivative. No comparisons were made with other tests or data.

5.2.7 Locational Strength

An additional location (Lawson's Farm) from the South Island of New Zealand, that has significant differences in climatic and vegetation characteristics, was chosen to test if the method would work with data that contained different vegetation characteristics. Lawson's Farm had significant populations of gorse (*Ulex europaeus*) and New Zealand tussock grasses (various species) that are not found on the North Island farm. This analysis was carried out using the SVM on data that had be transformed to first derivative. No comparisons were made with other tests or data.

5.3 Results

5.3.1 Patitapu Station Classification (Spring 2015)

Figure 5.2 provides a close-up view of one part of the farm as an example of the classification output. It is worth noting that the classification was able to distinguish even small pockets of pasture amongst the bush.

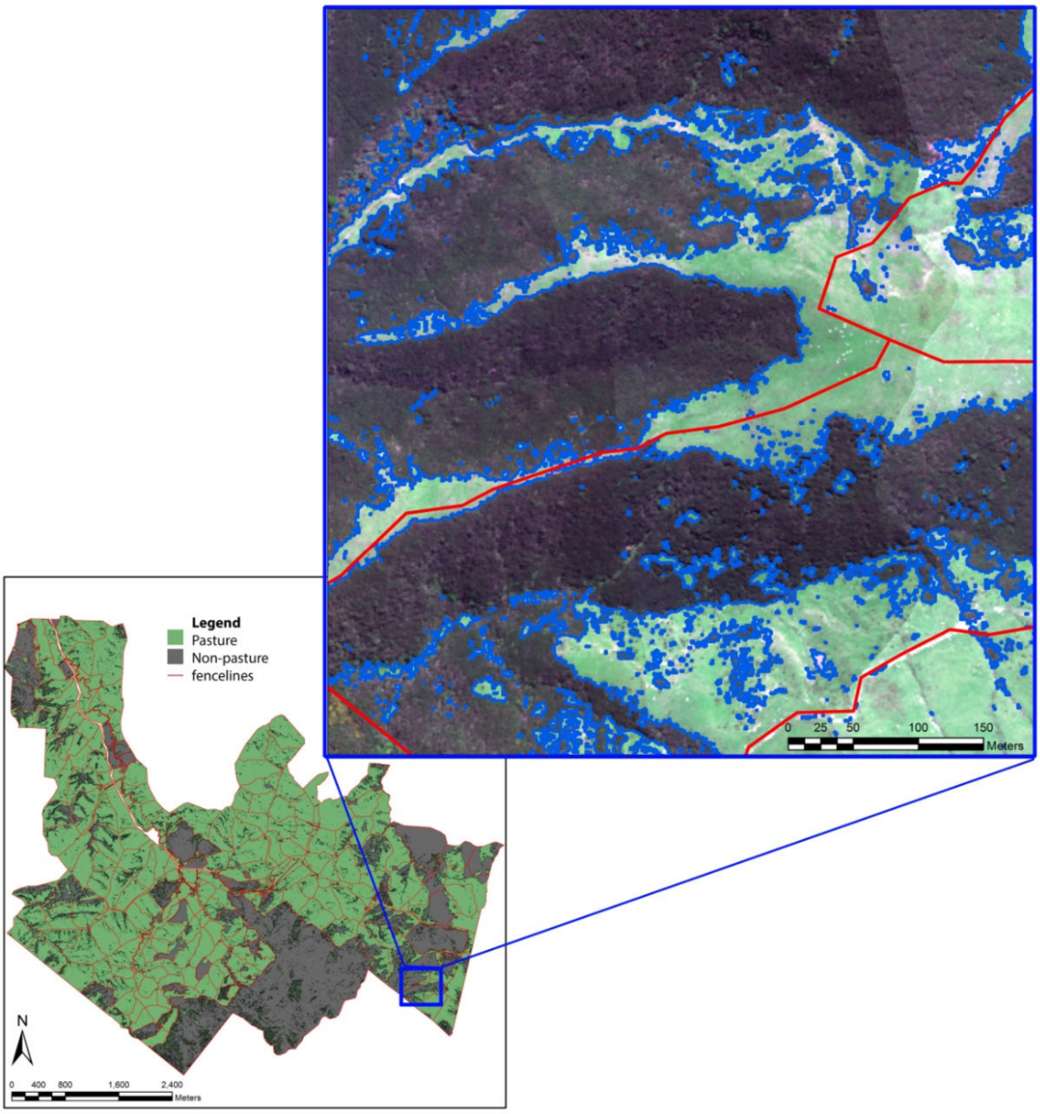


Figure 5.2: SVM classification map of first derivative data for the spring survey at Patitapu Station. The callout displays the true colour image with the pasture boundary defined by the blue outline.

One measure of classification accuracy, overall accuracy, is determined by summing the number of correctly classified pixels and dividing by the total pixels collected. Patitapu Station comprises 2,610 hectares, which equates to about 26 million pixels in the hyperspectral image. The classification was carried out using 8,393 of those pixels as training samples. The validation ROI collected 71,167 additional pixels to test the accuracy of the classification.

Results of the initial classification of the Patitapu Station (Spring 2015) image are summarised in Table 5.3 and classification image from one method shown in Figure 5.2. Both classification methods had accuracies >99%. The continuum removed (CR) data in combination with the MD classification was the least effective combination with a 92.76% accuracy. Continuum removed data did not affect the SVM classifier in the same negative way as it had for the MD classifier.

Table 5.3: Summary of accuracy results from various combinations of pre-processing and classifier on the initial (Patitapu Station, Spring 2015) classification.

Pre-Process	Mahalanobis Distance Accuracy	SVM Accuracy
Smoothed Spectra	99.43% (Kappa 0.988)	99.15% (Kappa 0.982)
Continuum Removed (CR) Spectra	92.76% (Kappa 0.853)	99.17% (Kappa 0.983)
Minimum Noise Fraction (MNF)	99.51% (Kappa 0.990)	99.59% (Kappa 0.991)
Smoothed 1st Derivative	99.45% (Kappa 0.988)	99.11% (Kappa 0.982)

Despite the attempt to minimise the amount of training pixels SVM and MD both performed extremely well in correctly classifying pasture with accuracies consistently >99%, except for the previously mentioned CR data which had an overall accuracy of 92.76%. MNF coupled with SVM had the highest classification accuracy of 99.59%. Table 5.4 summarises the results. ENVI also generates the Kappa coefficient (defined from -1 to 1) which is a measure of the agreement between classification and ground truth pixels (a kappa closer to 1 represents better agreement).

Table 5.4: Complete accuracy output for SVM classification of first derivative data from Patitapu Station for spring and autumn seasons.

	SVM of first derivative data for Patitapu (Spring 2015)			SVM of first derivative data for Patitapu (Autumn 2016)		
	Overall Accuracy (70534/71167) 99.11%			Overall Accuracy (66902/67904) 98.52%		
	Kappa Coefficient 0.982			Kappa Coefficient 0.9703		
	Validation Class (Pixels)			Validation Class (Pixels)		
Predicted Class	Pasture	Non-Pasture	Total	Pasture	Non-Pasture	Total
Unclassified	0	0	0	0	0	0
Pasture	39156	603	39759	35969	641	36610
Non-Pasture	30	31378	31408	361	30933	31294
Total	39186	31981	71167	36330	31574	67904

	Ground Truth (Percent)			Ground Truth (Percent)		
Predicted Class	Pasture	Non-Pasture	Total	Pasture	Non-Pasture	Total
Unclassified	0	0	0	0	0	0
Pasture	99.92	1.89	55.87	99.01	2.03	53.91
Non-Pasture	0.08	98.11	44.13	0.99	97.97	46.09
Total	100	100	100	100	100	100

Class Error	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Pasture	1.52	0.08	603/39759	30/39186	1.75	0.99	641/36610	361/36330
Non-Pasture	0.1	1.89	30/31408	603/31981	1.15	2.03	361/31294	641/31574

Class Error	Producer (Percent)	User (Percent)	Producer (Pixels)	User (Pixels)	Producer (Percent)	User (Percent)	Producer (Pixels)	User (Pixels)
Pasture	99.92	98.48	39156/39186	39156/39759	99.01	98.25	35969/36330	35969/36610
Non-Pasture	98.11	99.9	31378/31981	31378/31408	97.97	98.85	30933/31574	30933/31294

With most combinations of data and methods performing extremely well the choice of methodology for the other investigations was made with computational load and future work in mind. The combination of data converted to first derivative and the SVM classifier was selected to carry out the remainder of the classification testing as the other methods were computationally demanding.

5.3.2 Seasonal Strength

The ability of the classification approach to be used on data collected at various times of year was tested with a second image taken in autumn at Patitapu Station. The results from the Autumn 2016 image classification were very high and almost identical at 98.52% compared to 99.11% for the spring data (SVM of first derivative data). Table 5.4 shows the full classification accuracy output of the SVM from Patitapu Station for both seasons using the first derivative data. Overall accuracy is stated, and the confusion matrix provided should other metrics be of interest.

5.3.3 Locational Strength

Classification accuracy for Lawson’s Farm using first derivative data and SVM classifier was 98.9% (kappa 0.978). Table 5.5 shows the complete output from the accuracy assessment.

Table 5.5: Complete accuracy output for SVM classification of first derivative data from Lawson’s Farm.

SVM of first derivative data for Lawson’s Farm (2015)	
Overall Accuracy (46976/47498)	98.90%
Kappa Coefficient	0.978

	Ground Truth (Pixels)		
Class	Pasture	Non-Pasture	Total
Unclassified	0	0	0
Pasture	24142	272	24414
Non-Pasture	250	22834	23084
Total	24392	23106	47498

	Ground Truth (Percent)		
Class	Pasture	Non-Pasture	Total
Unclassified	0	0	0
Pasture	98.98	1.18	51.4
Non-Pasture	1.02	98.82	48.6
Total	100	100	100

Class Error	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Pasture	1.11	1.02	272/24414	250/24392
Non-Pasture	1.08	1.18	250/23084	272/23106

Class Error	Producer (Percent)	User (Percent)	Producer (Pixels)	User (Pixels)
Pasture	98.98	98.89	24142/24392	24142/24414
Non-Pasture	98.82	98.92	22834/23106	22834/23084

5.3.4 Classification Examination

With no similar analysis available in the literature for comparison the only comparison of these results was with the Horizons report on Patitapu Station's assets. As expected, for improved paddocks that are dominated by pasture, calculation was a simple matter of measuring the surveyed boundary, so this analysis closely matched the Horizons report figures. Where it became more interesting, and the usefulness of this analysis became apparent, was when large areas of pasture were mixed amongst manuka or other scrub. This utility is typified by the classification of the area displayed in Figure 5.3 which as a mix of components.

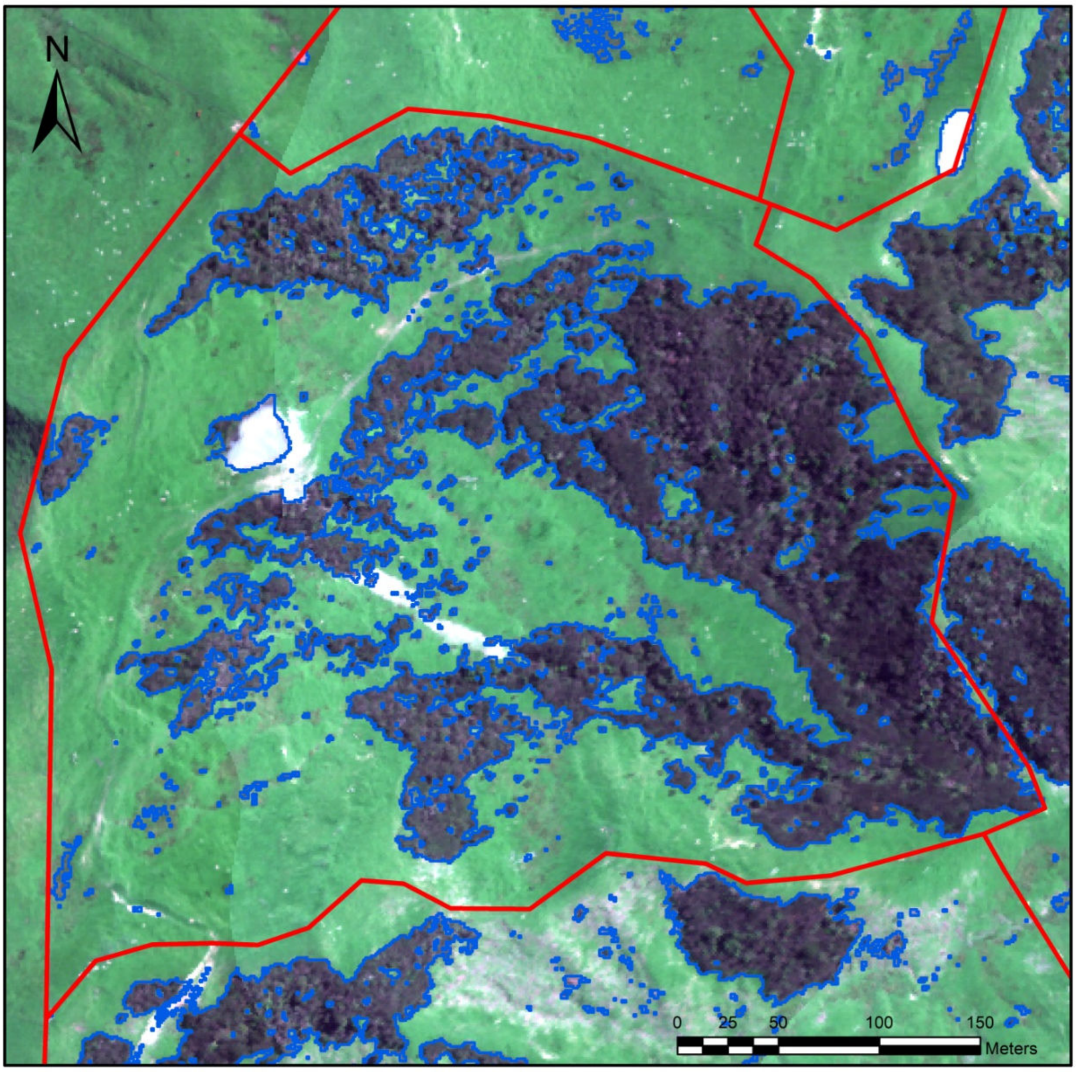


Figure 5.3: A paddock from Patitapu Station with a large area of bush included within its fenced boundary. Of the 15.57 ha within the paddock boundary, 8.65 ha (66%) was classified as pasture.

In comparison with the Horizons plan there were many paddocks, in particular those with very mixed content, where there were substantial differences in measured pasture areas. Table 5.6 lists a few of the paddocks (names are used by the farmer for orientation purposes), the quantities of pasture taken from the Horizons report and the quantities derived from the SVM classification.

Table 5.6: Table of comparisons between Horizons reported pasture estimates and the classification estimates for a few of the paddocks from Patitapu Station. Figures used are from the Autumn 2016 image classification using the SVM of 1st derivative data. Differences are listed as positive (+) meaning the classification identified more pasture than the Horizons report or negative (-) the classification identified less pasture. The classifications for paddocks marked with an asterisk are displayed in figures 5.4 to 5.7.

Paddock Name	Fenced area (ha)	Horizons estimate (ha)	Classification (ha)	Difference (ha)
Ross's	15.57	10.66	8.67	-1.99
Triangle Bottom*	18.74	11.58	14	+2.42
Steep Creek	13.4	12.1	11.26	-0.84
Top Triangle	17.69	15.1	15.65	-0.45
Soap	15.02	6.2	4.99	-1.21
Jungle	40.8	12.3	10.53	-1.77
Top Cowans 1	21.96	10.25	9.3	-0.95
60 Acres*	8.52	4.52	5.88	+1.36
Gorsey 2*	9.35	9.0	7.46	-1.54
Homestead	17.41	17	15.72	-1.28
Ruapaehu*	12.98	8.2	7.24	-0.96

The following figures show an overlay of the pasture classification boundary (in pale yellow) for a number of the locations (highlighted in Table 5.6 with an asterisk) so the reader might gain some understanding of the complexity of the environment and how well the classification has performed.

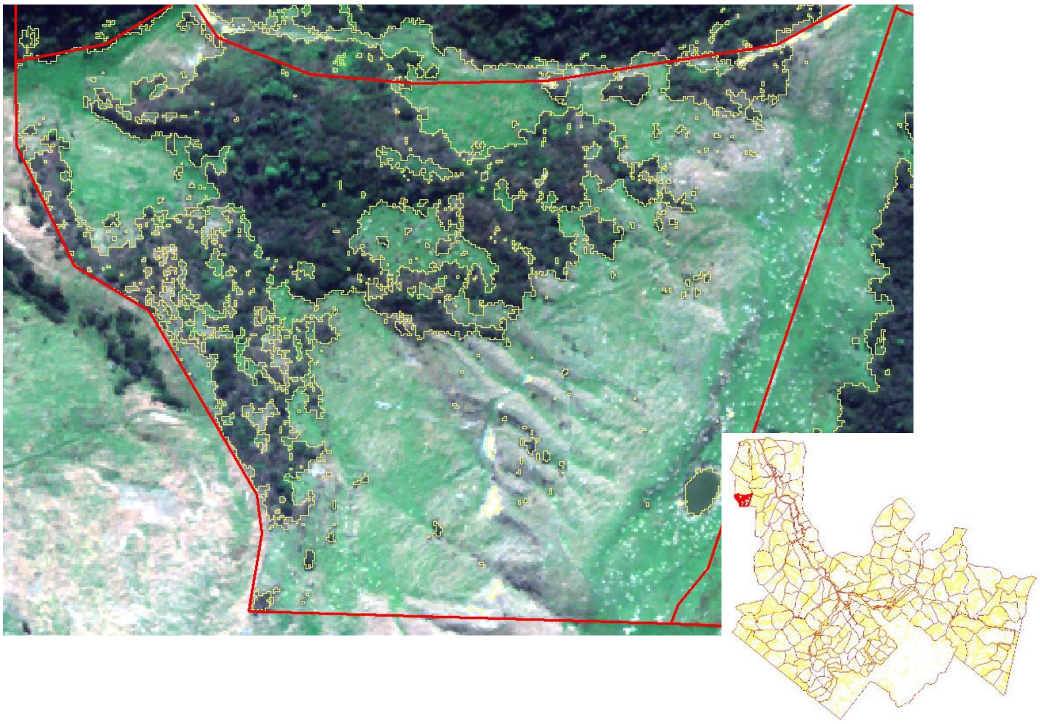


Figure 5.4: The paddock (named '60 Acres') from the classification of the 2016 Patitapu Station image. The pasture classification boundary is shown in pale yellow. Worth noting is variability of the pasture with dryer ridges and the wetter valleys clearly visible. There is also a small stock watering dam in the bottom right. Red lines are paddock boundaries.

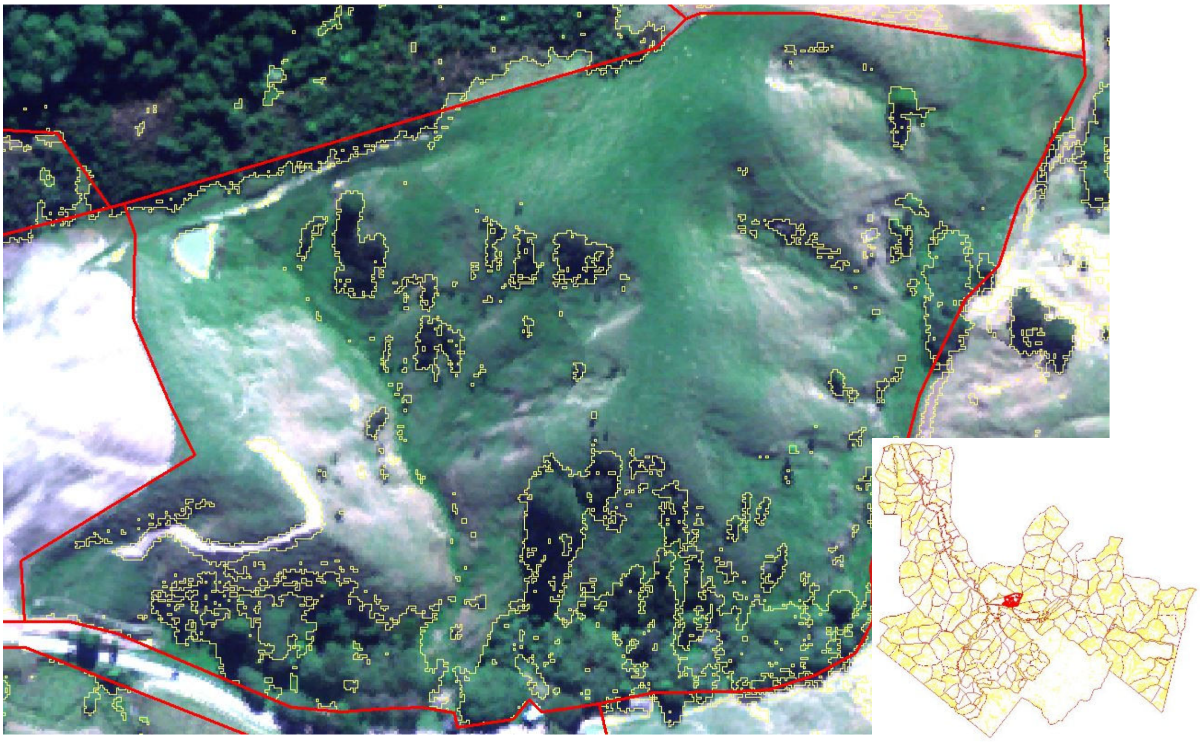


Figure 5.5: A paddock (named 'Gorsey 2') from the classification of the 2016 Patitapu Station image. The pasture classification boundary is shown in pale yellow. Note the stock watering dam top left and gravel farm track centre left. Red lines are paddock boundaries.

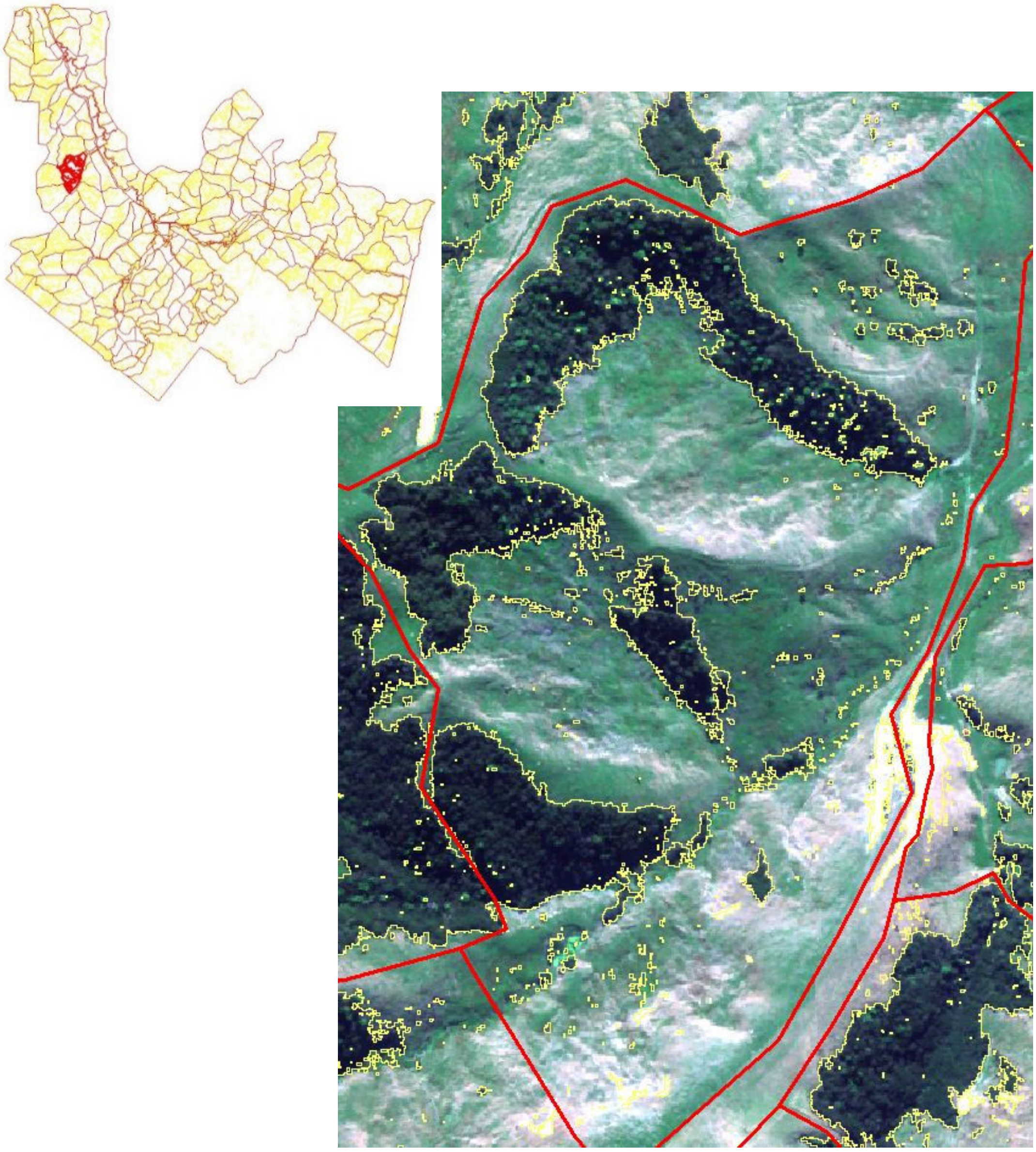


Figure 5.6: A paddock (named 'Triangle Bottom') from the classification of the 2016 Patitapu Station image. The pasture classification boundary is shown in pale yellow. Red lines are paddock boundaries.

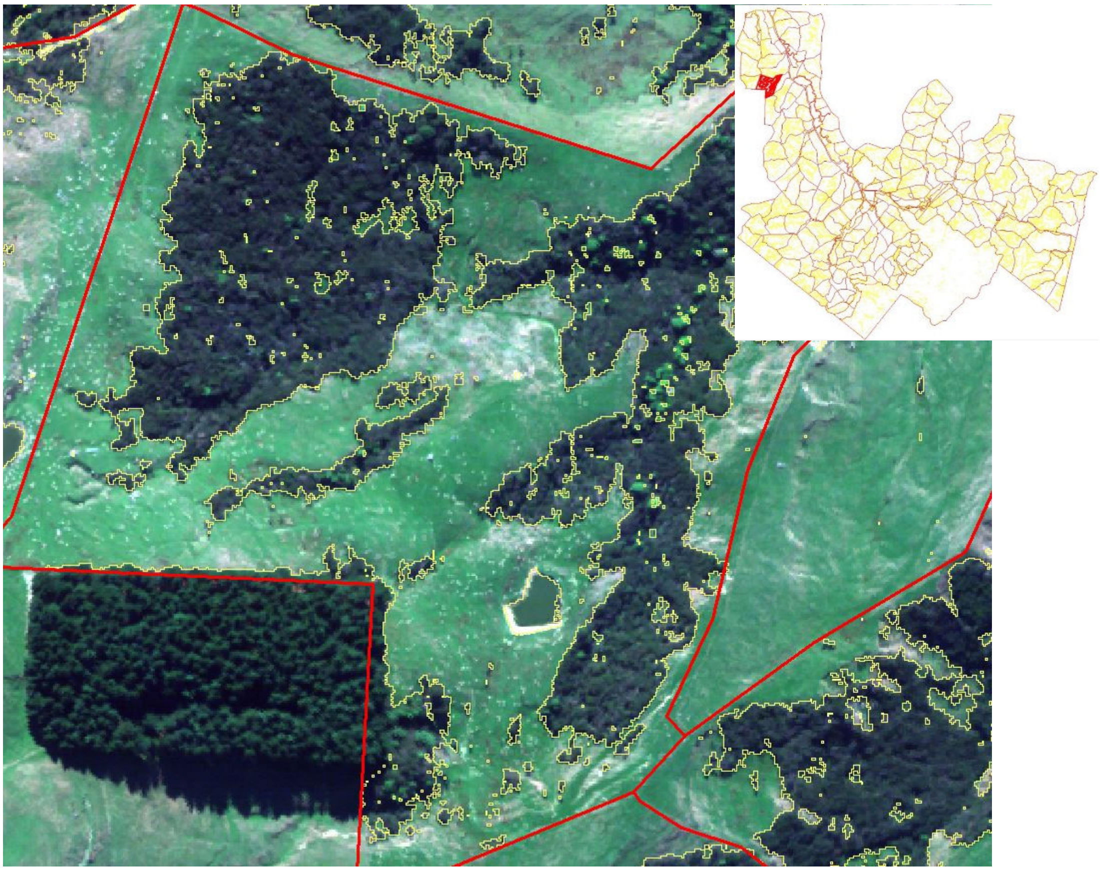


Figure 5.7: A paddock (named ’Ruapehu’) from the classification of the 2016 Patitapu Station image. The pasture classification boundary is shown in pale yellow. A small stock watering dam is located bottom centre. Red lines are paddock boundaries. The white speckled dots are sheep.

5.4 Discussion

The accuracy for the spring and autumn classifications of Patitapu Station using an SVM classifier (Table 5.4) were 99.1% and 98.52% respectively. This is a high accuracy level and shows the utility of the process over multiple seasons. Although remote sensing has been used for decades to measure farm output this is the first application that has sought to accurately map farm pasture area in a commercially feasible manner.

The reasons for this apparent lack of interest are likely centred around the fact that most other pastoral land is easily mapped with conventional methods using global positioning satellite systems to survey boundaries and calculate area. New Zealand hill farms are much less straight forward as they often have very mixed land use patterns, as illustrated in figures 5.3 to 5.7. That manifests as mixed vegetation classes in the same fenced area (i.e. grass and other vegetation) which adds complication to the measurement of pasture area. This gave rise to various ad hoc methods of the pasture estimation with associated operator error. With either of the classifiers capable of this classification to high accuracies the choice of classification algorithm can be made on other factors, such as processing time or the need for subsequent analysis. In this instance the previous work also gave more confidence that the 1st derivative data and SVM classification would be of more use in later work so it was chosen as the primary method.

The 288 additional ROI, that were manually included in the accuracy assessment, were intended to improve confidence in the classification by highlighting if the classes were bleeding into each other on class boundaries. If that was the case, they would have reduced the overall accuracy. It is not normal practice to use manually chosen validation points for reasons of operator bias. This bias was avoided by the collection of the validation ROI locations prior to the classification. Although it is not possible to remove them from the analysis, we can hypothesise what their influence might be in a worst-case bias scenario, which is that their inclusion added bias to favour the accuracy assessment. If we suppose a worst case that these 288 samples were actually biased to erroneously favour the classification, we can define a maximum impact from such a scenario. In that instance, the 99.11% accuracy shown in Table 5.4 would be reduced to 98.93% correctly classified. Therefore, the manual inclusion of the additional ROI locations had a maximum impact of improving the accuracy result by 0.18%. However, as boundary pixels are more likely to be mis-classified (Woodcock & Strahler, 1987), their inclusion was more likely to have reduced the true overall accuracy.

The results from the South Island farm also provide a strong indication that the methodology is robust enough for application to pastoral land regardless of location. An important feature of this classification is that soil background did not appear to disrupt the classification as even what appear to be small areas of grass, or open areas with low proportions of grass, were classified as pasture. That helps prevent underestimation of a farms pasture assets.

The spatial and spectral resolution is a key feature of this data that allows mapping of the vegetation features to be achieved in great detail. Target scale and its relation to image scale have been the subject of other research (Townshend, 1981; Strahler *et al.*, 1986; Woodcock & Strahler, 1987). From their work it is surmised that the target's spectral separability, size of the target compared to the image resolution and low proportion of boundary pixels may have worked in favour of this analysis. This is despite the high within class variance associated with high resolution imagery (Woodcock & Strahler, 1987). Some satellite imagery can match or surpass the spatial resolution of aerial hyperspectral sensors such as the AisaFENIX, but the combination of spatial and spectral resolution cannot be matched by satellites yet. For example, the Worldview-3 satellite has a spatial resolution (pixel size) down to 0.31m in the panchromatic band but only has 29 spectral bands (Kruse *et al.*, 2015). Even then, the 29 bands do not have the same spatial resolution with some having resolutions up to 30m. For mapping pasture in this heterogeneous landscape 30 metre resolution would not suffice for farm management. It would however be interesting to define what resolution would be needed for those management decisions. Satellites are also slaved to orbital mechanics, so a mission cannot be called off if the weather is not suitable over the target. That said even the aerial imagers are subject to weather delays and a particularly bad season can see a backlog of surveys build up rather fast.

The obvious three uses of this technology include the primary stated goal of improving fertiliser application accuracy, improving farm management decision-making and defining farm assets for the rural valuation sector.

The 99% accuracy attained with this method is more than adequate for the needs of Ravensdown and the PGP. The application swath width of an aerial top-dressing plane is around 20 metre (depending on product being applied). The pixel size of the AisaFENIX image is around 0.8 metres, which is too fine for fertiliser application. Ravensdown have already successfully used this classification in commercial applications by resampling to a 100-metre grid (White *et al.*, 2017). The novelty of the method and compatibility with their computer-controlled delivery system (Chok, Grafton, Yule, & Manning, 2016), led them to compare the pasture classification output produced for a third farm in the PGP program (data not shown). They compared it with their current in-house method. They concluded the current benefits of the delivery system would be enhanced by the classification with the automation of the time-consuming process and elimination of human error (White *et al.*, 2017). This classification was expanded to other farms and has been used as an input for aerial fertiliser applications. This classification could also be used to quickly exclude areas not intended for analysis in other remote sensing work. It could replace manual interpretation such as that used by Raab *et al.* (2018). This process was used as a pre-processing tool in Chapters 6 and 7.

The results of this analysis were discussed with the farm owner of Patitapu Station. He commented that he relied on his own local expert knowledge for major management decisions such as set stocking. When discussing the, measurement of pasture area the farmer said he thought that Horizons' *Whole Farm Report*" overestimated his farm's pasture area by about 50 hectares, which agreed with the level predicted by the classification. Subsequently, the farmer used the classification results while considering that season's set stocking decision-making. After deliberation, the farmer decided that he agreed with the classification results rather than the "*Whole Farm Report".* The following year the farmer also purchased a new block of land and asked if the classification could be extended to cover this new area. The farmer revealed the classification would provide a basis for decision-making in the absence of first-hand knowledge of those pasture areas.

The ability to classify land in multiple seasons and locations also makes this technology ideal for rural valuation applications that are likely to be time sensitive. Given the importance of the valuation sector in the rural economy (Sullivan & Taylor, 2014), and the absence of a highly accurate alternative, one would expect the sector to be early adopters of such technology.

An important attribute this approach offers to the valuation sector is superior accuracy, by the removal of human error. Pasture is the key component of any pastoral farm business, so accuracy in estimation of such assets is critical to the accurate valuation of the property.

The value of such a classification from a valuation standpoint is clear and illustrated in figures 5.3 to 5.7. With the pasture component mapped, the exact pasture area on paddock or farm scale can be easily generated. A detailed map can be taken to site and quickly checked or amended with additional notes or detail. The method leaves little room for argument by interested parties around the figures that form the basis for the valuation. This means buyer, seller and money lenders can be more confident in the result.

Importantly, knowing the actual area of productive pasture has economic value to the farmer. Farm land value for the 50 hectare difference reported here (for a Class 3, hard hill country farm) would be worth around $600,000 according to REINZ (2019). Thus, it would certainly be in the interest of all parties to know the correct area of pasture. Farm revenue is based on actual land area. Accurate information on farm area means that farm statistics (e.g. gross farm revenue per hectare) would also be more accurate. This figure is reported for various farm classes within the sector (BLNZ., 2016). Accurate income projections mean more realistic expectation from banks and less pressure on farmers.

The results support the ROI collection strategy for training the classifier, to gather samples from diverse regions across the image and from sites with obvious physical and therefore spectral differences. The work of Foody and Mathur (2006) suggested that a small number of well-chosen samples could adequately define the parameters for a hard classification. Their premise of "judgemental sampling" directed this work and has been shown to be a sound approach.

5.4.1 Challenges

A major issue remains in remote sensing around the handling and classification of shadow areas. This is a problem for all passive remote sensing that uses natural light as an energy source for data collection. Shadow is a problem with aerial photography in general (Abraham & Sasikumar, 2013; S. T. Wu *et al.*, 2014; Zou *et al.*, 2016) and remote sensing in particular (Lin *et al.*, 2016). Sun and slope angles can exacerbate this effect. Although not necessary in this instance, it is possible to manually adjust for, or remove shadow (Marcinkowska-Ochtyra *et al.*, 2018). These areas usually make up only a small proportion of the image, with limited overall impact to the classification but they can be up to 40% (Numata *et al.*, 2008). The autumn 2016 survey of Patitapu Station appeared to be slightly more affected by shadow error than the spring image. The autumn image of Patitapu Station was collected over two flights on subsequent days and this may have contributed the increased error, but this cannot be confirmed.

The cost of data capture and analysis is another possible barrier to entry for this technology. That topic is discussed in chapter 6.

5.6 Conclusions

The intended application of the novel approach outlined in this chapter was to accurately define the pasture for use in aerial top dressing or other on-farm decisions. It is therefore most important that the process be fast and inexpensive to implement, with a high accuracy. The project funder Ravensdown has already used this classification for fertiliser application, supporting the assertion that the approach developed meets their needs. This study therefore meets the objective defined in Chapter One for accurate definition of pasture as an input for variable rate aerial fertiliser application. This study also advances the field of remote sensing with its application of an existing method to solve a real problem for the farming industry. This is also the most detailed map of hill farm pasture yet produced. That level of detail has great relevance for applications that require such accuracy. Farm strategic decision-making, business management and rural valuation are potential beneficiaries of this detailed information.

The paper produced by Ravensdown (White *et al.*, 2017) answered the question of how this method compares with standard techniques and their assertion that it removes human error is likely reason enough to use the technology. Management and rural valuation are intrinsically linked. The better a farm performs, the more value it has. From that point of view both aspects of the rural economy can benefit from this form of technology by accurately defining the productive capacity of the land and improving management decisions from that knowledge. It is yet to be shown that this technology will be cost effective for everyone but all technology must find an entry point to a new market.

This chapter focused on pasture definition as it is a key asset and important component for strategic decision-making. There are many other landscape components that, if mapped, would have benefits for farm management, environmental compliance and valuation purposes. There are also variabilities within pasture that, if known, would further improve strategic decision-making and environmental stewardship. The next chapters will build on this work by adding detail to the landscape picture.

Chapter 6 : Hill Farm Vegetation Classification: A Benefit Analysis

6.1 Introduction

Chapter five established a case for pasture mapping and the associated benefits that detailed distribution maps could have for the hill farming and fertiliser sectors. This chapter presents a more detailed account of the benefits that wider classification of vegetation and other landscape components could have to hill farm businesses and ancillary industries. It does this by first defining the capability of hyperspectral image classification at the farm scale. The potential of the classification to influence or improve strategic management decisions and subsequent value is then discussed.

6.1.1 The case for vegetation classification on hill country farms

The main rationale for employing HSI technology to classify vegetation and other landscape components on hill country farms is that it rapidly delivers accurate data to support decision-making in unprecedented detail. Most farmers, valuers and other decision makers currently rely on data collected in an ad hoc manner using expert knowledge and estimation (Appraisal_Institute, 2000).

Hill country farming has become a complex business. This sector has had to adapt to keep their businesses viable after the removal of subsidies in the 1984 New Zealand Government budget (Gouin, 2006). Expansion into multiple enterprises such as forestry and manuka honey has diversified incomes to take advantage of the varied landscape. With limited resources and difficult terrain, hill country farms are at a disadvantage when it comes to farm management compared with arable and dairy systems. For example, controlling weeds such as Californian (*Cirsium arvense*) and Scotch (*Onopordum acanthium*) thistle, is more difficult in the steep terrain as ground-based control is often restricted to foot or aerially-applied controls. The spread of conifer seedlings, from forestry plantations, is also acknowledged as a major concern for native and farming landscapes alike (M.P.I., 2014b).

6.1.2 Rural Land Valuation

Chapters two and five touched on the subject of rural valuation that is seen as a key component in the New Zealand rural economy. Financial institutions with security over farmland have a direct interest in the value and productive potential of the land. A non-biased, evidence-based method could have a profound impact on the management of such businesses, allowing more certainty and lifting profits, that would ultimately improve business value. Improving the accuracy of rural valuations could better quantify financial risk to give banks more confidence in capital values when lending, making it easier for investors to access finance. The market approach to valuation, historically accepted as the preferred method, compares like with like, therefore accurate land classification of comparative properties is important to ensure accurate assessment of value. The income capitalisation method, which values property based on its potential to generate income, is proposed as a useful check method (Eves, 2005; Hargreaves & McCarthy, 2010). The income approach requires estimation of the productive potential of the land; this can only be made with detailed physical property information.

6.1.2.1 Valuation Data

Valuers consider a myriad of factors when valuing farms including access, drainage, soils, farm size, shape, productivity, climate and topography (Appraisal_Institute, 2000; Baxter & Cohen, 2009). Valuers must supply accurate property information to comply with compulsory international regulations (I.V.S.C., 2013). The diversity of New Zealand's hill country farm environments make collection of accurate information and valuation more challenging. A point of reference is the Valuer-General for Land Information New Zealand, Neill Sullivan who asserts that the task of valuation as becoming ever more difficult and complex (Sullivan & Taylor, 2014). With the value of rural property linked to the productive capacity of the land (Baxter & Cohen, 2009) proper estimation or measurement is essential to an accurate assessment of its value.

6.1.2.2 Current Valuation Data Collection Practices

Although broadly similar methods are used, each valuer uses their own method to gather detailed property information. Typical practice involves accessing a map or aerial photo. Various methods such as planimeters, mapping programmes and Geographic Information Systems (GIS) are used to measure specific areas of interest. Valuers conduct field inspections to add valuable visual assessment information for farm quality aspects. Questions on the mapping accuracy, raised during this process, prompt variations of the original mapping calculations. An example of the low-tech nature of the current methods employed for rural valuation is illustrated by Baxter and Cohen (2009). They say that measurement by pacing or visual estimation are skills *"worth acquiring"* by valuers. They also state *"that it is impossible to scale accurately from aerial photographs"*. Given the importance of the sector as espoused by Sullivan and Taylor (2014), one would expect the sector to be early adopters of technology that improves the accuracy of their assessments.

Variability in the initial farm data collection method can lead to errors that carry through the entire valuation process, possibly leading to inconsistency. Discrepancies and errors in valuations challenged in court have often been judged on the premise of variance, rather than the disparity with the sale price. Valuation variance is defined as the difference between valuations of a property made by two or more valuers. Values should sit within an "accepted margin" (Crosby, 2000) with a range of 10% either side of the 'right figure' suggested by (Watkins, J, 1977)*, Singer & Friedlander Ltd v John D Wood & Co [1977] 2 EGLR 84.* However, 10% of a $5 million-dollar property is a rather large margin of error.

6.1.3 Remote Sensing Technologies

Remote sensing techniques have been successfully applied to describe other heterogeneous environments such as wetlands (Adam & Mutanga, 2009; Carol, 2015), African savanna (Naidoo et al., 2012) and grasslands (Magiera et al., 2013). Hyperspectral aerial imagery can collect massive amounts of remotely sensed data rapidly and economically. Classification algorithms are useful for creating thematic maps of vegetation based on species (Cochrane, 2000). So far, these techniques have not been applied to hill country farms.

Thematic maps that identify various vegetation types could lessen the time taken to carry out an appraisal. They would also minimise initial variability and free the valuer to concentrate on valuation, rather than mapping. A high level of accuracy would be needed to comply with the international valuation standards, but the mechanical nature of a computer-generated classification would add validity to the data. The information that a vegetation survey would generate would be a valuable detail to include in a business plan for lending purposes. This information also has many potential benefits for farmers and ancillary contractors.

Perhaps because of data availability or sensor cost, previous remote sensing work in these environments has mainly employed multispectral sensors (Thompson et al., 2003; Vescovo et al., 2009; Pullanagari et al., 2013; Weeks et al., 2013). Some studies have used hyperspectral proximal sensing (Gianelle & Vescovo, 2007; Kawamura et al., 2009; I. D. A. Sanches, 2009; Pullanagari et al., 2012) to estimate various pasture parameters. However, there is a dearth of research examining the classification of this environment at farm scales, which is important for effective decision-making. Also, while there are studies at the paddock scale, these are not useful for farm-scale management, with little guidance on how to integrate the information into farming systems. The lack of farm scale management resources is addressed in this work. This study uses 'exhaust data' supplied from the PGP project *Pioneering to Precision*. This data arrives in the form of pre-processed one metre resolution Asia FENIX hyperspectral imagery with 448 available spectral bands to define many components within the hill farm environment.

6.1.4 The Benefits to Farming

The benefits of this technology fall into three interrelated categories; environmental benefits, resource calculation and resource management.

Automated variable rate application technologies (VRAT) can exclude areas from application (Grafton et al., 2012; Chok, Grafton, Yule, & Manning, 2016). This has obvious environmental benefits as well as potential cost savings for farmers. For example, classifying water bodies means they can be excluded from fertiliser applications. Besides saving the farmer unnecessary cost, the targeted fertiliser application would address concerns about fertiliser entering waterways, thus helping to maintain the farmer's social licence to operate. A baseline map would create a benchmark against which changes in the environment, for the better or worse, could be monitored.

Identification and measurement of features such as landslips would provide information for input into erosion models, which can be geolocated for longitudinal studies. Monitoring and mapping of mixed tree species for inclusion in New Zealand carbon stocks would also be a valuable outcome for the country.

A key benefit of vegetation classification is that it removes some of the guesswork from management decisions. Calculating economic crop area allows improved management of that resource, for example hive carrying capacity for manuka honey production. Weed location information e.g. thistle, Californian (*Cirsium arvense*) and Scotch (*Onopordum acanthium*) could inform and support integrated weed control programmes. The ability to identify particular native species could also help identify locations where native birds, with specific diet and energy needs (Castro & Robertson, 1997), might be successfully reintroduced.

6.1.4.1 Manuka Honey Production

Manuka honey production in New Zealand has been growing. In 2017, manuka honey exports were valued at NZ$329 million, up from NZ$121 million in 2012 (M.P.I., 2017a). The market is driven by manuka's proven antibacterial activity (Blair et al., 2009), which is effective even against antibiotic resistant variants (Kwakman et al., 2011). The antibiotic activity of the honey is contingent on the floral source harvested by the bees to make the honey. Manuka honey has superior antibacterial properties compared to honey made from other sources, including honey from manuka's close relation, kanuka (Jing Lu et al., 2013). This affects price and fuels the desire to assure purity. Unfortunately, regulation does not always keep pace with development or expansion in new markets. This is epitomised in the sale of counterfeit or adulterated products sold as high grade (and high cost) premium manuka honey. This prompted the New Zealand Government to implement product standards (M.P.I., 2017b) which are being enforced to protect the international reputation of the product.

The value of manuka honey has increased tenfold in the past twenty years (Stephens et al., 2010) but this value can be jeopardised by contamination or mixing of nectar from other sources. Manuka honey is worth up to ten times the price of clover honey (M.P.I., 2017a), depending on its grade. Yield from hives is the other factor impacting honey revenue, which has declined from its 2013 peak at 39.4kg/hive to 18.7kg/hive in 2017 (M.P.I., 2017a). Over the same period hive numbers have risen by 15% per year (M.P.I., 2017a). A crucial challenge for beekeepers is to balance beehive stocking rates. Not only can overstocking impede honey production, in extreme cases bees starve, and hives can die (Lloyd et al., 2017). Conversely, not having enough hives wastes resources. Supplying accurate information on the size of manuka plantations would support beekeepers in calculating sustainable stocking rates. Furthermore, it would provide landowners with more accurate information when valuing honey production areas.

Given the value of manuka honey has increased tenfold in twenty years, it is unsurprising that the value of the manuka covered land has also increased. A report released by Bayley's Real Estate company showed a 230% rise in the value of 'manuka friendly' properties between 2015 and 2016 from $1,500 per hectare to $3,500 per hectare (Cook, 2016). Valuing this type of land is complex, and not just because of the terrain. How would one assess the purity of a manuka stand in such an environment with limited resources? Species purity influences honey value (Bagrie et al., 2015). Therefore, a method that specifically measures the distribution of manuka may have a place in rural valuation. The existing term 'manuka friendly' is not specific and open to interpretation. A classification, with measured coverage of each category, would add a new layer of information to such valuations and would improve the accuracy. The information would also allow the valuer to meet the mandatory international regulations to provide accurate property information (I.V.S.C., 2013).

6.1.4.2 Weed Identification and Control

Unwanted, self-seeded vegetation (weeds) has an enormous impact on the rural economy (Brooker, 2016). Globally, weeds cause economic crop losses of more than US$115 billion a year (Sheppard et al., 2003), with the cost topping NZD$700 million in New Zealand (Brooker, 2016). Thistle is associated with reduced wool quality, lower animal weight gain and development of 'scabby mouth' in sheep. Control strategies have been developed for Californian thistle (Chalak-Haghighi et al., 2008; Bourdôt et al., 2016) but some control options such as mowing are not possible on the steeper slopes of hill country farms. Identification of the thistle locations is also more problematic when access is limited which is why remote sensing may be helpful.

Wilding pine are another problem throughout New Zealand. Wilding pine are self-seeded pine that are spreading at a rate of 5% a year from plantation forests into native and sensitive habitats despite control efforts (M.P.I., 2017e). Ledgard (2001) reported an estimated area of 150,000 hectares of wilding pine infestation. By 2007 the figure had risen to an estimated 1.15 million hectares of land affected by wilding pine of various densities throughout New Zealand (Froude, 2011). Lodgepole pine are reported to produce seed by the age of five (Ledgard, 2001) which has contributed to their rapid spread. Identification or quantification of such problematic species could aid in measures for their control.

6.1.5 Research Rationale

Although the PGP focuses on fertility, repurposing the imagery would enhance the overall project benefits and improve the return on investment from the survey. For this study, several non-pasture species were selected based on their financial or environmental importance to New Zealand farmers. Table 6.1 lists the species with the reason for their inclusion in this trial. This work excludes pasture and focuses on components that may add value for farmers or ancillary industries. Pasture is of primary interest to farmers and the PGP, which is why it was the sole focus of the previous chapter.

Table 6.1: Species and features included in the classification and general rationale for their inclusion.

Species/Landscape Feature	Rationale for inclusion
Manuka (*Leptospermum scoparium*)	Source of nectar for manuka honey production.
Kanuka (*Kunzea ericoides*)	Very similar species to manuka that has lower commercial value. Difficult to differentiate from manuka in standard aerial photography.
Thistle (*Cirsium arvense*) and (*Onopordum acanthium*)	Weed species with a detrimental impact on farm revenues.
Pine (*Pinus sp.)*	Commercial crop. Source of carbon inventory estimation. Wilding pine (self-seeded pine) is a problematic weed.
Totara (*Podocarpus totara*)	Long lived native tree chosen as an example of the selective mapping capability of the technology that shows carbon calculation of such inventory might be possible.
Water (static and moving)	A primary resource on the farm and areas where fertiliser exclusion is important.
Non-vegetation	Identification of roading assets and open soil including erosion or landslips.

The classification method must be cost effective to be widely accepted and utilised (Schellberg et al., 2008). The low profit margins common in hill farm pasture systems, reduce surplus capital. A high production cost for aerial surveys would be difficult to justify financially and therefore the technology would be less likely to be taken up. To keep processing and other costs low, a simple method must be available to carry out several classification tasks, preferably at the same time.

This study evaluates the practicality of using a simple approach to mapping important vegetation classes using Support Vector Machines (SVM). The simplicity of the approach was intended to allow easier access to the technique and keep the cost of processing low. SVM is a widely accepted method of classification (Foody & Mathur, 2004; Melgani & Bruzzone, 2004; Janz et al., 2007; Ben-Hur & Weston, 2010; Pal & Foody, 2010; Camps-Valls et al., 2014). SVM's wide acceptance and use means they are readily available and have been incorporated into a number of statistical and image analysis software. These include EnMap-Box (Van der Linden et al., 2015), developed to encourage interest and uptake of Environmental Mapping and Analysis Program (EnMAP) satellite hyperspectral imagery. SVM are also included in ENVI image analysis software version 5.1 (Exelis Visual Information Solutions, Boulder, Colorado) which was used for all the processing of this work.

Accuracy of the results can be viewed in terms of overall accuracy (OA) or individual class accuracy (CA). In this instance, overall accuracy is less important because the disproportionate area of each class adds bias to the OA result. It is argued that the accurate definition of each component has its own value. This means that poor accuracy in one class would not negate the utility of a high accuracy in another. Accuracy of the method for any given component is important if the results are to be taken seriously by the farming community.

The aims of this study are therefore to;

- Apply a readily available technique (linear SVM) to classify a series of components that are relevant to the hill farming community.
- Evaluate the effectiveness of the technique using the producer accuracies for each component.
- Discuss the benefits of the results for the farming community and industry service providers.

6.2 Materials and Methods

6.2.1 Site Location

The field survey for the current study was carried out at Patitapu Station on the North Island of New Zealand (Figure 6.1). The 2,617 hectare property includes around 1,800 hectares of pasture which supports almost 17,000 stock units with another 450 hectares of mixed indigenous bush. The terrain ranges from 150 to 534 metres above mean sea level with an annual rainfall of around one metre.

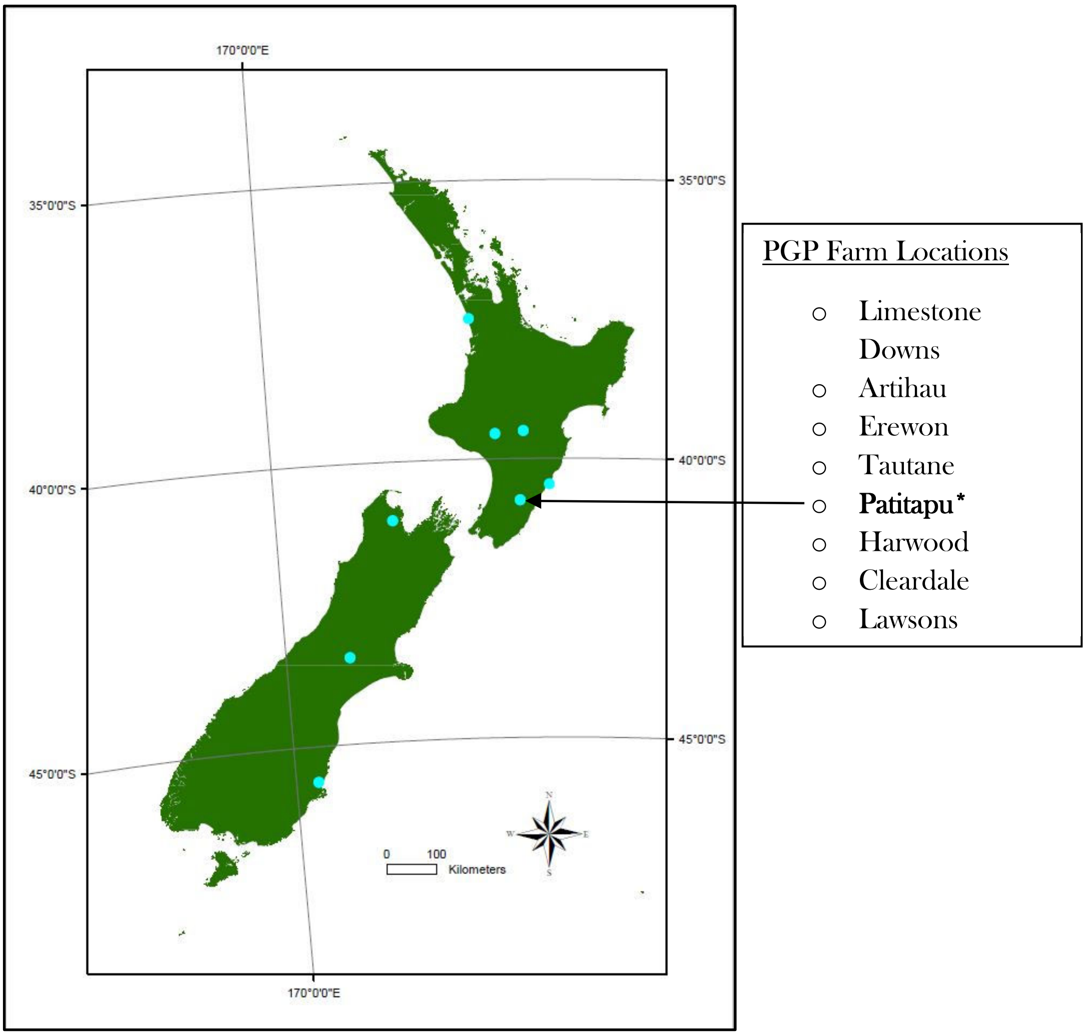


Figure 6.1: Patitapu Station is located in the Wairarapa region of the North Island of New Zealand at about 40° latitude south.

6.2.2 Hyperspectral Aerial Survey

An AisaFENIX hyperspectral sensor (FENIX) manufactured by Specim (Finland) as described in the methods chapter was used to obtain aerial imagery of Patitapu station beginning at 11.30am on March 2, 2017. The hyperspectral data were atmospherically corrected and mosaiced into a single georectified image prior to this work as Pullanagari *et al.* (2016).

6.2.3 Ground Data Collection

Collection of ground reference data occurred immediately before the hyperspectral image collection. The ground reference data were used both to train and test the accuracy of the classification. A simple random sampling or stratified random sampling design was not practical to implement for collection of ground reference data as many of the targets occupied tiny proportions of the farm. Collecting random samples was also impracticable because of the inaccessible nature of much of the landscape. Before their classification there was no understanding of the distribution of the targets that would enable stratification of the sample design. Therefore, a two-stage cluster sampling design (Stephen V. Stehman & Foody, 2009) was implemented with the first stage, primary sampling units (PSU), defined by locations where ground reference targets were sited. These targets were spread out across the farm and the data collected at, or *en-route* to, sample locations visited as part of another experiment. Although it would be better to include randomisation when identifying the PSU (Stephen V Stehman, 2001), it was simply not possible to implement. Randomisation of the PSU would have resulted in many PSUs being placed in areas with no targets present. Importantly, this is not a natural ecosystem, but a working farm with about 68% pasture and 17% of indigenous bush. Thus, the ground reference data collection focused on collecting as much relevant information as possible, with the randomisation of the sample data being introduced in the next stage, Region of Interest (ROI) definition.

Ground reference data for thistle and totara were collected in the form of GPS coordinates, site and scene photographs and species information. The location data were collected for larger instances of thistle infestation and for lone examples of totara (*Podocarpus totara*) using a Juno

SA (Trimble Navigation Ltd) with 2-5 metre positional accuracy. The Juno is a handheld device that records GPS and user defined input information that can be retrieved and used as an overlay in a GIS environment such as ArcMAP.

The GPS accuracy for the totara was used to identify the target in the aerial image produced by the FENIX (viewed as RGB). The GPS points for the Totara were accompanied by terrestrial photography that allowed confirmation of the correct target. The GPS positions for both Californian (*Cirsium arvense*) and Scotch thistle (*Onopordum acanthium*) (henceforth referred to as thistle) were collected from large >5 metre diameter patches. The large areas were selected to account for the Juno's lower spatial accuracy compared with a real-time kinematic (RTK) GPS system.

Identification information of 'relatively' homogeneous manuka and kanuka stands was supplied by the farm owner from an existing map produced for the setup of commercial manuka honey production. All other components were discernible from the colour aerial imagery and were defined during ROI collection with the use of terrestrial photographs and expert knowledge gained from site visits. Such use of mixed data is suggested by Gienko and Govorov (2017) to improve validation data.

6.2.4 Data Pre-Processing

The data were transformed to 1st derivative as it had been shown to improve results in previous chapters. Transformation to 1st derivative defines the rate of change from one wavelength to the next and can help lessen low frequency noise (Demetriades-Shah et al., 1990). Transformation to the 1st derivative was carried out with a filter width 5 and smoothing polynomial of 3. At the same time as 1st derivative transformation the first 9 bands, from 377-404 nm, were trimmed to reduce obvious signal-to-noise effects. The shortwave infrared region, band 155 to band 448 (904 nm - 2,498 nm) was also removed to dispose of a series of unwanted line noise artefacts. This process left a final spectral range from 408 nm to 901 nm which was carried forward to the analysis stage. The results from the previous chapter on pasture classification was converted to a mask and used to exclude pasture from this analysis.

6.2.5 Regions of Interest Collection

Regions of Interest (ROI) collection is a task carried out to identify representative examples of each target class. That information is used to train the classifier and estimate resulting accuracy without introducing erroneous data. Error can be introduced in the data during this process if two different ROI contain an example of the same class, for example selecting a specific tree species in one class and including an example of it in another class. One of the earliest observations on classification accuracy was that the choice of training sample can make large differences to classification accuracy, (L.A.R.S., 1966-1967) cited in (Fu et al., 1969). Considering this, ROI were carefully selected to represent each desired class from the RGB image. The GPS location information for totara and thistle samples were used, along with extra site photography, to identify examples for ROI collection. Unfortunately, many of the GPS location data for the thistle samples suffered from a rather large spatial error in the imagery. Thus, only a few samples were available for this analysis. The thistle samples used were those that were physically close to data collected for a contemporaneously run experiment. That information allowed for a spatial correction to be applied prior to ROI collection (the next chapter is a more appropriate context to discuss this spatial error in more detail). The remaining ROI classes of, roads, pine and water were easily defined and collected from the RGB aerial image in conjunction with site photography and site knowledge gained from numerous site visits. As well as the classes of interest in the study, three other classes were included to account for their potential negative influence on the classification. The extra categories, included in Table 6.2, were shadow, non-image and mixed trees. Including these categories proved essential in previous iterative testing stages.

The secondary sampling unit (SSU) of the two-stage cluster design were the individual pixels located within the larger primary sample units (i.e. the regions of interest). The ROI collected for the features of interest totalled over 82 hectares with manuka and kanuka occupying 63 hectares of that. To introduce statistical rigour, each pixel of the ROI groups was randomly assigned into either separate training (20%) or testing (80%) datasets before classification. Figure

6.2 shows an example of this with three of the ROI polygons collected for manuka. The training pixels have been removed (dark points) to illustrate the effect.

Figure 6.2: ROI polygons (blue) designated for manuka and overlaid on the true colour image. The blue line is a paddock boundary fence location. Missing pixels (dark points) within the ROI are where pixels were randomly removed for training the classification. Each pixel is approximately 0.8 – 1 metre for scale.

Although the classification was carried out for the entire property, only the testing pixels held for validation, from within the PSU were tested for classification accuracy. The full classification was examined for obvious signs of error, but accuracy statistics are only available for the pixels within the ROI. Table 6.2 lists each ROI and the number of pixels randomly assigned to the training or testing group. As each pixel represents around 1m^2 the pixel count can be used as a surrogate for area.

Table 6.2: Table of ROI pixel counts used for training and testing the classification.

Class	Training Pixels Collected	Testing Pixels Collected	Total Pixels Collected
Manuka (*Leptospermum scoparium*)	10,036	40,146	50,182
Kanuka (*Kunzea ericoides*)	2,662	10,650	13,312
Non-vegetation (roads, buildings & soil)	1,101	4,405	5,506
Pine (*Pinus sp.)*	589	2,358	2,947
Thistle (mixed)	64	256	320
Totara (*Podocarpus totara*)	110	442	552
Water	1,918	7,673	9,591
Mixed trees and other vegetation	567	NA	2,834
Shadow (very low reflectance areas)	504	NA	2,521
Non-image areas (black frame)	12,361	NA	61,805

6.2.6 Image Classification

One of the goals defined at the outset of this project was to ensure ease of operation for implementation of classifications. To respond to this aim, a simple linear SVM classification was performed in ENVI 5.1 (Exelis Visual Information Solutions, Boulder, Colorado) with regions of interest (ROI) used to train and test the classifier. SVM are a well-established approach with a long, successful history for classification of hyperspectral imagery (Foody & Mathur, 2004; Bazi & Melgani, 2006; Foody & Mathur, 2006; Janz et al., 2007; Tarabalka et al., 2010) so are a good choice.

The SVM was carried out in ENVI using a linear kernel setting, no pyramid levels, a penalty parameter of 100 and a classification probability threshold of zero that ensured all pixels were classified.

6.3 Results

The classification results displayed in Table 6.3 show high accuracies for each of the classes with producer accuracies >89%. It is not practical to survey ground conditions for the whole site, so we rely on samples to understand what is going on (Stephen V. Stehman & Foody, 2009).

6.3.1 Classifier Accuracy Assessment

Assessing accuracy is an important component in discovering the utility of classification results (Stephen V. Stehman & Foody, 2009). In this study, the individual class accuracy (CA) is of more interest than the overall accuracy. This is because it better defines how the classifier has performed for each class and is not influenced by the disproportionate class sizes. Table 6.3 shows the confusion matrix and producer accuracies for the classification. The confusion matrix also identifies where and how the classifier has been in error.

Table 6.3: Confusion matrix and producer accuracies for the classification of image components from Patitapu Station hyperspectral survey. Results are listed for total pixels classified. There were no unclassified pixels.

Actual Class Classified	Manuka	Pine	Non-Veg	Totara	Water	Thistle	Kanuka	Total classified
(Manuka)	**39,221**	0	0	0	1	3	1,152	40,377
(Pine)	0	**2,326**	0	0	0	0	1	2,327
(Non Vegetation)	0	0	**4,396**	0	0	0	0	4,396
(Totara)	0	0	0	**382**	0	0	0	382
(Water)	0	0	3	0	**7,668**	0	0	7,671
(Thistle)	0	0	2	0	0	**199**	0	201
(Kanuka)	920	13	0	6	1	0	**9,357**	10,297
Total in class	40,141	2,339	4,401	388	7,670	202	10,510	65,651
Producer Accuracy	**97.71%**	**99.44%**	**99.88%**	**98.45%**	**99.97%**	**98.51%**	**89.03%**	

The totals in the final column of Table 6.3 represent the total pixels classified, for a given class, by the classifier. The totals in the bottom row represent all the pixels defined in ROI collection (by the operator) as being of that class. The figures on the diagonal are the number of instances where both definitions agree, that is the number of correctly classified pixels in each ROI. Overall accuracy (OA) is the number of correctly allocated pixels divided by the total pixels used in the classification, for example 63,549 out of 65,651 (96.8%).

6.3.1.1 Overall Accuracy

Although high overall accuracies were not deemed critical in the early stages of the study (due to variability of target scale), the classification did yield a high overall accuracy of 96.8% with a kappa coefficient of 0.9447. The close relationship between OA and kappa indicates a good agreement between all classes. However, the OA can be biased when the proportions of each class are different. For example, in Table 6.2 the large proportion of pixels collected from manuka (50,182) will have a greater impact on the OA than the 202 pixels available for the thistle class. Therefore, overall accuracy will not be discussed, instead class producer accuracies will be used when examining the results as suggested by Foody (2008).

6.4 Discussion

This section examines the results for each class in terms of producer accuracy with discussion on the potential benefits such information might have. The classification output from ENVI was converted to a shape-file and imported into a GIS environment for further exploration. The classification was segmented into paddocks so results could be analysed at the paddock scale. Each class has potential benefits to the farming system so each component is individually explored to unearth the potential uses and class error in more detail.

6.4.1 Manuka and Kanuka

Manuka and kanuka are intrinsically linked by their location, growth habit and association with honey production so are examined together. The individual producer accuracies for the manuka and kanuka classes were the lowest of all the classes tested at 97.71% and 89.03% respectively. A study of the confusion matrix suggests the largest proportion of the miss-classified pixels in each of these classes were miss-labelled as each other. Some 920 pixels of manuka were classified as kanuka and 1,152 pixels of kanuka were classified as manuka. This misclassification is not surprising given the species have many similarities. Indeed, the two plants are easily confused and often require close inspection by a botanist or other expert to distinguish (Boffa Miskell Limited, 2017). For instance, the presence of woody seed capsules is one of the defining and identifying features of manuka (Anon., 2017; Boffa Miskell Limited, 2017).

The ability to distinguish between manuka and kanuka has several possible benefits. Firstly, calculation of the area of available manuka allows the correct carrying capacity of hives to be calculated. Figure 6.3 highlights a paddock where although manuka is dominant there are other components present.

The ability to classify and measure this area of manuka as 27.37 hectares within a 40.8 hectare fenced paddock provides much better information for decisions than a visual estimate. The classification also shows the relatively low levels of kanuka present, which will help the purity of the honey.

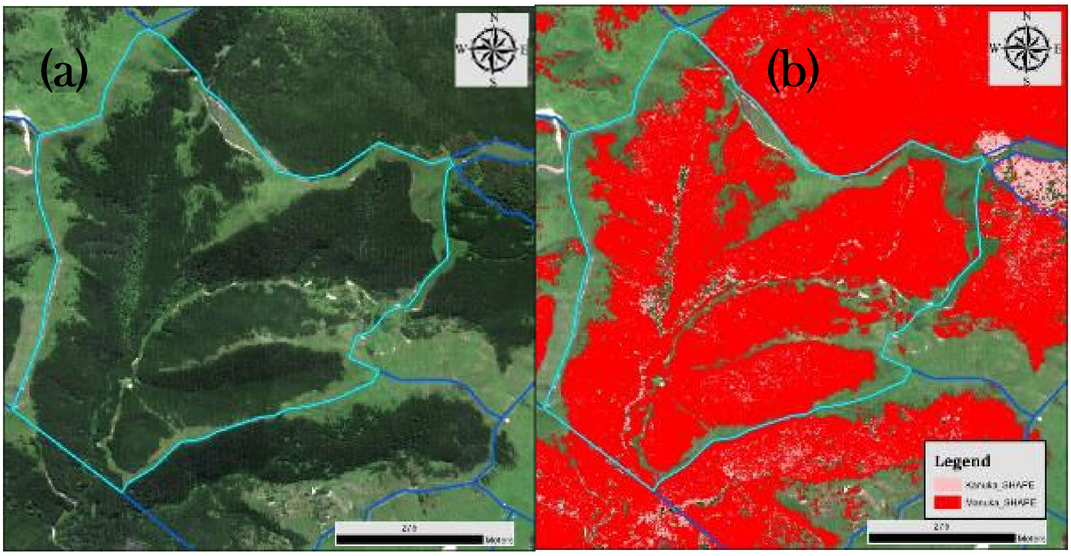


Figure 6.3: RGB (a) true colour image and (b) classification of a 40.8 ha area of Patitapu that has a large proportion of manuka (red) and some kanuka (pink). The classification indicated 27.37 ha (67%) of this area was Manuka.

Mapping manuka and kanuka would support decisions when placing hives, so the beekeeper can favour higher concentrations of manuka plants and optimise profitability. Manuka and kanuka have some overlap in flowering times (Boffa Miskell Limited, 2017) so to preserve honey quality it might be necessary to understand the population dynamics. Figure 6.4 shows a part of the farm where proportions of manuka and kanuka are likely to produce a honey with a lower value because of product mixing. However, bees can forage more than five kilometres from the hive (Newstrom-Lloyd, 2016). Therefore, it might be practical to place hives to collect the less lucrative product and use resource competition (Lloyd et al., 2017) to reduce contamination of the higher value product. Having classified maps of the various resources would allow apiarists to consider these and other micro management techniques.

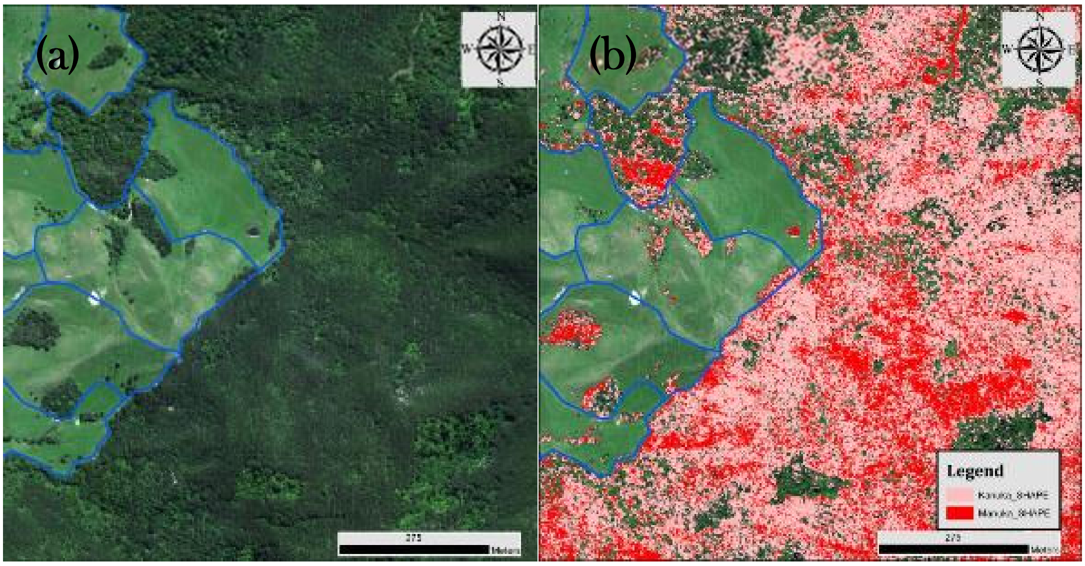


Figure 6.4: RGB (a) true colour image and classification (b) of an area of Patitapu that has high proportions of both Manuka (red) and Kanuka (pink)

The added information provided by this form of classification would also improve confidence in other management decisions. A landscape classification may provide farmers and consultants with a tool to alter farm practices in other ways. For example, it may identify where more manuka can be planted or where selective clearing of other species might yield a return on investment by improving honey quality. A definitive understanding of manuka distribution and volume would help take full advantage of the resource.

Unlike other farm livestock, bees cannot currently be fenced to keep them within a farm boundary (Newstrom-Lloyd, 2016). There are already reported instances of hive vandalism and theft which are considered a major concern for the industry (M.P.I., 2017a). Practices such as placing hives near to boundaries are more likely to end in court. But, the question of how one proves a neighbour has overstocked his farm and is therefore affecting the financial return of the other would be difficult and expensive to answer currently. A remote sensing classification could provide unbiased figures for the area of manuka on each farm. Experts could use the information to resolve such disputes. It may also prevent them entirely if used to define how many hives each should have at the beginning of the season. Such rules would require regulatory support, but that is difficult to envisage when there is not even basic data on landscape coverage.

Although the classification had high accuracies there was some evidence of misclassification. For instance, the northeast corner of Figure 6.3b shows a small area that, from first-hand site knowledge, is misclassified as kanuka. This area may contain some kanuka, but ground observations revealed this area is dominated by another unrelated native species. For the classification accuracy to be improved misclassifications of this type, however small, should be addressed.

6.4.2 Pine

Pine classification had a producer accuracy of 99.44%, see Figure 6.5 for an example. Classifying pine may have several uses such as valuing carbon inventory, but one considered for this research was for the identification of wilding pine, considered an invasive weed in New Zealand (M.P.I., 2017e). Pine, like other landscape elements, can be difficult to monitor in the steep terrain and dense vegetation associated with hill country farm landscapes.

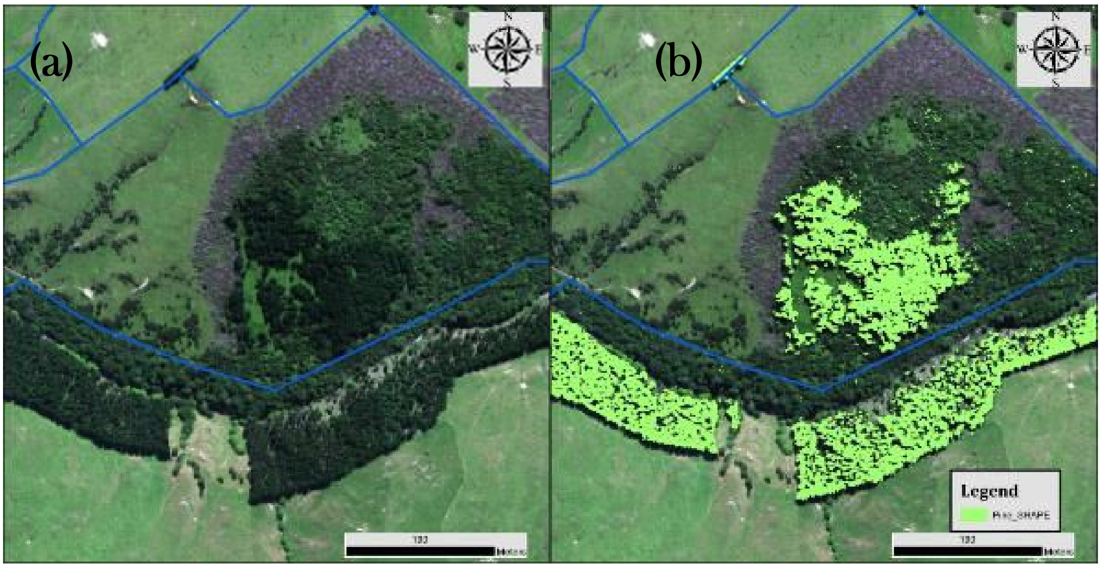


Figure 6.5: RGB (a) and (b) classification of an area of Patitapu showing the location of pine (lime).

The New Zealand Government has a programme underway to eradicate wilding pine. The approach outlined in this study could support the programme by identifying the pines and targeting controls. This approach would improve the efficiency of the programme and ensure maximum return from the programmes annual $11 million (NZD) investment. Introducing remote sensing mapping to aid eradication efforts sits within two of the four stated management principles; those of cost effective and timely action and prioritisation and co-ordination (M.P.I., 2014b). Seeds of most pine are viable for up to six years. Thus, even after carrying out control, the site will need to be monitored to detect regrowth. This is where remote sensing could provide a cost-effective mapping solution. Froude (2011) reported several cases where pine had reestablished after an initial clearance operation because no follow-up had occurred. Ledgard (2001) suggested checking about seven years after the first clearance to identify remaining seedlings. The ability of remote sensing to cover large areas rapidly makes this a viable tool for such work.

6.4.3 Non-vegetation

The classification producer accuracy for non-vegetation components was 99.89%. Non-vegetation components such as roads and buildings are important assets on a farm, so identification of their location would be important to ensure they are included in an asset inventory for valuation purposes. Similarly, bare soil on a hill could represent a landslip which might point to the need for soil stabilisation measures. In either case, having a map of such features would be worthwhile. The classification shown in Figure 6.6(b) includes the main stockyards (South-east) and two cultivated paddocks (West). Farm roads and some heavy wear areas are also visible in the classification.

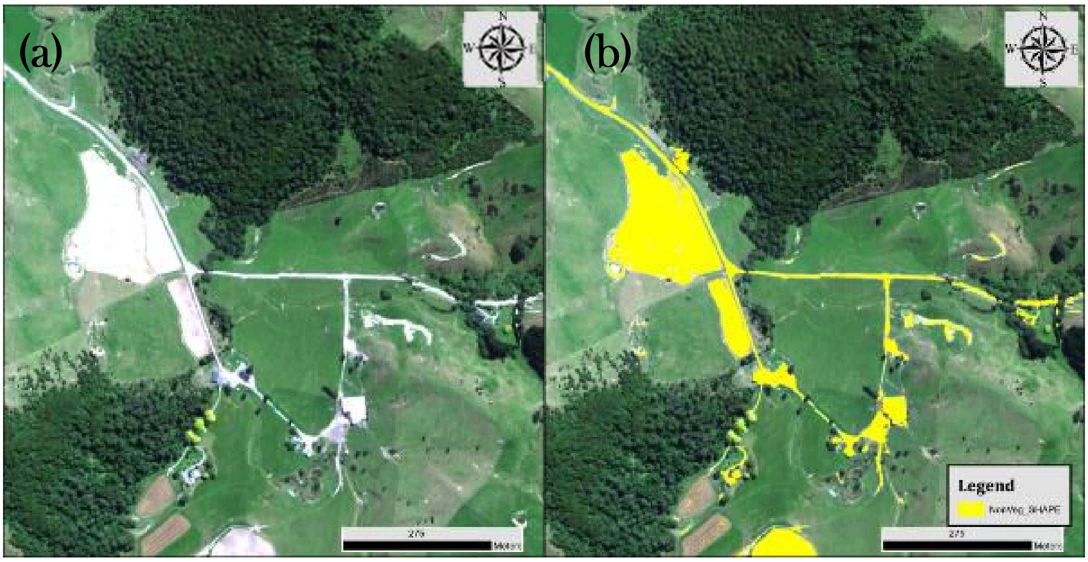


Figure 6.6: RGB (a) and classification (b) of non-vegetation areas (yellow) of Patitapu. Roads, bare soil and buildings are included in this class allowing for their location and area to be easily measured. Paddocks classified as non-vegetation had been cultivated at the time of the survey.

6.4.4 Totara

The classification producer accuracy for native totara was 98.45%. This study includes totara to show the targeted discriminatory capability of the technology for a New Zealand native species. Knowing where totara or other native species are located is useful for creating inventories of the plants and their spatial distribution. Figure 6.7 highlights an area of the farm where there is a larger totara population. These trees exist among native vegetation stands and grow individually or in small groups within the paddocks. It is possible to map individual trees with conventional mapping approaches, but those specimens mixed with other (often dense vegetation) would be more difficult, time-consuming and expensive to identify without remote sensing techniques.

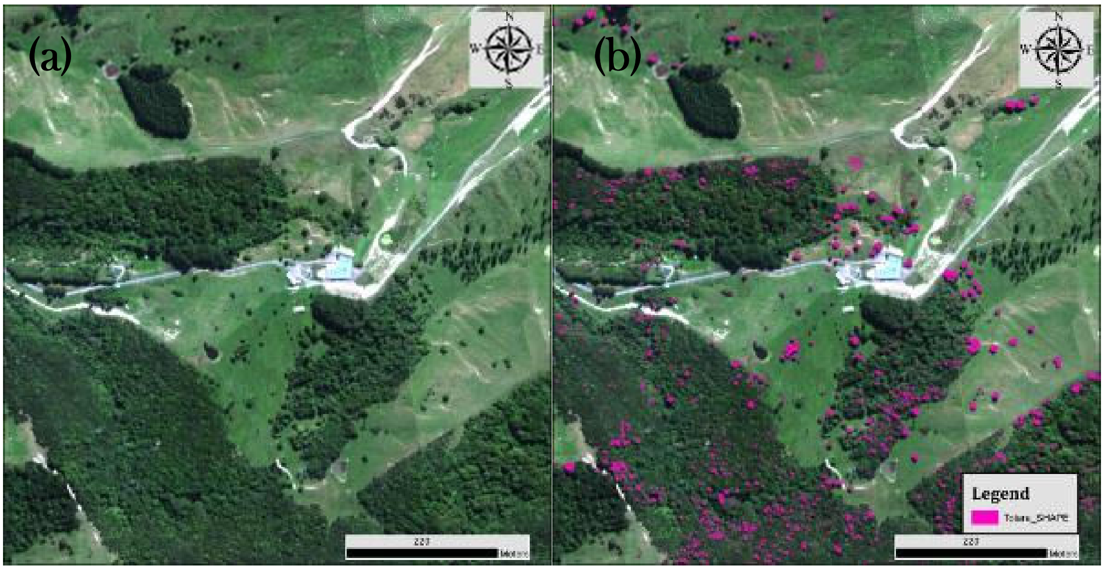


Figure 6.7: RGB (a) and classification (b) of an area of Patitapu Station, highlighting locations of totara (magenta).

Although not related to hill farming, this form of classification also has potential to identify native kauri (*Agathis australis*). Currently, kauri dieback disease is devastating the populations of this species (M.P.I., 2017c). A method to map kauri distribution could help record the disease's progress. It could possibly be used to identify affected and unaffected trees, and produce spatial referenced information to help guide interventions aimed at protecting these important native plants.

Presently, carbon inventories are calculated for five different forest types; *Pinus radiata*, Douglas fir, exotic hardwoods, exotic softwoods and indigenous forest (M.P.I., 2015). Calculations are straightforward for single species plantations. Calculations for mixed species are more difficult and the dominant species must be defined in the calculations (M.P.I., 2015). These categories and definitions are blunt instruments that do not account for subtle variations in forest structure. All native forests are treated the same, despite the potential for large variations in dominant species and their carbon content. The incumbent government's billion-tree programme (Forestry New Zealand, 2018) would encourage more planting. However, accurate estimation of carbon may not be possible without a good understanding of species composition of native plantings.

For example, Emissions Trading Scheme (ETS) participants with more than 100 hectares must undertake field measurements of their forest (M.P.I., 2018b) for assessment of carbon. The Field Measurement Approach (FMA) requires that a minimum number of sample plots be assigned by the Ministry of Primary Industries (MPI). The plot number minimums, used for measuring carbon were defined as a *"compromise between sampling effort, cost and accuracy"* (M.P.I., 2018b). Using remote sensing techniques, such as described in this study, could improve accuracy, while reducing the effort and cost of sampling, especially for native forest. A stratified design could replace the random allocation of sample sites to better represent the key species or the forest's diversity. Thus, the measurement accuracy could improve with less effort.

6.4.5 Water

Open water in the form of streams, ponds or other water bodies are important for environmental and farm management. The classification producer accuracy for water was 99.97%. Water has been one of the easiest classes to identify in other iterations of this work. Farmers prefer to avoid water bodies when applying fertiliser for environmental and financial reason so accurate maps are useful. Furthermore, water is a major asset and valuable resource for livestock management, especially where cattle are grazed. Classifying water bodies on farms makes it easier to count, label and measure them. Figure 6.8 shows a part of Patitapu Station with several stock watering dams. The dams are difficult to identify in the colour image in Figure 6.8(a), but are more obvious when classified in Figure 6.8(b).

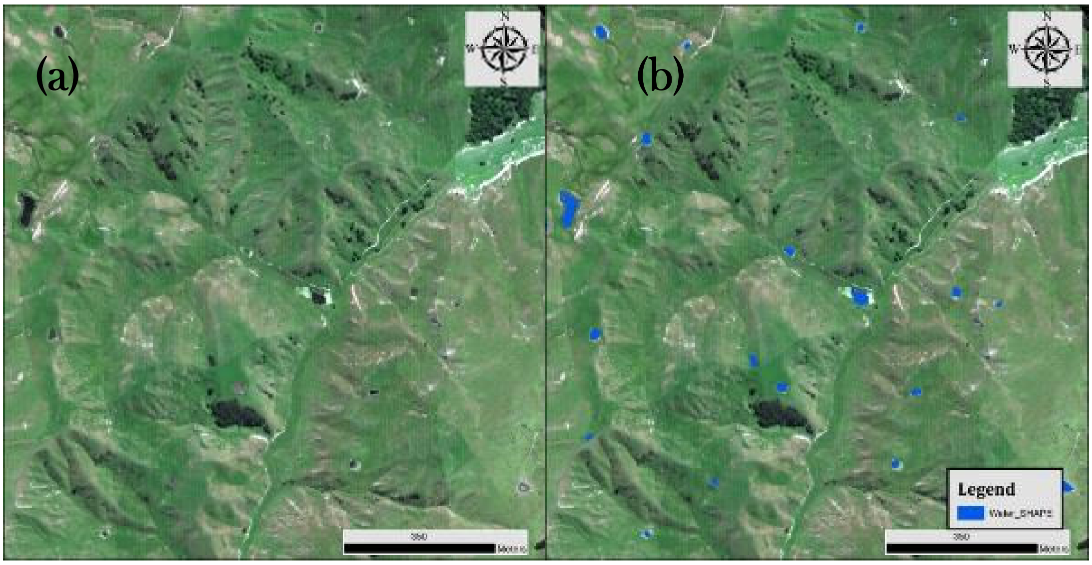


Figure 6.8: RGB (a) and classification (b) of an area of Patitapu. The classification highlights the water (blue) bodies allowing their distribution and numbers to be easily examined.

An accurate inventory and map of water locations on the farm can be used to add specific exclusion zones for fertiliser application. Furthermore, the maps can be used as a check sheet for inspections and repairs. As water storage is viewed as an asset, reliable maps of water bodies would also be useful when valuing hill country farms.

6.4.6 Thistle

The classification producer accuracy for thistle was 98.51%. Developing an understanding of the distribution of weed species such as thistle could have important implications for farm profitability. With about 1,800 hectares of pasture on the property even a 0.25% distribution would represent the loss of production on 45 hectares. This inaccuracy could lead to the farmer unwittingly overstocking the remaining pasture; thus, it is worth identifying and managing such problems. Detecting larger patches of thistle would inform application maps so controls can be applied efficiently via helicopter. Figure 6.9(b) correctly detects large amounts of thistle in the highlighted paddock. However, it also predicted large amounts in an area to the Southwest (not shown) that was sprayed bush, and it missed some known areas to the Northeast of the farm. The results show promise, but more work is needed to improve classification accuracy to support effective targeted treatments.

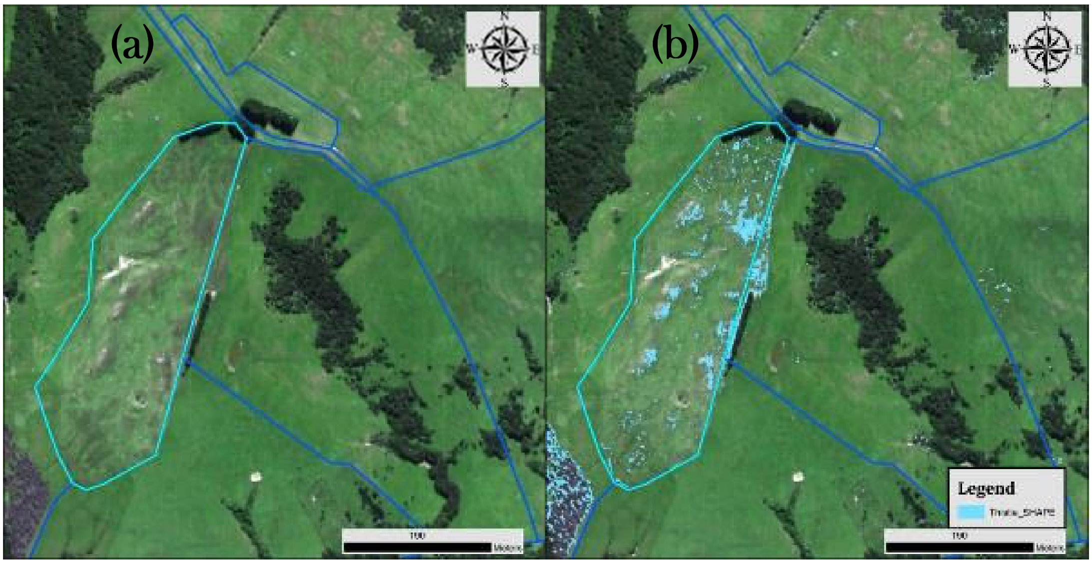


Figure 6.9: RGB (a) and classification (b) of an area of Patitapu Station classified as having thistle (cyan).

The financial costs of thistle and other weeds is an incentive to improve these results. The use of the AisaFENIX for that work would be a major benefit as that analysis could form a part of the overall suite of results. This would enhance the cost benefit of the survey and avoid the need for a separate data collection to account for weeds. However, this study does not offer clear evidence that the AisaFENIX can effectively complete that task, so more work is warranted.

6.4.7 Return on Investment Costs

To recognise how this work can help farmers, we consider the wider PGP programme which focuses on improving fertiliser placement and efficiency. The predicted cost for aerial survey (including ground data collection and data analysis) is around NZD$15/hectare (Personal communication, Ian Yule). That means the 2,600 hectares of Patitapu Station would cost about NZD$39,000 to map. In 2017/18, hill country farms in that region spent on average around NZD$90/hectare on fertiliser(BLNZ., 2018b). For the projected cost of NZD$15/hectare to be feasible, farmers would expect to see a return on that investment well within the period for repetition of the survey. If we multiply the average fertiliser spend by the pasture area at Patitapu Station (about 1,800 hectares) we can predict they spend about NZD$160,000 a year on fertiliser. To justify this initial investment required for surveying, this survey would need to save the farmer 25% of the fertiliser budget (or increase productivity by that amount) if the repeat cycle for the survey was one year. It may be easier to define the cycle period by estimating the potential savings. Assuming a 10% saving in the fertiliser budget (or NZD$16,000 revenue increase), a three-yearly repeat cycle is needed to offer a positive return on investment. For accounting purposes, the farmer would need to save around $10,500 per year on fertiliser cost (with a 3-year repeat cycle) at the net present value discount rate of 5%. However, this saving is sensitive to the duration of repeat cycle and discount rate.

This work aims to add value to the survey, boosting the overall return on investment. The approaches proposed in this chapter promise efficiency gains and substantial knowledge that would make these surveys more viable for many farmers. That knowledge also has a value to the farmer and should be considered in the return on investment calculations.

6.5 Conclusion

This study represents the most detailed analysis of the hill country landscape to date. The high accuracies for most components support its integration into strategic farm management, rural valuation and environmental monitoring. Multiple layers of value were identified which could improve business performance and environmental management practices, and ultimately boost fiscal returns. The success of the classification meets the goal to study the benefits, that wider classification of vegetation and other landscape components, could have to hill farm businesses and ancillary industries.

6.5.1 Farm Management

Farm management decisions are currently made with expert knowledge of the property built up over many years. Even with this knowledge, there is uncertainty that detailed landscape information can address.

The purchase of a new or additional property often comes with no or limited historical first-hand knowledge. So, the first few years are likely to be very much trial and error or based on experience from other property that might not represent the best approach. Purchasing a property with a classification map included would circumvent much of the early guesswork associated with a new property. The first few years on a new property are also critical from a financial point of view. Lifting economic returns and business confidence in this period would also have major benefits to the industry both in terms of confidence and fiscal returns.

6.5.2 Farm Valuation

Farm valuations will be enhanced by improved financial returns associated with better management decisions. Valuations will also be directly improved by the uptake of remotely sensed mapping. Production of clearly defined, detailed, farm maps will negate the need for the tedious and subjective mapping operations currently undertaken by the rural valuation community. Also, valuers would no longer need to identify the distribution of important plants that require some expert knowledge to differentiate, such as manuka and kanuka.

A potential weak point of the current valuation system is the reliance on the accuracy of the previous analysis. The method for farm landscape mapping, developed in this study, may enhance its long-term accuracy and utility for valuation purposes. Knowing the exact assets of a comparison property being used to guide the valuation, enables a more detailed comparison of value to be formed. Highly accurate mapping would provide the seller, purchaser and lender greater confidence in the outcome of the valuation.

6.5.3 Remote Sensing

The only large-scale land classification resource in New Zealand is the New Zealand Land Cover Data Base (NZLCDB). It uses satellite data to map 40 classes of landscape throughout the country (Thompson et al., 2003). The resolution is very different and thus not comparable with this work for farm scale analysis. If classifications produced from high resolution aerial hyperspectral imagery were more accessible, they could be added to the NZLCDB. Eventually the classification resolution for the country could be raised to this level when technology catches up and is applied more widely.

The classification carried out in this study uses just 145 of the 448 bands produced by the AisaFENIX hyperspectral sensor. This suggests that the SWIR bands 904 nm to 2,500 nm are unnecessary for this form of analysis. So, it may be possible to produce a simpler (and potentially cheaper) sensor to focus on such classification tasks. The AisaFENIX has both a visible/NIR and a SWIR sensor. The specifications of the visible/NIR sensor indicate a higher signal-to-noise ratio and the ability to increase it within the software via spectral binning (SPECIM, 2013). Thus, it may be possible to fly the visible/NIR sensor in lower light levels (or under clouds) than is possible with the current unit. Given the probability for cloudy days in New Zealand, such options might be needed to keep costs low enough that even a small portion of New Zealand farmers could adopt this technology. These topics would make a good follow on study from this work.

This study shows that remote sensing technology has great promise for use in hill farming and would have tangible benefits to other aspects of the New Zealand rural economy.

Chapter 7 : The Classification of Plant Functional Groups Within New Zealand Hill Farm Pasture

7.1 Introduction

Previous chapters have established that hyperspectral imagery can be used to delineate pasture and other landscape components. Not all pasture is the same and variability in quality has management implications. Because of the difficult terrain that exists across large portions of hill country farms, pasture renewal is often impossible, so management practices are the primary means of influencing pasture and production. The decision-making process heavily relies on the farmer's expert knowledge, pasture growth models and blanket fertiliser applications (Lambert *et al.*, 2004). Reliable and economic variable rate aerial topdressing equipment has become commercially available in recent years. However, methods of allocating fertiliser rates lag the application technologies, limiting their usefulness (White *et al.*, 2017).

This study uses hyperspectral imagery to map hill country pasture Plant Functional Groups (PFG) as a proxy for pasture quality. Information on pasture quality has great potential to inform many of the on-farm strategic decision-making processes.

Three primary groups of pasture species, low fertility tolerant, high fertility responsive and legumes are mapped using hyperspectral data in conjunction with SVMs. The validation of the results was carried out firstly, by splitting off a proportion of the ground data collected, then by adding additional larger areas to the validation, by on-site assessment and lastly by seeking the opinion of the primary expert on the land, the farm owner.

7.1.1 Background

In the New Zealand sheep and beef sector, the species composition of pastures has a major effect on farm productivity as measured by animal performance (D. Stevens *et al.*, 2007; Sanderson & Webster, 2009). Greater understanding of the relationships between soil, pasture and environmental factors improves management decisions, provides guidance for fertiliser applications and protects the environment. Invasion of weeds and less nutritious species such as browntop (*Agrostis capillaris*) into new pastures lessens pasture productivity as measured by animal live weight gain (D. Stevens *et al.*, 2007). Pasture composition and production is linked to farm economic performance and environmental sustainability as pasture responds to biophysical resources such as soil moisture, soil fertility and erosion (Lambert *et al.*, 1996). Pasture species in these low input grass ecologies are heavily influenced by the extreme variability of the landscape (López *et al.*, 2006) and are difficult to predict as they can change rapidly in time and space (Peter Kemp, personal communication).

Researchers have studied the dynamics of grassland species flux since the 1850s (Hill & Carey, 1997). The species distribution models employed are usually based on relationships with spatial and physical characteristics of the landscape and environmental interactions (B. Zhang *et al.*, 2005). Unfortunately, many plant-environment relationships are poorly understood in the complex hill country environment, limiting progress (Lambert *et al.*, 1996) and the accuracy of resulting models in all but localised areas.

Categorisation of species along fertility and nutrition gradients has proven useful in explaining pasture production variability and species composition. Classing grasses into High Fertility Responsive (HFR) and Low Fertility Tolerant (LFT) groups has been used to describe pasture and relate environmental factors to their presence (Lambert *et al.*, 1986; Lambert *et al.*, 1996; López, 2000). How the growing environment affects the way plants adapt to survive has been studied since the beginning of the last century (Warming, 1909; Raunkiaer, 1934). A key advance was the idea that plants are genetically adapted to take advantage of specific environments; grouping plants with similar adaptations together provides insights from the resulting generalisations (Grime, 1974, 1979; Ellenberg, 1988). Plant functional groups in hill country settings have been studied to define interactions between vegetation and environmental factors (B. Zhang *et al.*, 2005) and to classify vegetation (Wan *et al.*, 2009). A few plants usually dominate species composition in hill country pastures; more than half of the available biomass at any location usually comprises three or fewer species. Wan *et al.* (2009) simplified these complex interactions by focusing on three species and their relative abundance to identify variables that can influence management. Importantly, the research showed that soil Olsen P and slope influence the competitiveness of perennial ryegrass (*Lolium perenne*) versus browntop.

Often found on dry hill country soils, browntop tolerates a wide range of growing conditions. Ryegrass is more competitive than browntop in moist, fertile soils and both species are common throughout New Zealand (Lambrechtsen, 1972). Browntop and ryegrass belong to different plant functional groups of CSR and CR/CSR respectively as defined by the Grimes C-S-R ecological community triangle (Hodgson *et al.*, 1999). The aim in understanding these environments is to improve production for better farm returns. The New Zealand Government's policy to increase production (M.P.I., 2014c) and the increased awareness of environmental sustainability (Lambert *et al.*, 1996) are also key factors. Stock management, chemical topping, pasture renewal and fertiliser application are some of the current tools available to farm managers to meet internal and external productions goals (Lambert *et al.*, 2004).

The aim of the Primary Growth Partnership 'Pioneering to Precision' (PGP) is to improve fertiliser placement and response (M.P.I., 2017d). To this point, the project has modelled the fertility of the pasture based on sample data and extrapolated it over the farm (Pullanagari *et al.*, 2016). The researchers reported distinctive spatial patterns and a wide range of values at local scale, possibly caused by growth limiting factors such as water availability and underlying soil nutrient status. Water and soil nutrient availability also play a major role in defining the plant functional group that occupy a particular space (Grime *et al.*, 1997). Mapping PFGs could therefore help to identify the impact of these environmental factors. There is evidence of a link between species composition and environmental conditions in nutrient deficiency (Cornforth, 1984); better information on species distribution may help mitigate or manage these effects. Pasture nutrient status information would thus be more valuable if the underlying species were identified.

Some species such as ryegrass respond well to higher fertility conditions. Browntop although less well adapted to high fertility can be highly competitive with white clover in the uptake of phosphate (Jackman & Mouat, 1974). Thus, it would be useful to include habitat and species information when selecting fertiliser applications rates. Fertiliser application rates could be adjusted to increase soil fertility and encourage desirable species or to capitalise on existing dominance to increase pasture production without wasting resources. Accurate species information would also inform decisions on stocking rates and pasture quality information would be relevant to rural property valuations.

7.1.2 Remote Sensing

This research examines two remote sensing techniques, classification (Melgani & Bruzzone, 2004) and spectral unmixing (Bioucas-Dias *et al.*, 2012) to advance the knowledge of key species or functional groups in hill country pastures. In spectral imaging, each pixel represents an individual sample whose real-world combined constituents contribute to the total reflectance of that pixel. When the pixel represents a single component it is easily classified. However, when a pixel comprises multiple components the classification is complicated, and researchers have developed techniques to unravel or 'unmix' them. The end use of the information usually guides the decision to classify or unmix components of each pixel.

7.1.2.1 Classification

Classification approaches try to map image elements into thematic classes using techniques of object-based, pixel-based or combination approaches (Bioucas-Dias *et al.*, 2013). Examples of classifying homogenous crops exist in the literature, for example (Galvão *et al.*, 2005) and some work has been carried out to map grassland composition (Möckel *et al.*, 2014) and grassland diversity (Möckel, Dalmayne, *et al.*, 2016). As pasture is a diverse mixture rather than distinct plant groupings, the pixel-based approach is more valid as a classification approach than object-based methods as objects would be difficult to define. However, classification does not detect the abundance of the components within pixels, it defines the pixel based on its appearance being closest to a given group. This can result in a loss of information when minor pixel components are not defined. That is why unmixing was developed and why it may provide complementary information.

7.1.2.2 Unmixing

Unmixing tries to disseminate the various sub-pixel components of a given spectra into relative abundances of its constituents, referred to as endmembers (Keshava, 2003; Bioucas-Dias *et al.*, 2012). Linear and non-linear approaches continue to be explored as a way of understanding the sub-pixel detail carried by the spectra. The use of linear approaches is appropriate when the mixing is from distinct patches (Keshava, 2003; Bioucas-Dias *et al.*, 2012), such as a pixel containing paving and an area of grass or soil. Non-linear approaches are preferred when pixels contain multiple layers or intimate mixtures where photons of light can interact with more than one component before being collected (Keshava, 2003), e.g. a photon of light reflected from soil then to a leaf before collection, or from one chemical component to another in a suspension. Such scenarios create almost infinite combination of interactions and may result in more than one combination of interactions leading to the same recorded outcome (Bioucas-Dias *et al.*, 2012). Although non-linear unmixing approaches are being improved most unmixing processes employ variations on the simpler linear methods of which there are many variants, e.g. Mixture Tuned Matched Filtering (MTMF) (Boardman & Kruse, 2011) or linear spatial spectral mixture model (Shi & Wang, 2016).

7.1.3 Research Rationale

Reliable evidence of species composition or habitat distribution is essential to advance pasture management and decision-making. This is more difficult in a diverse environment. However, the simplification of the landscape character using plant functional types and species dominance has proven useful in ecological studies (Schmidtlein, 2005; Ustin & Gamon, 2010) and in modelling grasslands or pasture (López *et al.*, 2006; Wan *et al.*, 2009; Möckel, Löfgren*, et al.*, 2016).

The process employs the supposition from phytosociology that species can be grouped based on environmental adaptations with the use of indicator species to support habitat classification (Grime, 1974; Ellenberg, 1988; Schmidtlein *et al.*, 2010).

The goal of this research is to develop and validate a technique to map the spatial distribution of species previously identified as key indicators of pasture condition, i.e. ryegrass, browntop and/or legumes such as clover (*Trifolium sp.*) (Lambert *et al.*, 1986; Lambert *et al.*, 1996; Nicholas, 1999; López *et al.*, 2006; Wan *et al.*, 2009; P. Kemp & Lopez, 2016) via species habitat. In this study, three groups were defined to represent the abundance and dominance of species. The groups will help decision-making relating to pasture management, stock management, pasture renewal and rural valuation. More importantly for the success of the PGP, it is an important component in the definition of fertiliser application rates. Ease of implementation is an important consideration if this technology is to gain widespread uptake as complicated methods produce a major barrier to entry, increase potential for mistakes and require more advanced training and understanding to operate; the methods selected for inclusion in this research considered all of these factors.

7.2 Methods

Training data allows hyperspectral imagery to be used to map species or habitats; the data must include the range of species of interest and their accurate locations so they can be located and defined in the survey image as regions of interest (ROI). The classification can then be trained with known samples to define the unknown samples.

7.2.1 Site Location

Field survey for the study was on Patitapu Station on the North Island of New Zealand (Figure 6.1, Chapter 6). The 2,617 hectare property has around 1,800 hectares of pasture that supports almost 17,000 stock units with a further 450 hectares of native bush. The terrain ranges from

150 to 534 metres above mean sea level with an annual rainfall of between 800 mm and 1,200 mm. Figure 7.1 provides an aerial view of the property.

Figure 7.1: Aerial image of Patitapu Station produced from AisaFENIX data. Paddock and farm boundaries are in red.

7.2.2 Method Overview

Figure 7.2 summarises the workflow for the classification and unmixing of the hyperspectral imagery. Ground data collected from tarpaulin sites within two days of the aerial survey were used to define ROIs to train and test the classification and unmixing. The classification and validation had three stages:

1. A combination of hyperspectral imagery and surveyed ground data is used to classify and unmix the pasture into three classes representing HFR (ryegrass), LFT (browntop) and legumes (clover) in a method similar to that used by Lambert *et al.* (1986).
2. Information was collected on homogeneous paddocks to expand the validation of the original classification and provide greater confidence in the results.
3. Another site visit was made to identify specific features visible in the classification results; the features were cross-checked and discussed with the farm manager and owner to get their perspective.

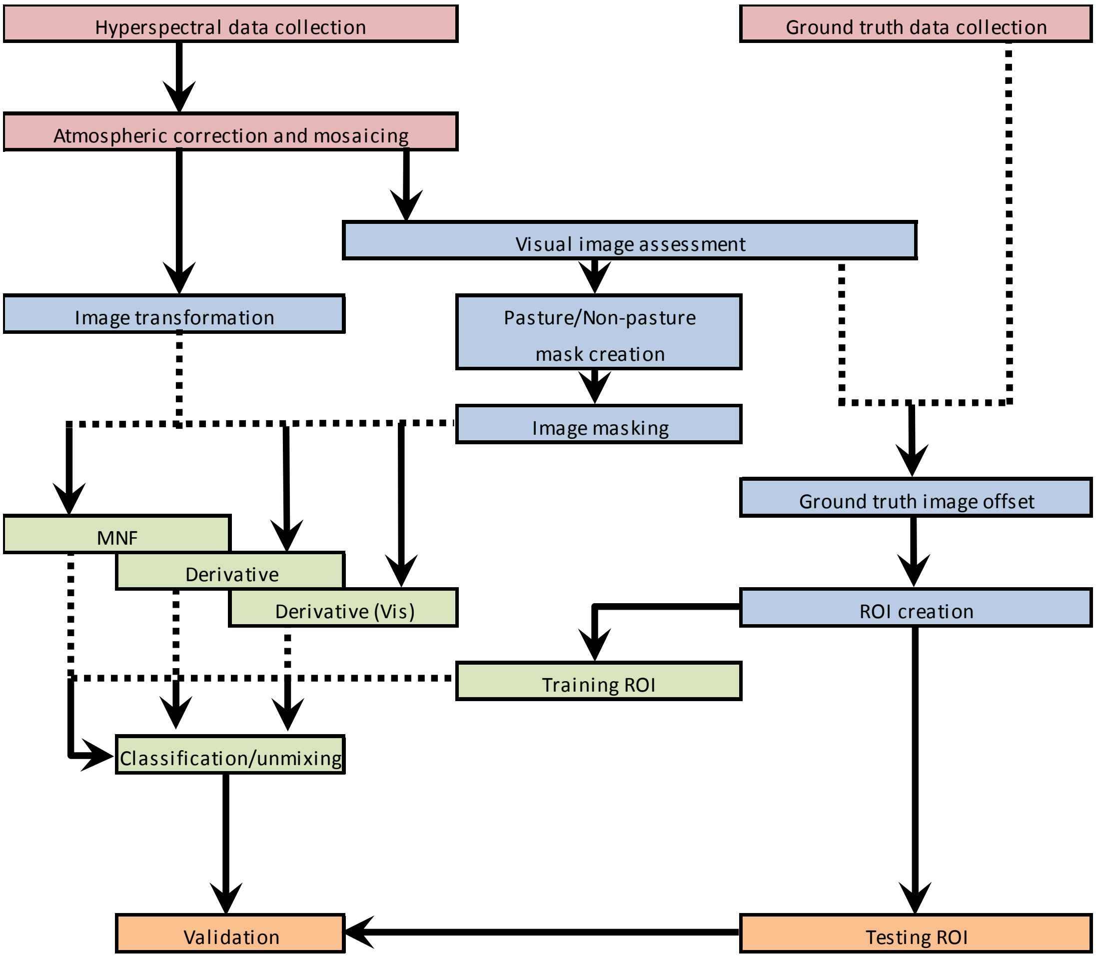


Figure 7.2: Simplified workflow diagram of the steps taken for this analysis. Colour coding defines the stages: data collection and automated atmospheric correction (red), image transformation and data preparation (blue), classification and unmixing (green) and interpretation of results against ground data.

7.2.3 Hyperspectral Aerial Survey

An AisaFENIX hyperspectral sensor made by Specim (Finland) as described in chapter 4 was used to obtain aerial imagery of Patitapu Station in the Wairarapa region of New Zealand (Figure 7.1) beginning at 11.30am on March 2nd, 2017. The hyperspectral data were atmospherically corrected and mosaiced into a single georectified image by the PGP team before all other analysis as Pullanagari *et al.* (2016).

7.2.4 Ground Data Collection (Tarpaulin Site)

The field survey at Patitapu Station in March of 2017 was different from those previously conducted for the PGP as it included visual references (3 m x 3 m blue plastic tarpaulins) large enough to appear in the survey image. Each survey site was placed five metres north of a tarpaulin with both the site and tarpaulin geo-located using a real-time kinematic (RTK) DGPS system. This confirmed the actual site locations to allow any positional error in the mosaiced hyperspectral image to be calculated so a correction could be applied.

Fifty-two tarpaulin sites were selected to represent a wide range of pasture quality parameters from a contemporaneously run experiment (data not published). The pasture quality parameters (nutrient status of the pasture) influence, or correlate to, pasture species composition (Wan *et al.*, 2009) and therefore provide suitable sites for collection of species data.

The tarpaulins were staked out at 52 locations. A 2 m^2 sample site was marked out five metres from the tarpaulin edge for ground-based data collection. GPS coordinates for the corners of each tarpaulin and associated data collection site were recorded.

Botanical composition data were collected using a 0.9 m x 0.9 m (0.81 m^2) quadrat divided using elasticated cord into 36 equal sections representing 2.77% each. The quadrat was randomly dropped into the 4 m^2 sample site. The percentage of cover was estimated for browntop, ryegrass, clover, dead material and other pasture components. Other pasture components included broadleaved weeds and other grass species. Two agronomists performed the visual assessment together to minimise bias or estimate drift (Bacaro *et al.*, 2009; Morrison, 2015).

7.2.4.1 Class Assignment Before Training and Validation

The ground data collected was a visual estimate of the percentage of each species within the defined site. The data were converted into a mutually exclusive class of HFR, LFT or Legumes to enable classification. Each tarpaulin site was assigned a user-defined class based on the content (%) of each of the indicator species before data segmentation into training and test groups. LFT sites were mostly browntop, HFR sites were mostly ryegrass and the legume class were defined by sites where legumes (clover) was dominant; the classification and subsequent validation assumes these defined classes are correct. Assignment into mutually exclusive classes reduces the resolution of the ground data collected to 1m^2, that is in pixels where a species was dominant information on concentrations of other species was lost. Considering the farmer currently has no map of pasture quality and works on paddock averages, 1m^2 resolution across 1,800 hectares is an improvement on existing practice.

7.2.5 Ground Data Collection (Paddock Sites)

It is important the validation of the classification includes as much of the farm as possible to increase confidence in the results. Given the difficulty and expense associated with surveying individual point locations, homogeneous paddocks, clearly defined within the image, represent the best opportunity to collect larger sample areas to validate the resulting classification.

In collaboration with the farm owner, operator experience and site photography (Gienko & Govorov, 2017) a series of paddocks were identified for inclusion as additional validation. These had ‘relatively’ uniform composition as they were recently renewed (primarily flats) or because they had a stable browntop-dominated population. These areas were visited and marked on a farm map with clear paddock boundaries. The paddock boundaries were overlaid on an aerial photograph that facilitated paddock location and identification. The paddock data were held separately and only used for additional validation of the primary classification, i.e. they were not used to train the classifier.

7.2.6 Positional Accuracy

A discrepancy between the tarpaulins in the imagery and the GPS point data collected for each in the field was detected by means of visual interpretation of the hyperspectral image in combination with GPS data. This issue was most likely a result of the absence of differential GPS correction on-board the survey plane but the misalignment may also be connected to the poor quality of the digital elevation model (DEM) used in orthorectification (Kereszturi and Grafton, Personal Communication). This manifested in the GPS points collected in the field not aligning with the specific features in the image (see Figure 7.3). Interestingly, each location was affected differently; in one instance the measured offset was 11.1 metres. Features visible in the image, for example fence lines and roads, suggest this was not an isolated case. To identify the correct location of the ground survey site in the image an offset was applied. The direction and distance of the offset was calculated by the difference between the tarpaulin in the image and the GPS points for the tarpaulin. Table 7.2 (section 7.3) lists each site and the associated positional and directional error recorded between GPS points and image that was applied to each site.

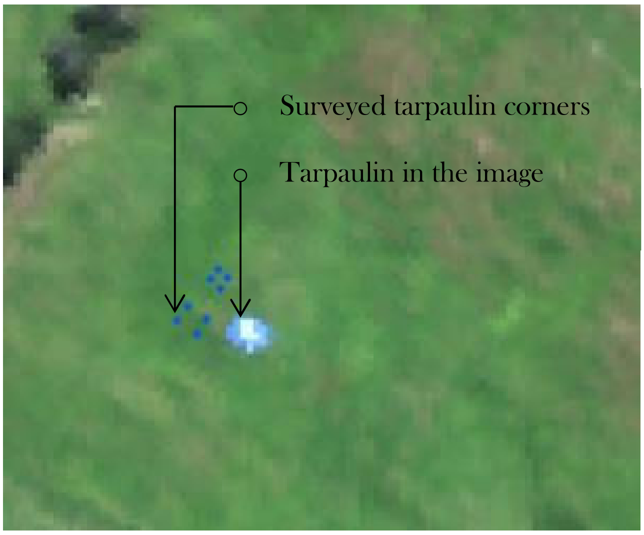


Figure 7.3: View of one site (V12) showing the 4.8m spatial offset between the image and tarpaulin site GPS co-ordinates collected during the ground survey.

7.2.7 Non-pasture Masking

It is not always helpful to include the entire scene in an analysis especially when the scene is complex (Boardman *et al.*, 1995). Masking is a useful form of data reduction and given the focus on pasture in this study, it constrains the classification and unmixing to only the pasture component. This mask is defined using the technique described in the previous chapter that involves the collection of pasture and non-pasture ROI before applying a linear SVM classification; thus, non-pasture components are discarded from the image and excluded from analyses.

7.2.8 Image Transformation

Two forms of data transformation, minimum noise fraction (MNF) and calculation of first derivative were applied to the data. MNF is similar to a principal component analysis (PCA) that rotates the data to form new variables. The MNF carries most of the useful information in the first few components and the noise in the latter components (Green *et al.*, 1988). Transformation to 1st derivative defines the rate of change from one wavelength to the next and can help reduce low frequency noise (Demetriades-Shah *et al.*, 1990). These transformations proved more informative from iterative testing as described in previous chapters. Results from Chapter 4 suggest the lesser importance of the shortwave infrared (SWIR) so a dataset was also created that truncates reflectance at 970 nm which removes the SWIR as well as a portion of the near infra-red (NIR). 970 nm was used as the cut-off point because that is the point where the two detectors within the AisaFENIX sensor meet (SPECIM, 2013). Those sensors have slightly different specifications including signal-to-noisesignal-to-noise ratios. Table 1 summarises the various combinations of transformation and analysis performed. The image mask was applied to isolate the pasture during the transformation.

Table 7.1: Combinations of data transformation and analysis performed including linear spectral unmixing, Mixture Tuned Matched Filtering (MTMF) and SVM classification.

	Analysis Method			
Data Transformation	Unmixing	Unmixing (unconstrained)	MTMF	SVM Classification
MNF	X		X	X
1st Derivative	X	X		X
1st Derivative (no SWIR)	X		X	X

7.2.9 SVM Classification

Support Vector Machines (SVM) generate an optimal separating hyperplane using training points that lie on the boundary between the classes (support vectors) (Ben-Hur & Weston, 2010). The hyperplane is used to define the class of each pixel. SVM is a supervised classification method that has an exhaustive history in remote sensing. With ease of operation in mind a simple linear SVM was implemented in ENVI to classify the image and validate results.

7.2.9.1 SVM Region of Interest Collection

Supervised classification methods require the user to train the method by supplying examples of each class and regions of interest (ROI) are used for this study. The diversity species data can be a problem for selection of ROI for training and test data. For instance, a small training data set can reduce the accuracy from some methods such as artificial neural network type classifiers (Foody & Arora, 1997). SVM are not so constrained, requiring only the support vectors to be identified, so fewer training samples are selected which effectively define the classes of interest (Foody & Mathur, 2004; Foody & Mathur, 2006; Foody *et al.*, 2006). This was borne out in iterative testing undertaken earlier in the project that proved the superiority of the SVM for this work. Another advantage of the reduced training dataset is that a relatively large portion of the total dataset remains available for testing the classification accuracy. Training and test data were held separately as suggested by (2009).

Reinke and Jones (2006) state that positional accuracy of remote sensing data is important. In their case, an offset of a few meters would have placed some of their sites in different environmental settings, this was also the case for this study. Collected ground data must be registered to the correct measurements (pixels) in the image to justify assertions made from analysis. Using tarpaulins for this survey allowed positional inaccuracies to be corrected. When collecting regions of interest manual adjustment was used to match the ground data locations to the correct pixels in the image (e.g. Figure 7.3). The quadrat was randomly dropped within the 2m x 2m site area, so a number of pixels were needed to ensure the quadrat location was represented in the ROI. This meant that either 4 or 9 pixels were collected to ensure a match with the site data.

The mosaicing overlapped the tarpaulin with another image strip and 'erased' the tarpaulin from the composite image twice in the study. These sites were eliminated from the analysis as GPS correction could not be applied. A third site was excluded as it was erroneously placed outside the property boundary by a setup team, leaving 49 tarpaulin sites available for analysis.

ROI for validation were collected from the true colour image prior to classification to avoid operator bias (S. Stehman *et al.*, 2003). Those sites included in the training set are highlighted in Table 7.2. Another class was created to account for the non-data portions of the image as previous testing indicates the SVM would classify these non-data areas into the nearest class. Legumes were included as a class because clover was prominent in several locations by the survey and there were also pastures present sown with 100% clover which provided good training sites. Nitrogen fixing plants have been singled out by other authors as deserving of their own category as they uniquely generate their own nitrogen in the root (Asner *et al.*, 2008). Four classes were defined in total. The sites used to train the classification had higher proportions of the desired species with low amounts of the other species. In the SVM feature space these sites were expected to identify appropriate support vectors with fewer training components (Foody & Mathur, 2004; Foody & Mathur, 2006).

7.2.9.2 Farm Pasture Regions of Interest

Farm paddocks, identified as fairly homogeneous (in terms of hill farm pasture), were added as additional, large-scale, regions of interest. *These ROI were only used as additional validation of the classification generated from the tarpaulin site data.*

7.2.10 Unmixing

The location of spectrally pure pixels is often unknown and much effort has been spent on methods to define and collect these from imagery (Plaza *et al.*, 2002; L. Li *et al.*, 2005; Roth *et al.*, 2012) even when ground information is not available (Tompkins *et al.*, 1997). Plaza *et al.* (2004) describe and compare several techniques for endmember extraction. The unmixing workflow in ENVI (Harris Geospatial) involves a series of steps starting with dimension reduction via minimum noise fraction (MNF), endmember determination via Pixel Purity Index (PPI) and then unmixing (Boardman *et al.*, 1995). The PPI repeatedly projects multidimensional scatter plots recording the extreme pixels. After multiple iterations the process allows projection of those pixels in the n-D Visualizer for user selection of endmembers. In ENVI, automated endmember selection is available or user defined endmembers may be selected via the n-D Visualizer or imported via a spectral library.

This study uses the method outlined by Garcia and Ustin (2001), which was carried out in ENVI. MNF transformation followed by PPI was used for endmember selection prior to linear spectral unmixing. A poor result (data not shown) prompted the process to be repeated with user defined endmembers introduced via a spectral library collected from the most homogeneous survey sites.

As per the recommendation by Keshava and Mustard (2002), the spectral library was generated from pixels located at the coordinates of the purest browntop, ryegrass and clover ground sites.

A spectral library collected from imagery is thought to better represent the image components than one created in the laboratory as calibration problems can arise from such comparisons (Garcia & Ustin, 2001). However, this introduced the potential for endmembers, that themselves represented mixtures and because they were collected from training samples may not represent all endmembers in the scene. J. Li *et al.* (2015) report similar problems and propose that those issues were acceptable in their instance. Given the difficulty of finding 100% pure pixels in an image (Keshava & Mustard, 2002) and the goal to define the distribution of key pasture components this compromise was deemed to be acceptable in this study.

Mixture Tuned Matched Filtering (MTMF) is a linear unmixing method that allows partial image components to be detected and does not require the description of every endmember to function (Boardman *et al.*, 1995). This process was performed in ENVI through the spectral hourglass wizard similar to the approach taken by Parker Williams and Hunt Jr (2004). MTMF and the standard linear spectral unmixing workflow were also performed in ENVI on transformed data as outlined in Figure 7.2.

7.2.11 Post-Classification Site Visit

A site visit was made after the classification to confirm if features prominent in the classification were accurate. Five days after the first ground data collection an agronomist visited the site with a member of the farm staff to assess the general species composition for large areas of the farm. Prominent features were located in the classification before the site visit. The site visit assessed if the conditions at the chosen sites could be matched with the results of the classification.

7.3 Results

New Zealand hill country pastures are notoriously variable (Wan *et al.*, 2009; P. Kemp & Lopez, 2016) and this is supported by the species composition data in this study. The overall accuracy (OA), assessed using the ground sample sites only, was 56% - 57%. When paddock ROIs were added to the validation the accuracy was 84% - 88%. The results are presented for the classification followed by unmixing. The first classification accuracy to be defined and discussed is for the tarpaulin survey sites. These results are followed by the paddock scale validation. Overall accuracy (OA) and Kappa accuracy are discussed and compared. A number of farm locations were selected prior to being revisited post-classification to examine how on-farm conditions related to the classification results. Results for eight regions across the farm are discussed with added commentary from the farm owner.

Extracts of the statistical output for the classification are used within this text; see Appendix 1 for the entire statistical output for each classification.

Class assignment of the ground survey data were challenging for several sites. For example, sample V8 (Table 7.2) has relatively uniform coverage from each of the indicator species. The classification demands that each site is assigned to a single class so expert knowledge is used to 'force' inclusion into a single exclusive category. The contribution from the other categories guided the class decision. In instances where a single indicator species is not dominant other species were combined to define the class. Browntop was combined with the group 'other species' into LFT and ryegrass combined with legumes into HFR. Ryegrass and clover are commonly sown together to promote a symbiotic partnership (D. Stevens *et al.*, 2007) so it is reasonable to combine them into the HFR class when ryegrass is present. The contribution of the 'other species' in the pasture was combined into the LFT class as the ingress of many other species signals a possible decline in pasture quality (Lambert *et al.*, 1986). Table 7.2 lists the user defined category for each survey site; nine sites needed extra consideration before class allocation. Twenty-one of the forty-nine sites are categorised as LFT, ten sites were legume and eighteen were **HFR** (Table 7.2). Figure 7.4 displays the whole farm pasture classification results from the 1st derivative transformed data.

*Table 7.2: Details of the botanical composition collected for the 49 tarpaulin sites. Classification Training identifies if the site was used to train the classification. Cells with "T" had trace amounts of the component present but not enough to make 1%. An asterisk * alongside the user defined class indicates sites where class assignment was 'forced' by inclusion of the 'other species' in the determination.*

Classification Training	Point ID	Browntop %	Ryegrass %	Clover %	Dead material %	Other pasture %	Offset Direction	Offset Distance (m)	User Defined Class
N	V1	80	0	10	1	9	65°	3.0	LFT
N	V2	77.5	T	2.5	10	10	130°	3.9	LFT
N	V3	65	5	20	T	10	110°	8.4	LFT
Y	V4	85	0	T	5	10	110°	8.4	LFT
Y	V5	T	70	25	0	5	110°	6.5	HFR
Y	V6	50	5	0	2	43	135°	3.1	LFT
Y	V7	90	0	T	5	5	130°	4.0	LFT
N	V8	35	35	20	5	5	270°	1.0	HFR*
Y	V9	80	0	15	5	0	60°	0.8	LFT
N	V10	75	5	10	5	5	110°	5.9	LFT
N	V11	20	55	20	2	3	50°	3.6	HFR
N	V12	20	40	20	2	18	80°	4.8	HFR
N	V13	25	15	25	T	35	105°	11.1	LFT*
N	V14	25	0	60	T	35	295°	3.5	L
N	V15	10	10	50	T	30	110°	6.7	L
Y	V16	10	5	60	T	25	120°	1.6	L
N	V17	20	0	50	T	30	90°	4.3	L
Y	V18	10	5	60	T	25	105°	2.9	L
Y	V19	40	5	10	2	33	130°	5.5	LFT
Y	V20	58	5	25	2	10	140°	4.1	LFT
N	V21	20	20	20	2	38	135°	5.7	LFT*
Y	V22	0	99	T	0	1	205°	2.3	HFR
N	V23	5	5	50	T	40	90°	3.5	L
Y	V25	3	5	65	2	25	90°	2.9	L
N	V28	10	80	10	0	0	110°	7.0	HFR
Y	V29	0	50	50	T	0	110°	3.7	HFR*
N	V30	0	80	15	0	5	100°	0.6	HFR
N	V31	5	15	5	T	75	80°	1.7	LFT*
N	V32	10	0	0	T	90	110°	6.7	LFT
Y	V33	0	75	25	T	0.1	130°	7.1	HFR

Y	V34	0	0	100	0	0	110°	5.8	L
Y	V35	0	0	95	0	5	90°	2.8	L
Y	V36	0	75	5	1	19	105°	5.6	HFR
Y	V37	0	30	40	T	30	50°	3.8	HFR*
Y	V38	50	30	10	1	9	310°	1.0	LFT
N	V39	40	40	5	1	14	110°	3.7	LFT*
Y	V40	40	T	T	15	45	350°	2.3	LFT
N	V42	15	20	40	1	24	100°	5.6	HFR
Y	V43	85	5	0	5	5	70°	6.7	LFT
Y	V44	10	50	5	5	30	120°	5.8	HFR
Y	V46	10	85	0.1	T	5	140°	4.0	HFR
N	V47	0	60	35	0	5	130°	4.8	HFR
Y	V48	0	90	5	0	5	130°	4.9	HFR
N	V49	5	39	40	1	15	110°	6.0	HFR
N	V50	5	40	40	T	15	110°	6.5	HFR*
N	V52	10	30	2	2	56	135°	3.9	LFT*
N	vt2	60	0	5	3	32	140°	2.4	LFT
Y	vt27	T	70	30	T	0	130°	3.8	HFR
N	vt3	20	10	10	60	0	45°	4.1	LFT

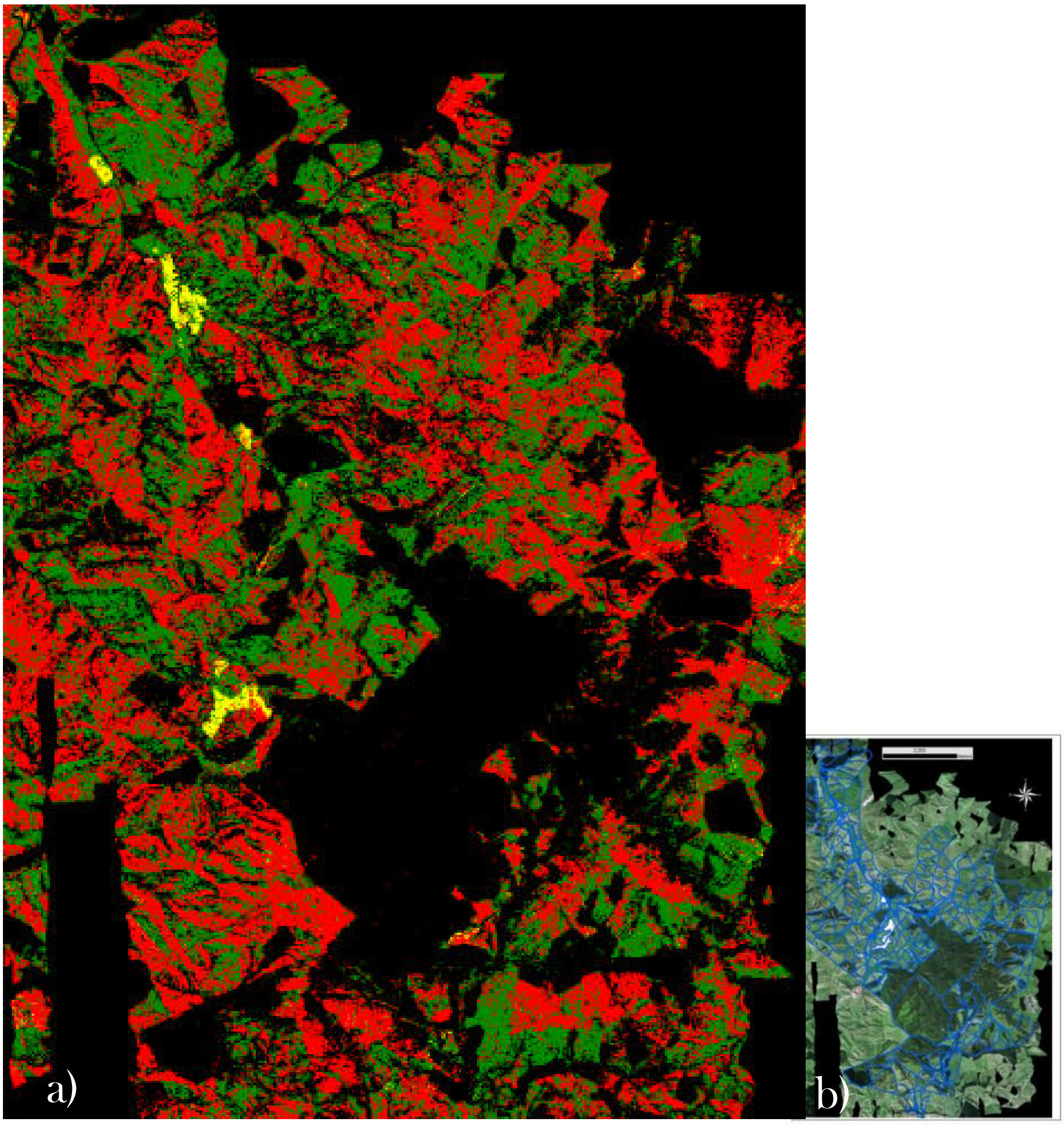


Figure 7.4: (a): SVM classification of the pasture at Patitapu Station using the 1st derivative data with green representing HFR, red is LFT and yellow as legumes. (b): Colour image of the study site with paddock boundaries defined by blue lines. Black regions were masked out prior to the classification.

7.3.1 Classifier Performance Assessment

The OA of the classification considers the accuracy for all the classes combined. Many in the remote sensing community define the acceptable classification accuracy as >85%, although this target appears to have been adopted without regard to its origin (Foody, 2008). It is suggested that a project's individual objectives define acceptable classification accuracy as lower accuracies may still represent a success, although one that may later be improved.

7.3.1.1 Tarpaulin Sites

The OA was consistent (56% - 57%) for all data types used in the classification. Table 7.3 lists the OA and kappa for each result. This is a major advance in the research of hill farm pasture composition and distribution given the current lack of any spatially referenced information on pasture composition. The tarpaulin site assessment accuracy was generated from the 25 test sites isolated from the training set. Although the OA was relatively good the kappa statistics did not match as well (14% - 27%), suggesting poor agreement of class as defined by Monserud and Leemans (1992). The disagreement is due to the very high commission and omission error associated with the legume class, for example Table 7.4. The omission error for the legume class in Table 7.4 is much higher than other classes; 91% of the pixels defined by the operator as legume are described by the classifier as one of the other classes. Possible reasons for the error include the need to collect ROI from areas much larger than the sample and the variability of the species present around the area surveyed on the ground.

Table 7.3: Overall accuracies and associated kappa for each classification with each form of data transformation.

Data Transformation		Tarpaulin Sites	Paddocks
1st Derivative	OA	57.44%	88.75%
	kappa	24.48%	82.72%
MNF	OA	56.02%	86.03%
	Kappa	27.28%	78.11%
1st Derivative (No SWIR)	OA	56.02%	84.46%
	Kappa	14.66%	75.65%

Table 7.4: Error types and rates for the 1st derivative data from the tarpaulin sites (OA 57.44%).

Class	Commission (%)	Omission (%)	Commission (Pixels)	Omission (Pixels)
LFT	30.49	28.75	25/82	23/80
HFR	59.26	40.54	32/54	15/37
Legume	60	91.67	3/5	22/24

Grasses usually dominate hill country pastures. Legumes are only strongly competitive for short periods of the year and populations can fluctuate wildly depending on grazing practices (De La Hoz & Wilman, 1981). The peak of ascendance of a species of interest might not coincide with data collection and this should be considered when reporting or relying on results. The botanical composition analysis from the previous PGP survey from spring 2015, November (data not shown), found only five of 395 sites had a clover content over 35% (the highest was 40%). The results collected for the current survey showed high concentrations of legumes across the farm (Table 7.2). A solution to the issue of legume visibility is to time the survey to take advantage of the spectral visibility, or invisibility, of the targets of interest as advised by Cole *et al.* (2014).

Where surveys cannot be timed to ensure the visibility of all relevant species then multiple surveys may be necessary. For farm management decisions, accuracy of each species might be considered less important than the goal of defining primary habitat as habitat distribution could provide an acceptable proxy for many species.

Results from the tarpaulin sites do not meet the 85% target accuracy suggested for such maps. The diversity of the landscape means the pasture class can change over small distances (López *et al.*, 2006). Operational constraints limited the number of tarpaulins, so it was not possible to gather more samples. Other potential sources of error include the small areas surveyed and need to collect ROI from areas larger than the survey site, within the image. Ground reference error is often a problem when validating remote sensing outputs (Foody, 2010). While a classification may approach 100% accuracy, the absence of highly detailed ground reference information from a great number of sample sites makes validation in highly variable landscapes difficult. Spatial error of imagery is another likely source of error for the validation and more importantly for the definition of training samples for the classification. While the spatial error for this imagery was previously reported as only 2-3 metres (Pullanagari *et al.,* 2016), this study revealed the real error is two to four times greater. This revelation prompted concern the targets of the validation were too small to be relevant to farming and for the objective of mapping pasture quality. To address this and the relatively small sample size, attention was focused towards validation using larger targets, those targets with known, homogeneous pasture content.

7.3.1.1 Paddock Sites

The more homogeneous paddocks were identified, and ROI created. Figure 7.5 shows the class image produced from the ROI of those paddocks. The original classifications were compared against the ROI of the homogeneous paddock areas.

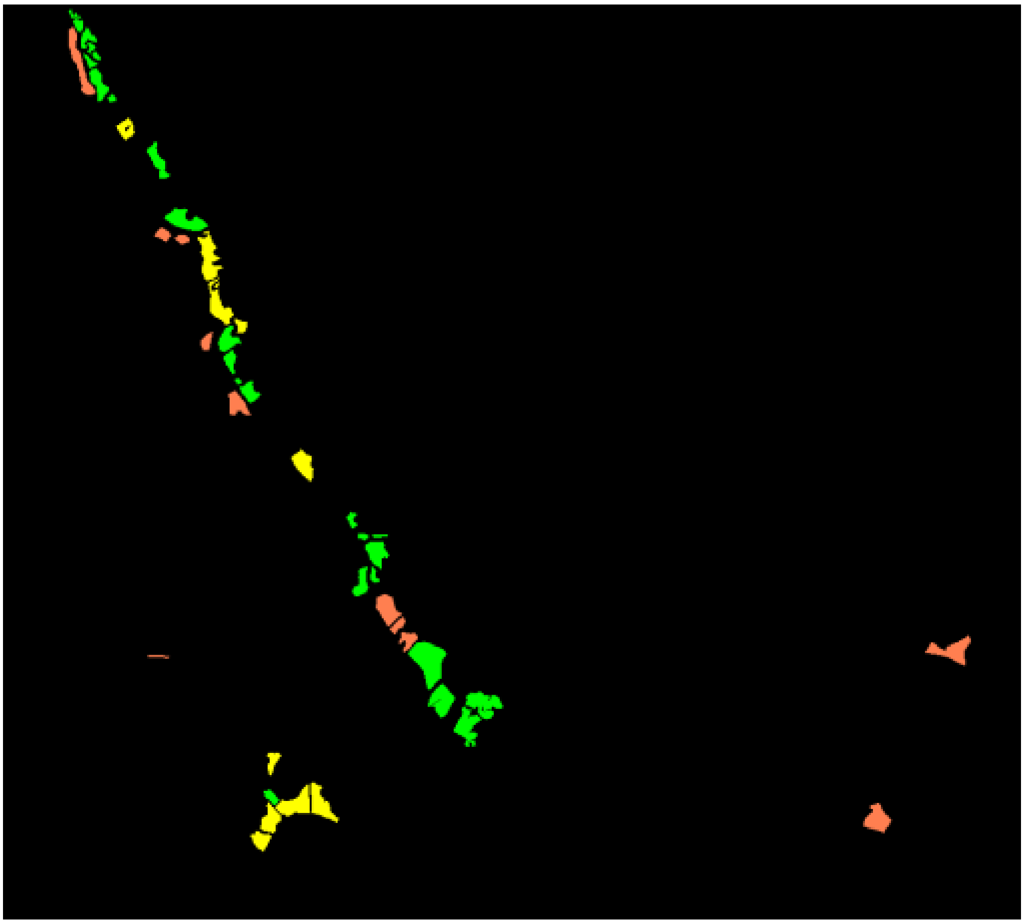


Figure 7.5: Region of interest image created from on site assessment and with the aid of the farm manager. Green are paddocks seeded with a ryegrass (HFR) dominated seed mix. Yellow are paddocks sown with 100% legumes (white and red clover). Red are locations where browntop (LFT) dominated the sward in most, or all, of the paddock.

The overall accuracy and kappa both increased markedly to >84% (e.g. Table 7.5) when the classification was compared to the homogeneous paddocks. Data transformation had little effect on the OA again. More importantly, the OA and kappa have much closer agreement signalling better overall agreement in each class. Including paddock data dramatically increased the proportion of the image assessed for accuracy from 141 pixels to 766,934 pixels (141 m² to 76.69 hectares. This is important when presenting results and discussing the validity or utility of such an analysis to a farm owner or manager.

Table 7.5: Producer accuracies (%) for each classification using tarpaulin sites and using additional paddock validation data.

	Tarpaulin Sites			Paddock Sites		
Class	1st Der.	MNF	1st Der. (No SWIR)	1st Der	MNF	1st Der. (No SWIR)
LFT	71.25	62.5	80	89.81	64.63	77.7
HFR	59.46	67.57	29.73	84.09	89.06	88.54
Legumes	8.33	16.67	16.67	94.99	99.81	83.71

The use of kappa statistics as a metric for assessing accuracy was questioned by Foody (2008) who suggested that 'producer' accuracies (100% minus the omission error) was a more useful metric. The 'producer' accuracies provide information for each class rather than just a total. Table 7.4 lists the producer accuracies for each analysis. They often show a large increase, particularly for legumes, when paddock data is used for comparison of the classification. The full spectrum 1st derivative data provided the best overall results, see Tables 7.4 and 7.5.

The key challenge with determining classification accuracy is the need to supply appropriate ground truth data. The term 'ground truth', while frequently used to describe ground data, is often criticised (Brogaard & Ólafsdóttir, 1997; Foody, 2008). Ground data points with associated compositions for this study are listed in Table 7.2. Nearly every site has a different composition and while 'other' species are not listed, PGP data identified more than twenty species in previous surveys of this farm (data not shown) and other researchers have found more than 40 species in hill country pastures (López *et al.*, 2006). Another challenge is the initial class applied may be incorrect and could provide a negative bias to the assessment of accuracy. Foody (2008) highlighted many of the issues relating to interpretation of classification accuracy.

Still, the highest classification accuracy of 88.75% is an important advancement in understanding the spatial variability of pasture. A key finding of the research shows the distribution of key indicator species can act as a proxy to map farm habitat without collecting vast amounts of ground data. Further, it is proposed that this form of classification can guide operational and management decisions. Consequently, it is important the classification relates to ground conditions recognisable by managers and industry professionals. Including larger homogeneous areas will almost certainly improve industry opinion of this work but to examine and reinforce the validity of the results a post classification visit was undertaken to produce further supporting evidence.

7.3.2 Post Classification Feature Analysis and Discussion

A classification accuracy statistic alone may be too abstract to gain the full confidence of industry practitioners. The post classification visit intended to examine prominent features, identified from the classification, to ascertain their existence, or not, in the landscape. These features ranged in size from paddock scale (hectares) down to specific features (hundreds of square meters).

The goal of the visit was to corroborate the results of the classification by adding some supporting evidence that features defined in the classification existed on the ground. This was achieved by finding clearly defined features within the classification and visiting the site to confirm its presence with additional species identification. The farmer also visited the author to discuss various elements of the classification at length to incorporate some of his extensive knowledge into the discussion. The following sections relate those findings and discussions. The 1st derivative full spectrum data were deemed most accurate so was used in the subsequent site visit and owner discussions. Several features were examined, and the results grouped into seven regions for simplified mapping.

7. 3.2.1 Post Classification Feature Analysis 1

The series of paddocks highlighted in Figure 7.6 were all examined pre and post classification by an agronomist. Although no tarpaulins were sited in 'A' or 'B', pasture composition at several locations were assessed at the time of survey to contain at least 50% browntop.

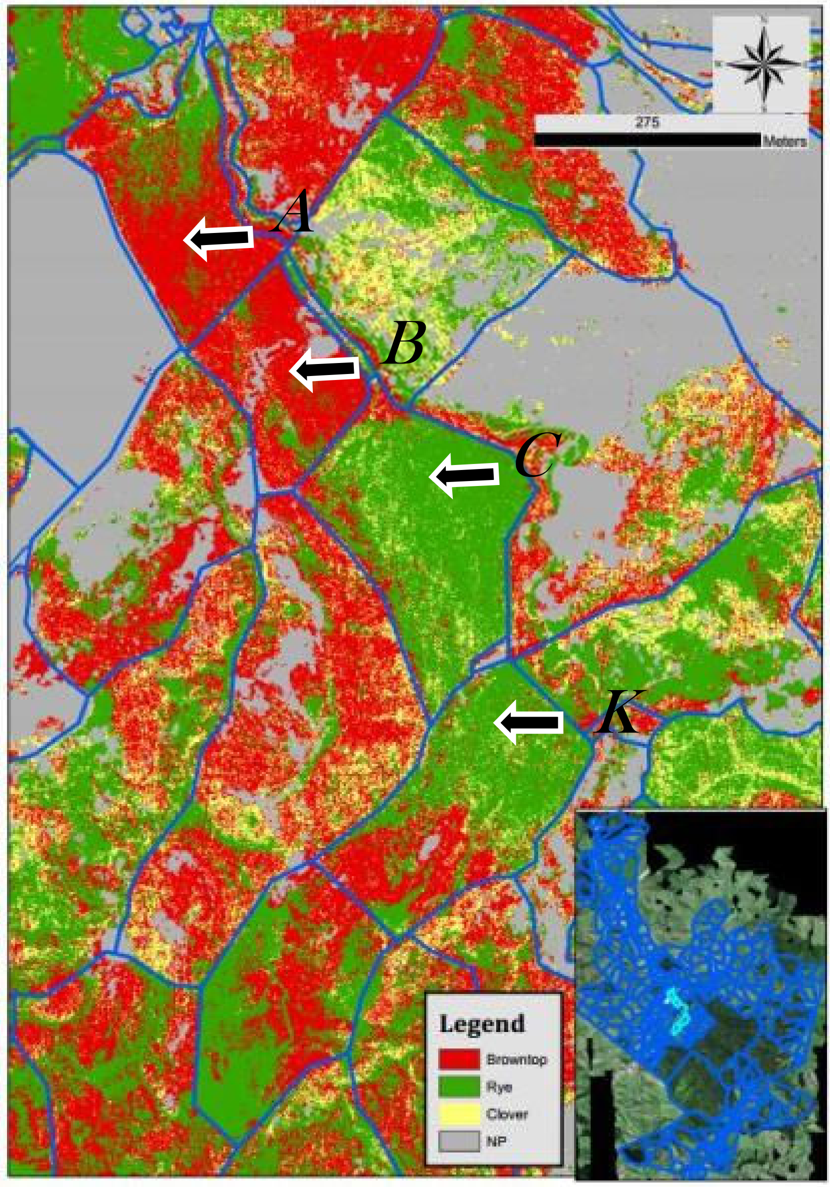
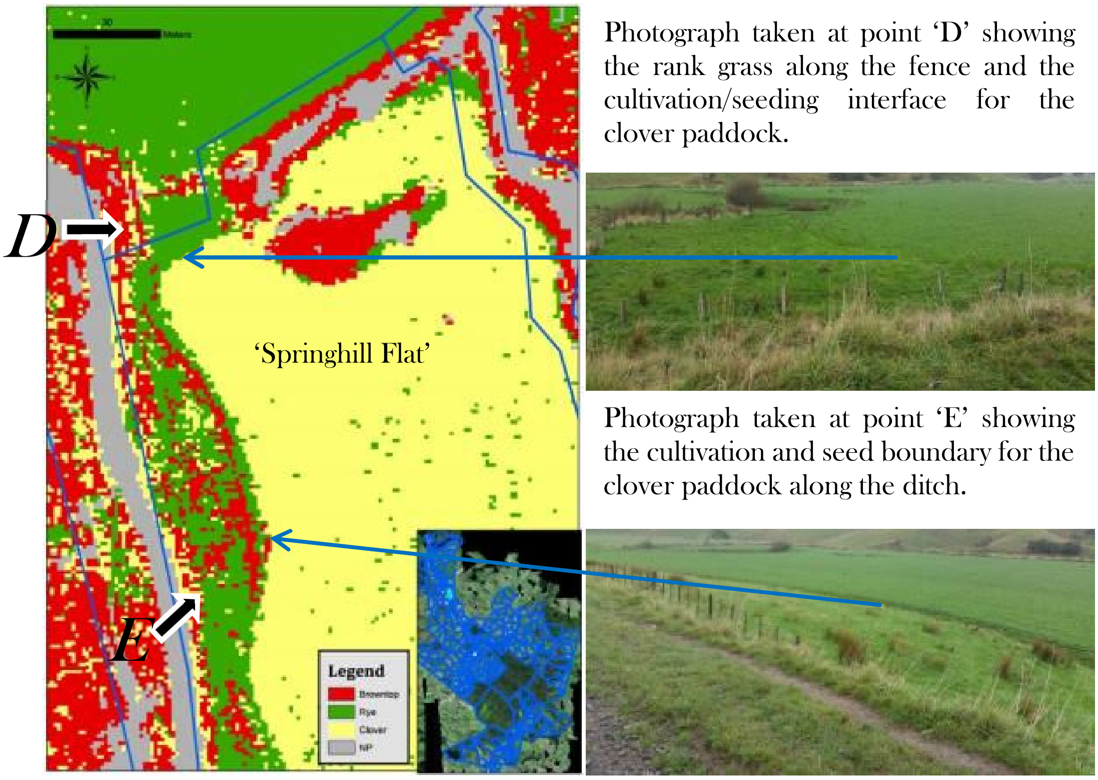


Figure 7.6: Classification results for 'Ram Flat' ('A'), 'Graemes Flat' ('B'), 'Smithies Flat' ('C') and 'Smithies Hill' (K) from 1st derivative data. Green = HFR, Yellow = legumes and Red = LFT.

The tarpaulin site located near point ‘C’ was assessed at 70% ryegrass and 30% clover (Table 7.2, VT27). According to the farm owner, three of these paddocks were renewed in recent years with a ryegrass/white clover mix. ‘Paddock C’ and ‘Paddock K’ were re-sown just two years before this survey and ‘Paddock B’ two years before that. Notably, this chronology suggests the site reverts to browntop in about three years and the ground assessment data strongly correlates with the classification results. The northern part of ‘Paddock A’ had more ryegrass, probably because browntop is less tolerant of treading damage from stock movement; historically, farmers have used heavy grazing coupled with treading to suppress browntop (Peter Kemp, personal communication). The farmer confirmed that ‘Paddock A’ is a holding paddock for the nearby sheep yards and suggested the northern entrance, that received heavy sheep traffic throughout the year, would not support browntop. The farmer described ‘Paddock B’ as wet and was unsurprised it was classified as LFT. He explained that despite being flat it reverted to browntop within a year of being sown in ryegrass.

7.3.2.2 Post Classification Feature Analysis 2

Figure 7.7 shows a close-up view for one portion of the classification of 'Springhill Flat', one of the twelve paddocks on the farm sown with 100% legumes. Physical and topographic constraints limited the cultivation and sowing. There is a slope leading down from the farm entry road where a ditch was installed to facilitate surface drainage (photo at point E). The ditch constrained the sowing operation. Assessment of the species on these boundaries by a trained agronomist confirmed the paddock was legumes while the boundary area was dominated by ryegrass. Although GPS data were not collected (and would have been unhelpful with the error in the imagery) the feature appeared closely replicated in the classification. The clear definition of the sown extents of this crop supports the classification accuracy and provided the farmer with a result he could interpret from his own knowledge of the farm.



Photograph taken at point 'D' showing the rank grass along the fence and the cultivation/seeding interface for the clover paddock.

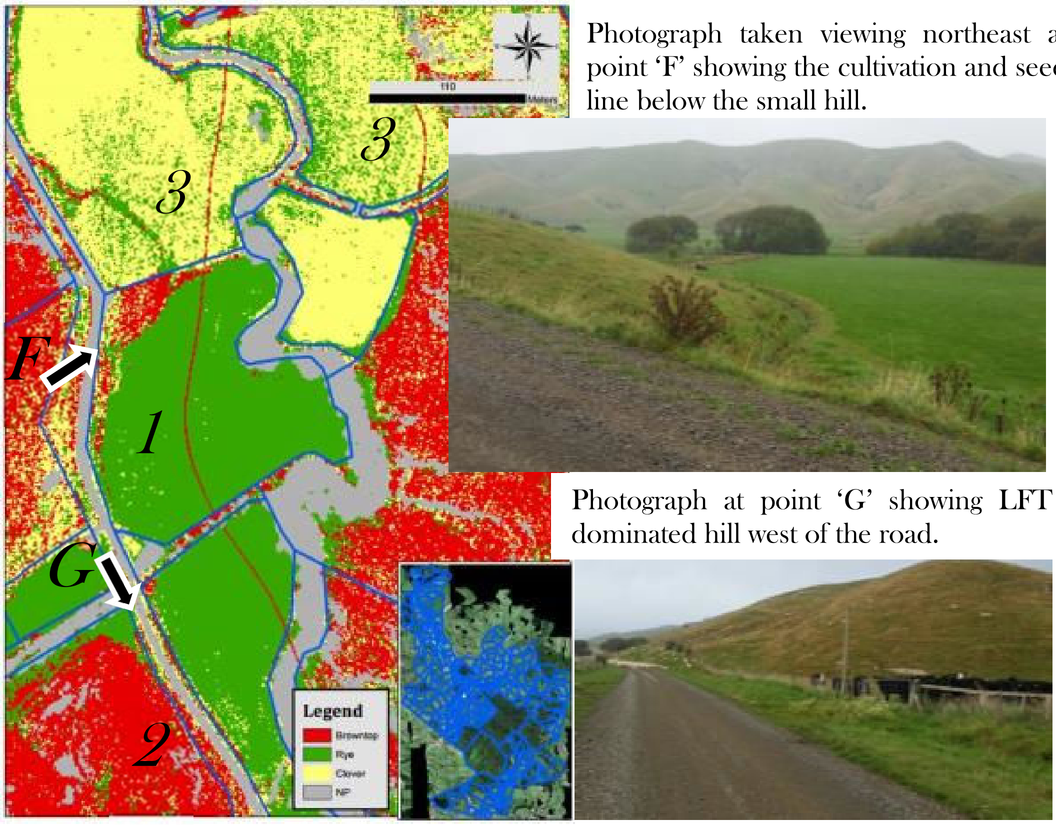
Photograph taken at point 'E' showing the cultivation and seed boundary for the clover paddock along the ditch.

Figure 7.7: Classification of 'Springhill Flat' which was sown in legumes (yellow). Photographs were taken at the locations (A & B) in the direction indicated by the arrow. The blue arrows highlight the extent of the clover sowing operation. The extent of sowing was visible from point 'E' which is constrained by a drainage ditch. Green = HFR, Yellow = legumes and Red = LFT.

7.3.2.3 Post Classification Feature Analysis 3

Figure 7.8 shows another region of the farm classification. The images show that spatial features which have been visually verified are well defined in the classification. In Figure 7.8, the northern boundary of ‘paddock 1’ has a steep hill with a drainage ditch at the base. Unlike the rest of the paddock, that hill had not been cultivated nor sown in ryegrass. In discussion with the farm owner, the classification matched well with his understanding of the ‘real life’ situation.

The farmer confirmed the LFT classification of ‘paddock 2’ illustrated in Figure 7.8 is accurate and described the soil on that hill as “poor”. The site visit and farmer discussion support the overall accuracy of classification.



Photograph taken viewing northeast at point ‘F’ showing the cultivation and seed line below the small hill.

Photograph at point ‘G’ showing LFT dominated hill west of the road.

Figure 7.8: Classification of ‘Central Flat’ (1) with photographs taken at the locations ‘F and G’. The edge of sowing is clearly visible from ‘F’ which is constrained by a drainage ditch visible in the photograph. ‘Road’ paddock (2) as viewed from ‘G’ was validated as steep with high levels of browntop. Green = HFR, Yellow = legumes and Red = LFT.

The two clover paddocks, Figure 7.8 (3), were discussed at length with the farm owner because of the 'speckled' nature of the classification. This 'salt and pepper' effect is commonly attributed to a classification failure prompting majority filters or other post classification smoothing techniques to lessen the effect (D. Lu & Weng, 2007). Lessening these effects can improve the classification accuracy if the region is homogeneous. Note, there must be good confidence that areas are homogeneous if these smoothing operations are to be carried out.

The farmer recognised the location and agreed with the accuracy of the mixed 'salt and pepper' classification result. He explained that shortly after establishment the area was invaded by docks (*Rumex spp*) which were eventually removed by spraying selective herbicide. The resulting bare patches were colonised by ryegrass. Post-classification smoothing may eliminate true results in the heterogeneous environment so was not performed in this case. The farmer identified two other locations (data not shown) where a mixed classification occurred; one with a thistle infestation and the second was a missed herbicide application. These confirmations by the farmer that the classification is accurate justifies the decision not to smooth the results.

7.3.2.4 Post Classification Feature Analysis 4

Figure 7.9 shows an area that did not match the classification when examined by an agronomist for the post classification assessment. The part of the paddock classified as LFT (red) indicated at point 'H' was in fact mostly ryegrass (HFR). It had been allowed to go to seed and therefore had a lot of standing, non-photosynthetic seed head material, so much so that on first approaching and viewing the area from a distance the classification initially appeared correct. It was not until a close inspection and botanical identification that this opinion changed. In this instance the classification appears to have picked up on the quantity of seed head that was generally present in LFT areas during this survey and classified it as LFT. All the other locations checked within the surrounding area showed a strong correlation with the classification.

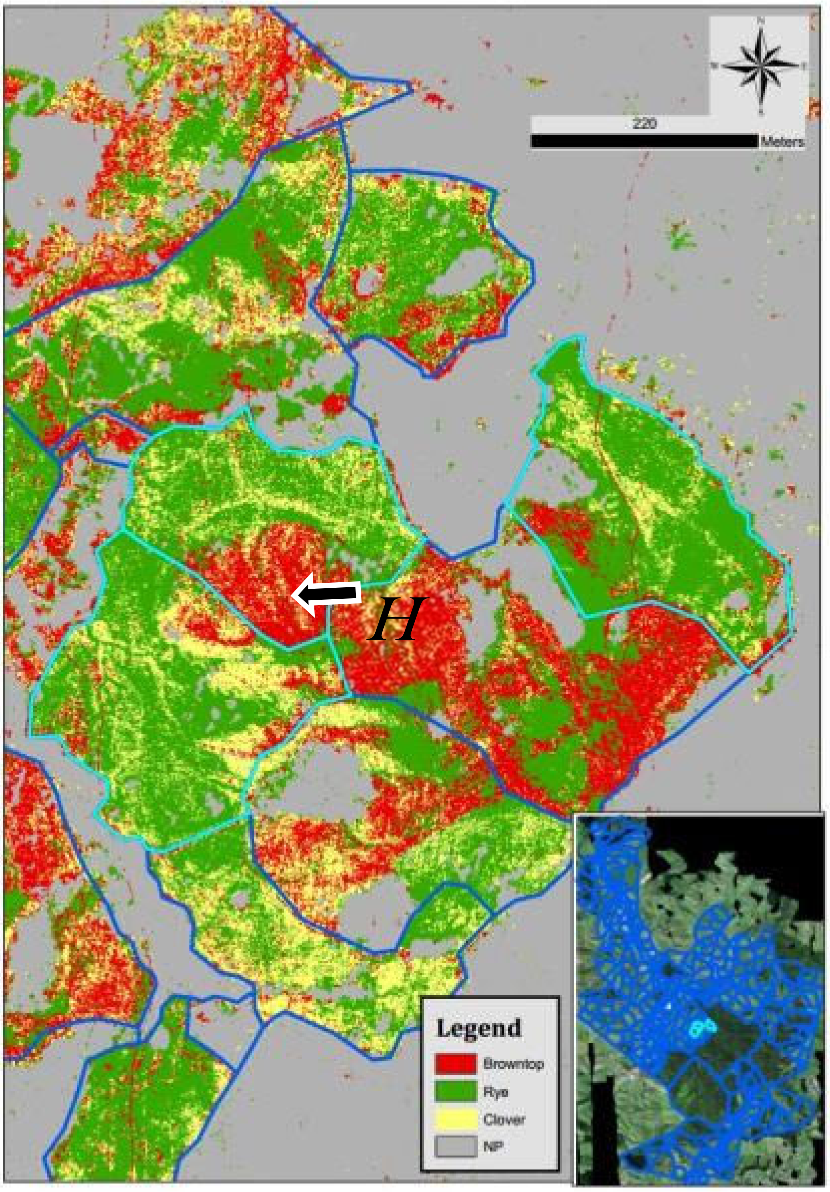
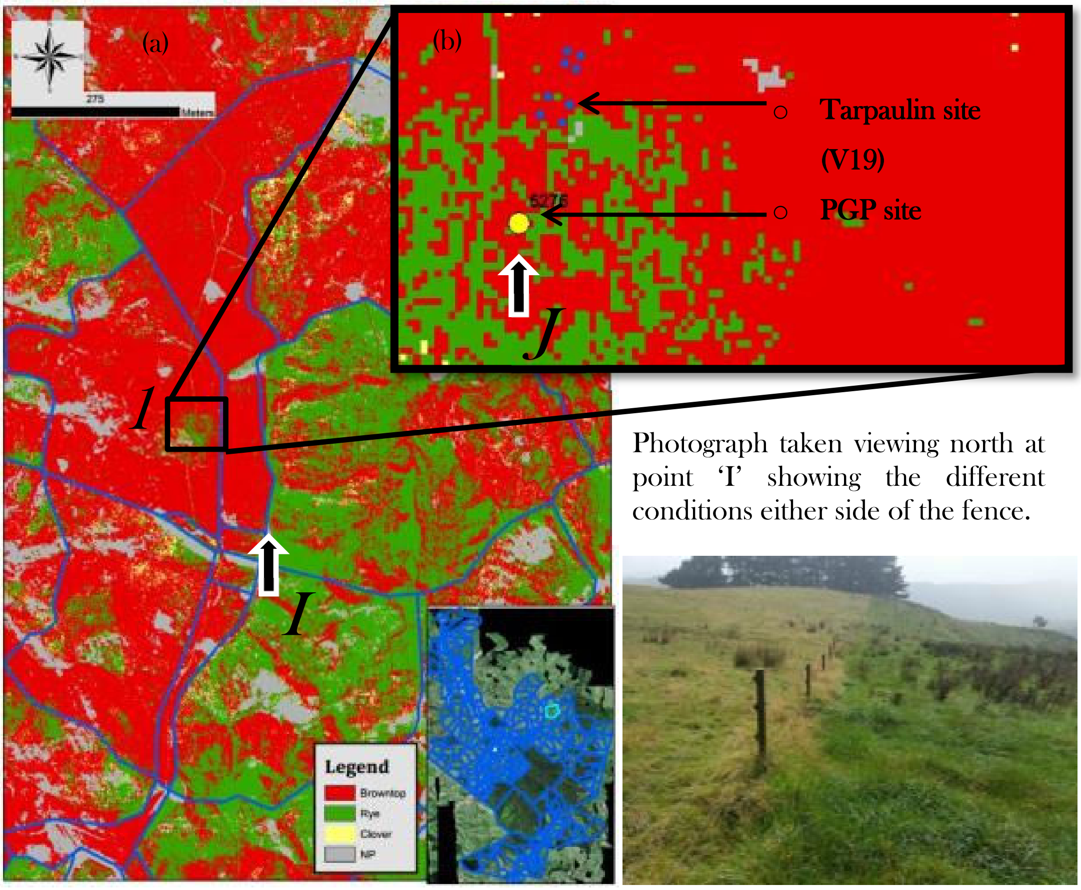


Figure 7.9: Classification of 'Taipos' ('H') which includes a portion of a hill. Green = HFR, Yellow = legumes and Red = LFT.

7.3.2.5 Post Classification Feature Analysis 5

Two more locations examined for their accuracy are shown in Figure 7.10. The photograph taken at point 'I' highlights the pasture growth produced since the autumn rains started. Although browntop was present on both sides of the boundary, ryegrass easily dominates the eastern (right in photo) side.



Photograph taken viewing north at point 'I' showing the different conditions either side of the fence.

Figure 7.10: Classification for 'Ridges Top' (1) with photograph taken at the location indicated 'I'. Point 'J' marks a PGP sample site classified as ryegrass dominant in both surveys. Green = HFR, Yellow = legumes and Red = LFT.

A visit to the former PGP location, Point 'J' in 'Paddock 1' (Figure 7.10) confirmed the validity of the ryegrass classification for that location. Point 'J' lies atop a hill with the surrounding area having high quantities of ryegrass. Strong slopes radiate down from this site, in particular to the north and west, all of which were assessed at multiple locations as being browntop dominant. The classification accuracy was confirmed by the difference between the PGP site and tarpaulin location. The PGP site consistently dominated by ryegrass in past surveys was only 25 m from the tarpaulin placement for this survey (V19). V19 was assessed as browntop dominant (40%). A farm worker commented the top of the hill was a stock camp and ryegrass is more competitive in high fertility situations (Matthew *et al.*, 1988) such as stock camps. The flat location and increased nutrient deposition from animal excreta could explain the ability of ryegrass to persist in a largely browntop dominated region of the farm.

7.3.2.6 Post Classification Feature Analysis 6

'Smithies Hill' (Figure 7.11, 'K' and 'L') is classified as LFT in the southern half of the paddock and a post-classification examination of the topography suggests the possible cause; the southern part of the paddock ('L') is a steep hill. The tarpaulin site near 'K', was 80% ryegrass with 10% browntop. The post-classification botanical assessment of the wider paddock suggests there was more browntop than the tarpaulin site analysis. Although not dominant, the species assessment identified browntop throughout the paddock especially on the hill to the south. The ryegrass population was higher on the flat ('K'), but there is much less ryegrass on the hill ('L') and the browntop was more prominent there. Notably, the classification accurately represents the field, suggesting it may be worth separating these flat and hill areas as they need different management. Fencing large paddocks into smaller zones is another management option to help with stock control and species manipulation. These results suggest that classification may be a useful tool to aid decision-making on-farm for fence placement for stock control and species manipulation.

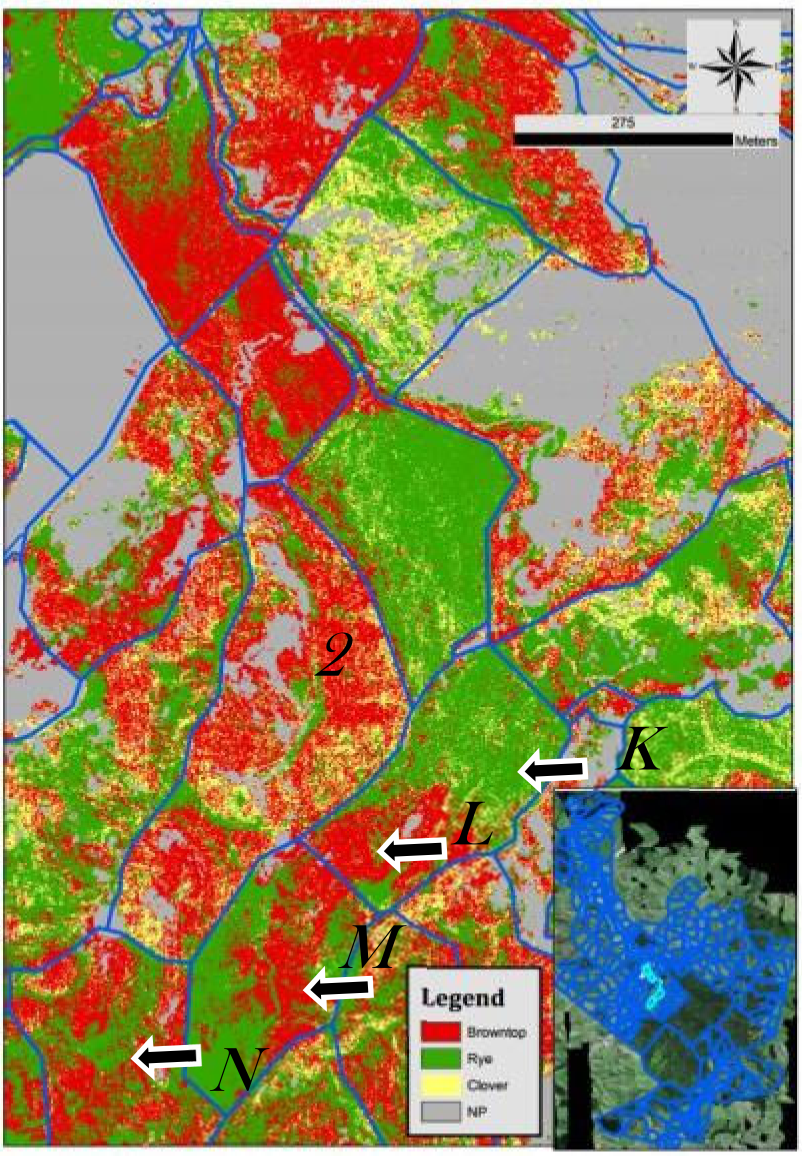


Figure 7.11: Classification of 'Smithies Hill' ('K' and 'L'), 'Top Smithies' ('M') and 'Top Ridge' ('N'). Green = HFR, Yellow = legumes and Red = LFT.

Tarpaulin site V31 in 'Paddock M' was dominated (75%) by non-indicator species. Field observations from the post-classification visit suggest a correlation with the classification. However it was not defined as clearly as other areas. According to the farm owner that area of paddock "M", which was classified as LFT, suffered from undiagnosed establishment problems after reseeding in 2015. This may be because of lower soil fertility or other underlying issues that warrant investigation; the classification provides a means to direct appropriate sample collection by helping define a possible zone of effect. Without this classification, a standard sampling protocol, designed to lessen spatial variability (Morton *et al.*, 2000) would combine samples from the whole area with the higher fertility areas balancing the low areas. The traditional approach would be unlikely to identify the problem areas and the farmer would be unable to resolve the underlying fertility, or other, issues.

7.3.2.7 Post Classification Feature Analysis 7

At first glance the paddock classification indicated by Figure 7.12 (P) appeared to be an error. The paddock is dominated (75% of area) by a very steep (>30°) south-facing slope. At previous PGP site visits the area was mostly browntop and other LFT species. The farmer explained that this paddock and some other areas (eg the paddock in the east of the image in Figure 7.10) were 'chemically topped' by spraying 200 ml of glyphosate, total herbicide, in 50 litres of water per hectare. The goal was to improve the pasture by inhibiting or killing the dominant low fertility species, allowing the suppressed higher fertility species to compete. The tarpaulin sites in this paddock bore evidence of the process working locally with low percentages of browntop recorded at each (Table 7.2, V36 & V37).

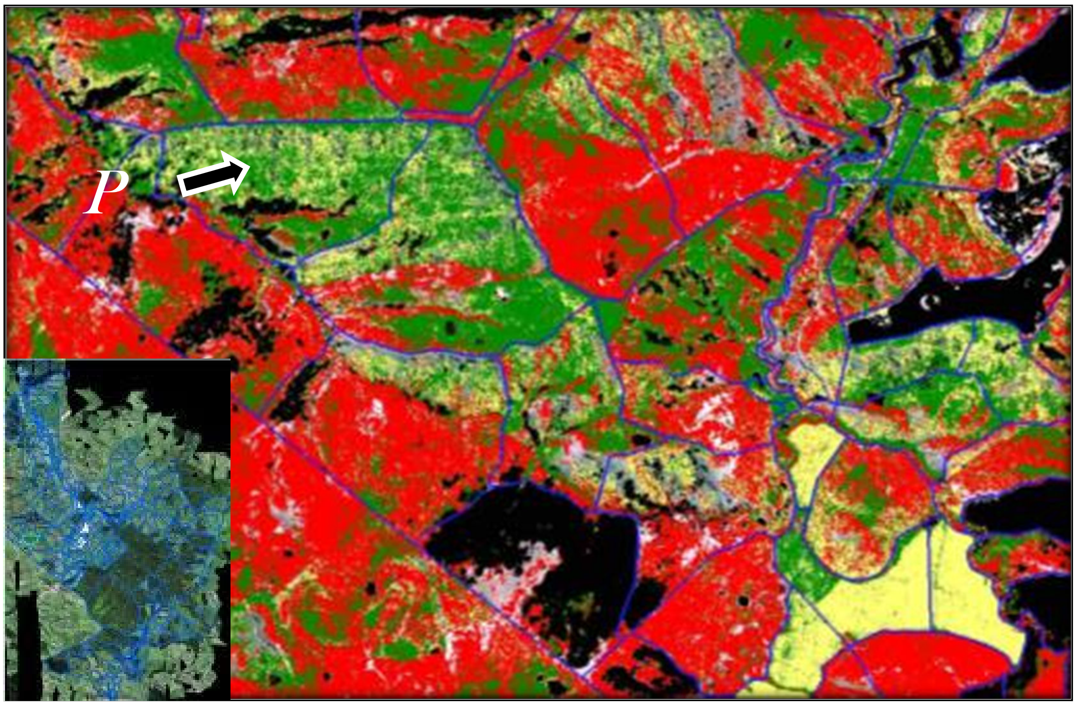


Figure 7.12: Classification image for 'Moaland' (P) and surrounding paddocks. Green = HFR, Yellow = legumes and Red = LFT.

The classification suggests the treatment worked very well over the whole area and as far as the farmer was concerned was justification of the expense of the spray application. While the farmer did not need a classification to inform his decision to perform 'chemical topping', it did provide evidence the treatment was successful and is a management tool worth considering in future. Chemical topping has reported benefits in animal performance (Casey *et al.*, 2000) and these results confirm the widespread effectiveness. Caution is advised with this strategy though, as chemical resistance can develop with repeated low doses of such chemicals (Harrington *et al.*, 2016). The results suggest that remote sensing has the potential to monitor pasture composition at the paddock scale. The information would be useful to farmers considering chemical topping and could alert them to when the benefits have worn off. The balance of performance against the risk of chemical resistance would be worthy of future research.

7.3.3 Unmixing Results

Unmixing of sub-pixel components has the potential to increase the detail on pasture species distribution throughout the farm. The previous sections focused on classifying each pixel into functional groups based on the dominance of species in that pixel. The resolution of the final classification output will remain at the native image resolution (1 m^2 per pixel) and only provide information about the dominant class to the exclusion of other components. Unmixing has the potential to provide sub-pixel details on each component. However, in this case the unmixing was unsuccessful. Details of the unmixing results are included in Appendix 2.

7.4 Key Findings and Potential Benefits

7.4.1 Classification

This study aims were to map the major pasture components that dominate their functional groups and show that a hard classification approach can represent the spatial distribution of these key pasture species habitats. The accuracies reported (>84%) support the hypothesis that it is possible to define meaningful information from hard classification techniques in this diverse and complicated landscape.

The difficulties of pasture classification in the hill country environment stem from the infinite variability of a pasture ecosystem that has over forty species interacting within a complex physical environment. Further, the components are sub-pixel in size and the sensor only receives an average total reflectance for each group of components. This average spectral signature could, in theory, be constructed in many ways, with different quantities of many varied components. Mapping such a complex system in great detail is not yet possible. However by simplifying it to a few dominant species to describe the functional groups this study advances the current model-based approaches with the addition of spatial information.

Ultimately, the complexity of the terrain, diversity of the species composition, sub-pixel nature of the targets, lack of spatial accuracy from the survey and the planned use for the results mean that this classification approach represents a more attainable solution than unmixing.

7.4.2 Landscape patterns

A useful finding revealed by the classification (particularly in Figure 7.11 at 'L' and 'M') is that, like the environment, the underlying factors that drive the results are not confined by fence boundaries. The ability to define patterns in the landscape provides opportunity to find, prioritise and address some underlying problems that might allow overall productivity improvements. At least it may be possible to redefine how fence boundaries are established as an alternative way to define management zones.

7.4.3 Grazing Management Support

The classification developed in this research provides a higher level of valuable information not currently available through other methods. The classification provides not only pasture content information but can also provide pasture area data to support farm strategic decision-making. Further, this classification can define detail that is spatially referenced, so the farmer can examine the results with a suitable map on a paddock by paddock basis without other equipment or interpretation. Such maps could support decision-making on ideal stocking rates or to identify suitable fence positions to enhance grazing management. The simplicity and user-friendly nature of the output would be attractive to an industry that, partially because of its remoteness, often has poor access to high quality internet and communications infrastructure. In addition, pasture quality information currently only resides with the farmer. Mapping pasture quality using this classification allows information to be easily exchanged digitally, allowing external farming consultants a window on the farm, which could form the basis for an advisory service.

7.4.4 Output Resolution

In the hill country environment, the existing scale (usually paddock or greater) relates to how the farmer and ancillary industries, such as fertiliser companies, might use the data. The resolution of data provided by this work (1 m^2) would require down-scaling and interpretation for fertiliser application (White *et al.*, 2017). The effective application width of present-day topdressing aircraft is around 12 - 24 metres. The 1 m^2 pixel represents a magnitude shift in resolution for today's farmers and technological limitations mean they cannot exploit fully the resolution of these maps. However, the availability of very high-resolution data may stimulate research to develop new applications and their implementation.

7.4.5 Decision Confidence

Farmers currently base their management decisions such as grazing, fertiliser application and pasture renewal on local expert knowledge, normally focusing on the most productive zones with lower slopes (Grafton *et al.*, 2016). Pasture performance information for the whole farm and VRAT technology could guide the expansion of this focus to allow experimentation into improving those pastures. This information would also help New Zealand's primary sector to meet MPI's goal to double productivity by 2050. This classification approach, supported by an understanding of the ideal growing conditions, could guide strategy on grazing, fertiliser application and pasture renewal. As these factors also influence rural property values and capital investment decisions, the detailed information could support business plans and add confidence that a farm could bear debt.

7.4.6 Model Building

Previous research on farm scale prediction of pasture components or production concentrates on the use of models (B. Zhang *et al.*, 2005; D. Stevens *et al.*, 2007; Wan *et al.*, 2009). Models are a great tool to help explain the unknown from a small number of known components but are limited by the quality of the input variables. A possible short-term use for this information is as an input variable for modelling of pasture production, replacing DEMs that are not yet accurate enough at the farm scale.

An improved model could create multiple scenarios to generate a risk profile for management decisions. Temporal surveys could be overlaid with management data to model the response to various grazing and fertiliser decisions that could form the basis for updating and individualising the model. A more detailed understanding of what factors are changing the species distribution over time would increase the overall body of knowledge to improve models in other locations. Eventually, the farm model would be a business asset that could transfer to a new owner as part of a sale agreement with the land. A high-quality farm growth model may also increase the value of associated land, especially if the model is accepted or proven to be reliable.

7.4.7 Paradigm Shift in Fertility Management

Improving fertiliser application and efficiency are central to the PGP and this research. The ability to deliver products accurately from variable rate systems is limited in hill country due to inadequacies of the current method for calculating fertiliser rates. The spatial variability of soil nutrients on hill farms is widely recognised (During & Mountier, 1967). Collecting samples along a series of transacts remains the best method to supply data for such decision-making and efforts to ensure the methods are as robust as possible have been made (Morton *et al.*, 2000). A more advanced, spatially accurate, understanding of the pasture will help hill country farmers fully realise the benefits of variable rate application technology. This research shows that remote sensing technologies can provide a better understanding of the pasture environment with information that can be integrated into pasture growth models, application maps and normal day-to-day decision-making.

Figure 7.13 depicts the current knowledge inputs with the blanket application of fertilisers as the current standard practice output.

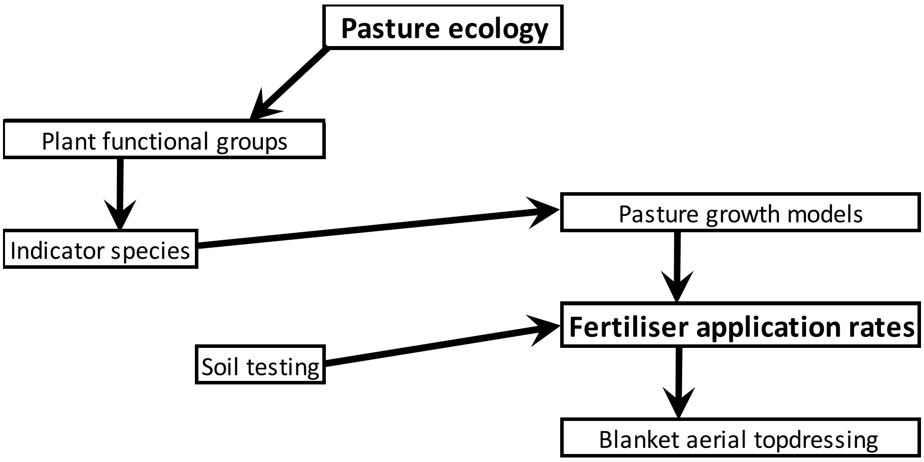


Figure 7.13: The information path by which blanket application rates for fertilisers are calculated with data supplied by a combination of soil tests and pasture growth models.

Figure 7.14 depicts how the increased and improved information might be integrated into a new solution for the allocation of fertiliser rates as well as providing maps for automated application technologies. The key advantage would be the ability to generate fertiliser application maps, rather than just rates, which can then be applied using VRAT technology.

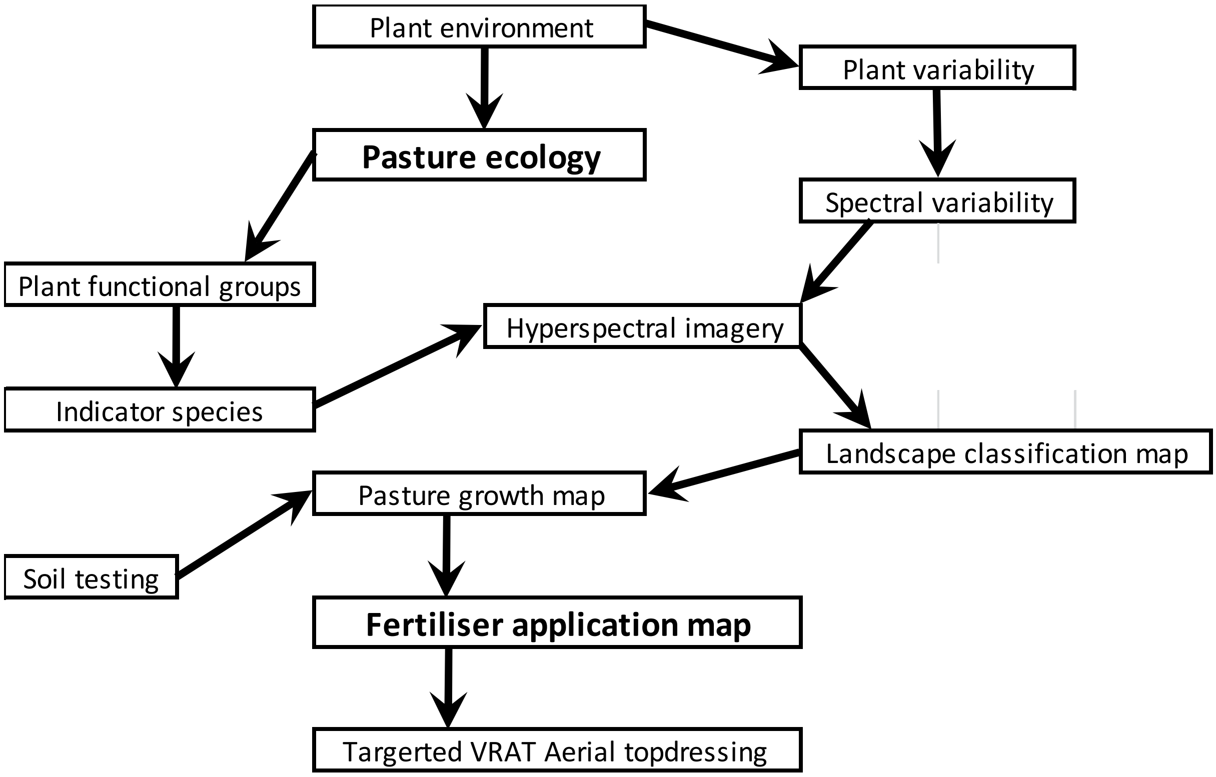


Figure 7.14: The increased information introduced by hyperspectral data analysis and the potential advantages that classification maps could have on fertiliser application.

The dataset collected for the PGP project was the most comprehensive of its kind in New Zealand, however there is no such thing as a perfect dataset. Like all datasets, the PGP data has advantages and disadvantages. The primary disadvantage was the inflexibility of the collection and generalised nature of the data collected. The data collection protocols were defined very early to meet the needs of a wider project and much of the data collected was not well aligned with the goals of this work. The addition of tarpaulins to the protocol allowed the actual spatial variability to be determined and thus for the ROI and ground survey information to be properly aligned. Despite the challenges, this work has developed new insights on the distribution of the key pasture plant functional groups which can be applied to a wide variety of tasks including fertiliser application, farm management and rural valuation.

Chapter 8 : Discussion of Results and Recommendations for Future Research

8.1 Introduction

This chapter draws conclusions on how the novel applications of remote sensing techniques explored in this study can advance hill country farming in New Zealand. The first section outlines the contribution to knowledge made by this thesis and following sections present key findings and describe how the research objectives were met. The practical implications of the research for the rural economy and the wider community are discussed. The final section presents this study's key research achievements and describes a vision for future research opportunities for remote sensing in these environments.

8.1.1 Contribution to knowledge

This thesis adds to our understanding of remote sensing in hill country environments in six general categories. First, the study responds particularly to the need articulated for a semi-automated method to accurately measure pasture area on hill country farms. Hill country farming has historically been neglected by researchers due to practical and economic limitations. The existing measurement approaches are time-consuming and lack the precision needed to inform variable rate fertiliser decisions. This study explored how employing airborne remote sensing can overcome many of the constraints experienced by researchers using traditional ground-based sampling methods. Multiple benefits and diverse applications of this new approach have been examined in this thesis, contributing to our understanding of how these technologies may be integrated into hill country farm systems.

Second, this study contributes to the scientific body of knowledge by presenting a novel remote sensing method for assessing pasture quality in the hill country farm environment. Pasture quality is an important metric in all livestock grazing systems and hill country farms are no exception. This study successfully applied aerial hyperspectral sensing techniques to classify pasture plant functional groups (PFGs), which are a proxy for pasture quality. Currently, knowledge of pasture quality is garnered from the first-hand experience of the farmer. The decisions that are guided by that understanding rely totally on the ability of the farmer to interpret that information from the land and transfer it. Mechanical knowledge provided from the interpretation of hyperspectral aerial imagery can add to and reinforce expert knowledge to improve decision outcomes.

Third, this study introduces a method to categorise various landscape components as input for the valuation of rural property or management of the wider natural environment. Mechanical knowledge provided from the interpretation of hyperspectral aerial imagery can add more certainty to the outcomes of a rural valuation. That has benefits to all the parties involved in such transactions. The same imagery can also assist with management of natural resources such as the financially important Manuka. The cost of the survey can be justified through various fiscal returns on the investment but the information can then also be used to assist management of many other environmental resources.

Fourth, this study adds to the body of knowledge by developing a novel approach to discriminate between the economically important species manuka and its lesser cousin kanuka in the field. Locating and mapping manuka is highly relevant to hill country farmers because pure manuka honey is a high-value commodity and contamination with honey from other species reduces the product's value. The unique application of aerially acquired remote sensing data in this study provides farmers and beekeepers with the means to map and manage manuka resources to optimise their returns.

Fifth, the interactions that are important for grass species identification were explored to add to our understanding of turf and pasture species using remote sensing. Proximal hyperspectral remote sensing was assessed for its ability to differentiate between several turf and pasture grass species and the results provided new insight into the implications of external factors such as time of day for categorising different grasses using remote sensing. While this work was intended as a stepping-stone to the application of the technologies and methods in the field, the findings are relevant to plant breeders and other researchers wanting a rapid, accurate and non-destructive method of discriminating between species.

Lastly, all of the mapping achievements for various species and categories were derived from individual surveys without the need for multiple or time-series surveys. This creates the groundwork for the commercialisation of the technology and its implementation into farming systems. This makes the research relevant to farming today, without the need to uncover deeper aspects of the technology. The support and acceptance of the results from the farming community are their own validation of the work.

8.1.2 Understanding spectral variability between turf or pasture species and the examination of its potential for use in plant breeding.

Chapter 3 explored the first research objective for this thesis, which is to *"investigate the variability of turf and pasture species reflectance, to develop understanding for pastoral remote sensing and provide insight to its use in pasture grass breeding programmes"*. Thus, the goals of this part of the study were twofold. First to develop our understanding the spectral variability between pasture grasses, and second to explore how that understanding might be applied to pastoral breeding programmes. A background goal of the study was also to develop understanding and knowledge from turf species and apply the knowledge to the final target, hill country pasture. This aspect of this study is significant because until now, much of the hyperspectral research literature has focused on forest and wetland species, which are structurally different from grasslands and thus may have different spectral interactions. This part of the PhD study tried to address some of the knowledge gap by exploring the interactions that are important for grass species identification.

The question of how data transformation can improve the results of hyperspectral data analysis was explored. Figures 3.7, 3.8 and 3.9 presented the improvements gained from processing the data from its unmodified state into Standard Normal Variate (SNV) and into first derivative. The Linear Discriminant Analysis (LDA) results had an overall accuracy of 73%, 78% and 81% with raw data, SNV data and with the 1st derivative data respectively. These results show improved relationship detection with derivative data, which aligns with the findings of (Demetriades-Shah *et al.*, 1990; Penuelas *et al.*, 1994; Becker *et al.*, 2005; Cho & Skidmore, 2006; Jin & Wang, 2016). Not all authors support the use of derivatives for this type of analysis, including J. Zhang *et al.* (2006) who suggests they may not be suitable for species identification. Although J. Zhang *et al.* (2006) did not find derivatives useful, in this case they provided better results than the other transformations, so their use was continued and expanded throughout the remainder of the study. The transformation to derivative is a simple process but the benefit it brings to the analysis of pasture species has not been well documented. This study suggests they should always be considered as part of a suite of options for analysis of pasture species, at least in the early stages of the research.

The differentiation of species by LDA was carried out with increasing numbers of spectral wavebands. The results of the analysis with various data transformations were all improved with increasing waveband numbers. This was shown in Tables 3.2, 3.3 and 3.4 where overall accuracies of 96.96%, 98.04% and 98.21% were achieved for SNV, 1st derivative and a series of random bands. The bands were chosen via a Mann–Whitney U-Test (U-Test), a method that had been used to define useful bands in other studies (Schmidt & Skidmore, 2003; Prospere *et al.*, 2014). However, given the success with random bands it is not clear if the U-Test was particularly sensitive. What was clear was that in this part of the study the derivatives produced high accuracies with fewer bands than the other comparisons, adding credibility for their continued use in this form of analysis.

The high accuracies of the randomly chosen bands highlighted differences in the U-Test outputs between the SNV and 1st derivative data transformations. This prompted the analysis of wavelength regions for sensitivity to species differences. The results were differentiation accuracies of 97.68%, 93.39% and 79.46% for visible, Near Infrared (NIR) and Shortwave

Infrared (SWIR). Both Vaiphasa *et al.* (2007) and M. I. Sobhan (2007) asserted some value in the use of the SWIR regions but both also indicated the Visible and NIR to be of greater importance. The results of this study, carried out on turf and pasture species, align well with their results which were focused on trees. Again, the decision to carry out initial trials with the proximal sensor bore fruit with results that support this position.

When applied to samples from different seasons, the algorithm predicted the season of sampling with an initial overall accuracy of 73.9%. The ensuing confusion matrix is displayed in Figure 3.12. The aim of the analysis was to broaden our understanding of seasonal changes and examine how those changes impact species differentiation. Seasonal variability of plant physiology is well known (Magney *et al.*, 2016). Several studies have exploited seasonal variations to distinguish plant functional groups (Foody & Dash, 2007; Adjorlolo *et al.*, 2012; C. Wang *et al.*, 2013; Crabbe *et al.*, 2019). The confusion matrix displayed in Figure 3.12 highlighted that most of the inaccuracies were between the three ryegrass cultivars. When two of these were excluded the accuracy of the analysis increased to 95.49% as seen in Figure 3.13. The difficulty to separate the three ryegrass cultivars suggests their seasonal changes are more similar to each other than changes associated with the other species in the study. That makes sense, differences in the strategies of how plants cope with environmental factors, is at the heart of understanding plant functional diversity studies (Pau & Still, 2014). This suggests that the changes could be relevant for species identification if that mechanism of change could be categorised. Although this study did not determine the reason for the variabilities it showed that remote sensing can contribute to its understanding.

The time which a sample was collected was predicted with an accuracy that ranged from 92.14% to 100% depending on the species and when a single species was examined, as shown in Table 3.5. The accuracy fell to 68.36% when all the species samples were included in the same analysis. The confusion matrix Table 3.6 displayed the results. Gamon *et al.* (1992) used their Physiological Reflectance Index (PRI) to measure diurnal changes in photosynthetic efficiency. In this study the metric being measured by changes in reflectance was not determined but was stable enough to be associated with the time of collection. Gamon *et al.* (1992) had difficulties when they applied their index to other targets. That appears to be consistent with the lower accuracies found when multiple species were examined together. Plant diurnal physiology is an active area of study (Carman & Bishop, 2004) and remote sensing techniques have been used by researchers (Van der Tol *et al.*, 2016) albeit with limited success. Van der Tol *et al.* (2016) put their limited success down to the many potential interactions that might have affected their chosen approach. This study indicates that the factors influencing the reflectance are not identical in each species. Thus, it may not be possible to have a single approach for all species, so species-specific approaches might be necessary. This analysis was carried out to add to the knowledge and better understand the level of detail that could be extracted from the reflectance data.

In this study the LDA was more than capable of defining species to accuracies >98%. This very high accuracy compares favourably with other studies that used LDA to separate species. For instance, Pu (2009) reported 86.8% accuracy for LDA identifying 11 tree species and 86.31% accuracy for just 5 oak species. In another study Acquah *et al.* (2016) identified various plant part components from logging residue with 96.7% accuracy. This study grew in complexity from the initial desire to investigate the spectral properties of pasture and turf species. The variability of seasonal changes were tested to discover if they would interfere with that species identification. The results suggested they were not a problem in this instance. This suggests that species identification should be possible regardless of the time of year.

Perhaps the most important result from this study for plant breeding is the possibility that hyperspectral reflectance data might be able to differentiate cultivars of the same species in the field. Cultivar differentiation would be an essential component of any electro-mechanical measurement tool used in plant breeding field trials. Such a tool could replace some of the expensive expert human knowledge that is currently essential in the system and provide the opportunity to both increase volume and throughput of the trial system. What is still missing for this application to be possible is a way to measure species percentages of a given field plot. That would be a good topic for future study as the information will be needed to define species persistence.. That system is likely to be an imaging spectrometer that can sub-divide the plot into small components, pixels of an image, and define the species component of each.

This part of the study was bound by two main limitations. First, the sites used were not replicated so more extensive sampling could not take place. Second, no tissue samples were collected for chemical analysis. Collecting tissue samples may have allowed more detailed inferences to be drawn from the results and should be a topic of future study. This research was primarily about the use of hyperspectral sensors for the investigation of spectral variability and subsequent separation of species. Species identification, one of the ultimate aspirations for remote sensing of vegetation, is still not possible but this work may help progress that in the future.

Despite these limitations, the study revealed several findings that proved relevant for the later work. In particular, the study yielded new information on turf and pasture species reflectance, especially in data transformation. These findings coupled with the success of the species differentiation underpin the success of this small study and legitimise the use of hyperspectral sensors for pasture research. Furthermore, some of the knowledge gained in this study, for instance around data processing, will be valuable for setting up this technology for breeding programs such as persistence trials.

8.1.3 The accurate definition of pasture area

Research objective 2, to *"identify a method to accurately define pasture area as input for aerial fertiliser application and to aid farm strategic decision-making" was addressed in Chapter 5*. This section of the thesis successfully applied a new aerial remote sensing approach to isolate and accurately measure hill country farm pasture. Importantly, this study showed how this information could influence farming and rural valuation decisions.

The pasture classification used two classifiers for imagery collected at Patitapu Station, exploiting data that had been processed or transformed using four methods. Table 5.3 lists the accuracies of this approach which were all above 92%, with three methods achieving accuracies above 99%.

The classification was repeated for an image collected on the same farm in the following autumn. The analysis focused on first derivative data with a linear SVM classifier which had an overall accuracy of 98.52% as shown in Table 5.4.

The classification was also repeated for an image collected on a different farm in a part of the country that is climatically distinct from the original target. The analysis focused on first derivative data with a linear SVM classifier which had an overall accuracy of 98.9% as shown in Table 5.5.

It is difficult to compare the results of this study with other research as this topic has largely been neglected in recent decades. Often the classification targets from other research are not similar enough for comparison or the sensors used vary in specification. However, other studies on pasture or grassland classification generally report high accuracies. For example Monteiro *et al.* (2008) reported accuracies up to 93.3% with an Artificial Neural Network (ANN) classifier. There are more studies that use SVM although the targets are less comparable. Foody and Mathur (2004) used SVM to classify arable farmland at 99.1% accuracy. Tarabalka *et al.* (2010) achieved an average accuracy of 94.79% classifying an image of the University of Pavia with an SVM. Bazi and Melgani (2006) tested an SVM classifier on an AVIRIS image of Indian Pines with nine classes including pasture, trees and farmland. They reported an overall accuracy for the SVM classifier of 87.66%. The high accuracies of this study compare well to those studies in this novel application.

Although the method accuracy is difficult to compare, it is possible to compare the accuracy of the farm pasture classification as a function of actual farm pasture area. Results of the classification were displayed for a series of farm paddocks in figures 5.3 to 5.7. Table 5.6 also listed eleven paddocks along with fenced area, pasture classification area, Horizons pasture estimates and the differences. The Horizons Regional Council's 'One Plan' environmental report for that farm listed, among other metrics, the farm pasture area by paddock. The availability of this report for comparison was crucial in the decision to use Patitapu Station for this study. None of the other seven farms involved in the PGP, had anything like the detailed information available for Patitapu Station. When the classification results were compared with the figures in the report there was a 50 hectare difference. That represented less than a 3% difference from the manual interpretation to the automated classification. That showed a close alignment with the previous manual analysis but with some differences in the more complex environments such as Figure 5.3. The farmer later agreed the classification aligned with his expert judgement of farm pasture area and gave better information than the current Horizons report. That fact is important for the practical acceptance and credibility of this type of analysis by the wider farming community. The farmer later showed his support of the method again when he asked me to apply the results to a new area of land that he had acquired.

While only 3% different, that 50 hectares of pasture difference is worth around NZD$600,000 (REINZ, 2019). That $600,000 difference would certainly matter to a purchaser, seller or lending institution. This also shows how added utility can be gained from the results which supply excellent base data for valuation of such complicated properties. As already noted, none of the other farms in the project had any documented information on their pasture area. The best they could provide was GPS data on fence lines and total land area.

The main objective of this part of the study was the creation of a classification system that could accurately define pasture area for use in VRAT. The current blanket fertiliser applications are carried out using the expert judgement of the pilot with variable results (Grafton *et al.*, 2012). Currently, automation involves programming information into the application equipment using time-consuming, labour intensive digitisation of maps. The results of this study show that SVM can carry out that operation with much less effort. As well as the favourable comparison with the Horizons report, the technique has also been shown to be at least as accurate as manual interpretation by Ravensdown (White *et al.*, 2017). In that trial Ravensdown took the pasture classification produced for another farm in the project and resampled it to a 100 metre grid. The classification detail produced from the 0.8 metre pixels turned out to be too fine for use with a plane that has a 20 metre application width.

The classification produced from this method has been compared with two independent assessments on different farms. It has been used to apply fertiliser through Ravensdown's VRAT system. It was used in later chapters to isolate the pasture component both for exclusion and inclusion purposes. It has been used by the farmer as a checkpoint when he was setting winter stock levels and it may one day be used to aid valuation of his property. The early uptake of this method by end-users is promising. and attests to the success of this work in meeting the defined research objective.

8.1.4 The identification of landscape components

The third research objective to *"Categorise landscape components to aid strategic decisions related to agribusiness and efforts in diversification" was explored in Chapter 6*. This part of the investigation focussed on identifying and mapping key farm resources.

Chapter 6 shows the utility of the imagery was enhanced by the classification of seven key landscape components. Those components were classified using a linear SVM. Table 6.3 lists the classes and producer accuracies for each which ranged from 89.03% to 99.97%. Like Chapter 5, comparison to other studies is not easy because so little work has been performed on these environments. The New Zealand Land Cover Data Base (NZLCDB) (Thompson *et al.*, 2003), categorised 43 classes of the New Zealand landscape. However, the 30-metre spatial resolution of the Landsat satellite imagery makes comparison impractical. Even the updated database that uses 10 metre SPOT satellite imagery (Landcare Research, 2019a) is not comparable because of the disparity in resolution. The most similar work is the study carried out by Pullanagari *et al.* (2017) who mapped multiple components over a series of sites including Massey University in New Zealand. Comparison can be drawn with the multiple and varied targets including six classes of rooftop, water and various vegetation. The hyperspectral imagery used for that part of their study was also the same as this study. However, in their case the less complicated SVM method, that most closely resembles the method of this study, produced an overall accuracy of 74% with class accuracies varying from 25.3% to 100%. It is difficult to understand how those class accuracies varied as the paper did not provide a confusion matrix for that part of the study. Their accuracies improved when more metrics were included in the analysis. This study compares favourably with their study, in that a simple linear SVM produced accuracies over 89%.

The density of vegetation and difficult nature of the terrain over the 2,600-hectare farm made ground sample collection difficult. Also, cost constraints made it impractical to visit and sample enough areas to credibly validate classification accuracy. This was understood by Gienko and Govorov (2017) who showed the use of expert knowledge and other evidence could support and improve interpretation of remote sensing imagery. In some instances of this study the regions of interest (ROI) were defined from large homogeneous areas as shown in Figure 6.2 that were impossible to adequately validate on the ground. This raised the possibility of erroneous data being included in the classification or validation with potential negative impact to both. One of the earliest observations on classification accuracy (L.A.R.S., 1966-1967) cited in (Fu *et al.*, 1969) identified that improper collection of training data can have greater influence on the results than the choice of classifier. However, the high classification accuracy indicates that, if it was the case, the impact was minimal.

The accuracy of the classification is important to help with credibility and confidence in the rural community. Equally important is understanding the relevance and importance of each class and how the classification can be of benefit to various parties within the farming community. Those benefits can be understood by looking at the key landscape components selected for the study.

Pine plantations are well defined crops but wilding (self-seeded) pine is considered an invasive weed and a major problem for the rural landscape and economy (M.P.I., 2017e). Identification and removal is therefore a priority of the New Zealand Government (M.P.I., 2014b). The classification accuracy for pine was 99.44%, suggesting this form of analysis can certainly aid identification programmes. Timely intervention of pine infestation can prevent wholesale regrowth which has been reported to occur after an initial clearance operation (Froude, 2011).

Farm tracks and exposed landslips are important farm categories that are often poorly documented. Farm tracks are important resources and should be detailed in asset registers defined for valuation. While tracks can be measured using GPS equipment on vehicles landslips are more difficult as they naturally occur in steep, inaccessible locations. Landslips are a major liability for farm productivity that take 20+ years to recover but will only return to 80% of their previous productivity (Blaschke *et al.,* 1992). The classification of landslips could be incorporated into land use development plans such as developed by Dodd *et al.* (2008). They could be used as additional weighting in the decision-making process to retire unproductive areas from pasture.

The isolation and classification of totara had a 98.45% accuracy. Including totara showed the ability to map such indigenous species. Another native species, the kauri tree (*Agathis australis*), is under survival pressure with many being killed by a disease commonly known as kauri dieback (M.P.I., 2017c). Mapping and monitoring kauri using this approach may aid efforts to save the species. Another possible application of this work is measuring forest carbon. New Zealand's Emissions Trading Scheme (ETS) compels forest owners with plantations over 100 hectares to use field measurements to confirm the plantation size (M.P.I., 2018b). The current allocation of sample locations is impractical as they are made without knowledge of the forest in question. Thus, there is potential to miss key components. A classification of the forest would allow a stratified sample design to be employed which would improve accuracy and potentially reduce sampling effort. That would reduce the compliance cost of joining the ETS and encourage more farmers to do so. Additionally, over time, it might be possible to generate models that use crown area, with other metrics from the hyperspectral data, and use them to define carbon stock for the entire forest with adequate accuracies. This would certainly be an area of study worth further investigation. The current version of the ETS does not include riparian plantings which have been the focus for a lot of farm environmental improvements in recent years. There are 11,862 dairy farms reported to have planted 24,722km of riparian zones (Telarc, 2018). Again, this would be a worthy topic of research to both measure the carbon being captured and to assess how remote sensing can assist the ongoing monitoring efforts.

The classification of water in the landscape was accurate to 99.97%, the highest of all classes. This classification in hill country landscapes is of great importance. These farms are quite large, so reticulation of water is both expensive and logistically difficult. That makes stock watering dams an important asset and vital to maintain productivity. Inclusion of water assets in the farm inventory would be necessary for valuation purposes. Identification of water locations also helps avoid fertiliser contamination, an important component for both animal health and environmental stewardship. Excluding waterways from fertiliser application would support the government's plan to improve freshwater quality, through action that stops the decline of water quality (M.P.I., 2018a). Until now, waterway exclusion on hill country farms has been difficult to realise using conventional technologies. Only, now, with the recent arrival of accurate aerial VRAT technology in New Zealand can we reliably avoid waterways when their location is known. Due to their varied visual appearance, water bodies are difficult to identify manually. Therefore, the aerial classification method outlined in this study is essential for water identification and protection.

The accuracy of the thistle classification was assessed at 98.51%. Although this was not the lowest accuracy of the study, it failed to meet expectations because of small undocumented commission and omission errors. Some areas known to be another class were mistaken for thistle. In other instances, areas of thistle were not included in the thistle class. These errors might have been better accounted for if there had been more ground data to work with and the resulting accuracy better defined. There was more data collected. However, an error in the spatial registration of the hyperspectral image prevented their use. In New Zealand, weeds reportedly cost the economy NZD$700 million (Brooker, 2016). Globally, that figure is USD$115 billion (Sheppard *et al.*, 2003). For sheep farmers the motivation for controlling weeds extends to product quality. Thistle in wool lowers quality and value while animals that graze thistle have lower weight gain. There is a clear commercial advantage to using the same imagery to produce a suite of results including weeds, such as thistle. While the results of this study show some promise for identification of the problem, they did not confirm whether the AisaFENIX platform was the most suitable for that work. The difficulty faced is one of resolution and occurrence. The spatial resolution of the image is not adequate to define some of the smaller occurrences of thistle and the total area of the thistle are tiny in comparison to the area of land. Also, the thistle is usually mixed at various concentrations within the pasture. Future work on this topic should be directed towards identification of a seasonal point where thistle is more prominent in the image and perhaps at the use of unmixing instead of classification strategies.

Perhaps the most valuable classes investigated are manuka and kanuka. The class producer accuracies for manuka and kanuka were the lowest of all at 97.71% and 89.03% respectively. In contrast to the thistle class though, the results exceeded expectations. Manuka and kanuka are very similar in many respects and they require some experience to tell them apart (Boffa Miskell Limited, 2017). Classification errors mostly occurred when manuka was classified as kanuka or vice-versa, see Table 6.3. This pioneering study is the first to accurately differentiate these two species at this scale and under field conditions. Thus, the results have important implications for the rural economy.

Manuka honey is an important export commodity in New Zealand. Importantly, manuka honey is worth up to ten times that of clover honey (M.P.I., 2017a). The industry faces several unsolved problems including overstocking, hive theft, sabotage and camping hives on the boundary of a property to access neighbouring honey (Bagrie *et al.*, 2015; Lloyd *et al.*, 2017; M.P.I., 2017a). Solutions seeking to address these issues will need to be supported with detailed information of the environment, including area and distribution of manuka plantations. It is also arguable that government is more likely to act if it can see that such intervention might have a positive return on the investment of time and energy. The methods for the detailed mapping of manuka plantations from this study could form the core information to address a number of the negative aspects of the industry.

Overstocking of hives is the most likely major reason for the steady decline of hive productivity reported by M.P.I. (2017a). It is inconceivable how one can effectively decide the hive carrying capacity of a property without detailed information on crop distribution and quantity. From the declining productivity of the sector it would seem they are not managing to do so with current methods or information. Farmers manage to do a reasonable job of defining sheep stocking levels because, in most instances, they have years of experience and first-hand knowledge of their property. The same cannot be said for honey production as the bees are only on the property for a short time during flowering. Any form of regulation that would address boundary camping or overstocking would require base information to help such definitions, the detailed maps produced in this study are, as far as is possible to define, unique in their accuracy and detail.

There is a possibility to improve honey quality by having good maps of the distribution of, not just their target crop, but potential contaminants as well. Such maps can also be used to improve the crop by expansion or by removing unwanted vegetation. Kanuka will outcompete manuka (Boffa Miskell Limited, 2017) so its early identification allows timely action to be considered in the management of the resources.

From the farmer's point of view the maps could form the basis of negotiations around hive space rental prices as purity of the base crop would have an impact on the purity and value of the final product. These maps would therefore assist in meeting one of the items suggested by Bagrie *et al.* (2015), to improve commercial arrangements with landowners. There has also been an increase of 230% in the value of 'manuka friendly land (Cook, 2016). For valuation purposes the results of this study could allow more accurate valuations of manuka land from the accurate assessment of manuka area and species purity.

8.1.5 Mapping pasture quality

The final research objective was to *"Map pasture quality to improve and inform decisions for aerial fertiliser application and to aid farm strategic decision-making."*. This was explored in chapter 6. The main focus of this part of the investigation was to improve knowledge of the pasture quality through the identification of the species that are present.

The classification of pasture plant functional groups (PFGs) was assessed for 49 sites using both 1st derivative and minimum noise fraction (MNF) data. The overall accuracy (OA) for the classification was 57.45% and 56.02% for the 1st derivative and MNF data respectively. The Kappa coefficient (measure of agreement) was 0.24 and 0.27 respectively as seen in Table 7.2. The very low Kappa statistic highlighted the inability of the classification to identify the sites that had high proportions of legumes and the poor overall results supported the decision to add larger areas to the validation

There was concern that 49 (2m x 2m) validation sites representing 141m^2, could not adequately represent 1,800 hectares of pasture so additional paddock areas were defined for improved validation. The addition of paddocks for validation increased the validated area to 76.69 hectares. The resulting assessment improved the OA to 88.75% for the SVM of 1st derivative data as seen in Table 7.2. The addition of these areas did not alter the classification which was carried out using a small number of the tarpaulin sites. These sites were only used to assess the wider accuracy of the classification over the farm. Including extra paddocks revealed the proper credibility of the original results that initially appeared to have low accuracy.

Further support for the credibility of the results was provided by the post classification site visit. figures 7.6 through 7.12 identified numerous locations where ground observations either supported or did not support the results. On balance the results of the study were well supported by this exercise and supported by the farm owner who identified a number of areas where his expert knowledge of farm conditions closely matched the results.

As well as the classification using SVM an effort was made to unmix the various components which would potentially provide increased fidelity of the output. Unfortunately, unmixing proved less reliable than the classification and results were only reported in appendix 2. This failure meant the final resolution of the output stayed at the (approximately 1m^2) native resolution of the image. This resolution however, represents magnitudes of improvement over existing knowledge which is confined to the farmer’s head.

The species content of pasture has implications for animal feed value (D. Stevens *et al.*, 2007; Sanderson & Webster, 2009) and pasture fertility needs (Jackman & Mouat, 1974). Understanding the species composition supports strategic management decisions with more accurate estimates of feed values. Setting stock levels for winter or carrying capacity for the farm would both be improved with this form of data analysis.

The study undertaken in Chapter 7 successfully mapped pasture PFGs and meets the objective to map pasture quality. As well as defining pasture quality PFGs provide a general measure of the underlying soil and environmental conditions that exist on a given site (López *et al.*, 2006). The information contained in these maps will be useful tools for farmers looking to affect change in soil fertility and to optimise pasture productivity. As with the work in previous chapters that information would be of potential use to other parts of the rural economy. Rural valuation and farm sale prices could arguably be influenced by this information. Two farms that are otherwise very similar might still be shown to be worthy of different valuations by the pasture composition and underlying growing conditions.

8.1.6 Research challenges

Many technical challenges were encountered during this study. The most notable are discussed in this section with a view to assisting future researchers.

The spectral error identified in some wavebands (figures 4.3 and 4.4) proved one of the greatest hurdles and considerable time was spent finding a solution. While too late to benefit this work, much of the error was eventually accounted for (Gabor Kereszturi, personal communication). The error limited the available approaches that could be tested throughout the trial. Ultimately the error was ring fenced and, as far as is possible to know, did not impact the results. SVM proved a powerful tool that was highly resistant to the spectral error. This was most likely because it only needed a few key 'support vectors' to define the decision boundary between groups (Foody & Mathur, 2006). In hindsight, little more could have been done as the technology was new to the entire PGP research team. Although, an incremental approach to the surveys with periodic assessments might have lessened the impact to the greater PGP project.

Chapter 7 is where a major spatial error of the image registration was identified. Figure 7.3 shows where the data points, surveyed using GPS, do not match the corresponding location in the image. In Chapter 6, the error meant that a lot of ground data collected with GPS coordinates was not usable as the position in the image could not be assured. Ground reference error is often a problem when validating remote sensing outputs (Foody, 2010). The magnitude of the error in the spatial registration of the imagery (up to 11 metres) was a surprise to the entire research team. Although the survey plane had an AIMS navigation system to keep it on track the AisaFENIX was connected to a GPS without differential correction. Once a plane with a differential GPS system was acquired, and connected, the error was reported to be reduced. Unfortunately, it was not identified until three years into the project so was too late to be of benefit to this research or Pullanagari *et al.* (2016), who stated the image positional accuracy as 2-3 metres at the time. The error led to total reliance on ground sampled data collected from GPS surveyed AND visually identifiable locations. Surveyed locations that were not identifiable in the image could not be used, so a lot of valuable data were lost. This problem should have been recognised earlier, as fence lines and other geographic features were often mis-aligned, but there was a general assumption within the team that the data were accurate. Hence, for future research it is recommended that data is checked to assure the researcher of positional accuracy or determine the magnitude of any error as early in the study as possible. Without that assurance it is not possible to be certain that results are accurate and such error might also lower resulting accuracies. And, of course, differential GPS should be employed to track the hyperspectral sensor for aerial data collection events where possible.

Most studies carried out in this work were centred around Patitapu Station with only one other farm used from the pool of eight available. That focus had several advantages and disadvantages for this study. The benefits included the availability of the Horizons WFP detailing pasture area by paddock, which was an important benchmark for the analysis in Chapter 5. The Station was also nearer than the other farms involved in the PGP project, which kept logistical costs down. Second, the farm was included in additional trials in multiple seasons for which I was involved in data collection. This developed a great deal of first-hand knowledge of the property. At 2,600 hectares, the Station has a very wide range of vegetation, slope, aspect and soil types for analysis. Most importantly, the farm owner had a deep understanding of his property that he works with his father. He has experience in rural valuation and formerly worked in the rural banking sector. The farmer is a keen proponent for the use of technology to improve his and other farmer's decision-making. He is an enthusiastic participant in the PGP, who went out of his way to assist this study. His insights and comments in Chapter 7 helped support and verify the results. The downside of centring this research around Patitapu Station alone, is the possibility that some of the research would to be considered less robust because it used this single environment. Of course, that objection can be dispelled when this research is expanded by future work into other regions of the country.

8.1.7 Summary of Findings

Several findings from this study represent a notable advance in our understanding of hill country farm and remote sensing research. These are:

1) Differentiation of pasture species was achieved with linear discriminant analysis to very high accuracies >98% confirming the suitability of hyperspectral data for remote sensing of pasture.
2) Transformation to 1st derivative improved the results for pasture species identification.
3) The U-Test did not appear to be particularly sensitive for identification of bands for pasture species differentiation.
4) This study could identify both season and diurnal data collection time with high accuracies >73% and >92% respectively.
5) Differentiation between very similar plants was more difficult than separating those that were very different. For example, cultivars of the same species were more difficult to differentiate than were monocotyledon from dicotyledon species.
6) This is the first study to successfully employ aerial hyperspectral data to identify and quantify pasture on a diverse hill country farm, from other landscape components at 1 metre resolution using a single survey. The quantification compares favourably with a previous manual analysis of Patitapu Station and importantly, this work was validated by a later study by White *et al.* (2017).

7) This is the first study to classify several key landscape components that are economically or environmentally important to the hill country farming community from a single survey. Importantly, the classification includes high classification accuracies for the mapping of New Zealand native plants. The mapped components were;
    - Manuka – classified at 97.71%
    - Kanuka – classified at 89.03%
    - Pine – classified at 99.44%
    - Soil/non-vegetation – classified at 99.89%
    - Totara – classified at 98.45%
    - Water – classified at 99.97%
    - Thistle – classified at 98.51%
8) This study created the most detailed map of hill farm pasture quality using plant functional groups so far. Importantly this was achieved with a single survey. When the larger validation areas were included the accuracies for the three plant functional groups, using 1st derivative data, were;
    - Low fertility tolerant – 89.81%
    - High fertility responsive – 84.09%
    - Legumes – 94.99%

8.1.8 Other Key learnings

There are a number of key learnings that came from the project and from the association with the overall PGP ‘pioneering to precision’. These are:

1) 1m pixel size was too much detail for a number of applications and not enough for others. The usefulness was determined by the resolution of the target compared to the pixel size.
2) The spectral resolution of the Asia FENIX was greater than needed for the work carried out within this thesis. A sensor that omitted the SWIR would be adequate

for these applications. It would be both cheaper and produce images with a smaller overall size (Gb/Ha).

3) Image data collected in both spring and autumn were used and provided good results in both cases.
4) The collection of ground reference data should be a primary consideration of the experimental design. It is important to collect reference data that can be correlated to the remote sensing data.
5) When changes are made to the experimental design it is vital that the implications of that change are examined.
6) When setting up a large project there needs to be an allocation within the project time-line to review progress and amend the methodology if progress is not as expected.
7) For projects that cross into multiple fields (e.g. agronomy and remote sensing), it is important that the research team has a wide variety of expertise.
8) This project was commercially funded which meant discussion with external parties was not possible for protection of intellectual property (IP). Careful consideration should be given as to which IP, produced from a project, is worth protecting. The consequences for completely locking down external collaboration may be greater than the value of the IP. Greater insight, and therefore value, might be realised from such external collaborations.

8.2 A Vision for Hyperspectral Systems in New Zealand Farming and Grassland Management

This section discusses important points that evolved during this study that have implications for the hill farm management and the future application of remote sensing technologies in diverse grassland management. In this section are also some recommendations for future research.

8.2.1 Resolution

Spatial and spectral resolution of data were found to be critical to the extraction of useful knowledge in this work. The spectral resolution is important for fine detail. Fine detail in this case relates to species or cultivar differentiation. It can be asserted with reasonable confidence that multispectral sensors are not capable of cultivar differentiation. It took the introduction of hyperspectral systems to allow this advance. Although other researchers are using remote sensing to identify traits of various pastoral cultivars for breeding purposes (Araus & Cairns, 2014) this appears to be the first work that was able to translate this into species differentiation. In the context of breeding programmes for improved pasture grasses the ability to differentiate between cultivars was shown to have important implications for persistence trials. As persistence can only currently be defined by experts using visual assessment the introduction of mechanical measurements could be an important advance with the possibility to vastly increase throughput at reduced costs.

Spatial resolution is also important to the task of species differentiation. The work discussed in Chapter six was made easier by the scale of the targets being larger than the pixels of the collected image data. Higher spatial resolutions mean there are more target pixels with spectral purity. This has two primary benefits;

1. First, they provided larger numbers of pixels where pure spectra for training data could be collected for the classifier.
2. Second, a substantial number of pixels remain to validate the classification.

Mixed pixels are problematic requiring a greater understanding of the physics involved and making the separation of similar classes more complicated. Mixed pixels also present the possibility that a combination of components, unrelated to the target of interest, can form a spectral signature similar to the target thus introducing error that cannot be accounted for.

8.2.2 Logistics, Cost and Management Implications

Chapter 6 discussed the potential costs to survey properties. These costs are estimated to be in the region of NZD$15 per hectare for survey and data analysis although that has yet to be tested in the marketplace. There are two ways to determine the return on this investment. First, the cost could be offset by direct savings in fertiliser spend, or the cost could be recovered from extra income generated by better fertiliser efficiency. The latter would be difficult to quantify and thus more difficult to sell to an end user. Likewise, the repeat interval for the survey can be defined by the savings or extra returns. For farmers to adopt this technology it will not be enough to balance the cost of the survey without additional benefit. It might be possible to stretch the duration between surveys (thereby reducing cost) by using cheaper satellite data. For instance, a satellite image taken at a similar time to the aerial survey might provide a comparison point. Other satellite imagery captured in following months or years could estimate interim change. When appropriate, another aerial survey can be used to reset the analysis. The utility of satellite data for interim assessment and necessary reset interval for the aerial survey could be key goals for future research.

Of course, the focus on fertiliser as the only way to define value for the survey or as means to define a return on investment (ROI), disregards the other demonstrated benefits of this study. Rural valuation is a key component of the rural economy and provision of accurate property information is a compulsory international regulation (I.V.S.C., 2013). The simple miscalculation of farm pasture area (50 hectares) reported in Chapter 5 represents a cost differential of around NZD$600,000 between the potential values. The NZD$39,000 cost to implement the aerial survey on that property would have returned NZD$561,000 of potential savings on the purchase price of the property. The same survey may have altered the quantity or quality metrics of other assets (Chapter 6 and 7) to further increase, or decrease, that ROI. Given the additional potential benefits, there is a strong incentive for the buyer and seller to employ this approach to negotiate the best price, provide detailed information on the property and enable a good business management plan to be implemented. With all those benefits the case is clearly there to justify hyperspectral surveys for hill country farm valuation and management independently of the other benefits to farm management.

There is a relatively small window of opportunity during the year to perform survey operations on pasture. This presents Ravensdown with a logistical and marketing problem. Spring has been identified as the ideal time for surveys, when growth is occurring in the absence of soil water deficits. However, spring is not always appropriate for survey operations with intermittent or total cloud cover present over much of New Zealand. Logistically, how aerial and ground teams will be coordinated to survey an adequate proportion of customer properties is not clear. For instance, consider a survey window opens in the south and another opens over another target 1,000 km north the following day. The logistics of transporting ground survey teams to keep pace with a survey plane have yet to be considered. One opportunity to increase the survey operational time and therefore relieve pressure on ground teams would be to increase the available survey window conditions. In the future it may be possible to reduce ground data collection but that could only be considered after a number of years of successful operation. In order to reduce ground data collection more research would be required to identify key landscape elements and interactions. Without that work and history of successful operation confidence in the results would be difficult to justify.

It is difficult to predict how this technology will look or to place a value on any of the information provided by a hyperspectral survey analysis without more study. It is likely that the level of utility garnered from this technology will be driven by the policy environment. Who pays for the survey and how the information might be distributed is key in this discussion. Commercial models where the user pays are arguably the obvious choice but the free distribution of information typified by the release of survey information by Land Information New Zealand (LINZ) has potentially greater benefits at the national level. The benefits from institutionalising protocols could include a unified data scale and quality control as well as the potential benefits from economies of scale. The problem with user pays is that only those who can afford the cost, or those projects with clear commercial benefit, would have access to the information. It is therefore suggested that if the collection of nationwide hyperspectral information were commissioned by the government and made freely available the benefits could be accessed by all and provide greater national benefit. These are some of the same arguments used to justify the capture and public release of nationwide LiDAR data by the New Zealand Government (Jones & Sage, 2018).

8.2.3 Environmental Management Implications

The work in Chapter 6 highlighted the versatility of hyperspectral imaging to be applied to a wide variety of targets including native and non-native species separation. It is a reality that environmental management, although important to everyone, cannot be carried out as a standalone operation. As discussed in section 8.2.2 all operations on-farm must pay their way so a specific survey operation for environmental management would be difficult for a farm business to justify or pay for. Obviously, a nationwide survey might solve this issue but until that happens, we still have to manage and care for our natural environment. The versatility of hyperspectral imaging however provides a mechanism to aid those environmental management operations. As each survey is carried out ground teams, who collect ground data information, can ensure they collect examples of locally and nationally important species so they can be located and mapped in the imagery. Doing so allows the managers to better understand the distribution and management needs of each important species. Currently this information, if it exists, is in the head of the local manager. The ability to generate spatially referenced maps for various species is perhaps the most important advancement for environmental management. Such maps allow multiple agents or agencies to participate or contribute to the management of that asset. They allow priorities to be set based on collected data but most importantly they allow management operations to be assessed over time for their effectiveness.

8.2.4 Recommendations for Future Research

This study reveals many exciting avenues of research and there are some elements of this study that can be advanced, including:

- Weather conditions in New Zealand are often cloudy, severely limiting the available survey days. Research into AisaFENIX's performance in sub-optimal (low light) field conditions is critical to its feasibility. The ability to survey during cloudy days has not yet been assessed as a viable strategy. Shadow is still a problem in remote sensing in the field, with some work focused on mitigation by (S. T. Wu *et al.*, 2014). Flying on partly cloudy days is a problem because of light intensity difference between sunny and shaded areas. No information is available on the utility of a survey carried out under total cloud cover, where light levels would be low but uniform. There are many considerations including inadequate light, scatter effects and reduced signal-to-noise ratios but performing short surveys under various conditions might clarify if addressing these is worth the effort.
- This study confirms that errors in the spatial registration of airborne hyperspectral imagery are often a problem when validating remote sensing outputs (Foody, 2010). It is recommended that detailed analyses be used to discover the exact positional accuracy of the system. This would guide ground data collection protocols and assure future users the data is valid.
- The spectral error encountered when using the AisaFENIX sensor proved a major problem for this study. In hindsight, the fact the error did not appear in the initial survey, collected with another unit, should have provoked greater inquiry. Although the quality of the data were improved, if the current sensor unit is to be used for other studies its output should be investigated. That could be a comparison to another unit to assess how much, if any utility is still compromised.
- The impressive accuracy of the classifications for the chosen components in these environments sparks the question of what other useful landscape components might this help quantify or find. Kauri dieback is a threat to the species with no known cure

(M.P.I., 2017c). Hyperspectral surveys and classification might help define locations for kauri specimens within a mixed forest environment to support monitoring and protection.

- Some of the results from this study have already been adopted by Ravensdown and the approach applied on other properties (White *et al.*, 2017). However, other elements of the studies were mainly limited to a single site. Applying the approaches developed in this study on other properties would add to the knowledge base and progress the technology, moving it closer to industry adoption.
- The success in defining pasture quality using plant functional groups unearthed a novel method to measure the success of various farm management practices at farm scale. Traditional methods for pasture management trials rely on specific plots to assess their effectiveness (Grant & Brock, 1974; Lambert *et al.*, 1983; Lambert *et al.*, 1986; Gillingham *et al.*, 1998; Aarons *et al.*, 2015), with models built to help define various interactions (B. Zhang *et al.*, 2005; B. Zhang *et al.*, 2009). The ability of airborne hyperspectral imaging analysis to define key pasture parameters could allow farm scale trails with observations over greater percentages of the property. To begin, some comparison trials using both methods would prove very interesting.
- Very little research exists on the accuracy of farm valuations, perhaps because of the financial and legal implications for the definition of accuracy. The introduction of airborne hyperspectral remote sensing analysis to rural valuation would require it to be first compared to existing methods. The difficult part in such research would be to control or quantify bias between methods with and without the survey data.
- The increasing focus on environmental protection provides several opportunities to use airborne hyperspectral analysis. The ability of such analysis to provide temporal snapshots of the environment offers the opportunity to assess change. This approach is not new (Cole *et al.*, 2014; Held *et al.*, 2015; Raab *et al.*, 2018), but is not widely used in New Zealand. Such analysis could help record progress for elements such as riparian

planting and may help define progress, or improve public perception of progress, to protect the environment.

- This thesis exploits well researched, readily available SVM techniques to define several landscape components to high accuracies. The search for superior accuracy is often the focus of research, typified by Bazi and Melgani (2006). However, Bazi and Melgani (2006) noted the advantage, of avoiding computational burden, that a simpler method had. This however came with a small reduction in overall accuracy. This raises the question for future researchers, “can we improve accuracy by tuning the method, and if so, will the improvement be worth the effort?”
- The analysis within this thesis focused on both proximal (ground level) and airborne hyperspectral sensors. It was not possible to study how satellite imagery might have compared. New generations of satellites are improving in spatial and spectral resolution (Ali *et al.*, 2016). The imagery may also be cheaper in the future. Satellites may suffer more from cloud obscuring the target, the aerial sensor mission can be delayed by a day or two, but satellite mission planning cannot be so flexible. Yet, satellite data may replace some lower value tasks, or it could provide an effective interim update between more expensive aerial surveys. Besides, research into the comparative utility of different forms of data for these same tasks would prove valuable.
- The classification of pasture quality using plant functional groups is another topic worthy of further inquiry. Future research could examine how to optimise or eliminate ground sampling, thus removing the reliance on small target locations. It would also be valuable to apply the research to other locations and conditions.
- This study does not include comprehensive economic analysis on the value of this approach to the fertiliser industry or farming community. However, White *et al.* (2017) did examine how results from this work could improve farm productivity and concluded the combination of hyperspectral analysis and VRAT applied fertiliser could improve farm productivity. A thorough study examining the specific benefits of airborne hyperspectral analysis in relation to fertiliser application and productivity would be an

essential next step to encourage farmer uptake. Savings made from lower fertiliser use are easy to calculate. However, the implications for productivity from increased fertiliser application to targeted zones also needs to be quantified. Besides the observations on productivity, there should be some analysis of the environmental implications for increasing fertiliser application rates.

- This study provides a possible avenue to address the bottleneck in pasture species breeding. Proximal hyperspectral sensors are clearly able to differentiate between species in the field (Chapter 3). The exact mechanism that would facilitate the use of this method for persistence evaluation is yet to be defined, and the benefits for the whole process are still to be determined. Given the shortcomings of the conventional approaches, this topic warrants further investigation.
- Although the 1m resolution output was too fine for use in aerial topdressing the resolution can be adjusted to better match that application. If the resolution were less detailed there is a possibility that the results would not be suitable for many other applications. It would be worth building on the work undertaken in this study to investigate how the spatial resolution of the survey would impact results and which applications would require higher resolution versus those that would require lower resolution. Such results would improve the practical application of this research.
- The results show there is no need for the SWIR so it would be possible to use a sensor that omitted that part of the spectrum. The next question in that line of thinking should be to consider if some of the work carried out could be done using multispectral sensing. It is recommended that future research considers this as a comparison of such data sources on multiple targets would be a good way to begin. Such results would improve the practical application of this research.

8.3 Conclusion

Each stage of this study examines a different challenge facing the scientific and rural communities in New Zealand and identifies how remote sensing could help address them. Overall, the study provides a robust response to the research objectives. The work meets the goal of employing aerially acquired hyperspectral imagery to better define key landscape components, especially pasture. This research demonstrates that these technologies can inform decision-making across the wider rural sector. Thus, the ultimate goal of the study, to demonstrate that the use of hyperspectral imagery can help to improve on farm outcomes for hill country farmers, has been met.

The common thread running through pasture species breeding, rural valuation, rural banking, aerial top dressing, honey production, environmental management and farm strategic management is that their decisions rely almost exclusively on expert judgement. Remote sensing and airborne hyperspectral imagery can inform decision-making, not to replace expert knowledge, but to improve it with mechanical knowledge. Just as more accurate information improves the ability of modern pilots to fly safely, more accurate environmental information can support rural experts to make sound decisions. This is important because New Zealand farmers face significant and complex environmental challenges around water quality and soil management, which need to be addressed. A key feature of this research is that many benefits, impacting a very wide range of rural actors, can be derived from a single airborne hyperspectral survey. This feature could be one of the most important elements, as it provides multiple value streams whereby the cost can be divided and justified.

Significantly, this research represents a paradigm shift for fertiliser application on hill country farms. Instead of a pilot switching his attention between flying and moderating fertiliser output from his plane, the pilot can focus on safe operation of the aircraft. The on-board software can handle binary decisions of where to apply and control how much fertiliser is applied by adjusting the aperture of the hopper door (Chok, Grafton, Yule, & Manning, 2016). Decisions of where to apply or not apply fertiliser can now be made without time-consuming manual interpretation

(White *et al.*, 2017) and (Chapter 5). Remote sensing information can also inform decisions on fertiliser application rates (Chapter 7).

Farmers no longer need rely on their expert knowledge. Remote sensing and hyperspectral imagery can add to available tools used for strategic farm management decision-making (Chapter 5; Chapter 6; Chapter 7). The effectiveness of grazing management can now be evaluated at the paddock and farm scale and knowledge quickly shared or replicated. The ability to disseminate maps of pasture area or quality to outside contractors could encourage more collaboration and better advice from consultants to improve outcomes.

Although this work has been applied in New Zealand, this research is relevant to any farming landscape that is poorly defined, has difficult access or has variability that is difficult to measure using conventional methods. It is particularly applicable to the roughly 9.3 million hectares of New Zealand hill country farms. Rural valuers and bankers have the unenviable job of assessing or defining land value and business value respectively. The accurate definition of landscape and components and business assets (Chapter 5; Chapter 6; Chapter 7) could help remove some of the uncertainty from the industry. This would benefit the seller, buyer and money lender, allowing fair prices to be paid and for realistic expectations of business performance to be set.

Good data builds trust from the users. The utility of this form of analysis should be tested to foster that trust. The results and maps produced in this thesis represent the most detailed information on pasture area and quality so far. Pasture agronomists now have a spatially referenced approach to measure how pasture responds to various fertility or cultural treatments at paddock and farm scale. This research also offered a glimpse of how remote sensing could improve how new generations of pasture are developed and brought to market (Chapter 3).

The success of this study will encourage and guide future research efforts that employ remote sensing techniques to help hill country farmers optimise production and address environmental challenges.

I would hope this research can be applied with increasing scale to hill country farms. It is also my desire that application of these or other methods would aid those farmers to improve outcomes from their decision-making processes. It is my ultimate hope that this research begins a period of renewed interest in remote sensing of the sector and that improved information brings improved prosperity to hill country farmers and better environmental outcomes for hill country landscapes.

9.0 References

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