PREDICTION OF SOIL OLSEN P THROUGH MIXED PASTURE LEAF TISSUE BIOCHEMICAL AND BIOPHYSICAL PROPERTIES, TOPOGRAPHY AND FARM MANAGEMENT IN NEW ZEALAND HILL COUNTRY

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ABSTRACT

In New Zealand hill country, soil Olsen Phosphorus (P) is a key piece of information used to decide rates, products and areas to which aerial applications of phosphate fertilisers are made. Laboratory based soil Olsen P measurements are made on bulked soil cores collected along transects, laid out across slope faces. On most hill country farms, aerial fertiliser applications are applied uniformly over large blocks or the whole property. Accurate, detailed soil maps are scarce, but essential for site specific nutrient management. Current soil sampling techniques provide spatially sparse information and attempts to interpolate point measurements of soil properties in hill country, have not been successful.

The potential improvement in nutrient use efficiency would lead to increases in pasture production and quality, and an increase in production of meat and wool produced off the same land area. As sheep and beef production is forced from more productive land into more marginal areas by other land uses, managing hill country landscapes efficiently will become critical for the sheep and beef industry. Increases in global food demand, a growing interest in product origins and production practices by the consumer, and tightening of environmental regulations will further put pressure on these systems. Appropriate soil and fertiliser management has suffered from a lack of information to make sound decisions. Maps of soil Olsen P are a first step, with much potential in the applications of hyperspectral imaging yet to be discovered.

The objective of this thesis was to develop a model that could be applied to readily available data layers, to make continuous predictions of phosphate availability in the soil (Olsen P) across New Zealand hill country farms. This research was one part of a larger project that firstly aimed to derive estimates of pasture parameters from hyperspectral imagery. This information could then be used in conjunction with ancillary data to determine soil nutrient status. Finally, this information would be used to inform variable rate fertiliser applications through a prescription map loaded into a computer controlled aerial top dressing system.

A multi-site, multi-seasonal database from eight commercial hill country farms incorporating a range of leaf tissue nutrient concentrations, pasture biophysical properties, and topographic, soil and farm management information was built up alongside soil chemical properties. Model development was based on in-situ measurements and laboratory analysis of leaf tissue and soil samples collected on 0.5m x 0.5m plots. A total of 3,030 plots were sampled in the autumn and spring.

Simple plant P indices are usually used on single species samples of actively growing tissue. Here they were used on mixed pasture samples at various stages of maturity with mixed success. Although overall correlations were weak, leaf tissue P concentration and PNI were more strongly correlated to soil Olsen P than the P:N ratio or PNI_c. Soil Olsen P was more strongly correlated to leaf tissue P concentration and PNI in spring (R^2 = 0.21 and 0.24 respectively) than in autumn (R^2 = 0.12 and 0.12) and both seasons combined (R^2 = 0.13 and 0.13). For individual sampling events, all P indices were generally more strongly correlated to soil Olsen P in spring than in autumn. Of the individual sampling events, the strongest correlation was at the hill country farm Cleardale in the spring (R^2 = 0.56) using leaf tissue P concentration.

The database was then used in exploratory analysis to identify important input variables across farms and seasons through stepwise multiple linear regression. Leaf tissue P and copper concentration, slope, fertiliser history, the proportion of green tissue in the sample and seasonal information were consistently selected. For all seasons and farms combined, 13 variables (slope, 30 day rainfall, soil moisture deficit, time since the last fertiliser application, rate of the last fertiliser application, leaf tissue P, Cu, Na, Mn and Zn concentrations, DM%, the dead vegetation fraction and legume content) were selected as predictors for soil Olsen P with an R^2 of 0.42 for the mean of the 5 plots at each site. For season specific models, different sets of predictors were selected and achieved higher levels of explanation, R^2 of 0.45 in autumn and R^2 of 0.50 in spring for the mean of the 5 plots at each site.

The approach taken to predict soil Olsen P was to develop Bayesian hierarchical multiple linear regression models. Models were developed using different parameters and hierarchical structures. The pasture biochemical and biophysical parameters along with topographic and farm management factors all contributed significantly to the model. The model fit was significantly increased and the residual error greatly reduced in the combined model compared to models containing only plant biochemical and biophysical or only physical inputs. The posterior predictive distribution from a Bayesian hierarchical multiple linear regression model provided an estimate of soil Olsen P and the uncertainty of the prediction made. A leave-one-out-cross-validation showed an improvement compared to an average value used to inform the most basic and risk averse uniform fertiliser application as a benchmark.

The Bayesian hierarchical model can be used for predictive soil mapping, which was demonstrated, however still needs to be validated. Predictive soil mapping exhibited the potential of using input data layers derived from hyperspectral imagery and digital elevation models, to provide continuous predictions of soil Olsen P across a hill country farm. Maps of

soil Olsen P were produced, where methods attempting to use interpolation techniques in hill country have been unsuccessful. These maps provide vast amounts of data compared to traditional spatially sparse soil sampling.

Soil phosphate availability has a significant effect on pasture productivity, and species composition which affects pasture quality. As considerable research and programmes have focused on genetics and breeding for animal performance, it is now thought that pasture productivity and management is restraining the potential performance of sheep and beef systems. Of the factors driving pasture productivity, fertiliser applications are one factor farmers have control over. The levels of P available in soils observed in this study suggest that much potential exists to increase pasture production and quality through increasing P availability in the soil.

In summary, a Bayesian hierarchical linear regression model significantly improved the predictions of soil Olsen P made across hill country farms compared to a benchmark traditional uniform approach. From this Bayesian hierarchical model, estimates of soil Olsen P can be made on locations and time points outside of the dataset with a known level of uncertainty. This model can be used in predictive soil mapping to produce maps of soil Olsen P across hill country farms.

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István, Boglárka, Angela, Gabor, Sue, Sophie, Nicky, Emma, Heidi, Linnea, Libby, Matt, Rach, Scott, Matthew, Kathryn, Kate, Rob and Tonee, thank you all for your amazing support and friendship over the past few years! A special thanks to Matthew and Kate, and an even bigger apology to Kate for causing you to miss out on that date scone. Sorry. I have learnt so much from you all, and I value your friendships immensely.

I would like to dedicate my thesis to Viv, my grandmother, who didn't get to see me complete my PhD but know she would be very proud.

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1 Introduction

1.1 Context and aim of research

The research undertaken in this thesis is part of a larger project, a Primary Growth Partnership (PGP) project funded by the Ministry for Primary industries (MPI) and Ravensdown Cooperative Ltd.

The pioneering technique of aerial topdressing in the late 1940's brought about a major improvement in hill country farming. Titled 'Pioneering to Precision' this project aims to take the next major leap forward in the approach to fertiliser application in New Zealand's hill country (Figure 1-1) through well informed variable rate application of fertiliser. Currently fertiliser is blanket applied; aerially spreading at a single rate and product over large areas or whole farms. Limitations in collecting soil fertility data have resulted in fertiliser decisions being based on spatially sparse information.

The new approach to aerial topdressing (Figure 1-1) proposes the use of remote sensing techniques, through hyperspectral imaging from an aerial platform, to capture pasture biochemical and biophysical information to infer the underlying soil fertility. This information would be incorporated into a decision support system that would generate a prescription map

to control the aircraft hopper and variably spread fertiliser accordingly to make best use of the nutrients applied. **A key part of the process is predicting soil nutrient status at high resolution. Research presented in this thesis focuses on linking pasture nutrient concentration (with additional topographical and farm management data) to soil fertility** as part of step 2 (Figure 1-1) in this new approach.

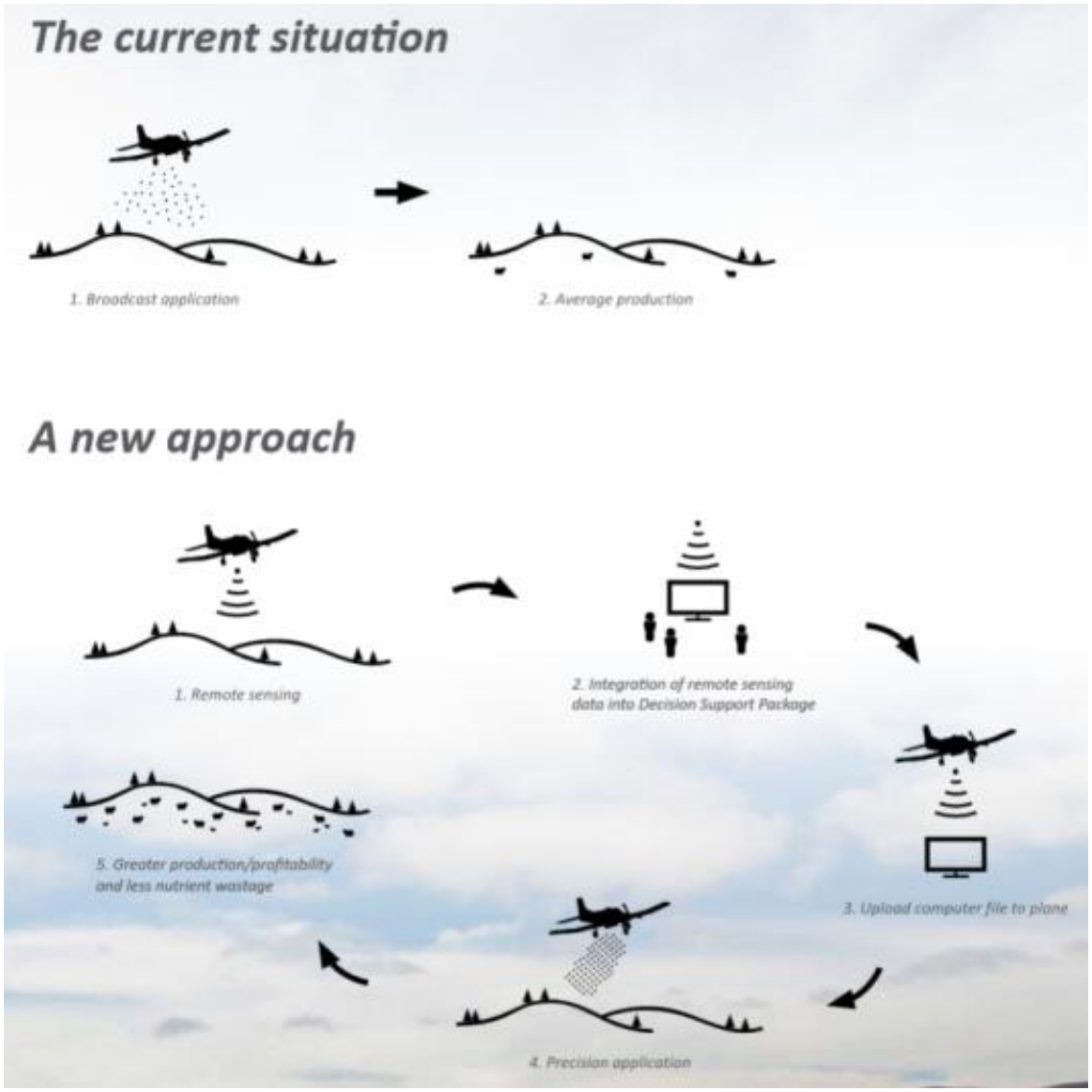


Figure 1-1 Diagram showing the current blanket application of fertiliser and the new approach to variable rate fertiliser application (source: RAE, Massey University)

1.2 Importance of the research on a local to global scale

Improving nutrient use efficiency is important from the local farming to the global scale. The pasture based sheep and beef sector relies on fertiliser to maintain and lift soil fertility to improve pasture productivity. Approximately four million of around nine million hectares, a significant area of New Zealand hill country, is classified as medium to steep slopes. The only practical way to apply fertiliser is through aerial top dressing (Yule, Grafton, McVeagh, &

Pullanagari, 2014). Major challenges identified for hill country farming include aspects related to fertiliser use and nutrient use efficiency, including: water quality, a major part of which is through reducing losses of P into waterways (Morris & Kenyon, 2014) and erosion control (Cosgrove & Field, 2016); reducing their environmental footprint (Morris & Kenyon, 2014); and appropriate management of soils (Cosgrove & Field, 2016; Scrimgeour, 2016). Ultimately improved nutrient efficiency narrows down the range in soil Olsen P across a farm through withholding nutrients from areas that are above optimal and mining these areas down, applying maintenance rates to areas around the optimal Olsen P, and capital applications to those areas below the optimal. The economic optimal soil Olsen P varies for different areas of the farm depending on the level of productivity, potential increase in production and cost of fertiliser application.

The phosphorus cycle in agriculture and globally is not self-sustaining and needs to be managed wisely. As agricultural enterprises intensify from pressure to produce more crops and food, the demand and reliance on phosphate fertiliser builds. Phosphate rock is a non-renewable resource mined predominately in China and Morocco (Cooper, Lombardi, Boardman, & Carliell-Marquet, 2011). Papers published in 2009 and 2011 (Cooper et al., 2011; Cordell, Drangert, & White, 2009) suggest that phosphate rock reserves will be depleted within 100 years, given current and future demands and estimates of known reserves. Phosphate is moved long distances from mines to agricultural fields where a large proportion is eventually lost from the plant available pool (Schröder, Smit, Cordell, & Rosemarin, 2011). Phosphate can become adsorbed to soil particles which is then unavailable for plant uptake and may be lost via erosion (Schröder et al., 2011). Over supplied P increases the risk of P loss to waterways. Phosphate entering waterways is an environmental issue as it is a major cause of eutrophication. The awareness of the effects, both environmentally and agriculturally, of inefficient fertiliser use has seen a change in attitude and regulations. From both an agricultural and environmental point of view, nutrient use efficiency deserves much attention.

1.3 Approaches to mapping soil properties

Improving nutrient use efficiency of P fertilisers requires an accurate estimate of the current soil P availability. Traditional approaches to mapping soil properties illustrated in Figure 1-2 include a) interpolation of point samples collected manually and analysed in the lab where samples are generally collected across a grid or transects and b) interpolation of points collected from a proximal sensor along swaths over a field. Emerging research has seen the use of remote optical sensors to capture images (imaging spectroscopy) of bare soil, Figure 1-2: c.

The new approach proposed within the PGP 'Pioneering to Precision' project is to capture hyperspectral imagery of vegetation to estimate pasture sward biochemical and biophysical parameters to infer the underlying soil parameter (Figure 1-2: d), in this case soil fertility. The steep terrain and permanent pasture cover in hill country limit the use of current techniques of mapping soil properties.

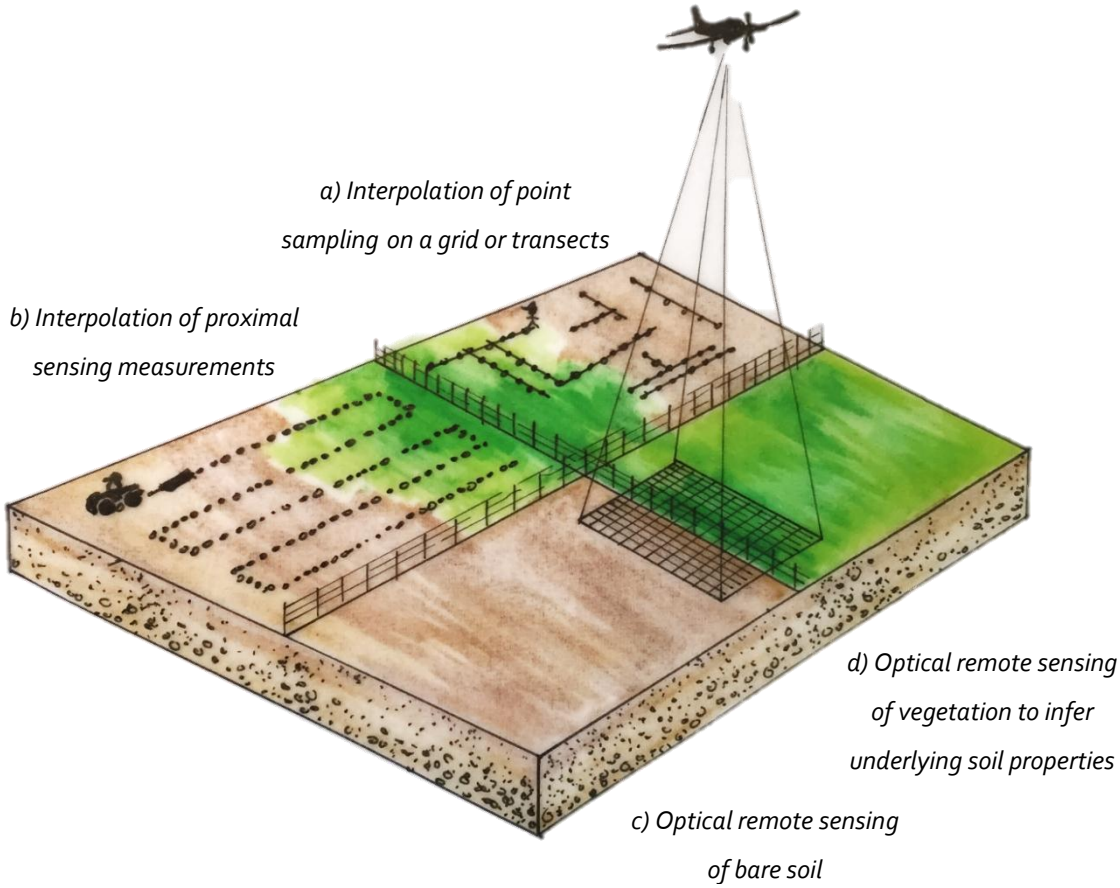


Figure 1-2: Traditional (a-b), emerging (c) and new (d) approaches to mapping soil properties.

1.4 PGP Project: 'Pioneering to Precision'

The first stage of the project required the development and validation of estimates of pasture nutrient concentration from hyperspectral imaging. This required interpretation of the pasture canopy spectra from the visible (VIS), near infrared (NIR) and short wave infrared (SWIR) regions to develop robust algorithms using cut pasture samples analysed in the laboratory for a range of pasture nutrients. Previous work at Limestone Downs (Yule, Pullanagari, & McVeagh, 2013) highlighted the large variation in pasture quality and showed the success of in-situ hyperspectral sensing of pasture to estimate pasture quality parameters, avoiding time consuming, costly and destructive cut sampling techniques. However, in-situ pasture sampling

to cover large areas in hill country would be impractical, so the next logical step was to use hyperspectral imaging. Pasture biochemical information derived from hyperspectral imaging would then be used with farm physical and management information to predict soil fertility. The use of imagery, having the benefit of full spatial coverage of a farm, removes any need for interpolation of spatially sparse data. This is particularly important in a landscape characterised by immense variability.

The ultimate goal of the project was to be able to apply the technology and methodologies developed to farms outside of the study dataset. Ideally the approach will be effective on any hill country farm in New Zealand and the project will give confidence that the techniques are applicable under a wide range of conditions. Many research projects have used small study areas and sample numbers due to objectives or limitations (Burkitt, Donaghy, & Smethurst, 2010; Fulkerson, Slack, Hennessy, & Hough, 1998; Joblin & Keogh, 1979; Rowarth, Gillingham, Tillman, & Syers, 1988; Wells, 1969). The challenge in this project was to collect and build up a multi-site, multi-season dataset from eight different geographic regions and develop techniques that were transferable to other locations. This required large field campaigns, vast amounts of data and collating data from multiple sources and resulted in the most comprehensive dataset collected on New Zealand's hill country.

1.5 Predicting New Zealand hill country soil fertility

The description and results presented in this thesis are an integrated part of the PGP project. An overview is presented in Figure 1-3. The aim was to build a model that incorporated pasture nutrient concentration with any other appropriate available data, for example topographical information, farm management data and weather data, to predict underlying soil P availability. Wet chemistry laboratory analysis of leaf tissue and soil cores were used for model development with ancillary data collected in situ, for example slope and aspect. The final model needed to incorporate only data that would be readily available for farms outside of this study to ensure practical applications and implementation was possible. As collecting samples and measuring slope in the field etc. across an entire hill country farm is impractical, model inputs were derived from alternate sources that also provided full spatial coverage. Hyperspectral imagery and digital elevation models were used to derive model inputs and demonstrate predictive soil mapping of soil fertility which could be applied continuously across the landscape.

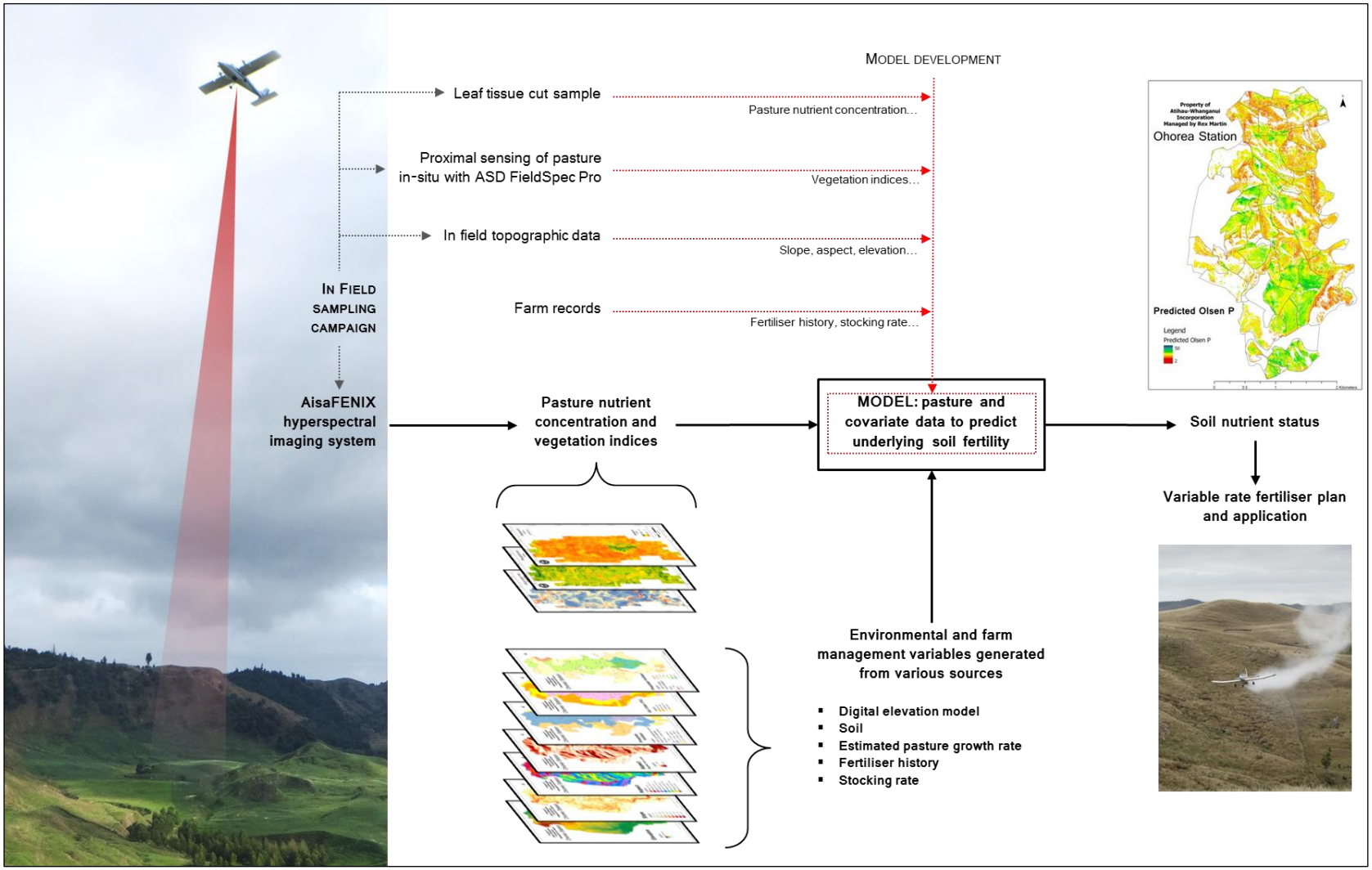


Figure 1-3: Thesis outline and context within the PGP project 'Pioneering to Precision' and the incorporation of field work and model development.

1.6 Thesis outline

This thesis explores the variability in mixed pasture and soil P within and between farms and seasons through extensive ground sampling. Data exploration, basic analysis and various modelling approaches were used to build an understanding of the relationship between the two. This study used leaf tissue P concentration of mixed pasture with ancillary data to estimate underlying soil Olsen P, not only to predict on farms within the dataset but ideally continuously across any hill country farm within New Zealand. This provided extensive valuable information for farmers, fertiliser representatives and farm advisors to make more informed decisions around fertiliser applications and improve nutrient use efficiency.

CHAPTER 2 examines the relevant literature surrounding the concepts explored within this thesis and includes broader ideas which hold important information in understanding the overall context of the research and wider project. A general introduction is given for New Zealand hill country highlighting the nature of the terrain and farming system, the economic importance of the sector and key challenges. Soil – plant – animal interactions are discussed and the causes of variation in leaf tissue and soil nutrient status are explained, illustrating the complexity of the system. The current procedures to acquire soil nutrient status to inform fertiliser decisions are presented. An overview of current and emerging techniques attempting to map soil properties and their suitability for use in the hill country environment are discussed. The use of optical sensing in agriculture is highlighted to understand the direction of the project and the application of the model. Research attempting to use vegetation as a proxy for soil properties is discussed, and finally the challenge of modelling grasslands is considered.

CHAPTER 3 covers an outline of the study sites, on eight commercial hill country farms from different geographic regions throughout the North and South Islands of New Zealand. A brief description of each farms physical characteristics and management highlight the differences between farming systems. This chapter also covers the site selection protocols, fieldwork and data collection methodologies, data collation and the development of the dataset. The dataset created is one of the largest and most extensive datasets collected exclusively on hill country.

CHAPTER 4 provides an outline of the dataset and its relationship to other studies conducted in New Zealand agriculture and explores the summary statistics. An understanding of how well the dataset covers ranges that are typically found in New Zealand hill country pastures is important to ensure the data and model are best able to be transferred to other farms. An understanding of the data itself and the differences between farms and seasons is also important step in model development. Preliminary analysis of predicting soil fertility (soil

Olsen P) through simple regression techniques were trialled and discussed. Direct soil Olsen P to plant P correlations are examined, plant P indices and nutrient ratios were all used in preliminary analysis.

CHAPTER 5 covers the use of stepwise linear regression for individual sampling events as well as combined datasets. Many variables were incorporated in the model to determine which variables were consistently selected across farms and seasons. Inputs included: leaf tissue biochemical and biophysical factors, fertiliser history, topography, weather data etc. Model inputs are discussed in terms of their selection, agronomic importance in the system and effect in the model.

CHAPTER 6 covers the development of a Bayesian Hierarchical model to predict soil Olsen P. Hierarchical modelling uses partial pooling to essentially share information across farms while acknowledging the uniqueness of each farming system. A number of models are trialled and the best model selected. An in depth discussion of the model inputs and their limitations are given.

CHAPTER 7 uses predictive soil mapping to show the outputs of predicted soil Olsen P on one of the commercial hill country farms, Ohorea station. A whole farm map of predicted soil Olsen P is based on a Hierarchical model. An example of a subset of the farm where predictions are made is used to show the potential for mapping estimates of soil Olsen P and the associated error in the predictions made.

CHAPTER 8 provides overall discussion, conclusion and recommendations for future work. This research was the first part of a large on-going project and included the groundwork for a new area of research which could significantly improve the accuracy of identifying fertiliser needs for New Zealand's hill country farming sector.

1.7 Thesis within the overall context of the PGP project

This PhD scholarship was agreed within the PGP project and certain experimental and research investigation activities were required. As this was the first time data from so many sources, using a number of different technologies was being used as the basis for a large modelling exercise, data quality and data integrity were paramount. A great deal of time was spent designing, and then managing the data collation process, to ensure the quality and integrity of the data was high and no errors were made.

Some of the basic steps within the overall PGP project are listed below. The ones in bold are activities where this research was directly involved.

PGP STEPS

- **Experimental design.**
- **Site planning through GIS analysis, site selection and marking out of plots on research farms.**
- **Collecting physical data around experimental sites on research farms.**
- **Collecting and dispatching pasture and soil samples to Analytical Research Laboratories (ARL) for wet chemistry analysis.**
- **Checking and recording results of sample laboratory analysis received from ARL.**
- **Collection of physical and management data off farm.**
- **Collating data from different sources around experimental sites and samples plots.**
- **Creating metadata around field data and data backup.**
- **Comparison of wet chemistry data from leaf tissue and soil samples on all research farms to other relevant studies.**
- **Summary analysis of statistics of wet chemistry data.**
- **Linear regression of wet chemistry and ancillary data.**
- Non linear regression of wet chemistry data and ancillary data.
- Collation of hyperspectral sensed Analytical Spectral Device (ASD) data.
- Analysis of hyperspectral data to create algorithms describing pasture nutrient content from hyperspectral information on each site and sample point.
- Regression analysis of hyperspectral data, sensed data, (linear and non-linear).
- **Bayesian linear regression analysis of wet chemistry and ancillary field sample data.**
- Deployment of hyperspectral imaging.
- Classification indicating effective pasture area and other vegetation types.
- Analysis of hyperspectral imaging data.
- Calibration and validation of hyperspectral imaging data from research farms.
- Formation of soil fertility estimation maps from vegetation cover.
- **External review of PGP, concept, experimental design and results to date.**
- **Introduction of hierarchical models using wet chemistry and ancillary data.**
- **Bayesian analysis of hyperspectral imaging to estimate soil Olsen P and establish uncertainty of prediction.**
- Independent validation of hyperspectral imaging data.

- Production of property maps indicating soil Olsen P over all pasture covered areas on each farm.
- Creating a fertiliser plan to optimise fertiliser use, for economically optimum performance.
- Refine workflows to integrate into Ravensdown system.

2

2 Literature review

2.1 New Zealand hill country

Pastoral land used for sheep and beef farming in New Zealand totals around 9.3 million hectares (Beef and Lamb New Zealand, 2017), approximately one third of New Zealand's land surface. Around five million hectares (18% of NZ) is regarded as 'pastoral hill country' (Kerr, 2016). The many definitions of 'hill country' include specified Land Use Classification (LUC) classes, land use (Cosgrove & Field, 2016) and slope and altitude parameters (Kerr, 2016). However for the purpose of this thesis, 'hill country' is land used for the production of sheep and beef cattle, where topography restricts the application of fertiliser to predominately the use of aerial top dressing.

Hill country carries a mix of sheep and beef cattle for the production of meat and wool, industries that is important to New Zealand both socially and economically. In the year ended 30th September 2016, the value of the red meat sector in New Zealand was estimated at $8 billion (Beef and Lamb New Zealand, 2016). The New Zealand meat and wool sector is the second largest export earner for the country. In the 2013-2014 financial year, 80% of beef, 92% of sheep meat, and 90% of wool produced in New Zealand was exported (Beef and Lamb New Zealand, 2014). This sector remains globally competitive due to year-round pasture based

farming, providing both a relatively low cost system and a brand or image that positions their product at the top end of the market, resulting in higher value returns.

Hill country livestock performance has benefited from research and industry work in animal performance and genetics. Approximately 28,252,000 sheep and 3,648,000 head of beef cattle are fed predominantly throughout New Zealand's hill country (Beef and Lamb New Zealand, 2016) with pasture making up 95% of their diet (Morris, 2013). The past 20 years have brought about vast improvements in per animal performance, in sheep and beef cattle. Evidence can be seen in the decline of sheep numbers but the total production of sheep meat and wool has been maintained (Morris & Kenyon, 2014). Animal genetics and breeding along with farm management have seen improvements in areas such as growth rates, reproductive rates, weaning weights and lamb survival (Morris & Kenyon, 2014), all contributing to an increase in per animal performance. On farm however, comparatively less focus has been placed on improving forage quality and quantity and understanding this in relation to animal intake and animal performance.

Increasing competition for land has driven change in the New Zealand rural landscape. Traditionally harder hill country has been run as breeding units, with lambs and fattening cattle sold store to finishing blocks on easier country. However as flatter land has been converted to dairy and other higher values enterprises or 'lifestyle blocks', it is even more important for hill country farmers to finish as much stock on farm as possible. This has resulted in pressure on sheep and beef farmers to intensify and better utilise their hills under increasing environmental scrutiny (Gillingham, Morton, & Gray, 2003). To achieve this, hill country farms will require sustainable intensification of easier country to provide the quantity and quality of feed required to bring lambs and cattle to killable weights and prime condition.

The temperate climate of New Zealand favours pasture production and creates an environment that is suitable for year round pastoral farming. However, topographic complexity presents hill country farming systems with a unique set of challenges. Aspect, in combination with a full range of slope classes from flat through rolling to steep; different soil types, depths and fertility; a wide range of climatic conditions; grazing behaviour of different stock classes; and the management of the farm result in a range of pasture growth rates, growth patterns, potential and actual production, quality, grazing efficiency and pasture species composition (Gillingham, Maber, Morton, & Tuohy, 1999; Ledgard, Sheath, & Gillingham, 1982; Murray, Yule, & Gillingham, 2007; Roberts & White, 2016). Pasture productivity is limited primarily by soil moisture, temperature, soil fertility and grazing

management (Chapman & Macfarlane, 1985). Less cultivatable land (due to steep slopes) means pasture renewal is impossible (excluding 'spray and pray') or uneconomic in these systems (Morris & Kenyon, 2014), leaving farm managers with grazing management and soil fertility as their major tools for increased pasture productivity and quality. Inherently low fertility in hill soils is rectified through fertiliser inputs, which is a hill farmers biggest single expense (Fraser & Vesely, 2011). The variability in the landscape and farm system leads to varying requirements for capital and maintenance nutrients (Roberts & White, 2016). Improvement in nutrient use efficiency would significantly increase pasture productivity on farm. Research in this area is justified equally for productivity gains and from an environmental perspective in reducing adverse environmental effects (Scrimgeour, 2016).

2.2 Soil - plant – animal and the overarching farm management interactions

After over 100 years of agricultural intensification, the hill country landscape has become a mosaic of grazed pastures. Seasonal distribution of pasture productivity and chemical composition is driven by a range of processes that stem from soil, climate and pasture management (Saunders, 1967, 1984). Nutrient availability is key to maximising productivity of grazed pastures, but is also a complex interaction between the soil solution and the soil solid phase (Jeffrey, 1988). The soil – plant – animal interactions are essentially driven by a complex and dynamic set of physical, chemical and biological processes. There are a lack of studies that observe the system as a whole (Brougham, 1970). These studies are time consuming, expensive and require a lot of resources. However there is a considerable body of literature available to help understand this system and the influences on soil nutrient availability and herbage nutrient concentration. Figure 2-1 summarises the interactions between soils, plants, grazing livestock and farm management, centred around pasture and soil nutrient concentration. The following sections (2.2.1 and 2.2.2) briefly cover the main factors causing variation in soil and herbage nutrients, with examples from the literature focusing on P.

2.2.1 Causes of variation in soil nutrient status

Soil nutrients are spatially and temporally variable, with many factors affecting not only the amount of a particular nutrient present in the soil, but availability to plant roots. The amount of P taken up by plants is essentially determined by the concentration of phosphate ions in the soil solution, the ability of the soil to resist or replenish phosphate ions as they are removed by plants, and the movement of ions through the soil solution towards the rhizosphere (Ozanne & Shaw, 1967).

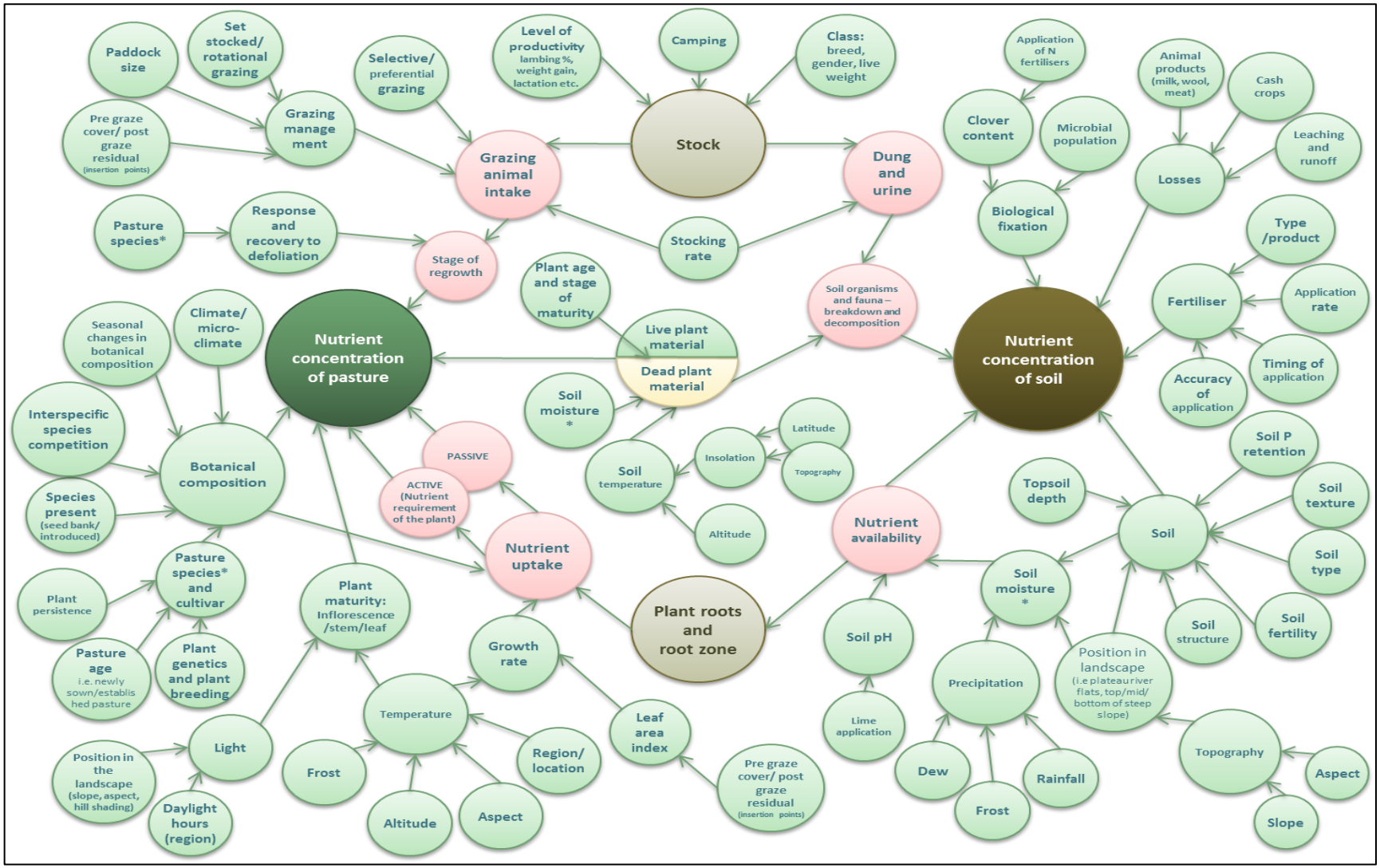


Figure 2-1 Relationships and interactions between nutrient concentration in soil and plant

Soil available nutrients depend on soil forming processes that result in unique **SOIL TYPES**. Parent material, topography, climate, biological factors (soil organisms and vegetation), and time all contribute to the development of soil (McLaren & Cameron, 1996; Molloy, 1998). Parent rock influences the chemical composition of the soil and soil texture, and therefore soil structure (Molloy, 1998). These properties affect the ability of a soil to store nutrients and water (Molloy, 1998) and their phosphate sorption capacity. This influences the ability of the soil to resist change or replenish phosphate ions in the soil solution as it is removed by plants (Ozanne & Shaw, 1967). Topography influences soil P through erosion. Steeper slopes tend to have shallower soils than more stable easier slopes (Molloy, 1998). The variation in topography in hill country can lead to complex soil patterns.

Increases in soil nutrient status in hill country are made through **FERTILISER INPUTS**. The fertility and nutrient availability of the soil is, to a large degree, a reflection of the history of soil management. In attempting to understand nutrient availability in soils it is important to consider the intensity of management. Many studies have examined the response of soil Olsen P at different rates or withholding fertiliser (Lambert & Grant, 1980; Lambert, Mackay, Ganesh, & Upsdell, 2014; Mackay & Lambert, 2011; Nguyen & Goh, 1992; Roberts et al., 1994; Rowarth & Gillingham, 1990), generally showing an increase in phosphate availability with increasing fertiliser application rates. Withholding fertiliser generally affects the steeper slopes first, as nutrient cycling in dung through animal transfer to flatter sites buffers an immediate response in soil phosphate availability (Rowarth & Gillingham, 1990). The fertiliser rate, product, and time of application and soil type will affect the availability of nutrients from the fertiliser applied. Fertiliser is applied in a relatively soluble form but not all of the applied nutrient will be taken up or even available for plant uptake (McLaren & Cameron, 1996). Applied phosphate reacts with the soil and a portion becomes unavailable for immediate plant uptake through fixation (McLaren & Cameron, 1996). Phosphate sorption will depend on the soil characteristics (Ozanne & Shaw, 1967).

The availability of soil nutrients are affected by the acidity of the soil expressed as **SOIL PH**. Soil pH can be increased through the **APPLICATION OF LIME**. The availability of nutrients varies over the pH range and the relationship is different for different nutrients. The target pH for the majority of hill country soils is 5.8-6.0 (Morton & Roberts, 2009) to achieve a balance of adequate availability of the required nutrients for plant growth and development, and avoiding toxicity (e.g. Aluminium toxicity in acidic soils) or antagonistic relationships in the oversupply of particular nutrients. Much of New Zealand hill country is thought to be below pH 5.6 (Roberts & White, 2016). Due to the cost of carting and spreading, the application of lime

has often been ignored. Phosphate is at near maximum availability around pH 6.5, with availability decreased in soils with pH above or below (Cornforth, 1998b). Phosphate in the soil solution in acidic soil is rapidly absorbed as iron and aluminium phosphates, or as calcium phosphate where soil pH is more alkaline (Parfitt, 1979).

Nutrient availability depends on **SOIL MOISTURE** content. Nutrients are available for plant uptake when they are present in a particular form in the soil solution. The total amount of a particular nutrient in the soil and the amount available for plant uptake differ, and it is largely controlled by the complex relationship between the soil solid and liquid phase (Jeffrey, 1988). The concentration of phosphate in the soil solution determines what is immediately available for plant uptake. The amount of phosphate available to plants is also determined by the rate of diffusion of phosphate through the soil solution towards plant roots (Ozanne & Shaw, 1967). The soils ability to store and drain water depends on soil texture and structure (Hall, 2008). In conjunction with water supply, which varies throughout the year, these factors influence the soils ability to supply nutrients to the plant (Cornforth, 1998b). Dry soils make the diffusion of P more difficult.

Phosphorus can be lost from the soil through **SOIL EROSION** and **NUTRIENT LEACHING**. Total P losses in hill environments are strongly linked to sediment (Parfitt et al., 2008) and P, held strongly in the soil, is therefore lost through surface runoff and erosion (Whitehead, 2000). This form of P loss is particularly important for hill country. Gillingham and Gray (2006) found dissolved reactive P (DRP) and total dissolved P (TDP) concentrations in surface runoff were directly related to soil Olsen P (R^2= 0.93 and R^2 = 0.90 respectively) status in their plots.

Phosphorus that is weakly held by the soil can be lost down through the soil profile. In soils with a low P retention capacity (or P sorption), P can be lost through leaching. McDowell and Condron (2004) researched the relationships between the concentration of dissolved P in subsurface flow (or leachate), and Olsen P and P retention. Their work was conducted on New Zealand soils. Dymond, Ausseil, Parfitt, Herzig, and McDowell (2013) developed DRP leaching maps across New Zealand agricultural land through estimates they made of subsurface flow based on complex interactions between agricultural intensity, climate and soil properties.

Nutrients are removed and transferred through **CROPS, FEED AND GRAZING ANIMALS**. Nutrients can be lost from the farming system through the removal of crops, feed and animal products that are taken off farm, or redistributed through the transfer of crops or feed within the farm, and through grazing animals. The extent to which the transfer and mining of soil nutrients occurs, depends on land use, management practices and intensity to which the area is farmed.

Nutrient transfer by grazing animals is significant. The majority of P ingested is returned to the soil in dung, with very little returned through urine (Whitehead, 2000). Approximately 64-90% of ingested P is excreted depending on live weight gain, wool growth, lactation of the animal (Gillingham, 1987), and P concentration in the pasture (Rowarth et al., 1988). Phosphorus return in dung increased with decreasing slope, with 60% returned to campsites (0-10 degrees) and only 5% returned to steep slopes (>31 degrees) (Rowarth & Gillingham, 1990). Dung results in a small but highly concentrated area of nutrient in the soil. Research has shown that the rate at which nutrients became available in the soil after cattle dung was applied, and the duration of increased soil concentration depended on the nutrient. For P, Truog P increased rapidly within a month and remained high over the following 14 months (Weeda, 1977). In areas of high grazing pressure, Saunders (1984) estimated that approximately 40% of a paddock was affected by dung and urine. This mosaic of dung return adds to the difficulty of determining clear spatial patterns in fields and has been shown to result in weak spatial autocorrelation of soil properties compared to cropped paddocks with other factors equal (Fu et al., 2013).

MINERALISATION and **IMMOBILISATION** of nutrients in the soil make nutrients available or unavailable respectively through soil microbial activity. Organic material is broken down and decomposed during mineralisation, a process where soil microorganisms release nutrients into the soil solution in a plant available form (Cornforth, 1998b). The breakdown and return of P to soil from senescent leaves and organic matter depends on soil biological activity and climatic factors. Immobilisation of nutrients occurs when nutrients are consumed by soil microbes (Cornforth, 1998b). These nutrients are eventually made available again when the organisms die (Hall, 2008).

TEMPORAL VARIATION in soil nutrient availability is well known, but clear patterns are still undefined. Olsen P showed temporal variation, but lacked a seasonal trend in the study carried out by Roberts (1987). Temporal variation in soil P was evident in the trials conducted by Tate et al. (1991). At the high fertility site, Olsen P fluctuated over the period of a year between 40-57 µg/g measured in 25 bulked soil cores from a 10 x 15m plot. Protocols for soil sampling collected for laboratory analysis recommend collection of samples occur at the same time every year to avoid this known fluctuation. This advice is based on attempting to limit soil sampling to when soil temperature and moisture are the same, however conditions can vary greatly between years. Variations in soil Olsen P across seasons differ between different published research (Roberts, 1987; Saunders & Metson, 1971; Tate et al., 1991).

2.2.2 Causes of variation in herbage nutrient concentration

NUTRIENT UPTAKE by plant roots from the soil varies, even when nutrients are in adequate supply. Many factors determine whether nutrients are made available for plants in the soil, and many factors also affect the plants' ability to take up nutrients.

Plants absorb nutrients held in solution in soil moisture at the surface of the plant root. Soil moisture status is important as plants cannot absorb nutrients from dry soils (Cornforth, 1998b). Nutrient concentration in the soil solution will affect the ability of plants to take up nutrients (Lambers, Raven, Shaver, & Smith, 2008). Nutrient uptake is through three processes: mass flow, diffusion, and root interception (McLaren & Cameron, 1996). Short bursts of growth can dilute nutrient concentration in the soil solution in the rhizosphere (Cornforth, 1984b). Plants have adapted different strategies to enhance their ability to absorb nutrients. For example, grasses are able to decrease the nutrient concentration of P at the root surface. This creates a steep concentration gradient and increases the movement of P via diffusion to the root surface (Barrow, 1975b).

The ability of plants to take up nutrients also depends upon their root surface area and the distribution of roots in the soil (Lambers et al., 2008). Root growth can be impeded in compacted soil, and growth and function can be limited by water logging, moisture deficits or poor aeration. Root growth and function can be limited by temperature, pests and diseases, and toxins (Cornforth, 1998b). Grass roots are thinner than clover roots increasing their surface area 8 fold, and have longer root hairs which have the ability to explore more of the soil (Barrow, 1975b).

Synergistic and antagonistic relationships exist between the uptake of nutrients. Mulder (1953) produced one of the first diagrams showing interrelationships between different macro and micronutrients. Interactions between the uptake of K, magnesium and sodium have been established and are more commonly known due to the animal health implications of any imbalance. The use of fertiliser high in K can induce magnesium and sodium deficiencies in the pasture (Smith, Young, & O'Connor, 1983), which can lead to imbalances in grazing livestock and hypomagnesaemia (Grace, Knowles, & Sykes, 2010).

Nutrient concentration varies within **DIFFERENT PARTS OF AN INDIVIDUAL SPECIMEN.** For some nutrients this variation is between different plant parts. For others a nutrient gradient from the top to bottom of the pasture plant has been identified. Nutrient concentration was measured for a range of nutrients in cocksfoot (*Dactylis glomerata*) (Davey & Mitchell, 1968; Fleming, 1963), meadow fescue (*Festuca pratensis*) (Fleming, 1963), perennial ryegrass (*Lolium*

perenne) (Fleming, 1963), switchgrass (*Panicum virgatum*) (Smith & Greenfield, 1979), timothy (*Phleum pratense*) (Fleming, 1963; Smith & Greenfield, 1979), white clover (*Trifolium repens*) (Wilkinson & Gross, 1967) and red clover (Fleming, 1963). Of the total P content in cocksfoot, 33.2, 8.9, 11.7 and 46.1% were measured in the spikelets, leaf blade, leaf sheath and stem, respectively (Davey & Mitchell, 1968). Phosphorus concentration in all seven species across all studies was highest in the inflorescence. Calcium concentration was highest in the leaf blades for the five grasses and red clover. Copper, calcium and boron were much higher, 2-3 fold that of grasses, in all plant parts for red clover (Fleming, 1963). The concentration of nitrogen (N) in leaves, leaf sheaths and stems decreased towards the base of the plant in switchgrass and timothy (Smith & Greenfield, 1979). This has implications for samples that are collected containing different portions of plant parts, for example when flower spikes are present.

The concentration of a particular nutrient can vary between **DIFFERENT SPECIES**. Nutrient concentration can vary between different species within the same sampling area at one time point (Harrington, Thatcher, & Kemp, 2006; Reay & Marsh, 1976; Wilman & Derrick, 1994). For example legumes and herbaceous pasture plants are known to maintain much higher concentrations of calcium than grasses (Loneragan, Gladstones, & Simmons, 1968). White clover is known to have higher concentrations of N, calcium and boron with typical concentrations in perennial ryegrass and white clover respectively of 2.0-3.5% N and 3.5-5.2% N, 0.4-0.8% Ca and 1.0-2.0% Ca, and 2-8mg/kg B and 10-40mg/kg B (Whitehead, 2000). Different species have different requirements of nutrients for near maximum pasture growth (McNaught, 1970).

Hill country pasture is highly heterogeneous and the **SPECIES PRESENT** and **PROPORTION OF DIFFERENT SPECIES IN THE SWARD** can also vary greatly, influenced by a vast number of factors. Hill country pasture in the North Island of New Zealand is reported to have 15-25 species per m^2 typically (Dodd, Barker, & Wedderburn, 2004) and has a marked seasonal pattern. Studies have measured and shown species make up a different percentage of the sward depending on the environment and conditions at a specific location (Gillingham, 1980; Schlegel, Wyss, Arrigo, & Hess, 2016). Environmental variables including climatic and topographic (Wan, Baisen, Kemp, & Li, 2009), slope (Grant & Brock, 1974; Sheath & Boom, 1985), aspect (Lambert & Roberts, 1978), soil moisture and drainage (Grant & Brock, 1974), and landscape position such as ridges, river flats, terraces, hills (Grant & Brock, 1974) all influence species composition, as species have adapted to particular conditions.

Interspecific and intraspecific competition also determines sward composition. The ability of species to compete for light and resources differs. Grasses and pasture species differ in their ability to compete for soil phosphate (Crush & Hunt, 1992). On approximately a 10 degrees slope and an Olsen P of 10 µg/mL, high fertility response grasses (HFRG) and low fertility tolerant grasses (LFTG) are equally competitive, whereas steeper slopes favour LFTG, and higher fertility favours HFRG (Zhang, Valentine, & Kemp, 2005). Fertiliser applications can influence the botanical composition (Chapman & Macfarlane, 1985; Lambert & Grant, 1980; Ozanne, Keay, & Biddiscombe, 1969) and the portion of different species in the sward (Gillingham, Morton, & Gray, 2008). Grazing pressure influences botanical composition of pasture (Dorrough, McIntyre, & Scroggie, 2011). Class of stock and stock management particularly through grazing regime (Dorrough et al., 2011) and paddock subdivision (Matthews, Harrington, & Hampton, 2011) affect the grazing pressure placed upon the pasture. Botanical composition can also be altered by dung and urine return (Saunders, 1984; Weeda, 1977). The botanical composition also reflects topography as it influences stock management, animal behaviour and nutrient transfer (Grant & Brock, 1974).

Nutrient concentration varies in plants through **DIFFERENT STAGES OF MATURITY**, although the pattern changes with element and species. The trend for most nutrients, but not all, is a decrease as the plant matures (Whitehead, 2000). The nutrient concentration in dead material of ryegrass and white clover was very low in N, P and K, but higher in calcium and sodium (Wilman, Acuna, & Michaud, 1994). Phosphorus concentration decreases with advancing maturity, which has been shown in a mixture of ryegrass, other grasses and herbaceous plants (Schlegel et al., 2016), in ryegrass and white clover (Wilman et al., 1994), and in white clover (Wilkinson & Gross, 1967). Known variation in nutrient concentration as plants develop and mature can lead to misinterpretation of nutrient concentration in leaf tissue samples. As a result, leaf sampling for mineral analysis is usually targeted at a particular growth or leaf development stage, for which the nutrient concentration criteria are already established (McNaught, 1970). Farmers aim to prevent grasses from becoming reproductive through grazing management, as pasture quality is much higher in a pasture with lots of young fresh growth and no dead vegetation (Chapman, Lee, & Waghorn, 2014; Gray et al., 2004). As supply and demand for pasture is not always equal, excess supply in late spring can result in pasture 'getting away' when the pasture advances in maturity, the extent and timing of which will differ between farms.

Nutrient concentration in pasture shows temporal variation. In some research, this variation shows a **SEASONAL TREND.** However in other research, no clear seasonal trend was identified,

depending on the nutrient of interest. In a study measuring nutrient concentration in samples plucked fortnightly for seven years, Roche et al. (2009a) found the strength and magnitude of seasonal trend depended on the nutrient. Repeatability for 11 measured nutrients was low to moderate (15-59%) with P highest. Seasonal trends in P concentration were consistent across the studies carried out by Gillingham and During (1973), Saunders and Metson (1971) and Walsh and Birrell (1987). Lowest concentration was found in the summer, increasing through autumn to highest concentrations in winter and early spring, and then decreasing through spring to low levels again in summer. Another study showed P concentration decrease from autumn through winter and spring to early summer, and then increased again late summer into autumn, on a ryegrass-clover dominant dairy pasture in Taranaki (Roberts, 1987). In contrast Fleming and Murphy (1968) found a clear seasonal trend in P nutrient concentration; highest in autumn, then spring, then winter, and lowest in summer. In studies of P concentration where ryegrass and clover were separated: Saunders and Metson (1971) found very little difference in seasonal patterns between ryegrass and white clover over seven sites; Tate et al. (1991) found temporal variation but not seasonal trend in ryegrass, but a seasonal trend in clover; and Reay and Marsh (1976) found a seasonal trend in young ryegrass leaves but no seasonal trend in red clover. Tate et al. (1991) cut samples to 1cm above the ground and Reay and Marsh (1976) selected the youngest leaflets of clover and young ryegrass leaves which, by selecting leaves at the same stage of maturity at each sampling, they suggested reduced the seasonal effect. There are a number of other reasons differences could have occurred during the trials including differing soil fertility status, the use of fertiliser, irrigation and herbicides, and climatic conditions.

Nutrient concentration in pasture plants varies depending on **WEATHER CONDITIONS** leading into and at the time of harvest of herbage. Light intensity and temperature affect nutrient concentration in pasture grasses and white clover (Bathurst & Mitchell, 1958). For example, three levels of light intensity showed a significant relationship to chemical composition of white clover in their study. An extensive study by Roche et al. (2009b) monitored weather conditions and measured nutrient concentration of 11 different nutrients in plucked samples collected over seven years. The range of weather induced variables included: air and soil temperatures, sunlight hours, radiation, rainfall, evapotranspiration, and wind run. Overall, weather explained up to 14% of the variation in herbage nutrient concentration over and above the effect of season and location. They noted that the effect of weather on nutrient concentration likely differs at different times of the year, and that seasonal effect (Roche et al., 2009a) had a greater effect on most nutrients concentrations than weather. The concentration

of P in the plucked herbage samples was more strongly affected by weather than any other nutrient. For example, P concentration in relation to the seven day maximum air temperature prior to harvest fitted a quadratic polynomial curve. At 12-18°C seven day maximum air temperature, herbage P concentration was approximately 0.4 g/100g, which declined as air temperature increased, to approximately 0.25 g/100g at 26°C (Roche et al., 2009b).

Nutrient concentration varies at **DIFFERENT STAGES OF REGROWTH AND THE INTENSITY OF THE GRAZING EVENT** which is determined by grazing management strategies. Turner, Donaghy, Lane, and Rawnsley (2006) measured nutrient concentration in the regrowth after defoliation of Prairie grass (*Bromus willdenowii*) from 1 to 6 leaf growth stages. Calcium, magnesium, P and K all decreased, while sodium remained stable. Intensity of grazing events and defoliation affect pasture utilisation and the rate at which leaf regrowth occurs. Brougham (1957) found that the removal of excess amounts of leaf area from ryegrass and red and white clover swards can result in pastures taking six times as long to reach maximum growth rates. Pasture defoliation and utilisation is affected by classes of grazing stock (Cosgrove & Field, 2016) and affects pasture regrowth and leaf senescence. Leaf senescence determines the amount of dead material present in the sward and this is of much lower nutrient content than that of green leafy pasture. In the first 30-40 days after hard grazing, leaf death will be low, at around 10%. If pasture is left for periods longer than 40 days, leaf death rates will be much greater unless the grasses are heading (Hunt, 1971). Lax grazing results in poor pasture utilisation, allows dead material to build up, and can shade out white clover (Chapman & Macfarlane, 1985). Although hard grazing opens up the pasture sward and creates an opportunity for weeds to invade (Chapman & Macfarlane, 1985), like legumes, weed content can be significant in the sward but contribute very little to the dead vegetation content (Gillingham, 1980).

Many studies have monitored the effect of **URINE AND DUNG** on nutrient content of pasture. Nutrients are returned to the soil in concentrated patches through dung and urine of grazing animals which then becomes available for plant uptake. During and Weeda (1973) applied low and high P dung collected from cattle grazing unfertilised and good quality pasture respectively, with usual weights of dung and area covered by grazing animals from previous work to assess the response in pasture yield and nutrient concentration. High P dung contained P equivalent to 750kg/ha of superphosphate. Their findings show that there was an increase in yield extending to 15cm beyond the dung patch, but the increase in pasture P concentration extended beyond this. Pasture response to the dung application was still evident after two years, longer than the response to equivalent rates of superphosphate. The effects of cattle dung on pasture P concentration were not as great as other nutrients,

including K, N, magnesium, calcium, and sodium (Weeda, 1977). Only 24% of the P was recovered in herbage after 1.5 years (Weeda, 1977) and nearly 40% in 3.5 years (During & Weeda, 1973). During and Weeda (1973) calculated that on heavily stocked pasture running 4 dry cattle beasts per hectare, typically excreting 12 times per day, in 1 year 40% of the soil and pasture in that area would be affected by cattle dung, and 75% within 3.5 years. However, as mentioned in section 2.2.1, on steeper hills dung and urine are predominately returned to stock camps concentrating returned nutrients in these areas. Potassium (K), P and molybdenum in herbage were higher, and calcium, copper, and selenium were lower under urine and dung areas identified in the paddock after it was grazed (Saunders, 1984). Sheep urine increased N and K in herbage and calcium, magnesium, P and manganese were lower than the concentrations in surrounding pasture. Iron, copper, zinc and sodium were not significantly effected (Joblin & Keogh, 1979).

It is not within the scope of this literature review to cover all the interactions within the soil-plant-animal, or as Jeffrey (1988) extends this to the soil solid phase - soil liquid phase – rhizosphere – root – shoot continuum, for each nutrient. In an attempt to summarise many of these interactions Figure 2-1 was developed. This does not cover all possible interactions, but attempts to cover the main areas and highlight the complexity and dynamics of the system. Interpretation of results from studies that focus on plant tissue concentration can be difficult. The majority of studies have only one or a few sites, carried out at one or a few sampling events. Leaf tissue samples can be collected in different ways. They may be either plucked or specific plant parts harvested or cut. But cutting techniques, particularly cutting height, vary. The time of harvest may be set to a particular calendar day, pasture height, or growth stage. The size of the sample support, the area over which the sample is collected, differs between studies. Species, time since the last grazing event, climate, pasture management, nutrient imbalances and many other factors vary between sites that influence pasture nutrient concentration and are not always stated or even measured. Caution must be taken when relating findings to new sites and sampling events. However general trends can be useful. It is important to understand these interactions as imaging of agricultural land and commercial hill country farms will capture whichever state the pasture is in at the time the image is taken.

2.3 Phosphorus in the New Zealand hill country environment

Phosphorus is an important nutrient for agriculture and in hill country soils is the most monitored of the 16 known essential nutrients for plant growth and development. New Zealand soils are inherently low in P and many unmodified New Zealand soils have low P

availability (Sparling & Schipper, 2002a). Phosphorus is less mobile in the soil than some of the other nutrients, so is not easily leached (Cornforth, 1998b). The concentration of P in the soil solution is generally low and relies on being replenished from labile P associated with the soil solid phase or from fertiliser or excreta returns. The form and availability of phosphate in the soil will depend on soil parent material, phosphate retention, fertiliser, soil pH, soil moisture, and nutrient return through breakdown of animal excreta and herbage material (McLaren & Cameron, 1996). Species have adaptive strategies to increase their ability to take up P from the soil solution, including altering concentration gradients at the root surface, root extension, increasing root surface area (Barrow, 1975a) and through mycorrhizal associations.

Phosphorus is an essential plant nutrient and is important for energy transfer and cell division for plant growth (Whitehead, 2000). Plants take up P as orthophosphate ions in the form of $H_2PO_4^-$ or HPO_4^{2-} from the soil solution in the rhizosphere. Critical P concentrations for active growth in ryegrass and white clover are reported to be 0.28-0.36 and 0.30-0.40 respectively (McNaught, 1970). Phosphorus concentration in hill country pasture is highly variable, with spatial dependency absent beyond 17m (Kawamura et al., 2009). Although slow moving in the soil, P is highly mobile once in the plant phloem (Whitehead, 2000). The ability of plants to remobilise phosphate means the visual signs of deficiency are seen in the older leaves first (Cornforth, 1998b). When P is limiting, plants appear to maintain root growth, but vegetative growth is decreased and therefore yield is reduced which causes an increase in root:shoot ratio (Atkinson, 1973). Vegetative growth deficient in P can be weak and spindly and leaves may appear dark green or have purple edges (Cornforth, 1998b).

Phosphorus is an essential nutrient for both plants and animals. Although P is often deficient in New Zealand soils in relation to plant requirements, there is very low risk of dietary P deficiencies for livestock in pastoral systems (Grace et al., 2010). Approximately 0.7-1.0% of a grazing animals' live weight is P; 86% of which is in the skeleton and teeth (Whitehead, 2000). Growing lambs and calves have the highest dietary P requirements in a beef breeding and finishing system, requiring 0.22 and 0.31 % (w/w) in pasture DM respectively (Grace et al., 2010). Of the P ingested only about 10% is used for live-weight gain and wool production, with the majority being excreted (Whitehead, 2000) and transferred to stock campsites (Rowarth & Gillingham, 1990).

Increasing profitability in hill country farms depends on the cost of lifting soil fertility and the ability of a farm manager to convert that excess pasture into animal product through good pasture utilisation and a viable market for that product. Lambert, Clark, Mackay, and Costall

(2000) observed an increase in pasture production and ryegrass content and a reduction in low fertility grass species in raising Olsen P. The increase in production translated to increased stocking rate but did not decrease individual animal performance. However pasture quantity and quality are suggested to be reducing the potential production of some of the high performing flocks. It has been suggested that the genetics and potential of well-bred animals are not fully expressed and that it is the nutritional intake that is holding these animals back (Dodunski and Cook, 2007).

Studies to identify overall trends in soil Olsen P in New Zealand agriculture have shown scope to improve production in sheep and beef through phosphate fertiliser as many areas are below target Olsen P (Wheeler, Sparling, & Roberts, 2004). An analysis of 246,000 soils samples from dairy and sheep and beef pastures between 1988-2001 taken from all over New Zealand show Olsen P on sheep and beef properties increasing from around 12 µg/mL in 1988 to around 17 µg/mL in 1996 and a slight drop to 15 µg/mL by 2001. Olsen P on sheep and beef farms were well below the average Olsen P on dairy farms which steadily increased from 15 µg/mL to 30 µg/mL by 1996 and have since plateaued. This highlights the possible opportunity that exists for sheep and beef farmers to increase productivity by lifting soil fertility through raising Olsen P, unlike dairy farms where it is likely fertiliser inputs could be reduced without affecting pasture productivity (Wheeler et al., 2004).

2.4 Fertiliser use and history in hill country

2.4.1 Fertiliser use and history in hill country

The importance of fertiliser in New Zealand agriculture to build soil fertility and increase pasture production and quality has long been recognised. Building soil fertility encourages higher producing and more nutritious pasture species to dominate the sward (Saxby, 1945). Phosphorus and sulphur (S) nutrient deficiencies in New Zealand soils (McLaren & Cameron, 1996) need to be addressed through the application of fertiliser (Cornforth & Sinclair, 1986; Gillingham et al., 2003). These nutrients need to be applied continually (Cornforth & Sinclair, 1986) to sustain production of a grass-legume dominant pasture (Roberts & White, 2016) if nutrients are being removed from the system via animal products, soil and environmental losses. Superphosphate has been the predominant fertiliser used on New Zealand's agricultural pastures. Phosphate is applied to encourage clover growth, which as a legume fixes atmospheric N through symbiotic bacteria in nodules of plant roots and increases growth of grass species (White & Hodgson, 1999), to lift productivity and make the pasture system as a whole more vigorous (Saxby, 1945). The current year's phosphate fertiliser input was the

most important factor identified by Wan et al. (2009) affecting the abundance of white clover in New Zealand hill country.

Many studies have examined the response of soil Olsen P (Lambert & Grant, 1980; Lambert et al., 2014; Mackay & Lambert, 2011; Nguyen & Goh, 1992; Roberts et al., 1994; Rowarth & Gillingham, 1990) and pasture productivity (Gillingham, Morton, Gray, & Roberts, 2008; Lambert, Clark, Grant, Costall, & Fletcher, 1983; Lambert et al., 2014; Morton, Sinclair, Morrison, Smith, & Dodds, 1998; Rowarth & Gillingham, 1990), nutrient concentration (Crush & Hunt, 1992; Lambert & Grant, 1980; Morton, Smith, & Morrison, 1998; Rowarth & Gillingham, 1990) and species composition (Lambert, Clark, Grant, & Costall, 1986) at different rates or withholding fertiliser. The general consensus of these studies show that when soil Olsen P lifts, pasture productivity increases, and the sward contains a larger portion of high fertility species such as ryegrass and white clover.

Pasture productivity is dependent on many factors, particularly in the complex terrain of hill country farms. Most of these factors are out of the control of the farmer, particularly in hill country where cultivation and irrigation are impractical. For sheep and beef farmers, increasing nutrient supply to the plant through fertiliser and lime is the main factor affecting plant growth which the farmer has some control over (Cornforth, 1998b). However, many farmers are heavily reliant on the advice of fertiliser representatives and farm advisors for fertiliser recommendations. Advice varies greatly and there is continued discussion around plant nutrient status, soil fertility and fertiliser requirements (Cornforth, 1998b). Soil fertility in hill country has held back productivity of farms. The missed opportunity of improving nutrient use efficiency has meant that potential production has not been met (Roberts & White, 2016). Roberts and White (2016) suggest that fertiliser advice in hill country is due for a rethink to optimise nutrient use efficiency.

The biggest expenditure for the sheep and beef farmer is fertiliser. During financially tight years rates may be cut back or fertiliser may be withheld altogether. The average farm expenditure in the 2015-2016 financial year was $61,100 for fertiliser, lime and seed (Beef and Lamb New Zealand, 2017). The average fertiliser use in the 2015-2016 financial year on a sheep and beef farm was 146.3 kg/ha or 22.7 kg/su (Beef and Lamb New Zealand, 2017).

2.4.2 Traditional soil sampling methods and fertiliser recommendations

Currently, routine soil sampling to aid fertiliser recommendations in hill country is based around bulked soil cores collected along a transect. The traditional approach is to divide the farm based on management units. These are defined by similar properties including: soil type,

topography, development, fertiliser use and farm history. Soil samples collected on a 100m transect, with nine sampling points at 10m intervals, from three representative paddocks within the designated management unit are then bulked together. Core samples taken to 75mm, should be taken within 0.3m of each sampling site at the same time of year in following years to reduce temporal and spatial variation. However if poor sites are chosen originally, this could lead to continually misleading results (Morton, Baird, & Manning, 2000). The traditional method attempts to reduce the variability within the core samples collected; the aim is to have a CV of about 20% (Morton et al., 2000). These bulked samples are the indication of soil fertility status and basis of fertiliser recommendations.

Soil Olsen P is regarded as one of the most important pieces of information in soil test results because P is often deficient in soil, there is a high requirement for P from plants, and it is the most expensive macronutrient applied in hill country (Morton et al., 2000). A chemical analysis developed by Olsen, Cole, Wanatabe, and Dean (1954), Olsen P is the most commonly used soil phosphate test in New Zealand and extensive calibration work has been completed in terms of likely pasture response to superphosphate fertiliser based on Olsen P values (Cornforth, 1998b). Available P or labile P is extracted using 0.5M sodium bicarbonate ($NaHCO_3$) solution at pH 8.5 for 30 minutes (McLaren & Cameron, 1996). P in the soil solution, P weakly adsorbed to the surface of the soil particles and some organic P are extractable, but absorbed P is non-extractable by the Olsen P test. It

Soil Olsen P is known to be variable and is associated with large errors. The laboratory test itself has an error of +\- 4 µg/mL. Variability in the Olsen P test from field sampling is estimated to be 20% (Cornforth, 1998b). The Olsen P test is well recognised, documented, and calibrated regularly in the laboratory. However error from multiple sources throughout the whole soil sampling process is inevitable. Samples are collected across transects from multiple paddocks. The bulked cores are homogenised, and then only a few grams used for the test. The variation in soil test results has led researchers to suggest that assessing trends over years rather than individual test results is the best approach (Cornforth, 1998b; Morton et al., 2000). Nevertheless, these results and trends are the best information available to indicate the current level of P availability in the soil and guide fertiliser applications.

Fertiliser applications aim to achieve one of two goals: either to build soil fertility through raising soil Olsen P, or to maintain soil fertility at current levels through balancing nutrient input and removal. High rate fertiliser applications are required to build soil fertility through the development phase. During the maintenance phase, lower rates are applied to maintain

soil fertility. By the 1930's topdressing, applying fertiliser via aircraft, was common practice. Rates for superphosphate were reported to be 6-10cwt. per acre for the first year of sown pasture on newly ploughed scrubland (Saxby, 1945). This is equivalent to 740-1200kg/ha. Applications of 1-2cwt. per acre, and for fat lambs and dairy country 2-3cwt. acre were normal practice (Saxby, 1945), equivalent to 125-250 and 250-375kg/ha. Maintenance rates were similar to the rates that are used today. At this time, experience was used to decide what amounts should be applied, and appropriate application rates were a debated point (Saxby, 1945).

Static or balance models were later used for fertiliser recommendations, where requirements were based on replacing what was removed from the system through animals and soil. Soil tests were used to assess the changes from previous fertiliser applications and allowed advisors to make adjustments to the recommendations given, as they recognised that all farms are unique (Cornforth & Sinclair, 1982, 1984).

Static models were unable to take into account the magnitude of the response of pasture to different rates of fertiliser applications. The response of pasture production to increasing soil Olsen P is curvilinear (Edmeades, Metherell, Waller, Roberts, & Morton, 2006). Production will increase with increasing soil Olsen P until maximum production is reached, where productivity will plateau regardless of any further increase in Olsen P. This is the biological optimum. General target Olsen P levels outlined in Morton and Roberts (2009) are defined as the levels for near maximum pasture production on the major soil groups on which sheep and beef farms are found. Applying fertiliser above the optimal, does not result in any additional increase in pasture production, even when low rates of fertiliser are applied regularly (Burkitt et al., 2010). Recommended fertiliser rates and optimal Olsen P targets for sheep and beef farms are outlined in Morton and Roberts (2009) including maintenance and capital applications for different soil groups.

Static modelling and generalised target Olsen P values do not include any kind of cost benefit analysis. Saxby (1945) questioned whether the use of fertiliser was sound, based on costs relative to the results achieved. Where fertiliser use resulted in higher stocking rates or a more valuable class of stock to be carried, it was thought to be profitable. While the biological optimum is the maximum productivity under non limiting circumstances, the cost of raising and maintaining soil fertility at this level is expensive and can cost more than is gained from the increased productivity. This is the fundamental idea of the economic optimum, and will vary depending on farm. The economic optimum varies depending on quantity and cost of

applying inputs required and the financial gain in production, which will depend on the magnitude of increase in production and stock or meat prices (Edmeades, McBride, & Gray, 2016; Roberts & White, 2016). This trade-off is encompassed in a comprehensive dynamic P model and econometric decision support tool that was developed (Metherell, 1994; Metherell, McCall, & Woodward, 1995). This approach incorporates pasture response to changes in soil fertility based on different fertiliser rates, and an economic component to assess financial returns, giving the ability to compare different fertiliser strategies and the best option identified.

2.4.3 Precision Agriculture and its application in hill country

Decisions regarding fertiliser applications make best use of the limited information derived from the results of traditional soil sampling. Soil sampling and laboratory analysis are time consuming and costly (Kawamura et al., 2011; Varella, Guérif, Buis, & Beaudoin, 2010). Laboratories follow strict procedures to ensure the most accurate and reliable results are provided for the samples they receive. However it is debateable how accurately those samples represent the land from which they are collected (Bramley & Janik, 2005), particularly when samples are routinely bulked. Traditional soil sampling is unable to represent the heterogeneity in soil properties (Bramley & Janik, 2005) and therefore loses the complexity of the system (Viscarra Rossel, Walvoort, McBratney, Janik, & Skjemstad, 2006). For soil sampling to be cost effective, the results have to translate into valuable information that is accurate and result in informed decision making (Bramley & Janik, 2005).

Farmers are feeling greater pressure from government, councils and the public around environmental effects and an interest in food production practices, coupled with financial pressures (McCormick, Jordan, & Bailey, 2009). Nutrient use efficiency has the potential to make a substantial difference for sheep and beef farmers. Farmers are well aware of the variability across their farms. With their knowledge and self-awareness increasing (Bramley & Janik, 2005), whole farm testing is becoming more popular (Bowie & Venter, 2017) in dairy systems. However detailed soil sampling in hill country is impractical (Kawamura et al., 2011) and a fast and inexpensive method (Bramley & Janik, 2005) to collect high resolution data is needed to provide the necessary information and help improve knowledge of the soil system which will make for more informed management decisions (Bramley & Janik, 2005; Viscarra Rossel et al., 2006) in these highly variable landscapes.

Fertiliser has traditionally been applied to hill country via aerial top dressing of a single product at a uniform rate over large areas or the whole farm (Gillingham et al., 2003; Roberts & White,

2016; Yule et al., 2014). This approach ignores variability, and results in over and under application of fertiliser (Betteridge, Schnug, & Haneklaus, 2008; Gillingham et al., 2003). Uniform rates miss an opportunity to make better use of nutrients (Betteridge et al., 2008), but is the most risk averse option (Whelan & McBratney, 2000). The technology to apply variable rates of fertiliser aerially is currently available (Morton, Stafford, Gillingham, Old, & Knowles, 2016) and spread patterns that have been typically uneven (Gillingham & Metherell, 2005; Yule et al., 2014) are now improving (Chok, Grafton, Yule, White, & Manning, 2016). In modelling scenarios of uniform versus differential fertiliser applications, the benefits to farm productivity (Gillingham et al., 1999; Morton et al., 2016; Murray et al., 2007; White, Metherell, & Roberts, 2017) and financial returns through differential fertiliser applications (Morton et al., 2016; Roberts & White, 2016; White et al., 2017) have been shown. However if inputs are not varied in an appropriate way, through poorly defined, mapped or quantified management units, then there is a large risk involved in differential fertiliser applications (Whelan & McBratney, 2000) and the results may not be better than uniform rates (Oliver, 2013). Correctly estimating soil fertility and defining appropriate management units is therefore of utmost importance.

Awareness of the importance of managing our soils efficiently is being raised (Sparling & Schipper, 2002b). With this, there is a growing demand for timely, high resolution, accurate soil data, with good spatial coverage to help understand soil as a whole system (Taalab et al., 2015; Viscarra Rossel et al., 2006) for environmental monitoring, and modelling and precision agriculture (Denis, Stevens, van Wesemael, Udelhoven, & Tychon, 2014; Gomez, Viscarra Rossel, & McBratney, 2008; Lu, Wang, Niu, Li, & Zhang, 2013; Viscarra Rossel et al., 2006). Whelan and McBratney (2000) proposed a decision tree for site specific nutrient management. First, variability must be present, then the causes determined and modelled, sensible definition of management units must be able to be achieved, and only then can variable rate management strategies be applied. Variation in soil properties are not random; they are the deterministic result of dynamic and complex interactions that we are unable to grasp (Webster, 2000). Our incomplete knowledge of soil properties (Varella, Guérif, & Buis, 2010; Webster, 2000) has limited models of soil properties, particularly at an appropriate scale (Varella, Guérif, & Buis, 2010). However, an accurate prediction of available P in the soil is essential to optimising nutrient use efficiency of P (van Rotterdam, Bussink, Temminghoff, & van Riemsdijk, 2012).

2.5 Traditional and emerging approaches to modelling soil properties

Mapping soil properties can be challenging, but is essential for site specific nutrient management in agriculture. Soil properties can be difficult to measure directly (Minasny, Vrugt, & McBratney, 2011) and though they can have a large effect on the landscape, their variation cannot always be readily observed in other environmental variables either (McKenzie & Ryan, 1999). The limited availability of detailed soil information (Viscarra Rossel, McBratney, & Minasny, 2010) is a barrier to the adoption and correct implementation of site specific nutrient management which relies on accurate and meaningful maps of soil properties (Frogbrook & Oliver, 2007). To generate meaningful maps of soil properties requires knowledge of the spatial variation across paddocks or whole farms (Frogbrook & Oliver, 2007) and the careful interpolation of data points using correct methodologies. This is often not the case, and leads to misinterpretation of the data (Oliver & Webster, 2014).

Currently, the most common approach to mapping soils and their properties is through Digital Soil Mapping (DSM). DSM is a discipline that involves the use of quantitative methods to describe spatial patterns in soil properties which are used to make continuous predictions between known point measurements or observations (Grunwald, 2010). A number of different statistical and geostatitical approaches can be used to incorporate field observations, laboratory analysis, proximal sensing measurements and ancillary data to map soils and their properties (Grunwald, 2010). Geographic information systems (GIS) have made storage, handling, processing, analysis and visualisation of spatial data much easier.

Three main approaches to mapping soil properties have been: 1. the collection of point data through observations or samples collected and sent for laboratory analysis which are then interpolated; 2. the collection of point data using 'on-the-go' sensors which are again interpolated; and more recently 3. the emerging field of image spectroscopy, where satellite or aerial multispectral or hyperspectral data is captured and analysed to estimate soil properties (see Figure 2-2).

One approach is to collect a finite number of **POINT OBSERVATIONS OR SAMPLES** at known locations. However soil properties are continuous across the landscape. To map them, predictions must therefore be made at all locations in-between, a process known as interpolation (Heuvelink & Webster, 2001; Oliver, 1987). Geostatistics is used for analysing spatial variation and for making estimates of continuous random variables (Minasny et al., 2011; Oliver, 1987). The variogram provides information of the scale and intensity of spatial variation of soil properties. Variograms determine the distance over which points are spatially

dependent and provides the necessary information for kriging (a method of spatial interpolation) (Oliver, 1987; Webster & Oliver, 1992).

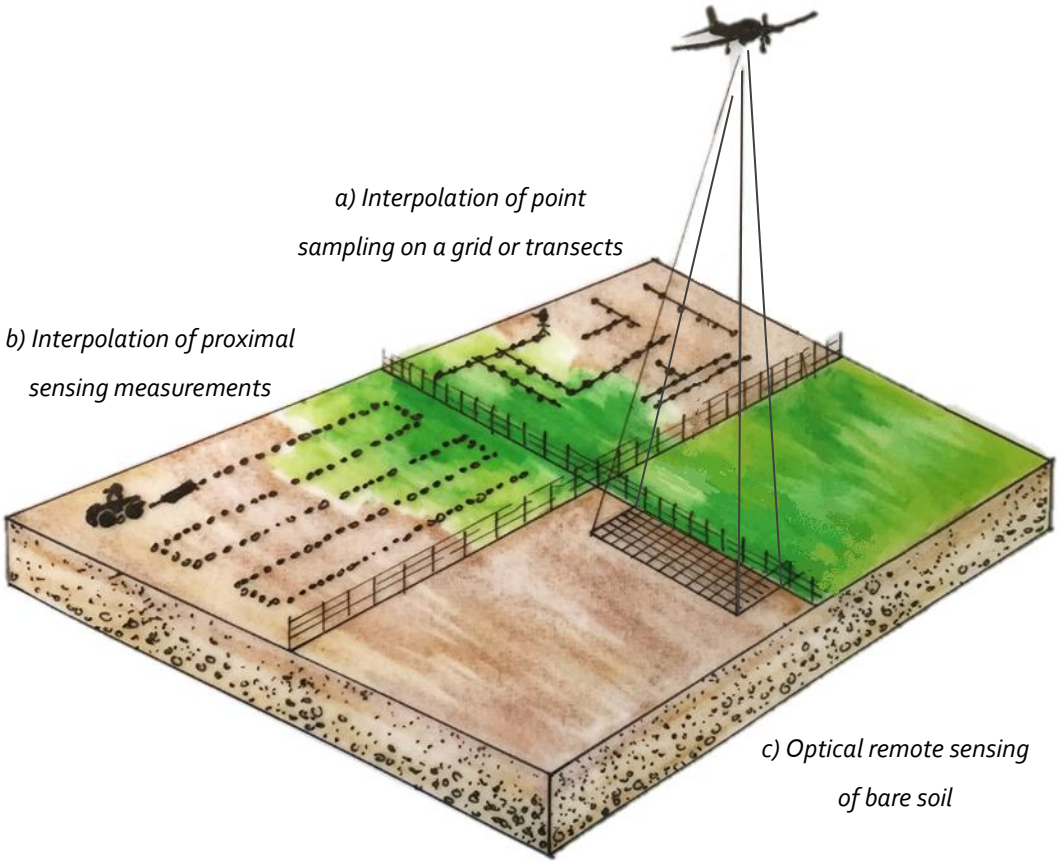


Figure 2-2: Traditional (a-b) and emerging (c) approaches to mapping soil properties.

Optimisation of point sampling locations is difficult, but important, as it has a major effect on the resulting maps. Point sampling locations need to maximise the accuracy of predictions of soil properties between them, with the least number of samples (McCormick et al., 2009). An optimal sampling design can be determined if the range or spatial dependence is already known (McBratney, Webster, & Burgess, 1981; Oliver, 1987). Generally, as sampling intensity decreases so does the detail in the variation observed (Frogbrook, 1999). Point sampling can be completed over a predefined grid or along transects. Irregular spacing between sampling points results in a range of sampling distances. This helps to determine short-range variation and large scale patterns and to define more precisely the distance over which a soil property is spatially dependent (Baxter & Oliver, 2005). Ancillary data such as crop yield, elevation or electrical conductivity, can be used to improve understanding of spatial variation of soil properties, inform soil sampling, for co-kriging, and for defining management zones (Frogbrook & Oliver, 2007). Grid soil sampling is expensive and time consuming. Alternates to grid

sampling that can capture the spatial variation are required if site-specific management is to be viable for farmers to adopt (McCormick et al., 2009).

Fine scale soil information has primarily been provided through **SENSING OF SOIL USING FIELD OR GROUND-BASED PROXIMAL SENSORS** (Viscarra Rossel et al., 2010). There are many examples in the literature such as: electromagnetic induction used by Hedley and Yule (2009) to infer soil available water holding capacity to inform variable rate irrigation; and a gamma ray sensor used by van Egmond, Loonstra, and Limburg (2010) to create topsoil maps of soil texture, organic matter and magnesium. These 'on-the-go' proximal sensors achieve spatial coverage through interpolation of many point measurements collected on the ground, along predetermined swaths over the field. This is time consuming and requires flat to rolling terrain which makes it unsuitable for the steep New Zealand hill country landscapes.

REMOTE SENSING through satellite imagery and imaging spectroscopy is an approach that is developing rapidly and can provide full spatial coverage, eliminating the need to make predictions between known samples. Remote sensing is a powerful tool; however it is a different discipline and requires knowledge and computation of a different kind, as explained in section 2.6.1.

Spatial variation in soil fertility in New Zealand hill country has proven to be high over very short distances. Studies that have examined spatial variation in soil sulphate-S overseas (Bloem, Haneklaus, Sparovek, & Schnug, 2001); soil K (Officer, Tillman, & Palmer, 2006); and P (Kaul & Grafton, 2017) in New Zealand hill country resulted in variograms with short ranges or pure nugget. Variograms resulting in pure nugget suggest that sampling units are not spatially correlated or that local variation occurs at scales finer than the sampling interval. Results are highly dependent on sample size and sampling method. Even in intensely sampled examples, their sampling distances where such, that kriging was not possible and therefore were neither able to make predictions at the locations in-between the point samples, nor map soil nutrient status. Remote sensing has an advantage over point sampling, in that interpolation or kriging is not necessary.

What is termed the 'range' of a variogram, estimates a distance which is a limit at which a particular point exhibits spatial dependence, beyond this distance there is no spatial correlation between the two points. In a silage field in Ireland, McCormick et al. (2009) identified a longer range of 460m and a shorter range of 150m for spatial dependency of soil Olsen P from grid sampling. Fu et al. (2013) also carried out work in Ireland. They found a range of 170m for soil P in a field managed for silage and a shorter range of 157m in a sheep

grazed field. They attribute the difference in range between the two fields to the effect of grazing animals. From the variograms calculated by Kawamura et al. (2009) in New Zealand hill country, the range for soil P was estimated to be 17m which is much shorter than the fields in the other two studies. The effect of grazing animals and the complex terrain in New Zealand hill country are likely reason for these differences. Morton et al. (2000) collected soil samples along a 100m transect in New Zealand hill country to assess the variability is soil nutrients, collecting and bulking 10 cores at each point 0, 0.4, 1, 3, 8, 20, 50 and 100 m from the start. The semivariogram for soil Olsen P, show most of the variation within 10m and no further variation after 20m and reported 38% of the total farm variance was measured within 1m of a fixed point. Soil variation is not random, but incomplete knowledge of the complex system means, to some extent, it appears this way (Webster, 2000).

2.6 Optical sensing in agriculture

Proximal and remote sensing is an ever expanding and improving technology across numerous disciplines. In agriculture and horticulture this technology is providing more information in all aspects, from pasture micronutrient concentration mapping (Pullanagari, Kereszturi, & Yule, 2016), to a range of soil properties (Ben-Dor et al., 2009), meat quality (Elmasry, Barbin, Sun, & Allen, 2012), and fruit quality (Cortés et al., 2017). The applications are many. Hyperspectral sensing provides more information than can be seen by the naked eye through the interpretation of unique hyperspectral signatures. Imaging spectroscopy has created new and exciting opportunities, as a non-destructive, fast, and relatively inexpensive (per sample) technology. Accuracy of single samples may be reduced by moving from laboratory based proximal sensing to airborne remote sensing. However given a reasonable level of accuracy can be achieved through remote sensing, the loss may be surpassed by a gain in spatial coverage.

2.6.1 Optical sensing of soils

Recently, the use of optical sensing or spectroscopy of soil has been growing. Laboratory based reflectance spectroscopy is commonly used to estimate soil properties and has a number of advantages. It is fast, accurate, able to provide results in a timely manner, cost effective and many soil properties can be derived from one measurement or spectral signature (Denis et al., 2014; Gomez, Oltra-Carrió, Bacha, Lagacherie, & Briottet, 2015; Gomez et al., 2008; Lagacherie, Baret, Feret, Madeira Netto, & Robbez-Masson, 2008; Lu et al., 2013; Viscarra Rossel et al., 2006). Viscarra Rossel et al. (2006) summarise the literature covering a wide range of soil physical and chemical properties predicted through laboratory based spectroscopy of bare soil samples.

More recent techniques have focused on moving from proven lab based spectroscopy to airborne or satellite hyperspectral imaging of bare soil fields. Traditional soil sampling and lab soil tests are unable to convey the complexity of the soil system. To capture the complexity and variation in chemical and physical properties (Ben-Dor et al., 2009), requires large amounts of data (Denis et al., 2014). Although image spectroscopy generates vast amounts of data, full spatial coverage improves our understanding of the soil system (Gomez et al., 2015; Gomez et al., 2008; Viscarra Rossel et al., 2006).

Recent research has focused on predicting a range of soil physical and chemical properties from hyperspectral imagery, including: clay content (Gomez et al., 2015; Lagacherie et al., 2008); soil texture (Casa, Castaldi, Pascucci, Palombo, & Pignatti, 2013); calcium carbonate (Lagacherie et al., 2008); soil organic carbon (Denis et al., 2014; Gomez et al., 2008; Lu et al., 2013); and total P and cation exchange capacity (Lu et al., 2013). Ben-Dor et al. (2009) provides a summary of the range of soil properties and classification that different projects have focused on using image spectroscopy, and express the potential for this technology and encourage research and adoption in this area.

Transitioning from lab analysis to airborne and satellite based hyperspectral imaging systems has proved challenging and requires further work, but results are promising (Ben-Dor et al., 2009; Casa et al., 2013; Gomez et al., 2015; Gomez et al., 2008; Lagacherie et al., 2008; Varella, Guérif, & Buis, 2010). Major challenges for using hyperspectral imagery of soil include: a low signal-to-noise ratio (Gomez et al., 2008); robust interpretation of the reflectance spectra (Gomez et al., 2008; Varella, Guérif, & Buis, 2010; Viscarra Rossel et al., 2006); handling and processing large datasets (Gomez et al., 2008; Viscarra Rossel et al., 2006); the vast amounts of ground data required to calibrate imagery (Lagacherie et al., 2008), covering different soil types and dates (Gomez et al., 2015). Robust calibration is essential to avoid issues with over fitted models that are suitable only for a particular survey or image and not transferable spatially and temporally (Casa et al., 2013). The accuracy of estimates of soil properties decrease from lab to airborne or satellite data (Denis et al., 2014; Gomez et al., 2008; Lagacherie et al., 2008) due to uncontrolled measuring conditions compared to controlled conditions in the lab. However, given the level of accuracy achieved to predict soil properties using lab based spectroscopy, Ben-Dor et al. (2009) believe it is only a matter of improving our knowledge and time, until similar results are achieved from image spectroscopy.

New Zealand agricultural hill country is covered in permanent pasture. This coupled with challenging terrain, means traditional and even the developing methods of mapping soil

properties are not feasible. However, important knowledge can be gained from these methods in other agricultural land, to improve our knowledge of this complex system. Knowledge of the spatial varition and patterns in soil properties collected via these techniques can help assess if results of work in hill country appear viable and reasonable. Permanent mixed pasture means that soil properties in New Zealand hill country must be inferred through remote sensing of patterns in vegetation.

2.6.2 Optical sensing of pasture and crops

Remote sensing of vegetation is progressing rapidly, particularly with higher spatial and spectral resolution data becoming more accessible. Remote sensing of vegetation can be used to monitor a wide range of characteristics including: species classification (Magiera, Feilhauer, Otte, Waldhardt, & Simmering, 2013; Roth et al., 2015); crop health (Goel et al., 2003; Strachan, Pattey, & Boisvert, 2002); biochemistry (Pullanagari et al., 2016; Suzuki, Okamoto, Tanaka, Kato, & Kataoka, 2008); biomass (Muñoz, Finley, Gehl, & Kravchenko, 2010); leaf pigments (Boggs, Tsegaye, Coleman, Reddy, & Fahsi, 2003; Inoue et al., 2016; Sims & Gamon, 2002); and changes in vegetation over time (Magiera et al., 2013; Roth et al., 2015). However, the predominant application of sensing in agriculture has been much simpler, using optical sensors to estimate stress and nutrient deficiencies in crops. Commercial sensors are available that provide 'on-the-go' simple vegetation indices, such as Normalised Different Vegetation Index (NDVI), of crops, to inform variable rate fertiliser applications on ground spreaders. Indices have long been used in remote sensing of vegetation for their simplicity in predicting biochemical parameters (Kawamura et al., 2011) and can be measured using simple and affordable multispectral sensing systems, many having only two or three channels.

Detailed information of crops and pastures are required to inform management decisions in agroecosystems. Remote sensing is hoped to provide the level of detail necessary to aid the progression and implementation of site-specific management that is the basis for precision agriculture (Dorigo et al., 2007; Goel et al., 2003; Suzuki, Tanaka, et al., 2008). Remote sensing can capture spatial and temporal variability without destructive sampling or the need for large field campaigns (Dorigo et al., 2007). Near infrared spectroscopy (NIRS) is already replacing wet chemistry in laboratory analysis of leaf tissue samples, for a range of biochemical parameters (Mutanga, Skidmore, & Prins, 2004) and will likely be replaced in the future by infield remote sensing. Aerial hyperspectral imagery provides continuous capture of reflectance spectra across a landscape which can be processed, interpreted, and then displayed as an image or map of vegetation, its biochemistry or the parameter of interest. Data

can provide information from a pixel, to a paddock, to a farm, and even on to a wider catchment or regional scale (Beeri, Phillips, Hendrickson, Frank, & Kronberg, 2007).

Insitu proximal hyperspectral sensing has been used in New Zealand dairy and hill country pastures to predict pasture nutrient parameters. Pullanagari et al. (2013) predicted a range of pasture nutritional parameters (crude protein (CP), acid detergent fibre (ADF), neutral detergent fibre (NDF), lignin, metabolisable energy (ME) and organic matter digestibility (OMD)) in dairy pastures in New Zealand over three seasons, using an Analytical Spectral Devices FieldSpec Pro and Canopy Pasture Probe (CAPP). The season specific models predicted nutritive parameters more accurately with R^2 values between 0.61 and 0.80 than the global model where seasons were combined, R^2 between 0.33 and 0.70. Quality parameters (ME, CP and OMD) of hill country pastures were measured in situ at Limestone Downs, a farm in the Waikato region of New Zealand (Yule et al., 2013). A total of 105 samples were measured over 14 sites where spectra were collected with a hyperspectral sensor (ASD FieldSpec Pro) and CAPP. Pasture samples were collected, dried, and ground. Accuracy was very high in the estimates of dried milled samples (R^2 = 0.95-0.96) and high in the infield measurements (R^2 = 0.80-0.85). Even with a small sample set, the large variation in hill country pasture quality was evident and highlighted the potential insight that could be gained from capturing variability across the landscape. Collecting spectral measurements with a handheld sensor over a 3,200 ha property is impractical, so imaging is the next step enabling continuous capture over the landscape (Yule et al., 2013).

Nutrient concentration of pasture in New Zealand has also been estimated using proximal and remote sensing techniques. Earlier work by Kawamura et al. (2009) showed the potential of in field hyperspectral data collected using an ASD FieldSpec Pro and CAPP to estimate pasture biomass and nutrients (N, P, K, S) in New Zealand hill country (R^2 = 0.86, 0.90, 0.94, 0.81, 0.94 respectively). A later study published by Kawamura, Mackay, Tuohy, Betteridge, and Sanches (2006) and Kawamura et al. (2011) collected spectra using an ASD FieldSpec Pro over two seasons. Mixed pasture on high and low fertility farmlets were measured to assess the use of vegetation indices and to develop their own indices to estimate, along with other nutrients, the P concentration in the pasture canopy. Both the established indices, Photochemical Reflectance Index (PRI) and Soil Adjusted Vegetation Index (SAVI) and those developed by the authors were found to give very strong correlations with pasture P concentration, $R^2 > 0.84$, in both spring and summer pastures.

Sanches, Tuohy, Hedley, and Mackay (2013) went on to collect herbage samples from dairy and sheep and beef pastures in the North Island of New Zealand over multiple sites and seasons. For P concentration, spring pasture was moderately correlated (R^2 = 0.53-0.60), summer was moderately to well correlated (R^2 = 0.65-0.74) and autumn well correlated (R^2 = 0.75-0.77). However the number of samples collected and different sites or farms sampled, was inversely proportional to the strength of the correlation, suggesting that it may not be a direct reflection of season but the suitability of a global model to perform accurately across a range of sites. Correlations were weak in winter, R^2 = 0.12-0.17, however the range in P concentration across the samples from all sites during winter was much narrower than in the other seasons.

Recently, hyperspectral imagery of mixed pasture on New Zealand hill country has been used to estimate and map macro and micro nutrients and pasture quality parameters across whole farms. Macronutrient concentrations (N, P, K and S) (Pullanagari et al., 2016; Yule et al., 2015), DM%, ME (Yule et al., 2015), micronutrient concentrations (Zn, Na, Mn, Cu, Mg) (Pullanagari et al., 2016) and the dead vegetation fraction (Pullanagari, Kereszturi, & Yule, 2017) have been presented and published in various forms. The macronutrients N, P, K, and S and pasture quality indicators of ME and DM% were strongly correlated for all parameters R^2 = 0.83, 0.80, 0.90, 0.88, 0.79, 0.78 respectively, between predictions using hyperspectral imagery and wet chemistry of dried and milled pasture samples (Yule et al., 2015).

The challenges in collecting, processing and interpreting hyperspectral imagery of vegetation includes many of those mentioned at the end of the previous section on image spectroscopy of soil. Hyperspectral images contain pixels that are a mix of both soil and plants, especially in agricultural landscapes (Lagacherie et al., 2008; Mutanga et al., 2004). The spatial resolution of imaging systems and satellites are improving, but for coarser resolution data, measures need to be taken into account for mixed pixels (Lagacherie et al., 2008) through techniques such as spectral unmixing (Gomez et al., 2008). Plant structure and leaf architecture can affect the shape of a spectral signature (Dorigo et al., 2007) and therefore the ability to predict vegetation parameters accurately (Kawamura et al., 2009; Mutanga et al., 2004). Many spectral indices used to analyse vegetation spectra have been developed on one or a few, often related, species and the performance of spectral indices on other species depends upon the species and their leaf structure (Sims & Gamon, 2002). Many ways to transform a spectral signature into biophysical and biochemical parameters have been published, however they can become less accurate outside the local study area (Dorigo et al., 2007).

The success of in-field discrimination of sward dominance of ryegrass and white clover (Suzuki, Okamoto, Takahashi, Kataoka, & Shibata, 2012) and the determination of legume content (Kawamura et al., 2013) highlights a real opportunity to inform appropriate choice of fertiliser product in hill country. With the proven mapping of mixed pasture biochemistry in New Zealand hill country (Pullanagari et al., 2016; Yule et al., 2015), pasture quality parameters (Suzuki, Tanaka, et al., 2008; Yule et al., 2015) and the variability that exists in hill country (Yule et al., 2013), hyperspectral remote sensing shows great potential for understanding and monitoring this relatively inaccessible landscape. Patterns in vegetation reflect the underlying soil properties to a certain degree. Schmidtlein (2005) suggests there is potential to utilise the rapid and continuous coverage of remote sensing to capture variation in vegetation across the landscape to infer characteristics of the underlying soil. Knowledge of which vegetation characteristics are able to be identified or quantified using hyperspectral remote sensing are important to know, to identify which variables are possible predictors of soil parameters.

2.7 Vegetation as a proxy for predicting soil properties

2.7.1 Predicting soil properties through vegetation

In the vast amounts of literature on agroecosystems, few papers are published in which researchers have attempted to predict soil properties from vegetation. More literature exists in the relatively simplistic monocultures of horticulture and cropping systems than in pastures. Diagnoses of mineral deficiencies in plants have been detected through chemical analysis of leaf tissue samples of single species and at a particular growth stage (McNaught, 1970), and have therefore been neither intensive nor expansive. In pasture, either grass only or clover only samples of actively growing leaves have been used to diagnose nutrient deficiencies in terms of the soil-plant interaction (McNaught, 1970). Davey and Mitchell (1968) expressed the desire to identify a plant part that varied as a direct result of soil fertility status and not with changes in climate or growth stage, however this has still not been, nor is likely to be, achieved.

Vegetation patterns can reflect soil properties (Kawamura et al., 2011; Schmidtlein, 2005), but to use this approach requires a good understanding of soil-plant interactions (Kawamura et al., 2011) and the response of individual species and the pasture community to different soil conditions (Schmidtlein, 2005). Soil properties have been inferred indirectly through indicator species and inverse dynamic crop modelling, or directly from biochemical properties of plant tissue.

Observations of presence or dominance of particular species along with knowledge of that species niche environment can be used to make assumptions about the ecological conditions at that location (Wilson & Ference, 2001). These plants are termed **INDICATOR SPECIES**. Plants have adapted to particular environments, though possessing such adaptive traits has meant they are essentially constrained to and restricted from certain environments through environmental conditions and intra-specific competition. The concept of plant functional groups has developed from the work of Grime (1977), who grouped species based on their ability to tolerate, and strategies to cope with stress and disturbance. 'Stress' as determined by Grime (1977) includes shortages of mineral nutrients and 'disturbance' includes the grazing and treading of herbivores. Plant functional groups have been developed for New Zealand hill country pasture species. Five functional groups (high fertility response grasses, low fertility tolerant grasses, legumes, mosses, and flat weeds) were identified by Zhang et al. (2005). Seven plant functional groups were determined by López, Valentine, Lambert, Hedderley, and Kemp (2006), categorising 41 hill country pasture species by accumulation of herbage as high and low yielding, hill slope and level of soil fertility through fertiliser inputs.

Plant functional groups and pasture species have been linked to soil P status. Medium fertility species (group II), high fertility grasses (group III) and generalist type B: Ryegrass (group V) were positively correlated to soil Olsen P; and low fertility species (group I) was negatively correlated (López et al., 2006). Soil Olsen P was the most significant factor affecting the presence and abundance of low fertility tolerant grasses (LFTG) and moss. However along with slope, Olsen P was a key factor in determining the abundance of the different functional groups from a range of climatic, fertiliser, topographic, and soil property variables (Zhang et al., 2005). In the development of a GIS based decision tree to model the abundance of ryegrass, browntop and white clover in New Zealand hill country, Wan et al. (2009) identified soil Olsen P as the most important factor affecting the abundance of browntop in the sward. Wan et al. (2009) also identified that at an Olsen P of 10 µg/g and a slope of 10.5°, browntop and ryegrass are equally competitive. It is evident that soil P has an influence on species presence and abundance in New Zealand hill country pastures.

INVERSE DYNAMIC CROP MODELS have been used in an attempt to utilise crop information to estimate site specific soil properties, as much of the variability in crops is due to variability in soil parameters (Florin, McBratney, Whelan, & Minasny, 2011; Varella, Guérif, & Buis, 2010). This approach can be an efficient way of gaining an understanding of fine scale variation in soil parameters from data that is already collected. Readily available data in cropping systems,

such as yield harvested, encapsulates information around soil, climate, crop and landscape interactions (Florin et al., 2011).

Florin et al. (2011) used crop yield to predict plant available water over different years and fields, with mixed success. Timlin, Pachepsky, Walthall, and Loechel (2001) also used crop yield to predict water holding capacity, as it has an important effect on yield and is particularly important in rain fed agriculture. Varella, Guérif, and Buis (2010) used an inverse dynamic crop model for wheat which used crop yield, LAI, and leaf N content to try and predict underling soil parameters such as clay, water content and soil N. They stated that the success of predicting the soil parameters depended on the climate in that particular year and the soil depth of interest. Cambardella et al. (1994) attempted to predict 28 different soil parameters over two sites with mixed results.

Inverse dynamic crop modelling could be improved through using multiple years of crop data to develop a more stable model (Florin et al., 2011; Timlin et al., 2001; Varella, Guérif, Buis, et al., 2010) or more variables (Florin et al., 2011) such as remotely sensed imagery to provide information about the crop status (Varella, Guérif, Buis, et al., 2010). This concept has been applied to monoculture crops rather than permanent pastures and more often for soil properties that generally do not change temporally, which are primarily soil physical properties such as water holding capacity.

LEAF TISSUE NUTRIENT CONCENTRATIONS, NUTRIENT RATIOS and **PLANT NUTRITION INDICES** have been correlated to soil properties. Phosphorus leaf tissue concentration, N:P ratios and P nutrition indices, and their relationship to soil nutrient status are discussed in the following section, 2.7.2, for P. Due to the high spatial and temporal variation in soil sulphate-S in a commercial cropping field in Germany, Bloem et al. (2001) were unable to find any correlation between soil sulphate-S and plant S concentration in winter barley at any of the soil depth categories covering 0-1.5m in either a loamy or sandy soil.

Few studies have taken a two-step approach, using remote sensing to predict vegetation characteristics and from there predict underlying soil properties. Vegetation patterns can be captured using remote sensing (Kawamura et al., 2011; Schmidtlein, 2005) through detecting changes in biochemical composition, physiology and canopy architecture (Kooistra et al., 2004), all characteristics of vegetation which can potentially reflect changes in environmental conditions (Kooistra et al., 2004), and easier to detect through remote sensing as plant species composition is difficult to map (Schmidtlein, 2005). Kooistra et al. (2004) used remote sensing of grassland on a floodplain as an indicator of the level of metal contamination of the soil. This

research showed the potential of this approach with R^2 values between 0.5 and 0.73 depending on the metal. They noted that this relationship would be better with more uniform species, and that herbaceous species deviated most significantly. However, metals are generally less mobile in plants than other nutrients (Whitehead, 2000). Hyperspectral remote sensing of leaf chlorophyll in cotton was significantly correlated to soil nitrate-N, and provided farmers sufficient information to identify areas of N deficiency which could be rectified through targeted fertiliser applications (Boggs et al., 2003). These studies highlight potential for, but also uncertainty around, this approach to be successful.

2.7.2 Direct plant to soil phosphorus relationship

In a global study assessing the relationship between leaf traits and soil fertility, 48% of the variation in leaf P was explained by soil P availability (Ordoñez et al., 2009). However most of the literature attempting to correlate leaf tissue P concentration to soil P availability has used few samples on one or two sites, at a particular growth stage, plant part or season, or with only one or a dominant species, rather than a highly heterogeneous botanical composition. Mixed species samples make the interpretation of nutrient concentration in herbage samples complicated, and can be further complicated by differing growth rates and by the synergistic and antagonistic interactions between different nutrients taken up by the plants (Liebisch et al., 2013).

Direct relationships between herbage P concentration in the leaf tissue and soil P availability have shown mixed results. Many different methods for measuring soil P availability have been used in these studies, including Olsen P. The reported correlation in pot trials has ranged from $R^2 > 0.90$ (Rowarth & Gillingham, 1990) to almost no correlation (Roberts, 1987). Most literature involving field studies report an R^2 anywhere between 0.30-0.80 (Burkitt et al., 2010; Jones & Tracy, 2014; Liebisch, 2011). Weaker correlations have been found in trials with a large sampling footprint for each sample (Jones & Tracy, 2014; Roberts, 1987). The relationship between soil P availability and herbage P content is linear (Burkitt et al., 2010; Jones & Tracy, 2014; Rowarth & Gillingham, 1990) or logarithmic (del Pino Machado, 1994; Kawamura et al., 2011; Liebisch, 2011) where plant P uptake reaches a maximum of approximately 0.40%P (Liebisch, 2011) and 0.50%P (del Pino Machado, 1994).

Phosphorus nutrition index (PNI) has been used as an indicator of plant P deficiency in herbage. A link between this diagnostic measure and soil phosphate availability has been investigated in few studies. The uptake of P and N was used to determine deficiency (Salette & Huché, 1991), optimal (Duru & Thélier Huché, 1997) and luxury (Salette & Huché, 1991) P

uptake. The P nutrition index (PNI) was developed by Duru and Thélier Huché (1997) for a ryegrass dominant sward and later confirmed on another grass species, Timothy (*Phleum pratense*) (Bélanger & Richards, 1999). An adjusted calculation was developed to account for the clover content in the sample, as legumes generally have a higher N concentration than grasses (Jouany, Cruz, Petibon, & Duru, 2004). The PNI was developed to help inform fertiliser decisions in managed grassland in France.

PNI has been correlated with different measures of soil P availability (Duru & Thélier Huché, 1997; Garnier et al., 2007; Jouany, Stroia, Farruggia, & Duru, 2002; Liebisch, 2011). Liebisch (2011) found a relationship between five different methods for extracting soil P and PNI. For soil P to PNI, the R^2 ranged from 0.51-0.80, with a logarithmic relationship with a maximum plant P of approximately 0.40%. Duru and Thélier Huché (1997) found PNI against the concentration of P in the soil solution in the top 0-5cm to follow a logarithmic curve, except for the soil with a high P buffering capacity. Jouany et al. (2002) found PNI was linearly correlated to the water-soluble soil P fraction in the top 0-5cm. They found this was a stronger correlation than with soil Olsen P.

Kawamura et al. (2006) took a two-step approach to use proximal remote sensing to calculate vegetation indices that were correlated to plant P content ($R^2 > 0.80$) and then to estimate soil P status ($R^2 > 0.86$). The results of a pilot study carried out by Kawamura et al. (2011) where they looked at the relationship between soil Olsen P and pasture P concentration from wet chemistry analysis and the potential to derive P leaf tissue concentration from a proximal sensor demonstrated that this approach was worth further investigation. Their study was limited to 30 plots sampled in spring and summer over two sites on a hill country property. Soil Olsen P ranged from 5-72 mg kg^{-1} over a high fertility perennial ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*) site, and a low fertility brown top (*Agrostis capillaris*), suckling clover (*T. dubium*) and broadleaf dominant site, pastures typical of New Zealand hill country. Kawamura et al. (2006) and Kawamura et al. (2011) believe this approach shows the potential to assess soil fertility, as categories of low, medium and high in relation to fertiliser response, but that there needed to be extensive fieldwork on other farms and seasons, to cover different pasture types, and regrowth stages and soil types.

2.8 Modelling grassland systems

2.8.1 Modelling phosphorus in the agricultural environment

Models of P in New Zealand agricultural systems have focused on: nutrient cycling to estimate P losses (Nguyen & Goh, 1992); for fertiliser inputs (Cornforth & Sinclair, 1986; Metherell,

1994; Metherell et al., 1995); modelling species abundance in relation to environmental factors of which an important factor is soil P availability (Wan et al., 2009); pasture growth driven by climate and soil P availability (Moir, Scotter, Hedley, & Mackay, 2000); pasture production and response to phosphate fertiliser applications (Wickham, Wake, Woodward, & Thorrold, 1997; Zhang, Tillman, Gillingham, & Gray, 2009); and monitoring the transfer of P in fertilised pasture (Saggar, Mackay, Hedley, Lambert, & Clark, 1990). However an extensive literature search found no studies attempting to model soil P availability primarily using pasture nutrient concentrations in New Zealand agricultural pastures.

In contrast, modelled uptake of P is widely published and has been completed for a range of crops including vegetable crops (Greenwood, Karpinets, & Stone, 2001), rapeseed (Brewster, Bhat, & Nye, 1976) and maize (Lu & Miller, 1994; Mollier et al., 2008). P uptake by roots (Comte, Coron, Guerrero, & Tournier, 2013) and root hairs (Leitner et al., 2010) has also been modelled. In a review of models predicting plant uptake of P, Hinsinger et al. (2011) state that models were better at predicting P uptake when inputs of P were large, and poorer when P inputs were low. They suggest that different processes are happening under low P inputs that are not incorporated in to models such as mineralisation and desorption. Nevertheless, this information is important in understanding how these processes can be modelled and likely limitations of modelling this system.

2.8.2 Environmental modelling and modelling of grasslands

Modelling that involves interactions within the soil – plant – animal system, like any biological modelling, is full of complex and dynamic interactions, and high levels of uncertainty and variation. Initial research in agriculture involved many “basic studies” which were based around controlled pot and plot experiments (Brougham, 1970). These studies focused on varying one or few inputs of known type and magnitude. In controlled trials, other factors can be maintained at levels that are non-limiting for growth and this must be recognised in the interpretation of results. Studies based on monitoring natural or real world situations may be unable to identify the causal factors as these systems have many unmeasured or unmeasurable factors and interactions that causality may be misidentified (Dorrough et al., 2011).

The level of complexity of models attempting to model grassland systems varies greatly. A grassland macromodel, proposed by van Dyne (1970) would require an interdisciplinary team approach to cover the complexity. Five different vectors of components include: ‘compartments’ such as vegetation fractions, litter, soil moisture and minerals; linked by

'processes' that control the transfer of material and energy between compartments such as photosynthesis, ingestion, decomposition, mobilisation-immobilisation; some overriding 'driving forces' as such solar radiation, wind, and temperature; 'parameters' and 'controls'. Others models are much more simple, such as nutrient ratios. Complex models can lead to overfitting and result in poor predictions outside the dataset (Clark, 2005). The appropriate level of complexity in modelling is difficult to determine and requires a fine balance, but Hinsinger et al. (2011) suggest that in modelling plant P, simplicity is better.

Environmental modelling has a high degree of variability and uncertainty. Bayesian hierarchical modelling has been used in a wide range of different environmental, agricultural and horticultural scenarios, as this approach is able to handle complex and uncertain domains common in agroecosystem and ecosystem modelling (Aguilera, Fernández, Fernández, Rumí, & Salmerón, 2011b; Moraes et al., 2014; Patrick, Martine, Latimer, & Stacey, 2007; Pirani, Panton, Purdie, & Sahu, 2016; Theobald, Talbot, & Nabugoomu, 2002). Muñoz et al. (2010) state that the predictions, in their case of biomass, and the associated uncertainty are useful for management of crops.

Often experiments are restricted to only a limited number of sites. To be useful in real world applications, models developed on a limited dataset need to be applied to situations outside of the bounds of the experimental dataset (Clark, 2005). In environmental modelling, research based on plot-scale data is often scaled up. In these models it is important that complexity and high spatial variability is appropriately handled (Kaye et al., 2008). Different sites can easily be incorporated into a hierarchical model. Kaye et al. (2008) used a hierarchical Bayesian model to predict soil chemical properties in Pheonix, Arizona, across the urban area and the surrounding agricultural and desert landscape. Theobald et al. (2002) used a Bayesian mixed-effects model to predict the yield of maize crops based on the effects of variety, location and year. Muñoz et al. (2010) state that using a hierarchical structure did not overly improve their model using NDVI to predict above ground biomass of red clover (*Trifolium pratense* L.) cover crops. Their sites were within one property in Michigan, USA and they note the small differences in field-level productivity in red clover. They do however recognise the importance of a hierarchical structure particularly when fields or study sites are from different environmental or soil conditions.

Often in environmental monitoring, the numbers of samples collected at different sites or time points vary, or the same individuals or sites may be measured more than once. Issues around imbalance in sampling can also be adjusted for in a hierarchical structure (McElreath, 2016).

Dorrough et al. (2011) looked at the impact of grazing management and nutrient enrichment of soils through fertiliser history, on species composition of grasslands in Australia. They used a hierarchical modelling approach, which among other benefits, allowed them to incorporate data on species that were rare. The uncertainty around the species present in relation to grazing management and fertiliser P in the data set is captured explicitly and is therefore able to be interpreted. This is particularly important for species with a low occurrence in the data set, as results are less likely to be misinterpreted. Species were grouped into trait groups, and species within the same trait group, but with low occurrence, could be informed by other more abundant species from the same trait group to improve knowledge and precision of estimates.

2.9 Summary: potential for image spectroscopy in the New Zealand hill country environment to predict soil fertility

Soil – plant – animal and overarching farm management interactions in New Zealand hill country are highly complex, spatially and temporally dynamic and unique to each farm. Few studies attempt to incorporate the system as a whole. Soil properties are not random, but the complexity of these processes operating from fine to landscape scales, results in a heterogeneous soil system which is difficult to comprehend.

The productivity of hill country can be lifted through improved animal performance. Individual animal performance can be improved through genetics and breeding programmes and improved quality of their feed intake. Productivity of a whole farming system can be further lifted through increased pasture production. Pasture quality and quantity can also be improved through soil fertility.

Farmers have little control over many factors that affect pasture production and quality, whereas grazing management and fertiliser use can be modified to increase production. As fertiliser is the highest expenditure on a farm, it is very important to provide as much information as possible for decision making around efficient fertiliser use.

To date, soil sampling in hill country has been minimal, and fertiliser generally applied at a blanket rate through aerial top dressing. The steep and relatively inaccessible terrain in hill country provides challenges for traditional soil sampling and can produce highly variable results. The complex topography limits the ability for point samples to be meaningfully interpolated. The traditional approach has been to bulk samples along a transect to provide one sample for laboratory analysis to represent a large area of the farm. This approach tends towards poor nutrient use efficiency and high risk of detrimental environmental impacts. One

of the key pieces of information required to improve fertiliser product and placement recommendations is the current soil fertility, as the technology to apply fertiliser variably from a fixed wing aircraft is available today.

Detailed mapping of soil chemical and physical properties has been predominantly researched and used in cropping, and to a much lesser extent dairy systems. Traditional soil mapping has used point measurements – either individual samples sent to the lab or through using 'on-the-go' proximal sensors infield. Data is then interpolated between the points. More recent research has used ancillary data to improve the accuracy of predictions. The nature of New Zealand hill country terrain, limits which techniques are feasible.

An emerging area of soil mapping is through the use of image spectroscopy on bare soil. Laboratory based optical sensing is a proven and reliable technology for estimating physical and chemical properties of pasture and soils. Moving from lab based, or point, to image spectroscopy loses accuracy in the measurements but opens up huge opportunities with spatial coverage, though with a new set of challenges in data handling and processing.

Like all permanent grasslands, New Zealand hill country is continuously covered in pasture. Therefore, in this environment, capturing spectral reflectance from bare soil is not possible. Research that has attempted to use remote sensing to predict soil chemical and physical properties, where the landscape is covered in vegetation has generally shown average to poor results. Biophysical and biochemical properties of pasture are both spatially and temporally dynamic which adds complexity to the analysis of vegetation characteristics and patterns.

However, in this environment, the only option is to use image spectroscopy where pasture is used as a proxy for soil nutrient status, with the possibility of incorporating covariate data. Vegetation patterns, which can readily be picked up using remote sensing, can sometimes reflect soil properties. However a good understanding of the plant-soil relationships and interactions is essential.

Laboratory based chemical analysis of soil for plant available nutrients is accurate, but with bulked samples and minimal spatial coverage, the ability of traditional sampling techniques to represent the whole farm is limited. A point sample soil core analysed in the lab is expected to be much more accurate than predictions of soil fertility, primarily through remote sensing of vegetation. However imaging spectroscopy could allow estimates of soil fertility to be made over the entire farm, identifying spatial patterns in soil fertility, which would provide a more representative picture of the whole farm on which fertiliser recommendations could be based.

3

3 Farm descriptions, field sites, fieldwork methodologies and collating the database

3.1 Introduction

Large datasets used in New Zealand pastoral agricultural research generally contain samples aggregated from multiple research projects, in particular, datasets containing samples covering a wide geographic area. In aggregated data sets, there are often a limited number of factors collected in each individual study, determined by the research focus. Therefore each dataset does not necessarily contain the same information for each sample or samples are often collected from varying areas or volumes referred to as sample support. To have a large dataset collected from within one study, such as this PGP research project, is a unique and significant opportunity to gain a better understanding of hill country systems. Such a diverse, yet complete range of information, with a consistent sample support, collected across such a wide geographic range is essential in order to have the best opportunity to create a model to predict soil fertility that could be extrapolated spatially and temporally. Collecting and collating a robust database, from multiple sources, including 7,162 separate data entries from 19 sampling events was achieved.

This chapter explains the work undertaken to collect and collate data to build and ensure a robust database was created for model development and prediction. This database is then used throughout the work presented in this thesis.

This chapter aims to describe:

- The eight study sites, highlighting the differences and individuality of these properties and commercial hill country farming systems.
- The methodology for selecting the sites within each property.
- An outline of the fieldwork schedule and the methodologies of the fieldwork undertaken.
- The additional information collected and acquired.
- The process of collating the data from multiple sources.
- Checks to ensure the dataset was robust.
- A summary of the final database available for model development and prediction.

3.2 Trial sites

A total of 3,030 plots (Table 3-1) covered a range of different slope, aspect, elevation, geographical location, climatic regions, soil type, botanical composition, age of pasture, stage of maturity, ratio of green vegetation to dead material, productivity, grazing management and fertiliser history. The diverse range of sites were selected in order to create a robust dataset that would be used to develop a model that would be transferable to other hill country properties throughout New Zealand.

Table 3-1: Code and colour references used throughout this thesis for the eight trial farms

Location	Farm	Code	Colour	No. plots
North Island	Limestone Downs	NLD		400
	Erewhon	NER		400
	Ohorea (Atihau)	NAT		400
	Tautane	NTT		400
	Pati Tapu	NPT		400
South Island	Harwoods	SHA		350
	Cleardale	SCD		280
	Lawsons (Moana Farm)	SLA		400

The study sites covered eight commercial hill country farms spread throughout the North and South Islands of New Zealand. The farms were chosen by Ravensdown Ltd to cover different regions in which hill country farming is a predominant land use. Five farms were in the North

Island: Limestone Downs, Ohorea/Atihau, Erewhon, Tautane and Pati Tapu; and three were in the South Island: Harwoods, Cleardale and Lawsons/Moana Farms (Figure 3-1).

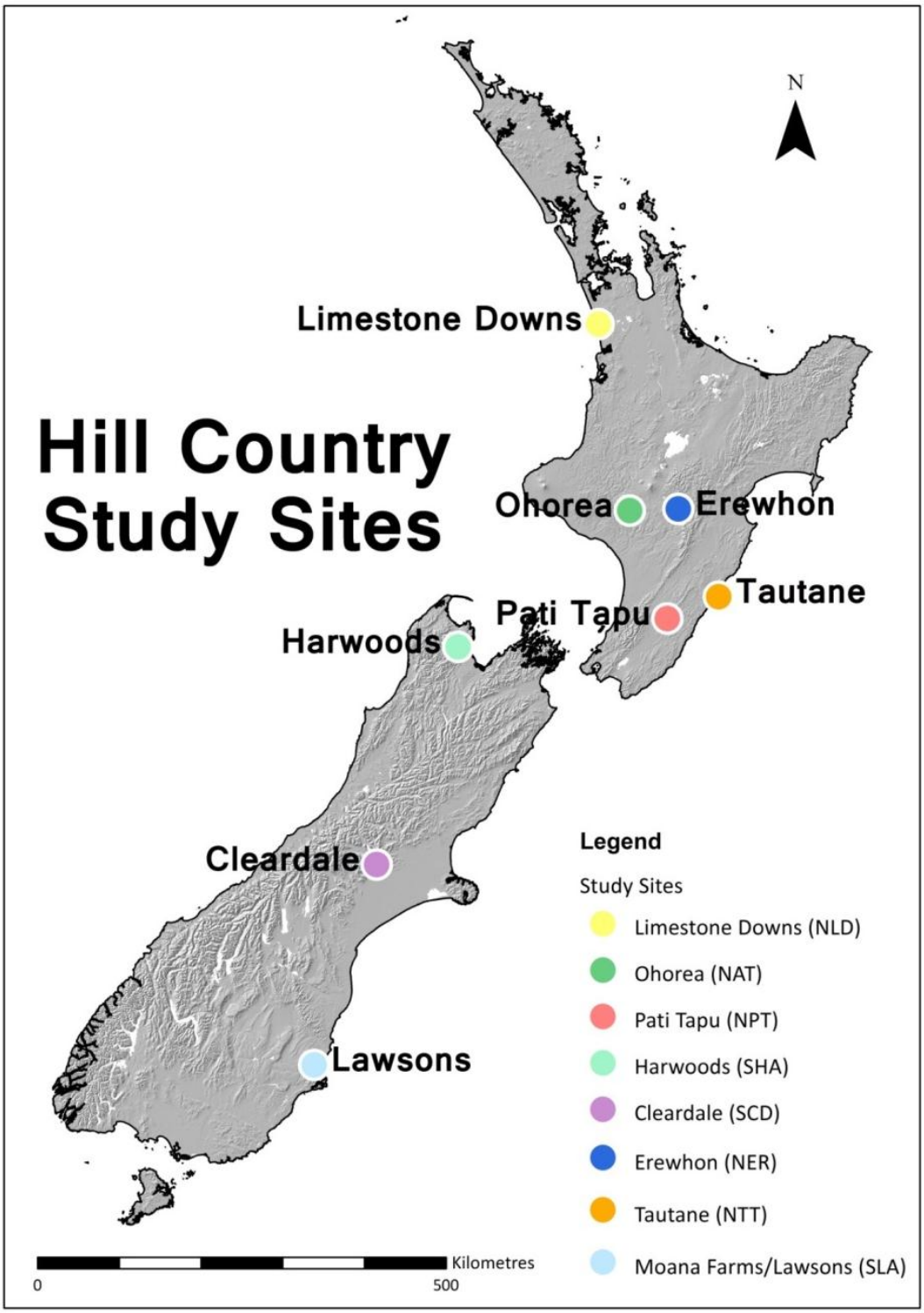


Figure 3-1: Study sites, the location of the eight commercial hill country farms spread throughout the North and South Islands of New Zealand (note: colours are used to represent farms throughout the thesis)

3.2.1 Limestone Downs

LIMESTONE DOWNS is located just south of Port Waikato (37.477103°S, 174.757579°E) in the northern Waikato region, on the coast of the Tasman Sea halfway between the Manakau

Harbour and Raglan. Limestone Downs is a 3,220 hectare coastal property rising from sea level to 180m a.s.l. (Figure 3-2 and Figure 3-3). The property encompasses a recent dairy conversion, run in conjunction with a sheep and beef unit that supports training and research projects. The property is governed by the C Alma Baker Trust, a UK based Trust, which has a New Zealand Committee for advice and decision making. The current farm manager had been on the property for over 30 years.

Figure 3-2: Panoramic view of the typical landscape at Limestone Downs.

GENERAL FARM DESCRIPTION: Limestone Downs is the most northern of the eight farms. It has a more temperate climate and the C4 pasture species, Kikuyu (*Pennisetum clandestinum*), is one of the dominant pasture species in the sward in summer and autumn. Limestone Downs has a mix of contour, with finishing country on flats and rolling hills, to steep coastal and inland hill faces (Figure 3-4).

CLIMATE: Limestone Downs is the furthest north of the trial farms and has a sub-tropical climate. The region experiences warm humid summers with maximum daily air temperatures approximately 22-26°C and mild winters with maximum daily air temperatures 12-17°C (NIWA). The average annual rainfall at Limestone Downs is approximately 1,200mm.

SOIL: In the Fundamental Soils Layer (FSL), the soils at Limestone Downs are classified predominately as Brown, with areas of Allophanic and Ultic; Recent and Gley soils in the valley bottoms; and Sandy Raw soils on the coast. The soils at Limestone Downs have been extensively mapped over recent years by Massey University 3rd year soil students under the guidance of Dr Alan Palmer.

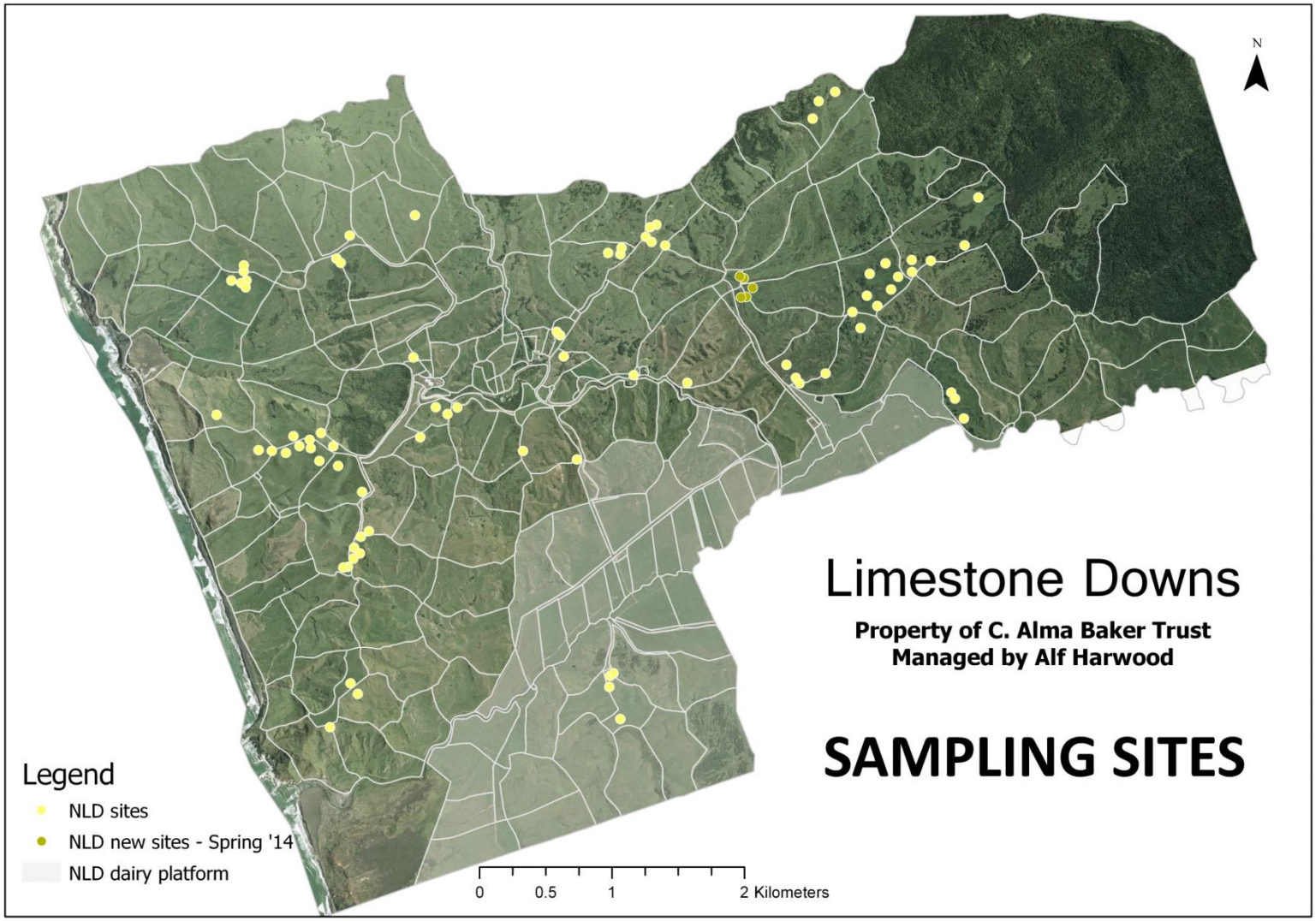


Figure 3-3: Sampling sites (yellow points) at Limestone Downs, showing the location of the 80 sites on farm.

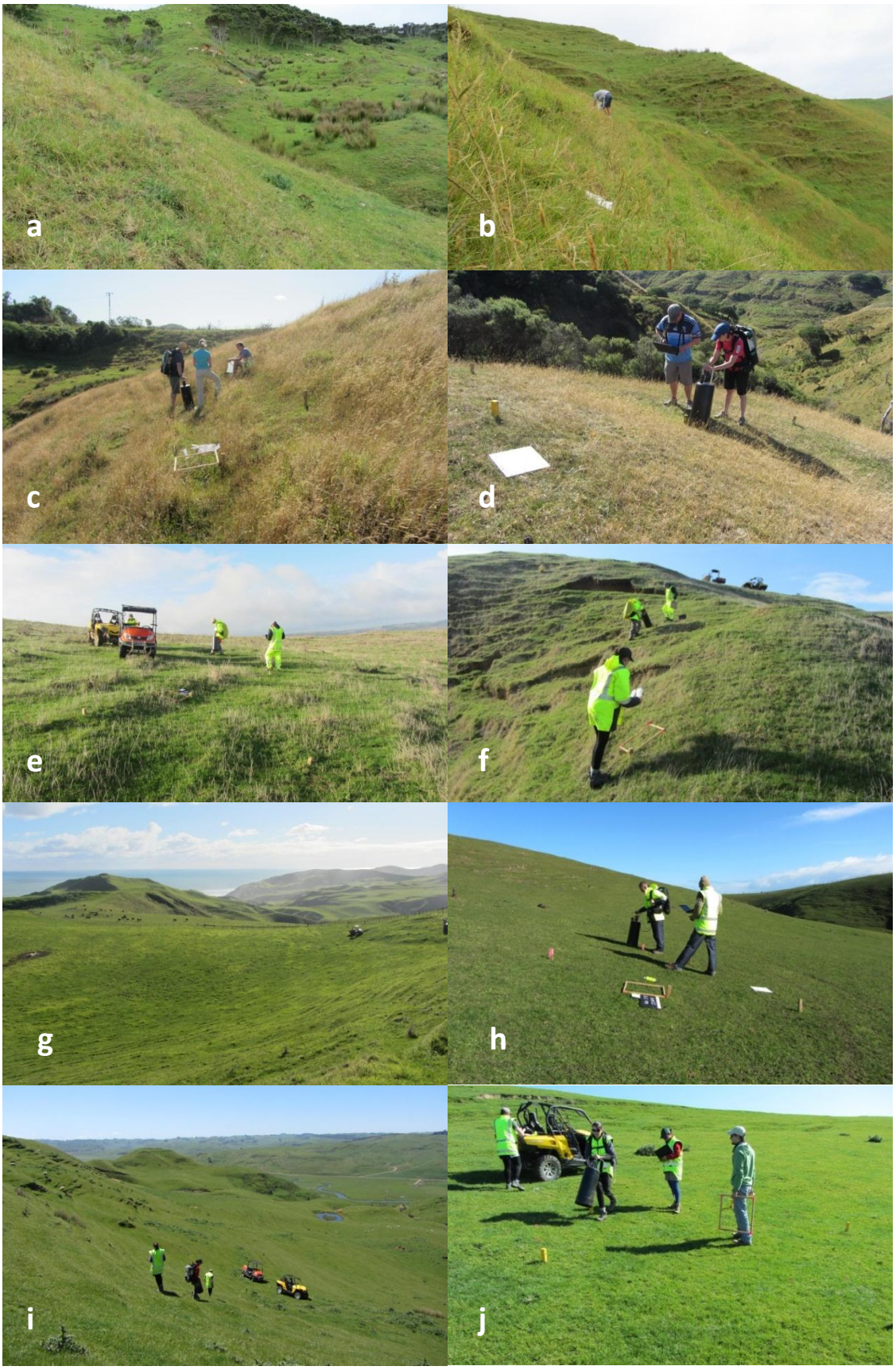


Figure 3-4: Limestone Downs over 5 sampling events: early summer – December 2013 (a and b), late summer – February 2014 (c and d), autumn – May 2014 (e and f), winter – July 2014 (g and h) and spring – October 2014 (I and j).

FERTILISER: The approach to fertiliser applications at Limestone Downs has been to double dose half of the farm every second year. The northern or southern half of the farm has received usually around 400-500 kg/ha (36-45 kg P/ha) of single superphosphate on alternate years, applied between December and February. A summary and comparison of generalised fertiliser policies between the farms is provided in Table 3-6.

PASTURE SPECIES: The most abundant pasture species in the plots at Limestone Downs were perennial ryegrass (*Lolium perenne*), kikuyu (*Pennisetum clandestinum*), sweet vernal (*Anthoxanthum odoratum*), Yorkshire fog (*Holcus lanatus*), white clover (*Trifolium repens*) and browntop (*Agrostis capillaris*). Plantain (*Plantago lanceolata*) and crested dogstail (*Cynosurus cristatus*) were also present in small percentages. Kikuyu became more dominant in the pasture sward in the late summer and autumn and least dominant in spring, following the opposite trend to perennial ryegrass, which was very dominant in spring. Sweet vernal was present in abundance over summer. Catsear (*Hypochaeris radicata*), dandelion (*Taraxacum officinale*) and thistle (*Cirsium arvense* and *C. vulgare*) were the most commonly noted weed species in all seasons, along with mouse ear chickweed (*Cerastium glomeratum*) in the winter and spring (AgResearch). A species summary table is presented in Appendix A.

GENERAL FARM STOCK POLICY: Limestone Downs has recently undergone a 570 hectare 800-cow dairy conversion on the southern flats. The sheep and beef unit now covers 2,280 ha with the remaining area retired and fenced off native bush (Figure 3-3). The dairy and beef units work together, with beef cattle numbers dropped back after the dairy herd was established, and buying in cattle was no longer necessary. Calves from the dairy unit are reared for replacements in the dairy herd or for beef cattle, with the replacements being grazed on the hills at times. The beef breeding herd now contains around 230 cows, and 140 rising one and two year old heifers, with around 650 fattening rising one, two and three year old bulls and steers. Breeding ewe numbers are around 7,000 – 8,000, with 3,000 hoggets also mated.

FIELD SAMPLING EVENTS: Limestone Downs has been more extensively temporally sampled than the other farms in the project. There have been five sampling events in total: early summer (December 2013), late summer (February 2014), autumn (May 2014), winter (July 2014) and spring (October 2014) (Figure 3-4). A total of 84 sampling sites were located over the property. During the project the dairy conversion meant that four sites were incorporated into the dairy platform and were consequently missed in the last sampling event during spring (Oct 2014). Five replacement sites (pegs numbers 401-425) were added to make up a total of 400 sample sites to replace these sites.

The sampling event in December 2013 was interrupted by a large amount of rain. Sampling was stopped and resumed when the rain had stopped. The number of plots sampled during the winter sampling event was reduced due to very low pasture covers and wet conditions. Areas where the pasture was too short to cut and collect sufficient material were soil sampled only. This was also the case for areas where wet muddy conditions meant that soil contamination from trampled pasture and splash back would have been an issue. As a result, pasture samples were only collected from 45 of the 80 sites.

3.2.2 Erewhon Station

EREWHON STATION is a large 3,680 hectare commercial sheep and beef property on the Napier-Taihape road near Moawhango (39.505731°S, 175.959355°E). Erewhon is located approximately 30 kilometres directly east of Waiouru and 30 kilometres northeast of Taihape. This property is located near the southern boundary of the Waiouru military area, part of the harsh and rugged central plateau landscape dominated by pumice, and borders on the mudstone dominant Rangatikei Region at the southern end of the property. The lowest part of Erewhon is 560 m a.s.l. and the highest 1000 m a.s.l.. The farm is owned by Rimanui Farms, who own a number of large sheep and beef properties, though the farms are run independently of each other.

GENERAL FARM DESCRIPTION: Erewhon is at higher altitude, enduring a cooler climate than most North Island hill country properties. The lowest part of Erewhon is at a higher altitude than the other trial farms, with the exception of the highest areas of Cleardale (which was classed as high country rather than hill country and was not sampled). Erewhon Station has a mix of contour, with larger areas of easy to rolling hills, some harder hill and some large very steep faces (Figure 3-5). With the Rangitikei River on the eastern boundary, the landscape is typical of the terraced landscapes associated with the Rangitikei Region (Figure 3-6 and Figure 3-7).

Figure 3-5: The steeper hills of Erewhon Station, looking north over the Northern part of the property.

CLIMATE: Erewhon Station has a cooler climate than the other North Island trial farms. Average maximum and minimum daily air temperatures in summer are 18.5°C and 7°C; in autumn 14°C

and 3.5°C; winter 8°C and 0°C; and in spring 13°C and 3°C (NIWA). Average annual rainfall is approximately 1,130mm.

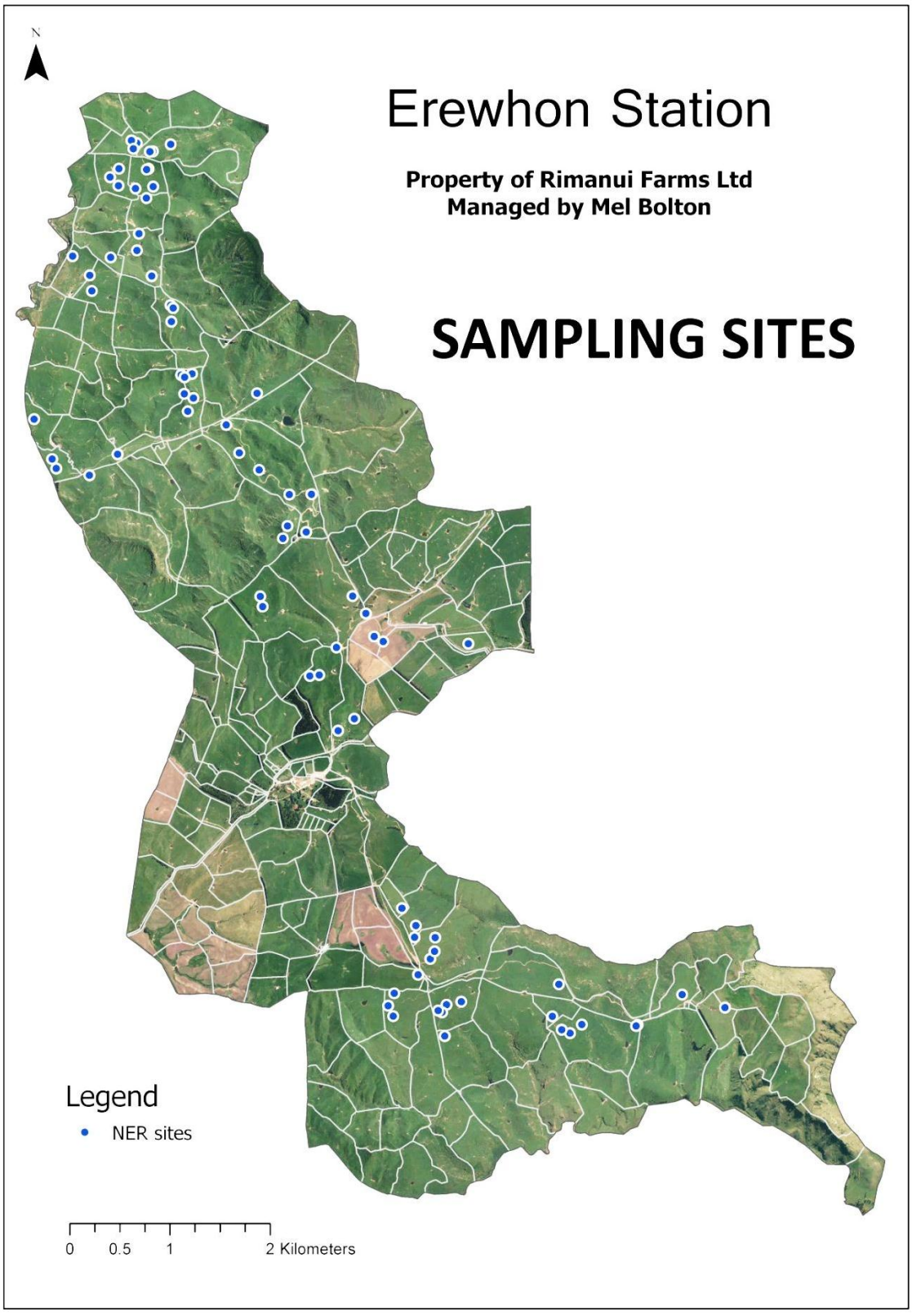


Figure 3-6: Sampling sites (blue points) at Erewhon Station, showing the location of the 80 sites on farm.

Figure 3-7: Typical landscapes at Erewhon Station in Spring highlighting the mix of contour from flats to some very steep faces.

SOIL: Erewhon lies between the Rangitikei River and one of its major tributaries, the Moawhango River. These rivers have cut deep-sided canyons in soft sedimentary material (Molloy, 1998) and created a terraced landscape with steep faces for which the Rangitikei is

renowned. The fundamental soils layer identifies Orthic Allophanic with Orthic Brown soils and Orthic Pumice soils in the northern part of the farm.

FERTILISER: A mixed fertiliser regime is in place at Erewhon Station. The farm is split into many different blocks, which do not have consistent geographic boundaries from year to year. Rates, products, and time of applications vary greatly, but as the majority of Erewhon is on volcanic soils, the rates are usually high. There is a large area of easy country in the centre of the farm which has been cropped and reseeded to improved pastures. These areas especially have received a highly varied fertiliser programme to suit the cropping and regrassing programme. Applications are generally made in August or March, though some areas receive two applications in one year. Commonly, 200-500 kg/ha (18-45 kg P/ha) single superphosphate is applied. DAP may also be applied regularly at around 140 kg/ha.

PASTURE SPECIES: The most dominant pasture species recorded at Erewhon Station were browntop (*Agrostis capillaris*) and perennial ryegrass (*Lolium perenne*). Yorkshire fog (*Holcus lanatus*), white clover (*Trifolium repens*), Chewings fescue (*Festuca ruba*) and cocksfoot (*Dactylis glomerata*) were abundant. Sweet vernal (*Anthoxanthum odoratum*) was abundant in spring and almost absent in the autumn. Crested dogstail (*Cynosurus cristatus*) was of note in autumn and almost absent in spring. Another species of note was poa (*Poa pratensis* or *P. trivialis*). A species summary table is presented in Appendix A.

GENERAL FARM STOCK POLICY: Erewhon station is a breeding and finishing farm, aiming to finish as much stock on farm as possible. The farm runs approximately 13,400 breeding ewes and 4,000 ewe hoggets, approximately 1,740 breeding cows, plus replacements and trading stock.

FIELD SAMPLING EVENTS: The field sampling at Erewhon was carried out on 80 sites with two sampling events. The first sampling event was scheduled for spring 2014. However due to the busy fieldwork programme and weather conditions, sampling was pushed back, and although the seasons are generally later at Erewhon, many pasture species were beginning to flower or were already flowering, on 1st -3rd of December 2014 when the sampling took place (Figure 3-8). The amount of flower stem present was dependent on pasture species, location and grazing management at that time. The autumn sampling at Erewhon Station was completed in May 2015.

Figure 3-8: Example of sites at Erewhon Station for the spring sampling event, where pasture species were flowering.

3.2.3 Ohorea Station

OHOREA STATION, BLOCK 4 is a 655 hectare block that is part of a larger 5,420 hectare property at Waimarino 15km south of Raetihi towards Whanganui (39.543707°S, 175.295223°E). Atihau-Whanganui Incorporation farm 30,000 ha (17,200 effective) over 6 sheep and beef stations and 1 dairy unit. Block 4 is considered the easier hill country of Ohorea Station (Figure 3-9).

Figure 3-9: Ohorea block 4 looking west from the north woolshed across the Mangawhero River valley.

GENERAL FARM DESCRIPTION: In the past the Ohorea block has seen little invested in improvements. However this has changed in recent times with fertiliser inputs, cropping, reseeding and general improvements to farm infrastructure for ease of management. Block 4 at Ohorea station has a complete mix of terrain (Figure 3-10 and Figure 3-11). A large area of flat to rolling country at the top of the farm has been cultivated and resown. This area has also received a large amount of fertiliser. A large portion of the block is medium to steep hill, with some very steep faces along the Mangawhero River.

CLIMATE: Ohorea has a cold wet climate. The annual rainfall is approximately 1,300mm. The average maximum and minimum air temperatures are 23°C and 11°C in summer, 18°C and 8°C in autumn, 13°C and 4°C in winter, and 17°C and 7°C in spring (NIWA).

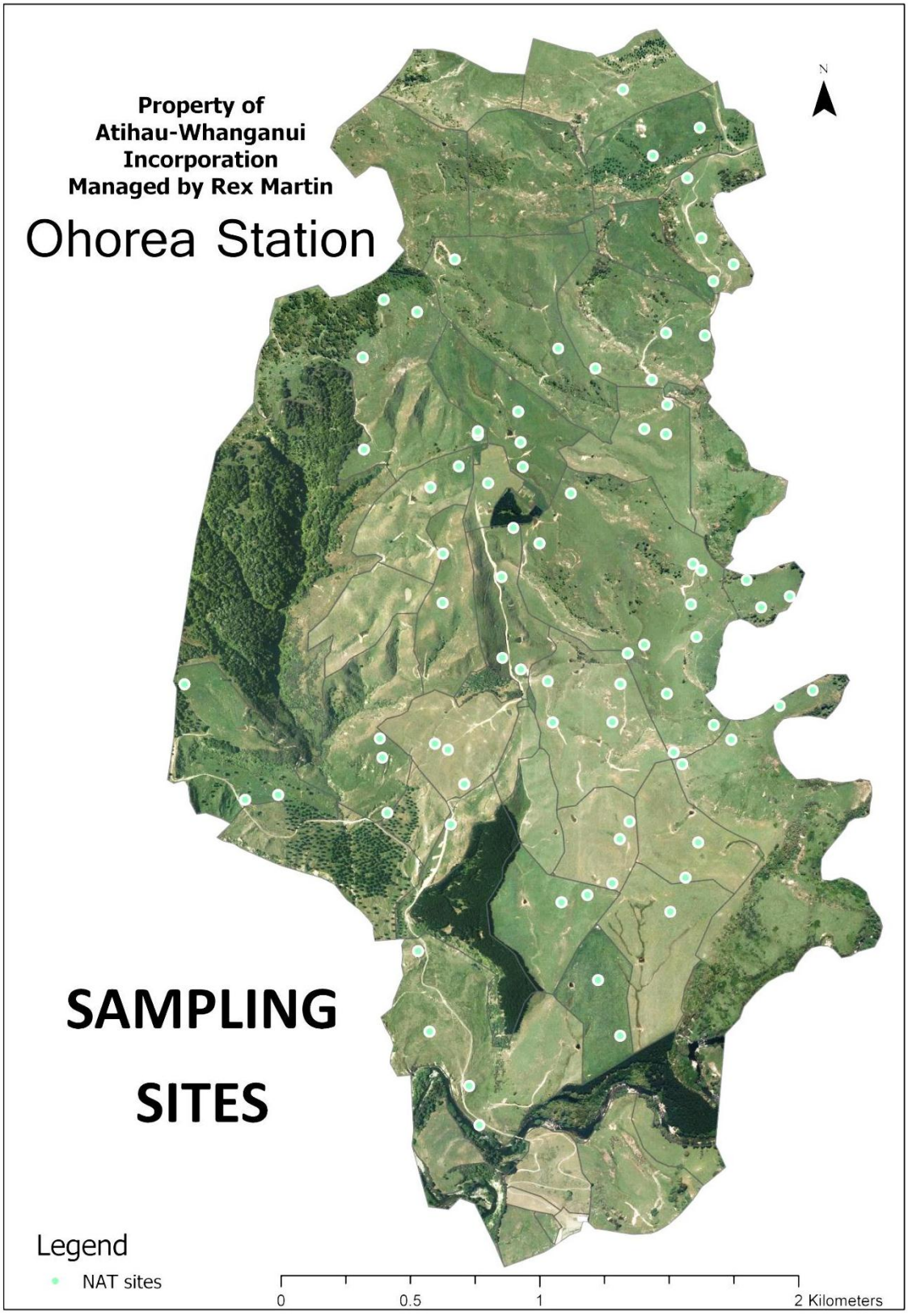


Figure 3-10: Location of the 80 sites (green points) on Block 4 of Ohorea Station.

Figure 3-11: Typical landscapes from Ohorea with rolling to steep hills, improved pasture (bottom row)

SOIL: The soils on Ohorea Block 4 are predominantly mudstone. A small area of higher altitude flats are fertile andesitic ash, with moderately rolling to steep hills derived from mudstone, with some sandstone, and stony alluvial flats alongside the Mangawhero River. Steepland soil

of the Whanganui hill country is often shallow and erosion prone (Molloy, 1998) which is evident in the steeper hills of Ohorea.

FERTILISER: Block 4 at Ohorea has generally been divided into the same management blocks year on year. Similar (in terms of kg P/ha) products and rates have been applied to all areas of the block with the exception of the new pasture flats, where around 45-60 kg P/ha/yr fertiliser has been applied, compared to 14-18 kgP/ha/yr for the rest of the block. Fertiliser is generally applied between December and February with the majority of the farm receiving superphosphate with some sulphur super products used at 150-200kg/ha.

PASTURE SPECIES: The most dominant pasture species recorded in the plots at Ohorea Station, block 4, were perennial ryegrass (*Lolium perenne*) and browntop (*Agrostis capillaris*). Yorkshire fog (*Holcus lanatus*) and white clover (*Trifolium repens*) were abundant. Sweet vernal (*Anthoxanthum odoratum*) was abundant in spring and less abundant in the autumn. Cocksfoot (*Dactylis glomerata*) and crested dogstail (*Cynosurus cristatus*) were of note. Chewings fescue (*Festuca rubra*) and creeping bent (*Agrostis stolonifera*) were of note in autumn. Danthonia (*Rytidosperma* spp.) and poa (*Poa pratensis* or *P. trivialis*) were of note in spring and almost absent in the autumn. Weed species of note recorded in the plots were buttercup (*Ranunculus* spp.), catsear (*Hypochaeris radicata*), dandelion (*Taraxacum officinale*) and thistle (*Cirsium arvense* and *C. vulgare*). A species summary table is presented in Appendix A. A 70 hectare area of the block has recently been cultivated, cropped and then regrassed in ryegrass and white clover. This resulted in a more consistent and pure sward across the area, compared to the mixed pastures that was evident at all other sites.

GENERAL FARM STOCK POLICY: Ohorea station runs a 60:40 sheep to cattle ratio. Exact numbers for the block are difficult to determine as Block 4 is only 655 hectares of a larger 5,420 hectare property. The blocks are run as one unit, with Block 4 being easier country and having a higher stock carrying capacity than the majority of the Station. Ohorea is a breeding unit, finishing only up to 15% of animals. The remainder is sent to other Atihau farms to be finished, which is not uncommon for this class of country. The cooler climate, tendency for reversion to native scrub, steep slopes and shallow soils of the Whanganui steepland soils make pasture production difficult to maintain, and the area is only suitable for store farming (Molloy, 1998).

FIELD SAMPLING EVENTS: Three sampling events were completed on Ohorea Station in the autumn and spring of 2014 and the autumn of 2015. In the autumn of 2014 there was a greater build-up of dead material and less clover. Fertiliser was applied to the farm between the spring 2014 and autumn 2015 sampling events.

3.2.4 Tautane

TAUTANE STATION is a 3,500 ha coastal property at Herbertville in the Hawke's Bay (40.478520°S, 176.590554°E). The property ranges from 0 to 290m a.s.l.. Owned by Ngāti Kahungunu and leased to Taratahi, an agricultural training college, Tautane is a working commercial farm that hosts students as part of their hands-on training.

GENERAL FARM DESCRIPTION: Tautane is an iconic coastal farm with 160 ha of coastal cliffs stretching along 12km of coastline bordering the South Pacific Ocean. The topography is a mix of 100ha of flats, some of which is cropped for fodder, and the rest is easy to steep hill with coastal hills to cliffs. Tautane differs from the other farms for the effects of its coastal location with a warmer, drier climate and erodible hills that have scarred the landscape (Figure 3-12, Figure 3-13 and Figure 3-14).

Figure 3-12: Typical landscape at Tautane Station, with scarred hills.

CLIMATE: Tautane experiences the hot dry summers typical of the East Coast of the North Island. With a summer dry and winter wet climate, the average rainfall at Tautane is 1,000 ml. Summer air temperatures are around 20-30°C and in the winter are 10-16°C in the East Coast region. Tautane encompasses the windy spot of Cape Turnagain, often measuring monthly record wind gusts in the country around 150-190km/hr (NIWA). The predominant drying north-westerly winds intensify the summer soil moisture deficit.

Figure 3-13: Locations of the 80 sites (orange points) spread across Tautane Station

Figure 3-14: Typical landscapes at Tautane Station: during spring and autumn sampling (top 6 images) and showing summer dry (bottom 2 images)

SOIL: Soils of the East Coast are poorly mapped and poorly understood (Molloy, 1998). Tautane soils are predominately mudstone with some derived from sandstone. The hills contain Pallic soils that are summer dry, winter wet, and prone to erosion; and brown soils that are the most common soil type in New Zealand. The flats are Orthic gley soils that are poorly drained and rocky raw soils dominate the coastal cliffs as classified in the Fundamental Soils Layer. The soils are prone to shallow slipping and slip scars are evident over the farm. These old scars have a very thin A horizon and can take years to develop and for pasture production to return to that of adjacent stable sites (Molloy, 1998).

FERTILISER: Tautane has been split into four areas for fertiliser management: the coastal block, north hills, south hills and flats. Of all the study sites, Tautane has had the most uniform approach to fertiliser applications, most years applying around 200kg/ha (18 kg P/ha) single superphosphate. Some sulphur super has also been applied. No fertiliser was applied in 2013, the year the farm changed ownership.

PASTURE SPECIES: The most dominant pasture species at Tautane Station were perennial ryegrass (*Lolium perenne*) and browntop (*Agrostis capillaris*). Yorkshire fog (*Holcus lanatus*), white clover (*Trifolium repens*) and cocksfoot (*Dactylis glomerata*) were abundant. Crested dogstail (*Cynosurus cristatus*) was more abundant in autumn than in spring. Soft brome (*Bromus hordeaceus*) and sweet vernal (*Anthoxanthum odoratum*) was of note in spring and almost absent in the autumn (AgResearch). A species summary table is presented in Appendix A.

GENERAL FARM STOCK POLICY: Tautane runs approximately 16,500 mixed age Romney ewes and 5,500 ewe hoggets. Maternal ewes are mated to Romney and Coopworth rams and terminals to Suftex. Around 20% of lambs are finished on the property, but the dry summers mean that the majority of lambs, 60%, are sold on the store market. Angus cattle are run on the station with approximately 650 cows, 500 R3 heifers, plus R2 and R1 heifers. Breeding cattle are mated to Angus bulls. A few R1 and R2 steers are also fattened.

FIELD SAMPLING EVENTS: Field sampling campaigns were conducted at Tautane Station in the spring of 2014 and autumn of 2015. Pasture green material was high in spring; with the dead vegetation fraction being quite large in the autumn sampling event. No fertiliser was applied between the sampling events.

3.2.5 Pati Tapu (Karakanui/Waimapu)

PATI TAPU STATION is a 3,779 ha property 5km south of Alfredton (40.746436°S, 175.889182°E) in the Northern Wairarapa. Pati Tapu, as it is today, has amalgamated 3 farms. Pati Tapu and Karakanui were purchased in the early 2000's by Bruce and Sue McKenzie. Their son Doug and his wife Jo have bought into the farm and taken over management. Pati Tapu is located in a hill country dominant area, approximately 20km east from the Tararua Ranges and 40km from Castlepoint on the east coast. The altitude is around 160-550 m a.s.l..

GENERAL FARM DESCRIPTION: Pati Tapu has a mix of terrain, with flats in the valley floors and moderate to steep hill in the northern part of the farm (Figure 3-15 and Figure 3-17). There is a large area of higher altitude rolling country on the western boundary. This area is noticeably cooler than the rest of the farm. The neighbouring farm, Waimapu, was purchased by Doug and Jo in 2017. A large area of manuka separates the newly added Waimapu Station which also has a mix of contour and low fertility due to the lack of fertiliser (Figure 3-16). This block was incorporated into the validation sampling in March 2017.

Figure 3-15: View of Pati Tapu looking out to some of the steeper hills

CLIMATE: Pati Tapu is classified as summer safe but this depends on the season. Some summers can get very dry. It is typical in the Wairarapa for the majority of the rainfall to occur in the winter and spring, with unreliable summer rainfall (Molloy, 1998). The average maximum and minimum air temperatures at the weather station in nearby Alfredton are approximately 23°C and 11°C in summer, 19°C and 9°C in autumn, 13°C and 4°C in winter, and 16°C and 8°C in spring (NIWA). Average annual rainfall in approximately 1050mm (NIWA).

SOIL: The soils at Pati Tapu, as classified by the Fundamental Soils Layer, are dominated by the most common agricultural soils, the Brown soils, with Gley soils in the valley floors. Some areas of the Waimapu block are classified as Pallic soils which are typically formed under conditions of dry summers and wet winters.

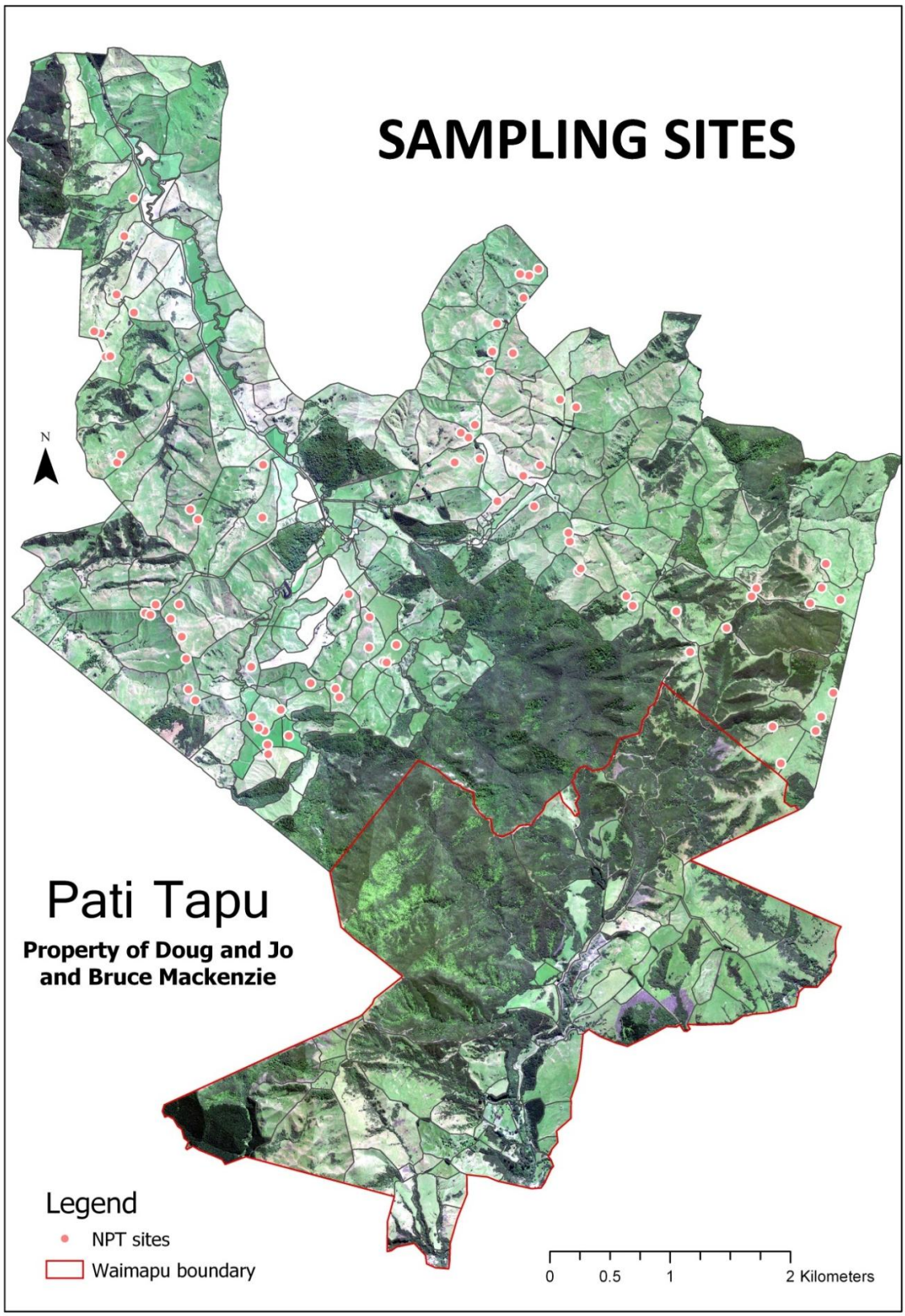


Figure 3-16: Site locations (red points) at Pati Tapu Station spread across the old Pati Tapu and Karakanui properties. The image also includes the recently purchased Waimapu Station (red outline). All areas are now farmed as Pati Tapu Station.

Figure 3-17: Typical Landscapes at Pati Tapu Station; a mix of improved flats, rolling to steep country with south very steep faces and higher altitude flats.

FERTILISER: The blocks that now make up Pati Tapu Station had a relatively poor fertiliser history prior to being purchased by the McKenzie family. Waimapu is believed to have not received any fertiliser or lime for the past 40 years. The current owners have been applying capital fertiliser in order to build up soil fertility. In some years, two applications of fertiliser have been made; one application in November which has generally been a maintenance rate, and a second application in February applying a capital dose. The management blocks on the farm are set, but the rate and product has varied. Each application has generally been single superphosphate at 200-300 kg/ha (18-27 kg P/ha). Around 20 to 25 kg P/ha is applied in each fertiliser application, but some areas have received this twice in one year.

PASTURE SPECIES: The most dominant pasture species in the trial plots at Pati Tapu was browntop (*Agrostis capillaris*). Perennial ryegrass (*Lolium perenne*), Yorkshire fog (*Holcus lanatus*) and white clover (*Trifolium repens*) are also abundant. Chewings fescue (*Festuca ruba*), cocksfoot (*Dactylis glomerata*) and crested dogstail (*Cynosurus cristatus*) were notable in autumn. Sweet vernal (*Anthoxanthum odoratum*) was of note in autumn and spring. A species summary table is presented in Appendix A.

GENERAL FARM STOCK POLICY: Pati Tapu Station runs Romney ewes and Hereford Angus cross cattle as their capital stock. Prior to the purchase of Waimapu Station this year, approximately 10,500 breeding ewes and 400 cattle made up their breeding stock, along with replacements and trading stock which varies depending on the season. In general, they run 75% sheep and 25% cattle (McKenzie, 2015). The farm aims to finish as much stock as possible, but is highly controlled by the climate. In more favourable years, 75%, and in less favourable conditions as little as 30% of their lambs are able to be finished.

FIELD SAMPLING EVENTS: Pati Tapu was one of the last four farms introduced as part the calibration phase of the project. Sampling campaigns were carried out in the spring of 2015 and autumn 2016. Fertiliser was applied in December 2015 to all sites prior to the April 2016 sampling event. The Waimapu block was purchased after the completion of the field sampling and therefore was not included in the sites. A validation exercise was carried out in late summer/early autumn of 2017, which included sites from the Pati Tapu (and Karakanui), and Waimapu blocks.

3.2.6 Harwoods

HARWOODS is a 2,000 ha mixed enterprise in Upper Takaka, surrounded by the steep hills of the Kahurangi National Park and Takaka Hill (41.049317°S, 172.816360°E). Located approximately 20 km inland and south of Takaka township in Golden Bay, at the top of the South Island. The farm has been in the Harwood family for many generations and is now farmed by brothers Nigel and Johnny. The farm ranges from 120m a.s.l. to 810m a.s.l. at the top of some very steep hill faces (Figure 3-18).

Figure 3-18: Typical landscape from Harwoods hill country block

GENERAL FARM DESCRIPTION: Harwoods farm is a diverse business. The area is split between a dairy platform, deer unit, sheep and beef unit, and forestry. The contrasting land uses reflect the mix of contour from flat valley floor to steep hill faces. The flatter area is used for dairy and deer and much of this area is irrigated. The sheep and beef unit is approximately 920 hectares of the steep hills (Figure 3-19 and Figure 3-20).

CLIMATE: The climate in the Takaka region is generally warm with high sunshine hours and reasonable rainfall. Rainfall at Harwoods is high compared to other farms in the study, receiving approximately 1800-2000mm per annum (NIWA). The average maximum and minimum daily air temperatures in nearby Takaka are 23°C and 11°C in summer, 19°C and 8°C in autumn, 14°C and 3°C in winter, and 18°C and 7°C in spring (NIWA).

SOIL: The Fundamental Soils Layer classifies the soils of the easier areas as Brown soils and the steep hills as Rendzic Melanic soils. Rendzic Melanic soils are limestone or lime rich at shallow depths (Molloy, 1998).

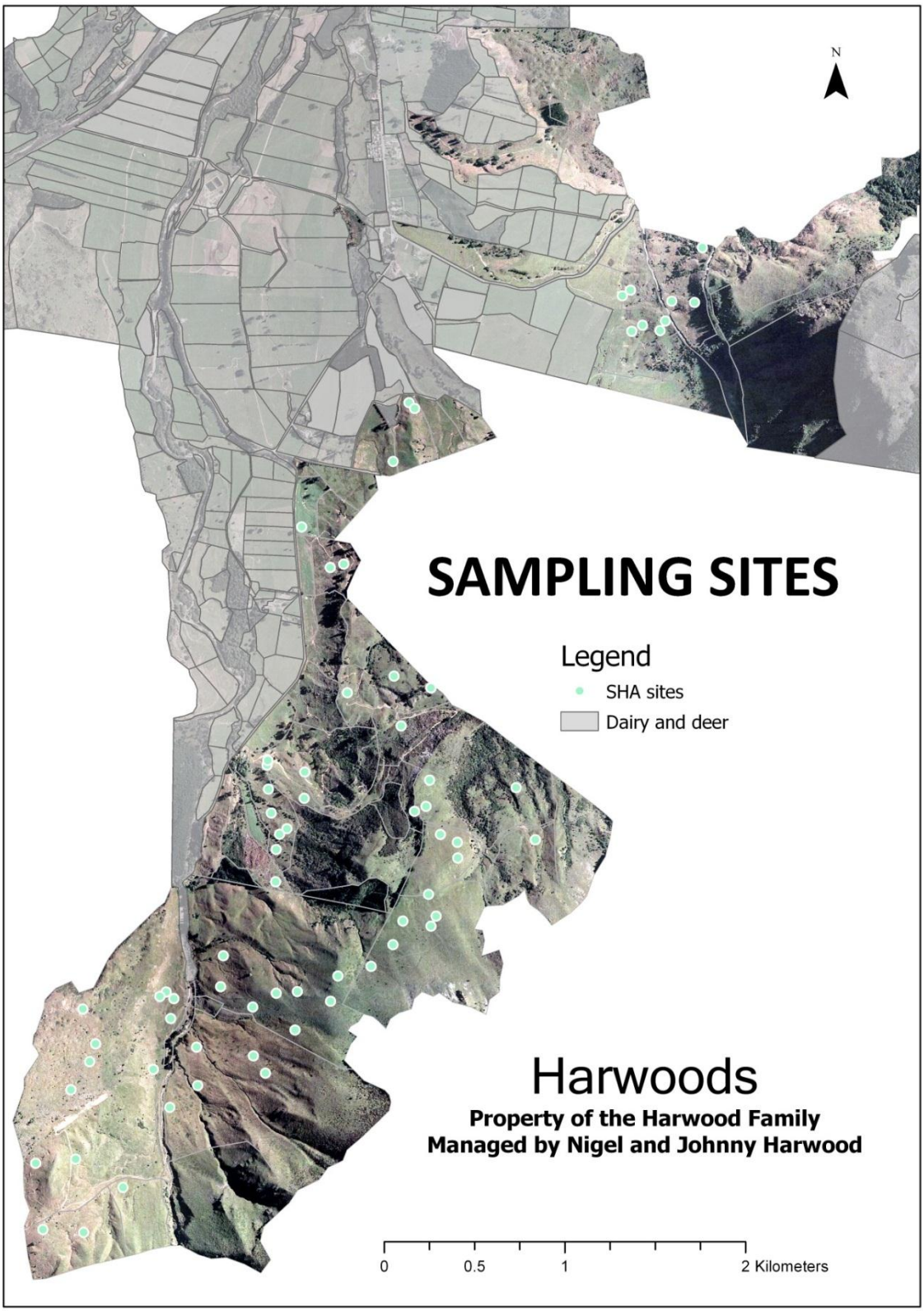


Figure 3-19: Map of Harwoods showing the location of the 70 sites (green dots).

Figure 3-20: Typical landscapes at Harwoods

FERTILISER: Harwoods received some of the lowest applications of fertiliser rates of the eight farms studied. The management blocks were kept generally the same. Often large areas received no fertiliser in any year. Slightly more fertiliser was applied to easier front country, and the back steeper country was missed in many years. Fertiliser applications varied but superphosphate applied at 100-200 kg/ha was commonly used.

PASTURE SPECIES: The most dominant pasture species Harwoods was perennial ryegrass (*Lolium perenne*). Sweet vernal (*Anthoxanthum odoratum*) was also very dominant in spring and less so in autumn, and browntop (*Agrostis capillaris*) was more dominant in the autumn than spring. Yorkshire fog (*Holcus lanatus*), white clover (*Trifolium repens*), plantain (*Plantago lanceolata*) and catsear (*Hypochaeris radicata*) were also abundant. Other species of note were Chewings fescue (*Festuca ruba*) and crested dogstail (*Cynosurus cristatus*). A species summary table is presented in Appendix A.

GENERAL FARM STOCK POLICY: The sheep and beef unit comprises approximately 3,100 Romney ewes and 80 Hereford cows as the capital breeding stock. Store lambs are also bought in to fatten along with calves reared from the dairy platform.

FIELD SAMPLING EVENTS: Two field sampling campaigns were completed at Harwoods in the spring of 2015 and autumn 2016. There were fewer sites located on this property than the other farms, with 70 sites, as the sheep and beef unit was a much smaller than the other farms in the study. Fertiliser was applied to approximately 25% of the sites between the two sampling events as part of the farms fertiliser programme.

3.2.7 Cleardale Station

CLEARDALE STATION is a 1,350 hectare property in the Rakaia Gorge spanning the foothills and river terraces from the Mount Hutt Range on the western boundary, to the Rakaia River on the east (Figure 3-21 and Figure 3-22). The farm is located 20km north of Methven, Canterbury (43.449902°S, 171.585392°E). The farm ranges from 320 to 590m a.s.l.. This family farm was originally part of a larger property passed through four generations since the 1920's. The land was split between two brothers in 1998. One brother inherited 19,600 ha of high country (now Mt Heron Station), and the other a smaller hill country block now Cleardale Station.

Figure 3-21: View looking back at Cleardale along the foothills of the Mount Hutt Range, taken from Coleridge Road on the plateau across the Rakaia River from Cleardale.

GENERAL FARM DESCRIPTION: Cleardale has four distinct landscapes or land management units over which 56 sampling sites (Figure 3-22 and Figure 3-23) are spread:

- a large area of rolling to flat land, the majority of which has undergone significant improvements, including cultivation, reseeding, fertiliser and a small area of irrigation;
- the river flats are mostly under pivot irrigation. Much of this has area been resown with varying degrees of success;
- rolling to steeper land that has a large amount of tussock and Matagouri (*Discaria toumatou*) cover;
- very steep faces of the foot hills of the Mount Hutt Range, bordering on high country.

The owners of Cleardale Station have invested heavily in pasture renewal and irrigation, with 660ha cultivated and 210ha now under irrigation. However they also see value in the unimproved landscapes and will leave areas of Matagouri and tussock for the ecological and aesthetic values these landscapes hold. The property runs sheep, cattle and has a cropping component for forage (e.g. beet, kale and rape), and other crops such as milling wheat, radish and potato.

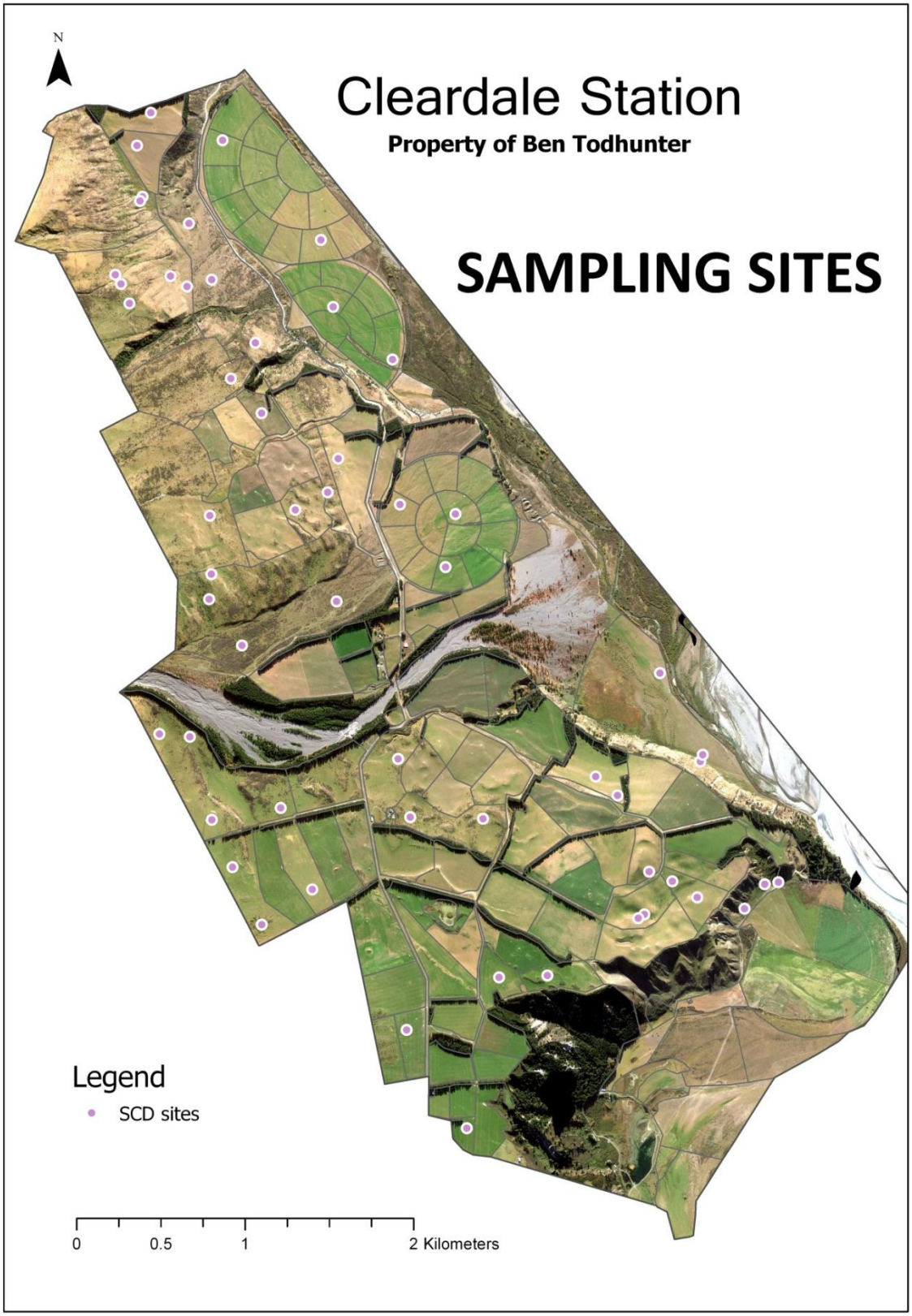


Figure 3-22: Cleardale Station showing the location of the 56 sampling sites (purple points).

Figure 3-23: Cleardale, examples of the different landscapes within the farm: improved flats and rolling hills (top row), irrigated stony river flats next to the Rakaia River (2nd row), unimproved pastures with Matagouri and tussock (3rd row), steep hill face of the Mount Hutt Range (bottom row).

CLIMATE: Most of the farm is facing east to northeast and exposed to drying winds off the Canterbury plains. Average annual rainfall on the opposite side of the Rakaia River at Snowdon

is approximately 880mm (NIWA), though Cleardale probably receives less rainfall than this. The region experiences seasonal drought, becoming very dry in the summer. The average maximum and minimum daily air temperatures are 21°C and 9°C in summer, 16°C and 5°C in autumn, 10°C and 1°C in winter, and 15°C and 4.5°C in spring (NIWA).

SOIL: The soil orders at Cleardale are recorded in the Fundamental Soils Layer as Brown, Pallic and Recent. The lower flats at Cleardale alongside the Rakaia River are shallow, very stony recent alluvial soils. Much of the upper terraces, for example alongside Little River, are loess covered sandstones with some recent gravelly soils.

FERTILISER: The fertiliser regime at Cleardale is highly varied. This is a reflection of the range in level of production over different areas and therefore maintenance rates required. The easy terrain allows for a large portion of the farm to be truck spread. As a result it is feasible to use a range of products, rates and timing at paddock scale. This approach, in conjunction with the cultivation and cropping regime has resulted in individual paddocks receiving different fertiliser applications. Applications are usually made in March and September to some parts of the farm. Phosphatic fertiliser is usually in the form of sulphur super 15 or 30 and single superphosphate at around 100-200kg/ha (9-18 kg P/ha).

PASTURE SPECIES: The most dominant pasture species was perennial ryegrass (*Lolium perenne),* along with browntop (*Agrostis capillaris*). Yorkshire fog (*Holcus lanatus*), white clover (*Trifolium repens*) and cocksfoot (*Dactylis glomerata*) were notable. Other notable species predominantly in spring were sweet vernal (*Anthoxanthum odoratum*), soft brome (*Bromus hordeaceus*), Vulpia spp. and poa. In the drier autumn sampling crested dogstail (*Cynosurus cristatus*) was present in the sward (AgResearch). A species summary table is presented in Appendix A.

GENERAL FARM STOCK POLICY: Cleardale Station has five stud operations - Merino, English Leicester, Halfbred, and Quarterbred sheep studs; and an Angus stud. The Halfbreds are a commercial flock with Poll Dorset and Southdown terminal sires. Other classes of stock are traded as it suits the farming and cropping operation.

FIELD SAMPLING EVENTS: The study site at Cleardale has been sampled twice, in spring 2015 and autumn 2016. The spring sampling was a full sampling event with 280 samples collected over 56 sites. However the autumn sampling was reduced, with 210 soil and 180 pasture samples collected. The reduced sampling was due to the dry conditions meaning pasture samples were difficult to collect without soil contamination or taking double or triple cuts (Figure 3-24). In

addition, fertiliser (sulphur super 15) had been applied to some of the easier country the day before and the day the ground sampling commenced. These areas were therefore excluded from the sampling. Areas of flats received Urea at 70kg/ha in early March, approximately 2 months before the ground sampling.

Figure 3-24: Example of the same site at in the spring sampling (left) and the dry conditions of autumn 2016 (right).

3.2.8 Moana Farm – Lawsons

MOANA FARM is a 2,336 ha (2,051 ha effective) hill country property in East Otago, located approximately 30km north of Dunedin (45.640077°S, 170.561816°E). The farm is close to the coast, approximately 8km inland from Karitane. The lowest parts of the farm are nearly at sea level, 20 m a.s.l., and the highest at 390 m a.s.l.. Moana Farm has been in the family since 1950 and is farmed by brothers Rob and Willy Lawson with their father Jim.

GENERAL FARM DESCRIPTION: There are four distinctive land types over the property (Figure 3-25 and Figure 3-26):

- intensively farmed flats, an area in the northeast that is the lowest elevation of the farm, the most accessible, and has been highly developed;
- improved hill country: a large area to the south of the flats and the easier country along the southeast boundary, much of this area has been cultivated and improved;
- rolling hill: an area in the centre of the farm, which has not been developed;
- native hill country: a relatively small area in the southwest of the farm, this area is reasonably steep and higher altitude and has a significant amount of native grass cover.

CLIMATE: Rainfall at Moana Farm varies from 750-1000mm. The farm is prone to droughts and has no irrigation. The average maximum and minimum daily air temperatures are 20°C and 10°C in summer, 17°C and 5°C in autumn, 11°C and 1°C in winter, and 15°C and 5°C in spring (NIWA).

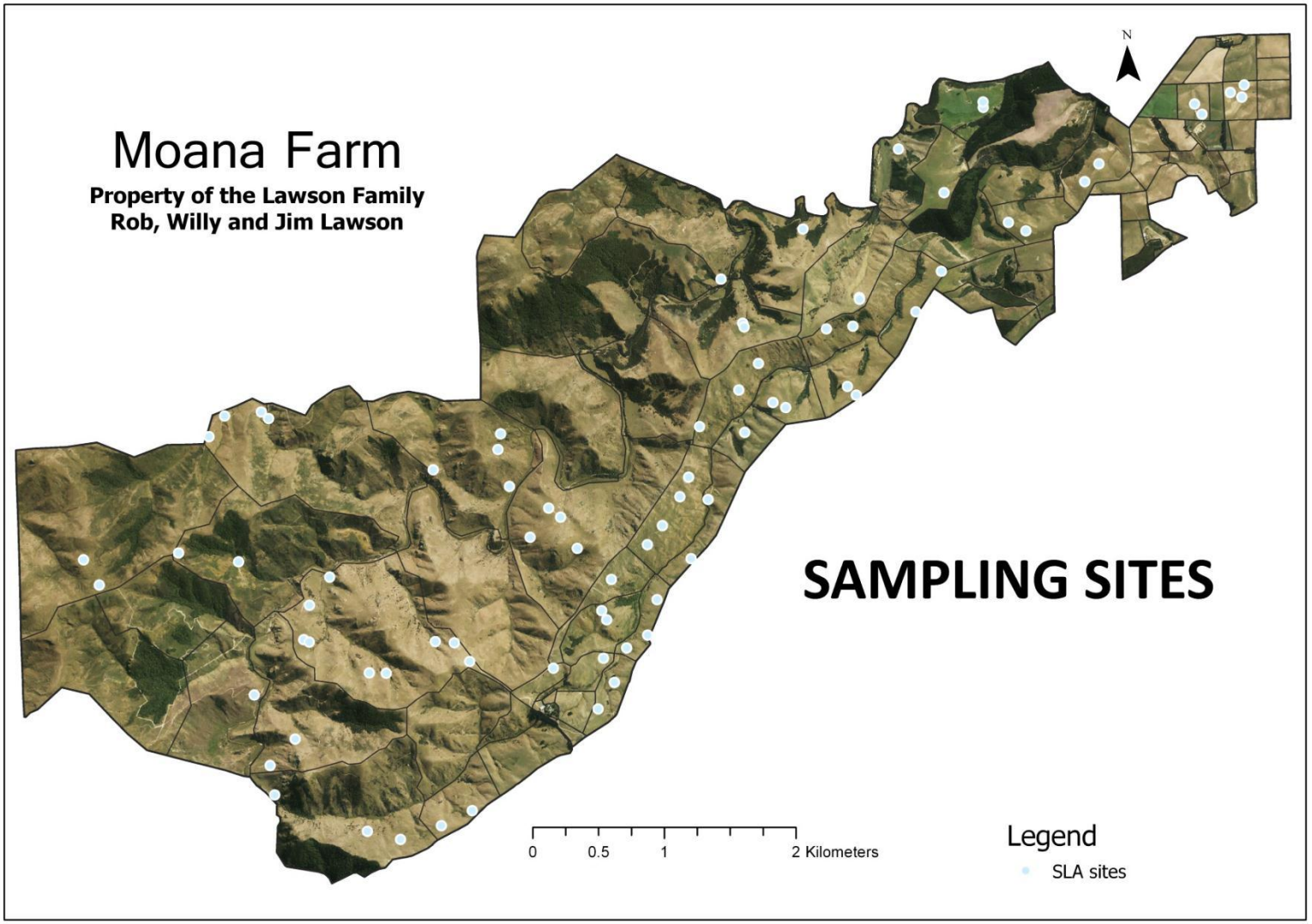


Figure 3-25: The 80 sampling locations (light green points) at Moana Farms, owned and managed by the Lawson family.

Figure 3-26: Typical landscapes at Moana Farm showing the range in land development and contour across the property.

SOIL: The soils as classified in the Fundamental Soils Layer are Brown soils, with Pallic soils on the intensively farmed flats.

FERTILISER: The management units are generally kept the same each year and follow the same boundaries as the different land types outlined in the general farm description. The amount of fertiliser applied varies each year, but the blocks receive the same rates relative to each other. The highest producing flats receive the highest rates and are fertilised every year. The least productive land receives much lower rates and is fertilised every second year. Sulphur super 15 or 20 is the most common fertiliser applied at 150-250 kg/ha (13.5-22.5 kg P/ha).

PASTURE SPECIES: The most dominant pasture species in the plots in the spring sampling was sweet vernal (*Anthoxanthum odoratum*) along with browntop (*Agrostis capillaris*) and perennial ryegrass (*Lolium perenne*). Cocksfoot (*Dactylis glomerata*), danthonia (*Rytidosperma spp.*), Yorkshire fog (*Holcus lanatus*), white clover (*Trifolium repens*) and dandelion (*Taraxacum officinale*) were also abundant at the time of the spring sampling (AgResearch). A species summary table is presented in Appendix A.

GENERAL FARM STOCK POLICY: Moana Farms has 5,500 Romney/Perendale ewes and 1,350 ewe hoggets. Maternal ewes are mated to Perendale and Romney rams. Lambs are aimed to be finished early as the farm is prone to drought. 250 Angus-Hereford beef breeding cows are run on the property with R1 and R2 steers and heifers to be fattened.

FIELD SAMPLING EVENTS: Only one field sampling campaign was completed at Lawsons, in spring 2015. The autumn 2016 sampling event at Moana Farm was cancelled as the conditions were too dry.

A summary of the eight farms follows in Table 3-2.

3.2.9 Summary of hill country farms

Table 3-2 Summary of farms

Farm	Region	Coordinates	Size (ha)	Elevation range (m a.s.l.)	Climate	Farm
Limestone Downs (NLD)	Waikato	37.477103°S, 174.757579°E	2280 sheep and beef unit (3200 total)	0-230	Warmer, sub-tropical climate, warm summer and mild winter.	Sheep and Beef – breeding and finishing, supporting replacements for their Dairy platform
Ohorea (NAT)	Whanganui	39.543707°S, 175.295223°E	655 block 4 (4033 total)	250-570	Cooler, wetter climate.	Sheep and Beef – breeding and semi-finishing
Erewhon (NER)	Rangitikei	39.505731°S, 175.959355°E	3680	560-1000	Cooler, high altitude for North Island.	Sheep and beef – breeding, finishing and fattening
Tautane (NTT)	Hawke's Bay	40.478520°S, 176.590554°E	3580	0-300	Summer dry, winter wet. Windy.	Sheep and beef – breeding and semi-finishing
Patitapu (NPT)	Wairarapa	40.746436°S, 175.889182°E	2611 (+1160 purchased later)	160-550	High spring and winter rainfall, summers highly variable	Sheep and beef – breeding and semi-finishing
Harwoods (SHA)	Nelson	41.049317°S, 172.816360°E	920 sheep and beef unit (whole farm 2000 ha effective)	120-810	Warm, high rainfall, high sunshine hours	Sheep and beef – breeding and finishing, fattening, dairy and deer
Cleardale (SCD)	Canterbury	43.449902°S, 171.585392°E	1348	300-930	Low rainfall, summer drought, cold winters.	Sheep and beef – breeding and finishing, fattening, cropping
Moana Farms/Lawson (SLA)	Otago	45.640077°S, 170.561816°E	2336 (2051 effective)	20-390	Low rainfall, drought prone	Sheep and beef – breeding and finishing

3.3 Site selection

Sites on each of the farms were selected using stratified random sampling. This technique was used to ensure that a representative number of sites were located proportionally on different slopes and aspects to accurately represent the property. The sites were spread geographically over the farm to cover a range of soil types, management zones, and microclimates. Sites were also selected based on reasonable accessibility. For practical reasons, travelling time with such large properties to cover, and accessibility with a lot of equipment was taken into consideration to ensure fieldwork could be carried out in a safe and timely manner.

A wide range of landscapes were required to ensure that a range of different pasture tissue samples were collected. A range in species, age and stage of maturity, defoliation and regrowth times were all required to ensure a robust model could be developed, which would be reliable in a wide range of pasture conditions. A wide range of pasture nutrient concentrations and soil fertility, from extremely low to very high, was also required for model development.

Slope and aspect were derived in ArcGIS using an 8m Digital Elevation Model (DEM) from Land Information New Zealand (LINZ). Each farm was split based on a slope and aspect criteria (Table 3-3 and Table 3-4). Using the work of Zhang, Valentine, and Kemp (2004). The land area in each of the category combinations (slope and aspect) was calculated in ArcGIS. The number of sites to be located on each category was then calculated as a proportion of the total number of sites. For example, at Pati Tapu, 102 of the 2074 ha is on east facing hills with slopes of 16-22.5 degrees. Covering 5% of the farm, calculated as a proportion of the 80 sites, 4 sites were located on this slope/aspect combination. An example of the map of proposed sites is given in Figure 3-27.

Table 3-3 Criteria for aspect categories for site selection

Aspect	
Aspect category	Aspect range (degrees)
100	300-360 + 0-60
200	60-120
300	120-240
400	240-300

Table 3-4 Criteria for slope categories for site selection

Slope	
Slope category	Slope range (degrees)
10	0-8
20	8-16
30	16-22.5
40	22.5-25
50	25 <

Approximate locations were navigated to, following the plan of proposed sites. At the sites, a representative area was selected, identifying the slope/aspect category and also ensuring that the site was representative of the area. Five permanent marker pegs were placed in the ground so that the exact plot locations could be identified on subsequent sampling events.

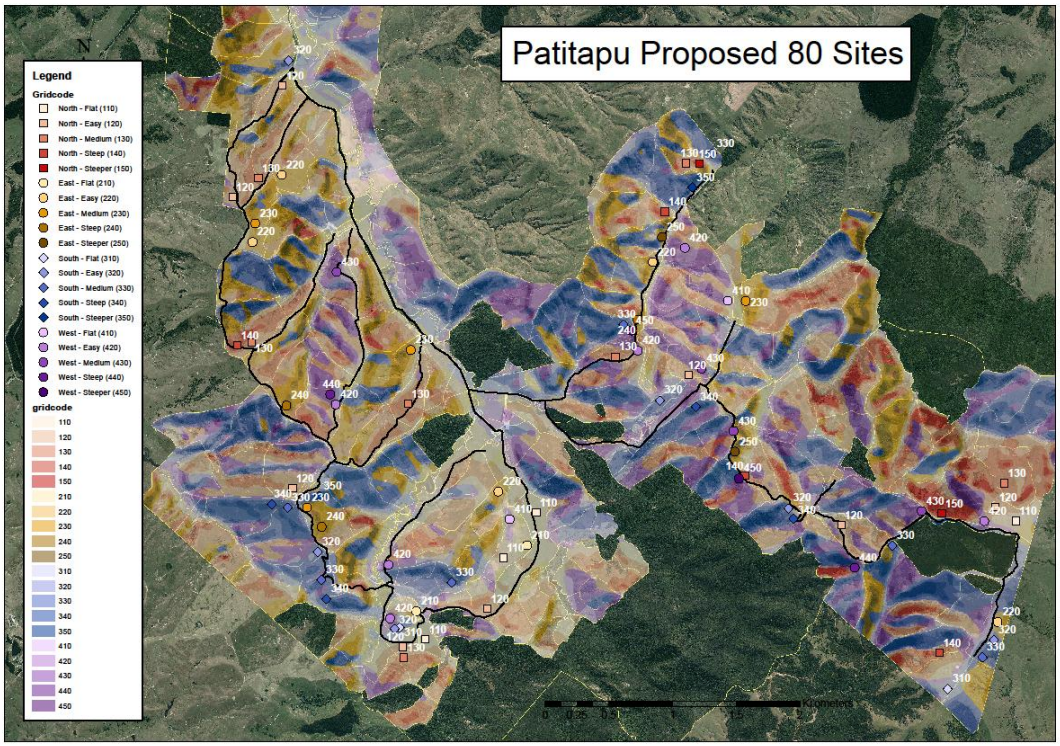


Figure 3-27: Example of site selection map, Pati Tapu. Red-north, yellow-east, blue-south and purple-west, darker shade are steeper slopes, symbols are located on the proposed sites.

3.4 Fieldwork

3.4.1 Data collection

An extensive fieldwork programme included 19 sampling events from December 2013 to May 2016 (Table 3-5). The sampling events were predominantly carried out in the autumn and spring. However, Limestone Downs was additionally sampled in the early summer, late summer and winter. Two validation sampling events were completed on Pati Tapu and Moana Farm in autumn 2017.

Data was collected as part of a Primary Growth Partnership (PGP) project: Pioneering to Precision. A team from Massey University completed the site selection, marking, GPS, topographic measurements, photographs, proximal hyperspectral sensing (ASD FieldSpec Pro) and ground work for the airborne hyperspectral imaging. A team from AgResearch completed the botanical composition, pasture cuts and soil cores. Protocols for all fieldwork were clearly adhered to as it was essential to ensure consistency in the data collection methodologies across all personal involved, and across farms and years of data collection.

Table 3-5 Summary of sampling events carried out as part of the PGP fieldwork.

Farm	Code	Location	District	Size (ha)	Early Summer 13	Late Summer 14	Autumn 14	Winter 14	Spring 14	Autumn 15	Spring 15	Autumn 16	Validation 2017	Number of sites	Number of pegs
Limestone Downs	NLD000	Port Waikato	Auckland	2280 sheep + beef, 3220 total	✓	✓	✓	✓*	✓					80	400
Ohorea - Atihau	NAT2000	Raetihi	Whanganui	655 (4033)**			✓		✓	✓				80	400
Erewhon	NER3000	Taihape	Whanganui	3680					✓	✓				80	400
Tautane	NTT4000	Herbertville	Hawkes Bay	3580					✓	✓				80	400
Patitapu	NPT5000	Alfredton	Wairarapa	2611 (+1160)***							✓	✓	Summer/ autumn	80	400
Harwoods	SHA6000	Takaka	Marlborough	920 sheep and beef, 1170 total							✓	✓		70	350
Cleardale	SCD7000	Methven	Canterbury	1348							✓	✓****		56	280
Moana Farms - Lawsons	SLA8000	Dunedin	Otago	2336, 2051 effective							✓		Autumn	80	400

*The winter sampling at Limestone Downs included a heavily reduced number of plant tissue samples due to soil contamination on the leaves in wet muddy conditions.

**The sampling sites were only located on Block 4 of Ohorea Station. The whole property covers 4033 hectares in total.

*** Doug and Jo Mackenzie purchased the neighbouring farm, Waimapu, in 2017. This 1160 hectare property was added to the validation sampling in March 2017.

**** The Autumn sampling at Cleardale was reduced. Some sites were unable to be sampled due to fertiliser applications that had occurred the day before and of sampling.

3.4.2 Quadrat-sample support

Sample support is a term used to describe the concept that the sample value depends on the attributes of how the measurements are made on the ground. The value depends on the sample's support attributes which have an area or volume, shape, and may also have an orientation. Examples of sample support are the pixel size of a DEM, the quadrat cut for a pasture sample, or the soil core taken. The sample support for soil cores, if bulked, is different from that of a single core. The sample support for a single core would be the diameter of the core or the volume taken (Oliver, 2015).

It is important to decide on one sample support and keep this constant throughout the data collection process. It is not comparable to use data collected from different sample supports as a larger sample support will include, and effectively remove more, variation (Oliver, 2015). All field measurements for the ground sampling campaign were taken with a 0.5m x 0.5m quadrat (0.25m^2).

The quadrat was placed rotating clockwise around the peg for each sampling event (Figure 3-28), to remove any difference resulting from artificial conditions created from the previous pasture cut and holes from previous soil coring.

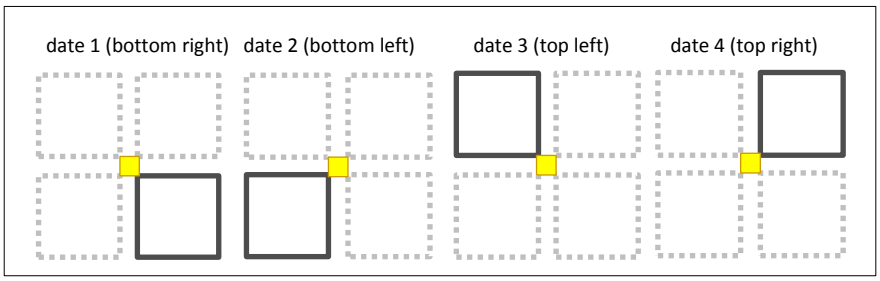


Figure 3-28: Placement of quadrat, rotating clockwise around the peg for each consecutive sampling event

3.4.3 Topographic data

Permanent marker pegs were used to locate the plots (Figure 3-29) to ensure that the exact same position was measured and sampled by different people working within a ground sampling event, and in return trips over the following seasons. The location of each of the pegs was measured with an RTK GPS (Figure 3-30). Latitude, longitude and elevation were recorded for individual pegs. Slope and aspect at each site were measured in the field, to ensure that the data was accurate for model development. One measurement was collected for each site to represent the local area. The range of sites over all farms in the field sampling campaign covered a full range of slopes and aspects (Figure 3-31). Slope was measured with an Abney level and a compass used to measure the aspect of the slope face.

Figure 3-29: Example site at Erewhon, 5 pegs within a 5m radius

Figure 3-30: Marking out a site at Erewhon Station, permanent pegs, RTK GPS location recorded and slope and aspect measured in the field.

Most sites remained accessible throughout the duration of the project; however a few sites were removed due to cropping of paddocks and five sites removed at Limestone Downs that were located on the area converted into the dairy platform.

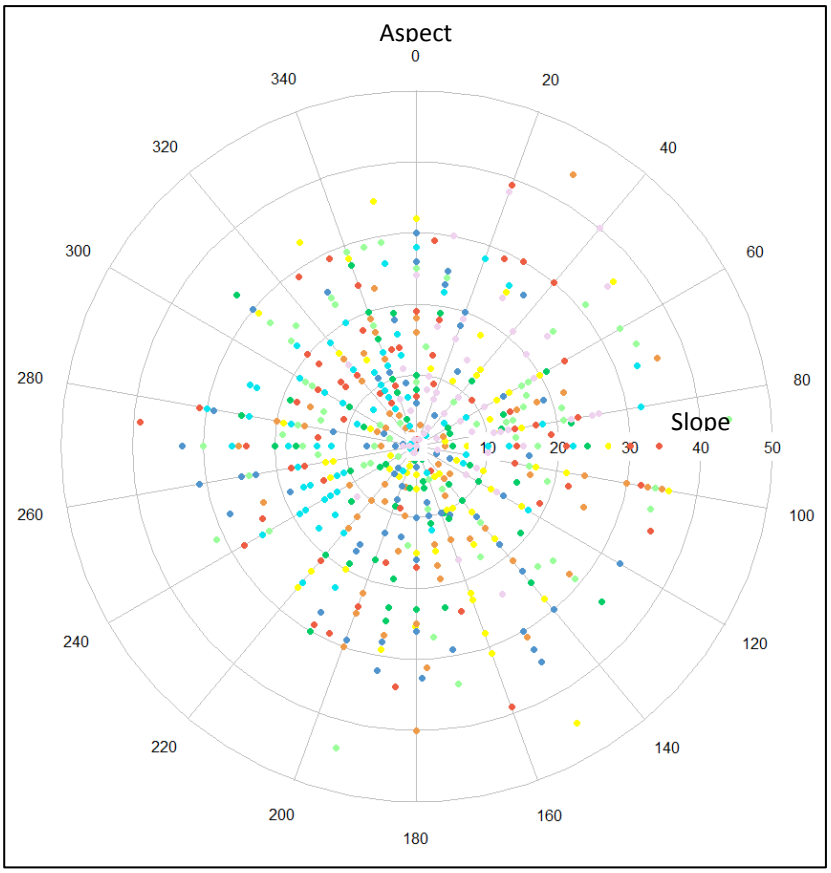


Figure 3-31: Range of slope and aspects covered across sites from all eight farms, NLD – yellow, NAT – green, NER – dark blue, NTT – orange, NPT – red, SHA – light green, SCD – purple and SLA – light blue.

3.4.4 Photographs

Photographs of all plots and sites were collected at the time of sampling. Photographs were taken as a reference to check back if anomalies were found in the results. Pasture species composition, cover, pasture maturity, time since last grazing, nearby patches of urine and dung and general state of the pasture could be checked if required. One photograph of every plot and one photograph of each site were taken at every sampling event.

3.4.5 NDVI

Pasture canopy reflectance was measured within each quadrat in the field. An Analytical Spectral Device (ASD) FieldSpec Pro FR spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA) was used with the canopy pasture probe (CAPP) (Sanches, 2009). The CAPP blocks all incoming solar radiation and ensures even and consistent illumination with a tungsten-halogen lamp. The ASD measures from 350-2500nm with a spectral sampling band width of 3nm in the 350-1000nm range and 8nm from 1001-2500nm. The CAPP was positioned in five locations within the plot, in each of the four quadrants and one in the centre (Figure 3-32). At each location an average of 20 spectral signatures were recorded. The spectral signatures for the five locations were averaged for each plot.

Figure 3-32 Measuring pasture canopy reflectance in the field at Limestone Downs.

A vegetation index, Red Edge Normalised Vegetation Index (RENDVI), was calculated using selected bands from the processed spectral data collected using the ASD. Normalised Difference Vegetation Index (NDVI) is the most widely known vegetation index. NDVI is a ratio between the bands in the red area of the electromagnetic spectrum that are absorbed by the leaf pigment chlorophyll which is used for photosynthesis, and the strongly reflected near-infrared bands due to the leaf cell structure (Kawamura et al., 2011). RENDVI is a modified version of NDVI, which is more sensitive than other plant indices to foliage content and senescence through using bands within the red edge area. RENDVI is more suitable for applications in precision agriculture, forest monitoring, and leaf water stress detection (Gitelson & Merzlyak, 1994; Sims & Gamon, 2002).

Two bands, 705 and 750, were used to calculate RENDVI:

$$RENDVI = \frac{750 - 705}{750 + 705}$$

3.4.6 Botanical composition

Botanical information was collected through in-field visual estimation of each plot by expert Grant Rennie (or on occasion a member from his team), from the AgResearch farm systems group. The visual assessment involved the identification of the three most abundant species, ranked in order. The percentage of the sample within each quadrat was classified into dead material, stem, and leaf, along with the legume, and weed content to total 100% of the dry matter. Weed content contained any species that is not a grass or legume, therefore included weed species and grazing herbs. Grass stem was classified as the reproductive stem and kikuyu stolon. Once the reproductive stem had turned brown it is classified as dead material. This classification is based on the Beef + Lamb New Zealand pasture quality calibration sheets (2002) which the assessor used to calibrate against. These are seasonal guidelines for quantifying the pasture components through visual estimation. Where the percentage was less than 2%, the presence was recorded as ‘trace’. The percentage of bare ground was also noted. An example is given in Figure 3-33.

a)

b)

Sample number	%Dead	%Legume	% Weed	% Grass Stem	%Grass Leaf	Percentage check	%Bare Ground	Most abundant species#1	Most abundant species#2	Most abundant species#3
NPT5311	35	tr	tr	0	65	100	0	Cocksfoot	Ryegrass	Yorkshire Fog
NPT5312	15	tr	2	tr	83	100	0	Browntop	Yorkshire Fog	Cocksfoot
NPT5313	30	5	tr	tr	65	100	0	Browntop	Yorkshire Fog	Sweet Vernal
NPT5314	20	5	tr	tr	75	100	0	Browntop	Sweet Vernal	Soft Brome
NPT5315	20	5	2	tr	73	100	0	Ryegrass	Browntop	Cocksfoot
NPT5316	15	20	tr	0	65	100	0	Ryegrass	White Clover	Yorkshire Fog
NPT5317	20	15	tr	0	65	100	0	Yorkshire Fog	Ryegrass	White Clover
NPT5318	20	20	0	tr	60	100	0	Ryegrass	White Clover	Yorkshire Fog
NPT5319	15	15	tr	0	70	100	0	Ryegrass	Yorkshire Fog	White Clover
NPT5320	20	2	tr	0	78	100	0	Ryegrass	Cocksfoot	Yorkshire Fog

c)

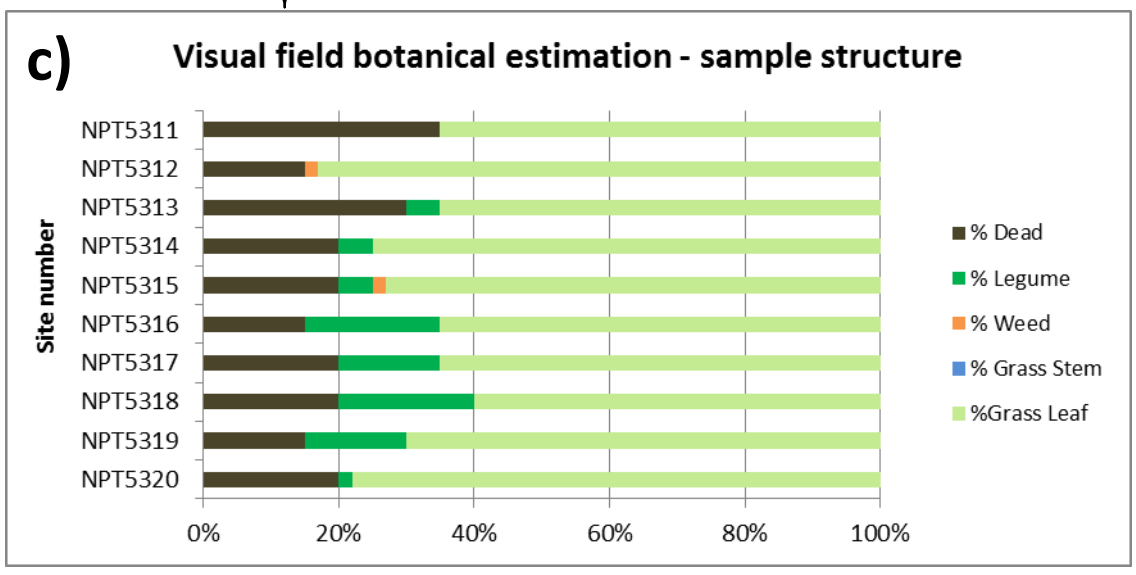


Figure 3-33 Example of the botanical information recorded for each plot. a) Photographic example of two plots, b) example of the raw data collected for two sites/10 plots and c) a graphic version showing the pasture components that make up the samples in these two sites.

3.4.7 Herbage samples

Leaf tissue samples were collected after the non-destructive sampling requirements (photograph, proximal sensing and botanical visual assessment) were completed. Samples were cut to the standard used for pasture quality and mineral assessment sampling to avoid soil contamination. Pasture was cut to grazing height (2 cm) from within the 0.5m x 0.5m quadrat using a portable battery powered handpiece. Leaf tissue was collected ensuring no soil contamination, faeces or foreign material was in the sample. Where pasture covers were too low to collect adequate leaf material to perform the required laboratory wet chemistry analysis, a second quadrat was cut adjacent to the original quadrat and noted as a double cut. Where soil contamination was unavoidable due to wet, muddy conditions, no leaf tissue samples were collected.

Herbage samples were collected into plastic bags, and were stored immediately after cutting in a polystyrene box with frozen chilly pads. Herbage samples were transported to Analytical Research Laboratories (ARL) at the end of each day to be processed the following day. Where this was not possible, herbage samples were stored in chillers and sent to the lab the following day with frozen chilly pads.

All leaf tissue samples were processed by ARL using their standard procedures. Samples remained heterogeneous in terms of species; no sorting for either species or plant parts was undertaken. The samples themselves were homogenised and subsampled. A subsample was dried at 105°C for 16 hours and used for the dry matter assessment. A second subsample was taken and dried at 65°C for 14-16 hours, and ground using a mechanical grinder to pass through a 1mm sieve. Wet chemistry analysis was carried out using the dried ground sample for: N, P, K, S, Ca, Mg, Na, Fe, Mn, Cu, Zn, B, and Ti. Near Infrared Spectroscopy was used on the dried ground sample to assess ME and OMD. Phosphorus concentration was obtained using microwave digestion followed by the ICP-MS analysis, and N concentration using the Dumas procedure. The concentrations of N, P, K, S, Ca, Mg and Na in the leaf tissue were reported as a percentage concentration on a weight per weight basis (% w/w). Fe, Mn, Cu, Zn and B were reported as mg/kg.

3.4.8 Soil sampling

Soil cores were collected from each quadrat after the leaf tissue sample was cut and collected. Soil samples were collected using a 30 mm soil corer to a depth of 75 mm. Nine cores were collected in a 3x3 grid within the quadrat (Figure 3-34). The nine cores for each plot were bulked and collected into a plastic sample bag. Soil samples were sent to ARL at the end of the

day, or stored overnight and sent the following day. Soil samples were treated using standard procedures at ARL. Samples were dried at 40°C for approximately 16 hours, ground, then passed through a 2mm soil sieve. Soil chemical properties were measured using standard laboratory tests including: pH, soil Olsen P, QTK, Sulphate Sulphur and Extractable Organic Sulphur.

Figure 3-34: Diagrammatic representation of the soil cores collected within the sample quadrat and photograph of a plot after soil coring.

3.4.9 Fenix surveys

A hyperspectral image of each farm was captured at the same time as the ground sampling campaign. An AisaFENIX (Specim, Finland) pushbroom airborne imaging spectrometer was used to capture an image of each farm during each sampling event. The senor measures reflectance from 380-2,500 nm covering the spectrum from visible to shortwave infrared (Vis-SWIR). The surveys were completed 2 hours either side of solar noon and in cloud free conditions. Weather and equipment constraints meant that imagery was not able to be completed for every survey. The raw images were radiometrically and atmospherically corrected – details are given by Pullanagari et al. (2016). A data cube was attained with 448 spectral bands and a 1m ground resolution from which a range of macro and micronutrient concentrations in the leaf tissue (Pullanagari et al., 2016) and the dead vegetation in the sward (Pullanagari et al., 2017) can be estimated.

3.5 Additional data

Additional data was collected and obtained outside of the main sampling events. This additional information helped to build up a large dataset for each of the farms. This includes: soil order, fertiliser history, stocking rates, predicted growth rates, soil moisture deficits around the time of sampling and weather data.

3.5.1 Soil information (FSL)

Soil information was obtained from the national dataset: the Fundamental Soils Layer (FSL). A data layer of soil order from the FLS was obtained and included in the dataset for each farm. Soil information was provided in more detail for some farms through the Horizons Regional Council Whole Farm Plans or Smap. However data at this scale was not available for all farms, so was not included. Soil order was incorporated into the database as classified in the FSL by the 15 soil orders described by Hewitt (2010), the highest level in the New Zealand Soil Classification (NZSC).

3.5.2 Fertiliser records

Fertiliser application records were collected and collated for each farm as far back as records were accurately kept. This was at least 3 years for all farms. Records were collected from:

- Landowners, farm managers and farm advisors records,
- Smart Maps accounts,
- Fertiliser representatives,
- Flight records from spreading aircraft.

Where multiple sources of records were obtained, the fertiliser applications were cross checked to ensure the most reliable data was used. The recorded fertiliser applications did not always match. This highlights the requirement of more accurate recording of fertiliser product, rate and time of application. To avoid extra work load and human error, this process should be as automated as possible. Providing farmers with a 'proof of placement' map identifying where fertiliser was applied, product and the rate applied would provide an accurate record and evidence of an even spread.

All fertiliser applications containing P were mapped over the properties. For phosphatic fertilisers the kg P/ha applied were calculated based on the product and rate spread on each block of each farm. The time elapsed since the last application at each site prior to the sampling event was recorded as the number of days that had passed. Depending on the farm, fertiliser was applied between sampling events to none, all, or part of the property. A summary of the general fertiliser application strategies of the eight trial farms is given in Table 3-6 and an example of the final mapped fertiliser variables are shown in Figure 3-35.

Table 3-6: Summary of the different approaches to phosphate fertiliser application at the eight hill country farms involved in the research

Farm	Brief description of general fertiliser programme	General approach	General time of year applied	General farm coverage each year	General application	Comparable P (kg P/ha) in fertiliser applications	Fertiliser applied between sampling events
Limestone Downs	Double dose half of the farm every second year. Majority of the sites are in the northern half of the farm, as large part of the southern block was converted to dairy.	Blanket	Dec-Feb	1/2 of the farm (alternates)	Approx 400-500 kg/ha Super (every 2nd year)	38 kg P/ha (every 2nd year)	No
Erewhon	Highly varied programme. Different blocks (a block does not always contain the same paddocks), rates, products, time of year. Mostly volcanic soils which require twice the kgP/ha to lift 1 Olsen P unit compared to other soils. Some areas receiving 2 applications a yr.	Highly varied, varied blocks	Aug or March	All	Super @ 200-500 kg/ha or DAP @ 140kg/ha	20-50 kg P/ha	Fertiliser applied to approximately ¼ of the sites
Ohorea	Apply reasonably similar products and rates to all areas of the farm except flat with new pasture, which have received heavy applications of fertiliser. Some (maybe 1/3 sites) on volcanic soils.	Varied, set blocks	Dec-Feb	All	Super @ 150, 175 or 200kg/ha. Flats: Super @ 500kg or DAP @ 300kg/ha	14-18 kg P/ha Flats: 45-60kg P/ha	Yes: to all sites
Tautane	Typically a blanket application for the whole farm. The farm was sold in 2013. Neither the seller nor the purchaser applied fertiliser in this year. This was 2 years before the first sampling event.	Blanket	March	All	Super @ 200 kg/ha	20 kg P/ha	No
Pati Tapu	Poor fertiliser history prior to the current owners (10 years ago). Current owners have been trying to build up fertility. Some years applying two lots of fertiliser, always in November, some years a 2nd application in February.	Varied, set blocks	November, some years 2nd application in February	All	Super @ 200-300 kg/ha some DAP	20 to 25kg P/ha in each application (so in some years will receive this twice)	Yes: to all sites
Harwoods	Rather light on fertiliser in general. Most sites missed every year. Slightly more applied to easier front country. Back steeper country missed many years.	Varied, light, set blocks	Varies but Feb-Mar and August	Few parts	Super @ 100-200 kg/ha	18-20 kg P/ha (many sites often missed each year)	Fert on 1/4 sites
Cleardale	Highly varied and very bitsy. They truck spread much of their fertiliser, so apply lots of different products and rates and to only small areas at a time. Uncultivated/old pasture areas have been skipped for a few years. Cultivated/resown areas received fertiliser every year.	Highly varied, varied blocks	March and Sept	Part	Sulphur Super 15 or 30, some Super @100-200kg/ha	10-20 kg P/ha	No
Moana Farms/ Lawsons	Blocks are generally kept the same. Amount of fertiliser applied differs each application, but the blocks vary respectively. One block always receives the lowest rate (every second year) and another block always receives the higher rate every year (more productive country).	Varied, set blocks	Jul-Aug	All and half (alternates)	Sulphur Super 15 or 20 @150-250kg/ha	12-23 kg P/ha	NA - Spring sampling only

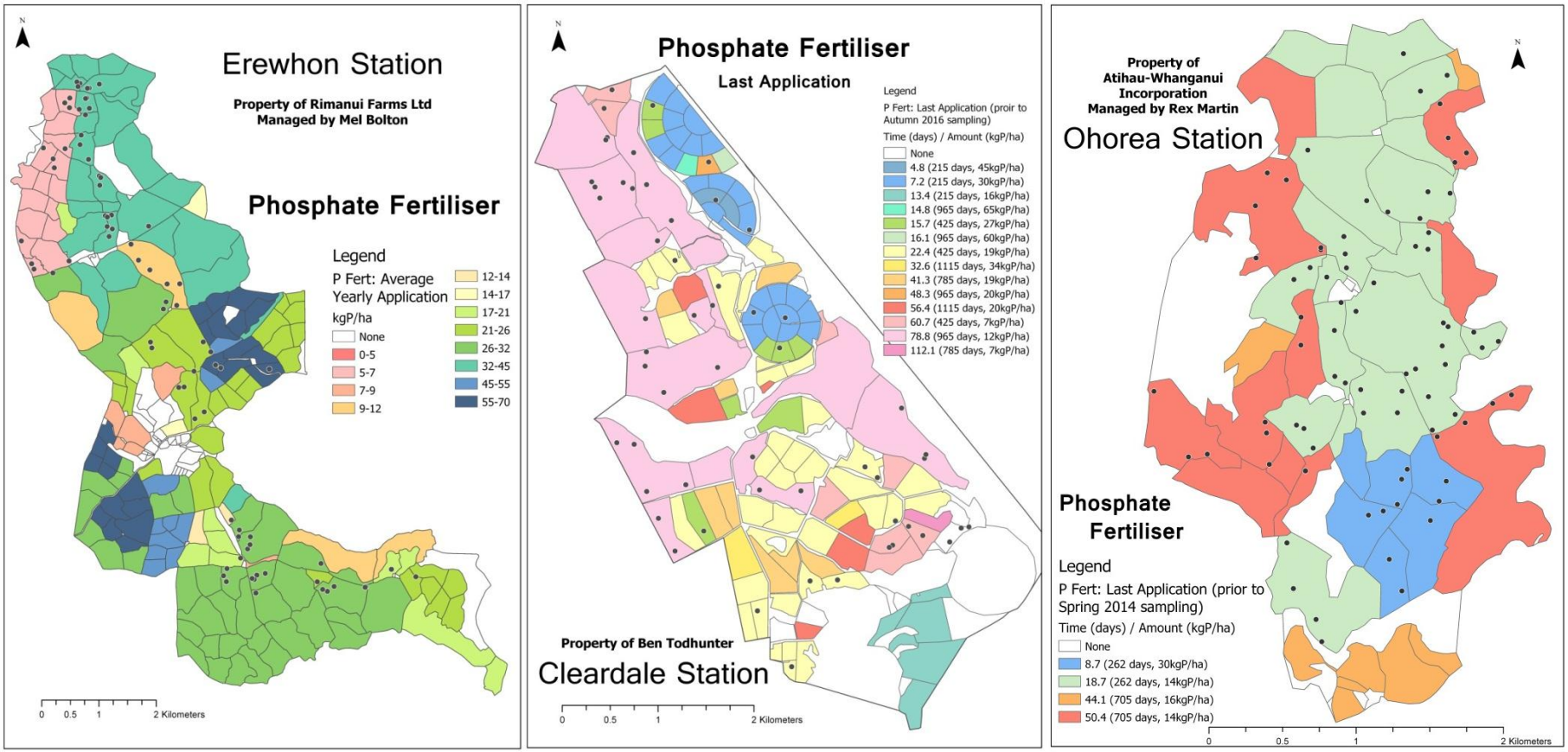


Figure 3-35: Examples of fertiliser maps created: average kg P applied annually at Erewhon Station (left) and time since the last application at Cleardale (centre) and Ohorea (right)

3.5.3 Stocking Rates

The research objective required an indication of the relative productivity across each farm. After consultation with farmers and agronomists involved in the study, it was concluded that stock units per hectare at set stocking was a practical and informative value. Farm and stock managers base set stocking rates on what each paddock can carry from late winter through to early summer, encompassing spring when the majority of pasture growth occurs. Set stocking rates were calculated per paddock. Ewe numbers were adjusted based on dietary requirements of ewes bearing single or multiple lambs. Cattle run amongst the ewes at this time were included (as outlined in 6.3.2).

3.5.4 Pasture growth rate and soil moisture deficit

Estimates of pasture growth rate and soil moisture deficit on the dates of ground sampling events were modelled using the Pasture Growth Forecaster (Ravensdown). The estimates were calculated from a range of data including: location, slope, aspect, current weather, and soil information.

3.5.5 Weather stations

Weather stations were installed at Limestone Downs, Erewhon, Tautane and Pati Tapu. A NIWA weather station at neighbouring Papahaua Station, was used to collect weather data for Ohorea Station. For the South Island farms: Harwoods, Cleardale, and Harwoods, the closest NIWA weather station was the most accurate data available. These recorded all the standard climatic variables including: rainfall, wind speed, wind run, temperature and humidity.

Figure 3-36: Weather station installed at Tautane Station.

3.6 Database

COLLATION OF DATA

The extensive database was built up over the years of sampling and incorporated data from various sources. Data from the field sampling events were collected and sent in various forms from raw data files to spread sheets of results already checked. Some datasets can contain millions of data entries. However these are often from automated systems and automatically collected and uploaded. Collecting, collating and checking data from multiple sources, as was required to create this dataset, was challenging and time consuming, but essential as data integrity is paramount. Formats of data provided and a brief outline of processing and checking required to create the database used for model development is summarised in Table 3-7.

The physical and topographic features of latitude, longitude, elevation, slope, aspect, and soil order, were recorded once for each site. However for other data inputs, the approximately 7,000 entries required varying amounts of manual entry and calculation. For example, there is no consistent record keeping of fertiliser applications and these were time consuming to collect, interpret, enter and digitise. They were sourced from: email conversations between farmers and fertiliser reps, files from the topdressing aircraft, different farm software programs, 'My Ravensdown' accounts, hand drawn maps, spreadsheets, notes, and consulting with farm managers and owners. To calculate annual applications and the last application prior to each sampling event was time consuming. Should these be important factors in the model the recording of fertiliser rate, placement and product would need to be automated as much as possible. Many systems are already in place, but currently they are not fully utilised. Each source of data required different processing and editing. The time required to build up a robust dataset was underestimated. The time and effort in collecting field data, collating the data and checking data was necessary to ensure a robust dataset that would provide the best opportunity for modelling to be successful.

DATABASE CHECKS

To ensure a robust database was created, data was carefully combined from multiple sources. It was vital that all entries for each sample were joined correctly. Data was combined using unique sample ID's that contained the farm, plot number and date. Once all data was combined, the entire row of random samples were checked with the raw data to ensure they were correctly matched.

Table 3-7 Summary of data sources, data format received and processing required

Data	Data format	Processing and checking
Latitude, longitude and elevation	Raw RTK GPS file (.csv)	Every data entry checked and mistakes corrected, added to database
NDVI	Processed bands (excel spread sheet)	RENDIV calculated, added to database
Laboratory plant tissue analysis	Raw results (excel spread sheet)	Entries sorted, every data entry checked, mistakes identified and remedied e.g. sample name double-ups, entries removed.
Laboratory soil analysis	Raw results (excel spread sheet)	Entries sorted, every data entry checked, mistakes identified and remedied e.g. sample code not possible, entries removed.
Slope	Raw data (hand recorded or .csv)	Entered and checked, added to database
Aspect	Raw data (hand recorded or .csv)	Entered and checked, added to database
Climate	Raw data (.csv)	Data downloaded and appropriate calculations made e.g. 30 day rainfall prior to sampling event; added to database
Fertiliser history	Raw data (handwritten notes, hand drawn maps, emails, shapefiles)	Data interpreted, sorted, crossed checked, entered, calculations made for each sampling site and event, including days since the last application and the application rate; added to database
Stocking rate	Raw data (Handwritten lists, hand drawn maps, spread sheets)	Data interpreted, sorted, entered and calculations made based on stock numbers and classes of stock; added to database
Soil order	Dataset (Shapefile)	Soil order extracted from shapefile for each site; added to database
Pasture Growth Rate	Calculated from PGF model (excel spread sheet)	Data sorted; added to database
Soil Moisture Deficit	Calculated from PGF model (excel spread sheet)	Data sorted; added to database
Botanical data	Final dataset (excel spread sheet)	Added to database

SOIL CONTAMINATION

The effect of soil contamination on macro and micro nutrient concentrations of herbage samples collected as part of the PGP dataset was assessed to ensure that soil contamination did not influence analysis. The contamination of soil in herbage samples is always present to some degree (Gillingham, Sheath, & Sutton, 1987; Healy, Rankin, & Watts, 1974; Metson, Gibson, Hunt, & Saunders, 1979a; Mitchell, 1960), especially in samples taken on hill country due to the nature of the uneven ground surface (Gillingham et al., 1987). It was vital for the integrity of the prediction of soil fertility from herbage, that model development used data that was not affected by soil contamination.

Soil contamination of herbage samples can come from a number of sources: accidental collection of soil, like worm castings, more often collected when samples are cut to ground level (Frame & Hunt, 1971; Gillingham et al., 1987; Healy et al., 1974; Michell & Large, 1983;

Mitchell, 1960); rain splash (Frame & Hunt, 1971; Healy et al., 1974; Metson et al., 1979a; Mitchell, 1960) which is determined by rainfall and how strong or weak the soil structure is (Healy, 1967); dust on the leaf surface particularly after prolonged dry periods (Benton Jones Jr. & Wallace, 1992; Mitchell, 1960); soil particles lodged in emerging plant parts, which varies with the habit of the plant (Mitchell, 1960); and pasture that has been recently grazed and trodden into the soil (Frame & Hunt, 1971; Healy, 1967; Healy et al., 1974; Metson et al., 1979a; Mitchell, 1960). The time since the last grazing event, and stocking rate affect the level of soil contamination of herbage samples collected (Frame & Hunt, 1971; Healy, 1967; Healy et al., 1974; Mitchell, 1960).

Titanium is used as an indicator of soil contamination in herbage samples, as titanium is not a major constituent of leaf tissue. Titanium concentration of the leaf tissue in the herbage samples collected in the autumn and spring sampling events of 2015 were analysed to ensure that correct precautions and procedures were followed to minimise soil contamination. Simple linear regression showed that iron was strongly correlated with titanium for most farms ranging from R^2 of 0.74-0.96 and moderately correlated on the Lawsons and Tautane farms with R^2 values of 0.57 and 0.60 respectively (Table 3-8). Soil contamination is known to have a significant influence on the measured levels of iron in the sample (Metson et al., 1979a). Iron concentration of the herbage sample was consequently removed from the potential variables and the database used for model development.

Table 3-8: R^2 values for simple regression of plant tissue nutrient concentrations (nitrogen, phosphorus, potassium, sulphur, calcium, magnesium, sodium, iron, manganese, copper, zinc and boron), and titanium concentrations; for autumn and spring 2015 sampling events.

Simple regression of plant nutrients with Ti (R^2)		N	P	K	S	Ca	Mg	Na	Fe	Mn	Cu	Zn	B
		(% w/w)							(mg/kg)				
Autumn 2015	Ohorea/ Atihau	0.06	0.02	0.04	0.04	0.04	0.16	0.01	**0.90**	0.05	0.17	0.11	0.05
	Erewhon	0.01	0.00	0.04	0.01	0.11	0.01	0.05	**0.96**	0.03	0.10	0.00	0.00
	Tautane	0.11	0.09	0.15	0.08	0.01	0.08	0.00	**0.60**	0.01	0.00	0.00	0.00
Spring 2015	Pati Tapu	0.00	0.01	0.01	0.00	0.01	0.10	0.01	**0.81**	0.02	0.02	0.16	0.19
	Cleardale	0.03	0.08	0.05	0.04	0.02	0.02	0.01	**0.94**	0.00	0.01	0.00	0.01
	Harwoods	0.00	0.00	0.00	0.00	0.01	0.04	0.00	**0.74**	0.00	0.02	0.00	0.01
	Moana/ Lawsons	0.01	0.01	0.04	0.02	0.01	0.03	0.00	**0.57**	0.03	0.01	0.02	0.01

Analysis of all plant macro and micro nutrients measured in the leaf tissue showed that iron was the nutrient of major concern if soil contamination was present. The next strongest correlations, though weak, with R^2 values of between 0.15-0.19, included Mg and Cu in the autumn sampling at Ohorea; K in the autumn sampling at Tautane; and Zn and B in the spring sampling at Pati Tapu. All other R^2 values were 0.11 or less.

SUMMARY OF FINAL DATA SET

The most accurate data was used for model development. The variables, data type, resolution and sources are summarised in Table 3-9. The summary includes all the variables that were collected and collated and available for inclusion in a model. However many of the variables were not used in the final modelling. For predicting soil nutrient status over whole farms, raster and polygon layers were required. These are summarised in Table 3-10.

Table 3-9 Set of data available for model development

Data type	Variable/s	Data type	Resolution	Source
Pasture chemical characteristics	Pasture nutrient concentration: N, P, K, S, Na, Mn, Cu, B, Zn, Ca, Mg	Continuous	0.5 x 0.5 m	Laboratory: wet chemistry analysis
Pasture physical characteristics	DM%			
Vegetation Index	NDVI	Continuous	0.5 x 0.5 m	ASD FieldSpec Pro: in field
Herbage sample	% Dead, % Legume, %weed, % stem, % leaf	Continuous	0.5 x 0.5 m	Visual estimation by expert: in field
	Botanical composition: 3 most abundant species	Discrete	0.5 x 0.5 m	Visual estimation by expert: in field
Topographical	Slope	Continuous	point	Abney: in field
	Aspect	Continuous	point	Compass: in field
	Elevation	Continuous	point	RTK GPS
	Latitude	Continuous	point	RTK GPS
Farm management	Three year cumulative total of P or S applied (3 years prior to sampling event)	Continuous		Calculated from: Ravensdown SmartMaps, fertiliser reps, farmers records
	Last P or S fertiliser application (last application/days since applied)			
	Stocking rate at lambing	Continuous	paddock scale	Calculated from famers records
Season		Discrete	NA	NA
Weather data	Rainfall, wind speed, wind run, temperature, humidity	Continuous	point	On-farm and NIWA weather stations
Soil	Soil order	Discrete	National dataset	Fundamental Soils Layer
	Soil type	Discrete	Regional/ farm scale	S-map, Horizons Whole Farm Plan
Modelled environmental data	Predicted pasture growth rate, soil moisture deficit	Continuous		Ravensdown

Table 3-10 Final dataset used for prediction of soil fertility over whole farm site

Data type	Variable/s		Resolution	Source
Pasture nutrient conc.	Plant P, N, K, S, Na, Mn, Cu, Zn, B	Continuous	1 x 1 m	Estimate from FENIX hyperspectral image
Herbage sample physical characteristics	DM%			
Vegetation Index	NDVI			
Botanical composition	% Dead, % Legume			
Topographical	Slope	Continuous	20 x 20m	DEM
	Aspect			
	Elevation			
Fertiliser history	Three year cumulative total of P or S applied (3 years prior to sampling event)	Continuous		Digitised from: Ravensdown SmartMaps, fertiliser reps, farmers records, advisors etc.
	Last P or S fertiliser application (last application/days since applied)			
Season		Discrete	NA	NA

3.7 Conclusion

Planning, preparation, fieldwork, data entry, data collation and data checking were significant and important processes. Collecting large amounts of data and combining 400 entries from 13 sources for 19 sampling events required careful and meticulous work. This has resulted in a comprehensive dataset, not only for each of the individual field sampling events, but the whole dataset is the largest collected in hill country of this kind. The range of variables provided much opportunity to develop a model to predict underlying soil fertility.

4

4 Hill country pasture and soil phosphorus, and the use of simple plant indices derived from leaf tissue analysis to predict soil Olsen P

4.1 Introduction

Phosphorus is the most measured and monitored element in soil fertility management in New Zealand agriculture and this is done through laboratory analysis of soil cores. The grass-legume based pastoral farming system has a high requirement for, and reliance on, P inputs to sustain high levels of production. New Zealand soils are inherently low in P (Sparling & Schipper, 2002a) and their deficiency is addressed through the application of fertiliser (Cornforth & Sinclair, 1986; Gillingham et al., 2003). Phosphorus comes at a high cost. It is the most expensive macronutrient applied in hill country (Morton et al., 2000), does not give gains in productivity when applications are in excess (Liebisch et al., 2013), and pose a risk to the environment if P is lost to waterways.

Managing P in agriculture is important for pasture and crop production not only locally, but on a global scale particularly as the demand for food increases and agricultural enterprises intensify. To improve nutrient use efficiency researchers and commercial companies have

developed and used simple plant indices to provide real time, non-destructive measures of P fertility to guide fertiliser application to crops. However this is for N based fertiliser products rather than phosphate. To be able to use phosphate fertilisers more efficiently, some approach to assessing the P status of the crop or pasture is required. However, this received little attention. Maleki, Mouazen, De Ketelaere, Ramon, and De Baerdemaeker (2008) developed a vehicle mounted on-the-go variable rate phosphate fertiliser system using a VIS-NIR sensor mounted on a subsoiler to estimate extractable soil P based on the reflectance of bare soil. Grasslands and pasture are more challenging with permanent foliage cover requiring leaf tissue to be interpreted. In addition, topography of hill country often prevents the use of vehicles. Studies developing plant indices to determine P status include: identifying critical P concentrations (McNaught, 1970), P:N ratios (Duru & Thélier Huché, 1997; Salette & Huché, 1991) and plant nutrition index (PNI) (Duru & Thélier Huché, 1997). Plant indices could provide a solution for timely, non-destructive measures of P fertility.

Vegetation indices are very simple, and in modelling the complex uptake of P by plants, Hinsinger et al. (2011) suggest that simplicity is better. Determining the appropriate level of complexity of modelling is not an easy task (Hinsinger et al., 2011); too simple and a model becomes too generalised, and too complex models lead to over fitting and poor predictive ability outside the dataset. In the particular case of this research it is important to cover a wide range of pasture types and farming systems to identify general trends and have the best opportunity to build a model that is fit for purpose. Vegetation indices rely solely on the interpretation of leaf tissue. Mixed species samples make the interpretation of nutrient concentration in herbage samples complicated (Liebisch et al., 2013). Phosphorus concentrations reported in previous studies comparing different species, age and stage of maturity, plant parts, critical, sufficient or deficient levels, illustrates the difficulty of interpreting leaf tissue.

This chapter aims to:

- Examine the range and level of variation in plant tissue and soil P across the eight commercial hill country farms and different seasons.
- Compare the range in plant tissue and soil P with concentrations reported in the literature, to assess the suitability of the dataset to represent a wide range of New Zealand hill country farming systems.
- Predict soil Olsen P using simple plant P indices (leaf tissue P concentration, PNI and N:P ratios) derived from leaf tissue analysis.

4.2 Methodology

4.2.1 Field sites and data collection

Pasture nutrient concentration and soil Olsen P along with many other variables were measured in the laboratory from samples collected during the field sampling campaign. The farms are described in detail in Chapter 3. The sampling locations were spread across eight commercial farms. The farms covered a range of geographic locations from hill country dominant regions throughout New Zealand. The sampling sites were spread across the farms to encompass a diverse range of microclimates. The environmental conditions, as a result of both the regional and local scale factors, induce a range of mixed botanical composition. The sampling regime and methods used in field data collection, including the collection and processing of leaf tissue and soil samples, are also explained in the sections of Chapter 3. Leaf tissue and soil samples included in this analysis were predominantly from the autumn and spring sampling events collected over 3,030 plots. Summer and winter sampling events at Limestone Downs are included in the summary statistics.

4.2.2 Summary statistics and analysis

4.2.2.1 Leaf tissue analysis

The summary statistics were calculated and plotted in Minitab17 to compare the range and variation of leaf tissue P concentration across farms and seasons. The leaf tissue P concentration collected from the same plot for each farm was compared between autumn and spring in RStudio 1.1.423. The linear relationship between the two variables was assessed using R^2 and RMSE. The effect of dead vegetation content in the sample on leaf tissue P concentration was also analysed in RStudio 1.1.423 for all samples. The range of P concentration measured in the dataset was compared to concentrations reported in the literature from a wide range of studies, which used varying methodologies.

4.2.2.2 Soil sample analysis

The summary statistics were calculated and plotted in Minitab17 to compare the range and variation of available P in the soil across farms and seasons. The soil Olsen P measured at the same plot for each farm was compared between autumn and spring in RStudio 1.1.423. The linear relationship between the two variables was assessed using R^2 and RMSE.

4.2.2.3 Exploratory analysis to predict soil phosphate availability from mixed pasture leaf tissue using simple plant indices

Preliminary analysis used the most straight forward approach to explore the potential of simple plant indices to estimate soil P availability. Plant indices included: P concentration in

the above ground biomass; a ratio of N:P in the leaf tissue (in relation to the P concentration required for maximum production given the N content); the Phosphorus Nutrition Index (PNI); and the adjusted version of PNI for samples which contain high portions of clover PNI_c. Linear regression was used to assess the relationship between the two variables: soil Olsen P and the leaf tissue P concentration or index. The R^2 is reported along with P values to indicate the level of significance.

SOIL OLSEN P (*LOGSOP*)

The natural logarithm of soil Olsen P was used, as soil Olsen P has a lognormal distribution. The log of soil Olsen P was approximately normally distributed and used as the response variable.

$$LogSOP_i = \mathrm{LOG}(OlsenP_i)$$

PHOSPHORUS CONCENTRATION AND PHOSPHORUS NUTRITION INDEX (PNI AND PNIC)

Phosphorus nutrient concentration in the leaf tissue, and P nutrition indices derived from N and P concentrations in the leaf tissue sample and clover content in the sward, were used as indicators of pasture canopy P status.

Phosphorus Nutrition Index (PNI) uses the optimal and measured P concentration in the above ground biomass (expressed as a percentage) to determine pasture P status using equation 4.1 (Duru & Thélier Huché, 1997). A PNI of 100 is optimal, while below 100 is deficient and above 100 is excessive. PNI is calculated as:

$$PNI = \left(\frac{\%\ P_{measured}}{\%\ P_{optimal}}\right) \times 100 \qquad [4.1]$$

The optimal P concentration for maximum grassland production is dependent on the N concentration in the sward. The optimal concentration of P in the above ground biomass (Duru & Thélier Huché, 1997) is calculated as:

$$\%\, P_{optimal} = 0.15 + 0.065\, \%N_{measured} \quad [4.2]$$

Clover, as an N fixing legume, has a higher N concentration in the leaf tissue than grasses and when it is a dominant species in the sward, has been found to influence PNI through having a higher N concentration than pasture grasses. Jouany et al. (2004) therefore developed the PNI_c to allow for the higher N concentration in the clover leaf. Phosphorus Nutrition Index adjusted for clover, where adjustments are made for samples with a clover fraction >20% is calculated as:

$$PNI_c = PNI + (0.5 \times legume\ \%) \quad [4.3]$$

P:N RATIO

Phosphorus to N ratios used to predict soil Olsen P were calculated using equation 4.4 as used by Morton, Smith, et al. (1998).

$$P{:}N = \left(\frac{\%\, P_{measured}}{\%\, N_{measured}}\right) \times 100 \quad [4.4]$$

For all equations about where: $\%P_{measured}$ = is the P concentration measured in plant tissue and $\%N_{measured}$ = is the N concentration measured in plant tissue.

Regression analysis was used to determine the relationship between available phosphate in the soil (natural logarithm of soil Olsen P) and P concentration, PNI and PNI_c over each farm in the autumn and spring. RStudio 1.0.136 was used to perform the linear regression analysis.

N:P RATIO

Nitrogen to P ratios were analysed as a simple ratio to determine pasture P status and its relationship to soil P availability. The data set was split based on the measured soil Olsen P in increments of 5µg/mL until 35µg/mL, ranging from extremely deficient through to luxury levels. Nutrient ratios of N:P in the leaf tissue for spring only were compared to the critical curves and associated areas of nutrient status as determined by Duru and Thélier Huché (1997) and Salette and Huché (1991), see Figure 4-1. Critical lines are used to define areas of 'insufficient', 'risk', 'satisfactory', 'optimal' and 'excessive' levels of P in the above ground biomass. The N:P ratios in relation to nutrition status areas were assessed as a predictor of soil P status. RStudio 1.0.136 was used to subset, plot and display data.

Nutrition status area	Phosphorus %	Reference
Excessive		
----------	$P\% = 0.17 + 0.07(N\%)$	Salette and Huché (1991)
Satisfactory		
Optimal/Critical-------	$P\% = 0.15 + 0.065(N\%)$	Duru and Thélier Huché (1997)
Satisfactory		
----------	$P\% = 0.13 + 0.06(N\%)$	Salette and Huché (1991)
Risk		
----------	$P\% = 0.10 + 0.055(N\%)$	Salette and Huché (1991)
Insufficient		

Figure 4-1: Nutrition status areas and associated critical leaf tissue phosphorus concentration to determine pasture status as: insufficient, at risk, satisfactory, optimal and excessive as defined by Duru and Thélier Huché (1997) and Salette and Huché (1991).

4.3 Results

4.3.1 Pasture phosphorus concentration

4.3.1.1 Pasture phosphorus concentration: whole dataset

The concentration of P in the leaf tissue was measured for all samples collected in the field sampling campaigns. The P concentration measured in the 6,800 mixed pasture samples from all eight farms covering multiple seasons over 19 sampling events had a mean of 0.32 % w/w with a standard deviation of 0.09 (Figure 4-2). Similar to the mean, the median was 0.31 % w/w with a minimum, lower quartile, upper quartile and maximum of 0.09, 0.25, 0.38 and 0.71 respectively.

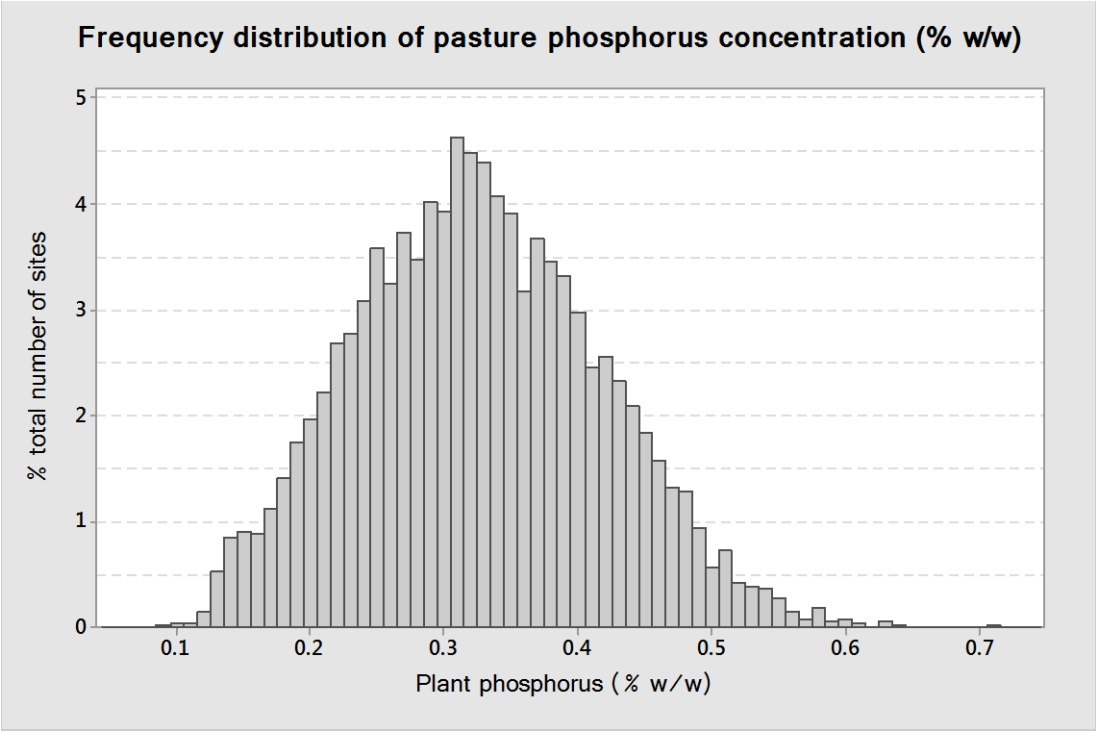


Figure 4-2: Frequency distribution of pasture leaf tissue phosphorus concentration as measured by wet chemistry analysis for the mixed pasture samples from all farms and all sampling events within the PGP.

The pasture samples collected within the field sampling campaign were typical of managed permanent mixed pastures in New Zealand hill country. Figure 4-3 illustrates the range in pasture type and condition where all samples had a leaf tissue P concentration of 0.31 % w/w, the median of the whole dataset, as measured by wet chemistry analysis. The difference in pasture cover or time since grazing, species, and dead vegetation fraction are evident in the photographs. These are all differences expected to be found on any commercial hill country farm.

Figure 4-3: Examples of plots sampled, all with phosphorus concentration in the leaf tissue of 0.31 % w/w, the median value for the entire dataset. Corresponding soil Olsen P at each plot are (from top to bottom, left to right) 13, 15, 42, 8, 26, 65, 10, 9, 27, 34, 50, 32 µg/mL

4.3.1.2 Pasture phosphorus concentration: ranges reported in relevant literature

The measured nutrient concentration covered a wide range compared to values stated in the literature; see Figure 4-4 for comparisons and references. Of the other studies containing large sample numbers, Smith and Cornforth (1982) collected 5,862 grass-clover samples of immature pasture and reported a range of 0.11 to 0.99 % w/w; and Knowles and Grace (2014) collated 976 mostly ryegrass-clover dominant samples from a range of seasons or pasture ages and reported a median of 4 g/kg DM and a range of approximately 1-7 g/kg DM. Table 4-1 includes P concentrations stated in the relevant literature along with details of the study including location, number of samples, pasture species, the plant part, and growth stage sampled, for a more in depth comparison and comprehension of leaf tissue P concentration under different sampling techniques and trials.

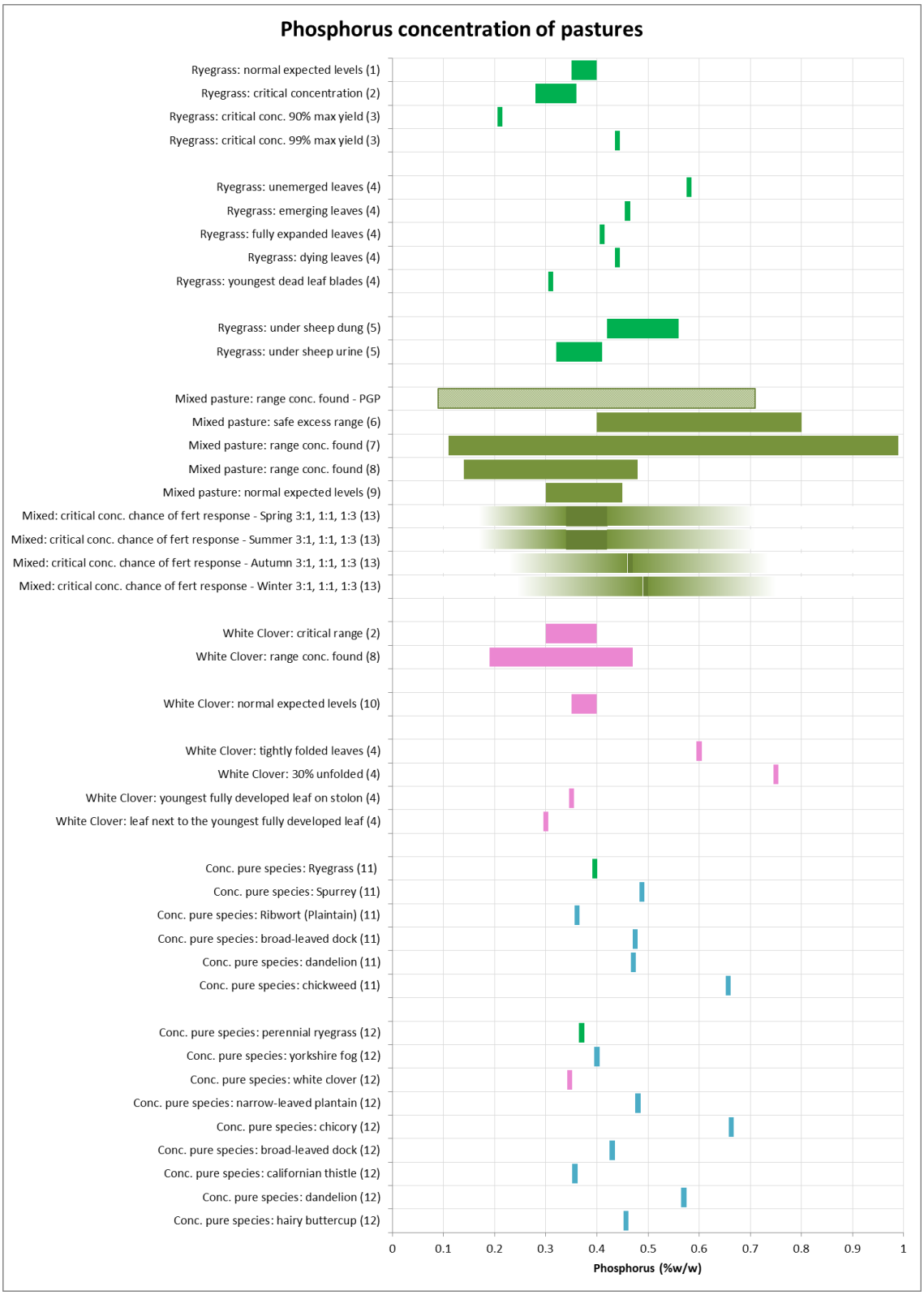


Figure 4-4: Phosphorus nutrient concentration of a range of pasture types from the relevant literature and definition of the range given in the publications. References: (1) Hill Laboratories (*Crop guide: Ryegrass*), (2) McNaught (1970), (3) Smith, Cornforth, and Henderson (1985), (4) Wilman et al. (1994)*, (5) Joblin and Keogh (1979), (6) McNaught (1969), (7) Smith and Cornforth (1982), (8) Wells (1970), (9) Hill Laboratories (*Crop guide: Mixed pasture*), (10) Hill Laboratories (*Crop guide: White clover*), (11) Wilman and Derrick (1994)*, (12) Harrington et al. (2006), (13) (Cornforth, 1984b). Mid green: Ryegrass, dark green: mixed pasture, pink: white clover, blue: other species. All New Zealand pasture, except *research carried out in Wales.

Table 4-1: Summary of phosphorus concentration reported in the literature and collected within the project, over a range of pastures, comparing sampling method and reported levels.

Reference	Country	Field/Lab	No. of samples	Species	Plant part	Stage of growth	Level stated	P (% w/w)	
PGP: Pioneering to Precision	New Zealand	Field: eight commercial farms throughout NZ	6,825	Mixed pasture	Whole plant cut to grazing height	All stages of growth, majority of samples collected through spring and autumn	Range of concentrations found	mean min median max	0.32 0.09 0.31 0.71
Pasture grasses									
McNaught (1970)	New Zealand			Ryegrass	Leaves	Leaves of actively growing plant	Critical ranges: min	min max	0.28 0.36
Smith et al. (1985)	New Zealand	Lab - Pots		*Lolium perenne* L.	Whole plant cut to grazing height	Young plants sewn from seed	Critical conc. (90% max yield) Critical conc. (99% max yield)		0.21 0.44
Hill Laboratories (*Crop guide: Ryegrass*)	New Zealand			Ryegrass	Leaf blades	Vegetative growth stage: late spring or autumn flush	Normal levels expected	min max	0.35 0.4
Wilman et al. (1994)	Wales (Aberystwyth)	Field: collected from plot, average of sample collected in May and August 1987		Ryegrass (*Lolium perenne*)	Samples collected at different growth stages from plots on same day.	Unemerged leaves Emerging leaves fully expanded leaves Dying leaves Youngest dead leaf blades	Approximate concentration measured (estimate made from graphs reported)	mean mean mean mean mean	0.58 0.46 0.41 0.44 0.31
Fulkerson et al. (1998)	Australia	Field: Dairy	188	Kikuyu			Mean concentration found	mean	0.28
Mixed pasture									
McNaught (1969)	New Zealand			Mixed pasture			Safe excess - range	min max	0.4 0.8
Wells (1969)	New Zealand	Field	35	Mixed pasture	Green matter plucked in short lengths	Late autumn	Range of concentrations found: mean (min-max)	min mean max	0.14 0.29 0.48
Hill Laboratories (*Crop guide: Mixed pasture*)	New Zealand	Field: drystock		Mixed pasture-drystock (i.e. Ryegrass-White Clover)	Leaf blades	Vegetative growth stage: late spring or autumn flush	Normal levels expected	min max	0.3 0.45
Smith and Cornforth (1982)	New Zealand	North Island	5862	Grass-clover pasture	Inconsistent sampling technique	Predominantly immature stage of growth, throughout the years from 1969-1979	Range found	min max	0.11 0.99
Knowles and Grace (2014)	New Zealand	Field: across New Zealand	1,106	Mixed, most ryegrass and clover-dominated swards		Unknown stage of maturity, botanical composition or season collected, 2001-2006	Median		0.4
Fulkerson et al. (1998)	Australia	Field: Dairy	211	Perennial ryegrass-white clover			Mean concentration found	mean	0.3
White clover									
Andrew (1960)	Australia			White clover	leaves and petioles	immediate pre-flowering	Critical conc.		0.23
McNaught (1970)	New Zealand			White clover	Leaf plus petiole	Leaves of actively growing plant	Critical ranges	min max	0.3 0.4

Wells (1969)	New Zealand	Field	30	White clover	Leaf plus short petiole	Late autumn	Range of concentrations found	min mean max	0.19 0.34 0.47
Hill Laboratories (*Crop guide: White clover*)	New Zealand			White clover	Leaf plus petiole	Vegetative growth stage, usually late spring/early summer or autumn	Normal levels expected	min max	0.35 0.4
Wilman et al. (1994)	Wales (Aberystwyth)	Field	Collected from plot, average of sample collected in May and August 1987	White clover (*trifolium repens*)	Samples collected at different growth stages from plots on same day.	Tightly folded leaves 30% unfolded Youngest fully developed leaf on stolon Leaf next to the youngest fully developed leaf	Concentration measured	mean mean mean mean	0.6 0.75 0.35 0.3
Pasture affected by dung									
Joblin and Keogh (1979)	New Zealand	Field: sheep grazed pasture	8	Perennial ryegrass (*Lolium perenne*)	Plucked regrowth (6 weeks after sheep grazing)	Autumn	Range of concentrations found: mean (min-max)	min mean max	0.42 0.48 0.56
Pasture affected by urine									
Joblin and Keogh (1979)	New Zealand	Field: sheep grazed pasture	9	Perennial ryegrass (*Lolium perenne*)	Plucked regrowth (6 weeks after sheep grazing)	Autumn	Range of concentrations found: mean (min-max)	min mean max	0.32 0.37 0.41
Pasture affected by dung and urine									
Saunders (1984)	New Zealand	Field: beef or sheep grazed pastures	25	Grass-clover mix	21+ days after grazing, cut to 2cm above ground	Spring	Beef: 'High' - dung and urine Beef: 'Low' - no dung and urine Sheep: 'High' - dung and urine Sheep: 'Low' - no dung and urine Sheep 'High' - dung and urine Sheep: 'Low' - no dung and urine		0.54 0.48 0.63 0.53 0.59 0.42
Grazing herbs and weeds: comparison of species									
Harrington et al. (2006)	New Zealand	Field: Organic and conventional dairy	100g of each species across 3 paddocks	Perennial ryegrass White clover Chicory Narrow-leaved plantain Broad-leaved dock Californian thistle Dandelion Hairy buttercup Yorkshire fog			Concentration of sample collected. Figures in bold are significantly higher in that element as compared to perennial ryegrass or clover.		0.37 0.35 **0.66** **0.48** 0.43 0.36 **0.57** **0.46** 0.40
Wilman and Derrick (1994)	Wales (Aberystwyth)	Field: sheep grazed pasture	Sample collected from 333.5m^2 single species plot	Chickweed Dandelion Broad-leaved dock Ribwort (Plantain) Spurrey Ryegrass		Average of samples collected during autumn	Concentration of sample collected. Figures in bold are reported by the authors as being particularly high.		**0.66** 0.47 0.48 0.36 0.49 0.40

4.3.1.3 Pasture phosphorus concentration: in leaf tissue samples across all sites and seasons

The P concentration in the pasture leaf tissue ranged from 0.09 to 0.71 % w/w in the whole dataset. The P concentration was lower in the samples collected in the autumn than in spring, Figure 4-5. Limestone Downs (NLD) shows clear seasonal differences over the five sampling events carried out at the same locations from the beginning of summer in December 2013 to spring 2014. However, the sample numbers collected in the winter sampling event were significantly less in number. Limestone Downs, Tautane, Pati Tapu and Cleardale, showed greater differences between spring and autumn than the other four farms. The distribution of measured P concentration in the leaf tissue varied between farms even within the same season.

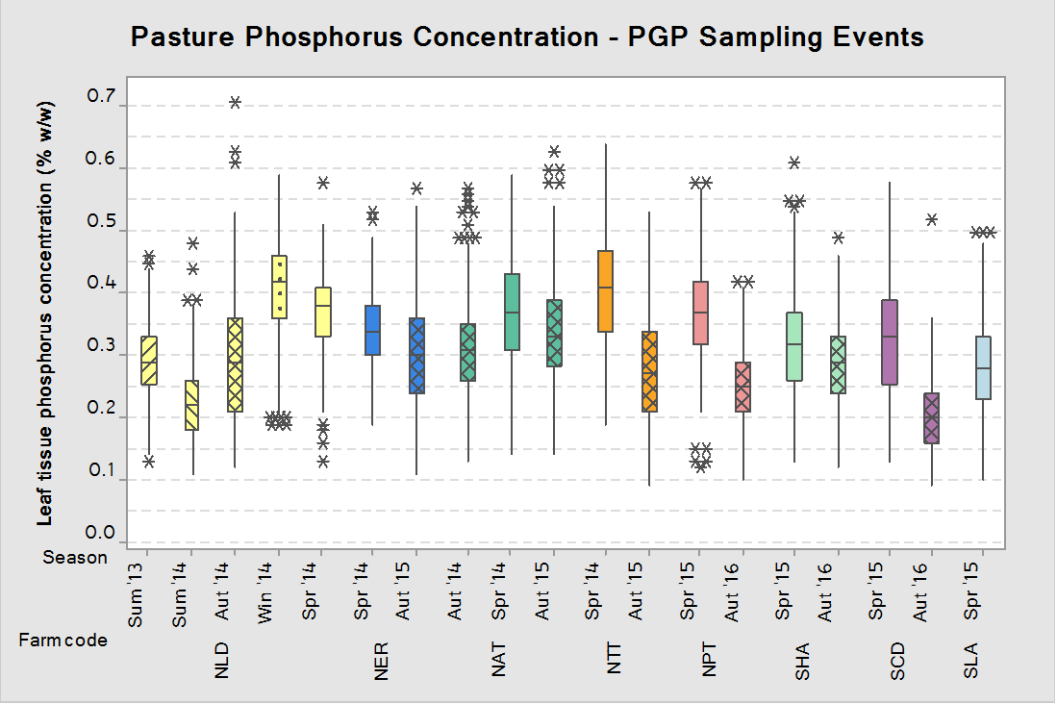


Figure 4-5: Box plot showing the range of phosphorus concentration in pasture leaf tissue samples collected at each sampling event over different farms and seasons. Asterisk (*) symbol identifies outliers: observations that are at least 1.5 times the interquartile range (Q3 – Q1) from the edge of the box.

The summary statistics for leaf tissue P concentration across all farms and all seasons are presented in Table 4-2. The average P concentration across the eight farms was 0.20-0.34 % w/w in the autumn and 0.28-0.40 % w/w in the spring. The coefficient of variation was greater in autumn sampling events than in spring, although very similar in both seasons at Ohorea, Pati Tapu and Harwoods. The spring sampling at Tautane and the winter sampling at Limestone Downs were the highest distributions of P concentrations in the leaf tissue with a mean of 0.40 % w/w, while the autumn sampling at Cleardale and the late summer sampling at Limestone Downs were the lowest with means of 0.20 and 0.22 % w/w respectively.

Table 4-2: Descriptive statistics of leaf tissue phosphorus concentration across farms and seasons.

	Leaf tissue phosphorus concentration (% w/w)									
	Season	Mean	Standard dev.	CV	Minimum	Lower quartile	Median	Upper quartile	Maximum	n
Limestone Downs	Sum 13	0.30	0.06	19	0.13	0.26	0.29	0.33	0.46	400
	Sum 14	0.22	0.06	26	0.11	0.18	0.22	0.26	0.48	399
	Aut 14	0.29	0.10	34	0.12	0.21	0.29	0.36	0.71	398
	Win 14	0.40	0.09	22	0.19	0.36	0.42	0.46	0.59	223
	Spr 14	0.37	0.06	17	0.13	0.33	0.38	0.41	0.58	365
Erewhon	Spr 14	0.34	0.06	18	0.19	0.30	0.34	0.38	0.53	399
	Aut 15	0.30	0.09	30	0.11	0.24	0.30	0.36	0.57	351
Ohorea	Aut 14	0.31	0.08	25	0.13	0.26	0.31	0.35	0.57	400
	Spr 14	0.37	0.08	21	0.14	0.31	0.37	0.43	0.59	395
	Aut 15	0.34	0.08	24	0.14	0.29	0.33	0.39	0.63	392
Tautane	Spr 14	0.40	0.09	23	0.19	0.34	0.41	0.47	0.64	400
	Aut 15	0.28	0.09	32	0.09	0.21	0.27	0.34	0.53	393
Pati Tapu	Spr 15	0.37	0.08	22	0.12	0.32	0.37	0.42	0.58	395
	Aut 16	0.25	0.06	23	0.10	0.21	0.25	0.29	0.42	390
Harwoods	Spr 15	0.32	0.08	24	0.13	0.26	0.32	0.37	0.61	340
	Aut 16	0.29	0.07	25	0.12	0.24	0.29	0.33	0.49	347
Cleardale	Spr 15	0.33	0.08	25	0.13	0.26	0.33	0.39	0.58	276
	Aut 16	0.20	0.06	31	0.09	0.16	0.20	0.24	0.52	181
Lawsons	Spr 15	0.28	0.08	26	0.10	0.23	0.28	0.33	0.50	356
All	All	0.32	0.09	29	0.09	0.25	0.31	0.38	0.71	6800
	Aut	0.29	0.09	30	0.09	0.22	0.29	0.34	0.71	2852
	Spr	0.35	0.08	24	0.10	0.29	0.35	0.41	0.64	2926

Leaf tissue P concentrations of the samples collected from the same plot in the spring and autumn were moderately to weakly correlated, Figure 4-6. Limestone Downs, Erewhon, Tautane, Harwoods and Cleardale were moderately correlated with R^2 values of 0.32, 0.35, 0.44 and 0.48 respectively. Ohorea and Pati Tapu showed weaker correlation in leaf tissue P concentration between spring and autumn events, with R^2 values of 0.19 and 0.27 respectively. Ohorea and Pati Tapu were the only farms where all sites received fertiliser between the two sampling events. The root mean square error (RMSE) ranged from 0.05 to 0.08.

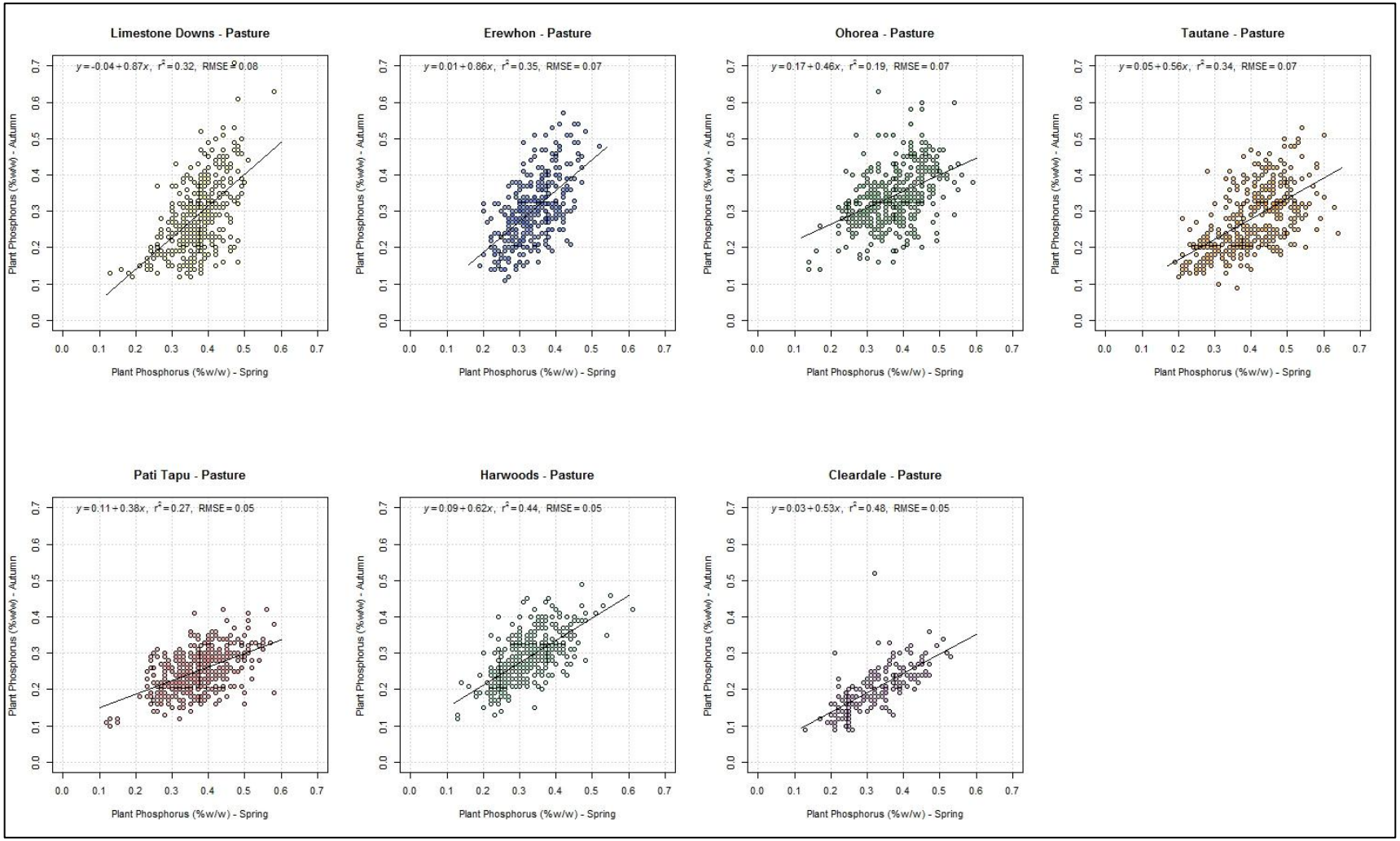


Figure 4-6: Pasture phosphorus concentration in spring and autumn for each farm (except Lawsons which was only sampled in spring). Fertiliser applied to all sites at Ohorea and Pati Tapu between sampling events and a few sites at Harwoods and Erewhon.

The dead vegetation fraction was however recorded and has an effect on the P concentration in the sample (Figure 4-7). As the dead vegetation fraction in the samples increases, the P concentration in the leaf tissue samples decrease. The variation in P concentration between samples decreases as the dead vegetation content increases.

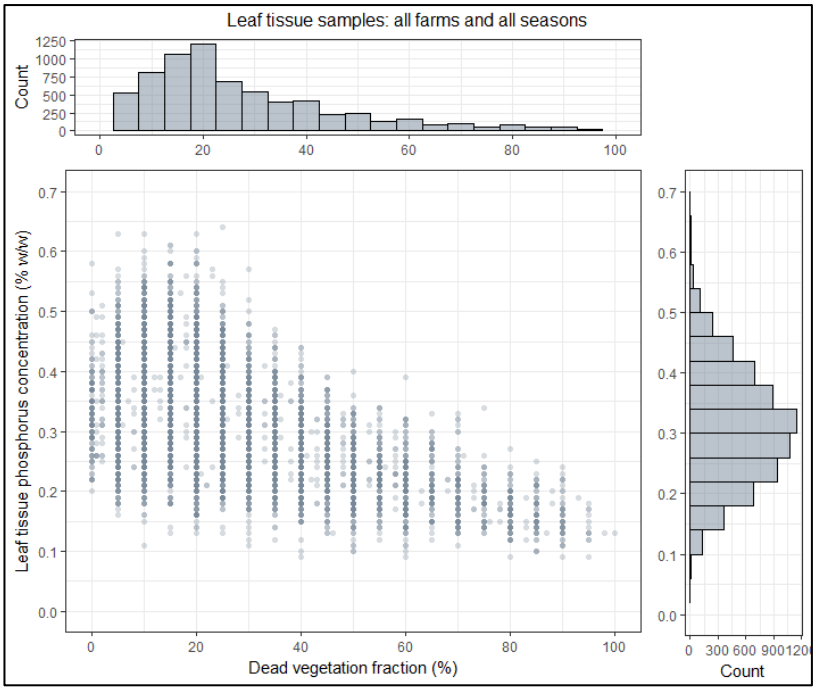


Figure 4-7: The effect of the dead vegetation fraction on the leaf tissue phosphorus concentration in the mixed pasture leaf tissue samples.

4.3.2 Soil Olsen P

4.3.2.1 Soil Olsen P: in the dataset

Soil Olsen P in the whole dataset ranged from 2 to 130 µg/mL (Figure 4-8). The range and distribution of soil Olsen P was very similar in the autumn and spring with a median of 17 and 16 µg/mL respectively.

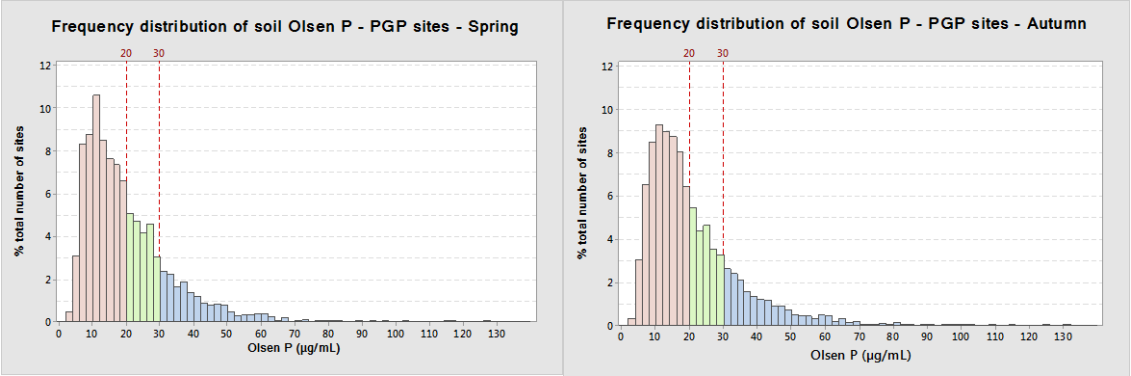


Figure 4-8: Frequency distribution of soil Olsen P for the trial plots from all farms during the spring (left) and autumn (right) sampling events in relation to the target Olsen P (20-30 µg/mL) for sedimentary and ash soils.

The soil Olsen P estimates in both the spring and autumn indicate approximately 60% of the plots sampled were below the target range of soil Olsen P (20-30 µg/mL) for near maximum pasture production on sedimentary and ash soils (Morton & Roberts, 2009). Approximately 20% were optimal and the remaining above optimal, Table 4-3 and Figure 4-8.

Table 4-3: Percentage of sites below optimal, optimal, and above optimal Olsen P for sedimentary and ash soils, as defined by Morton and Roberts (2009) when sampled in spring and autumn.

	Spring			Autumn		
Target	Below	Optimal	Above	Below	Optimal	Above
Olsen P	0- 20	20-30	30+	0- 20	20-30	30+
% of samples	61	22	17	60	21	19
n	1840	646	513	1749	619	559

4.3.2.2 Soil Olsen P: across sites and seasons

Soil Olsen P shows less variation between sites and seasons than leaf P concentration. Pati Tapu showed the greatest difference between seasons, with the distribution of soil Olsen P noticeably higher in autumn than spring (Figure 4-9). Limestone Downs and Erewhon had the highest median values of approximately 20 µg/mL for all sampling events, while Harwoods the lowest at 10 µg/mL.

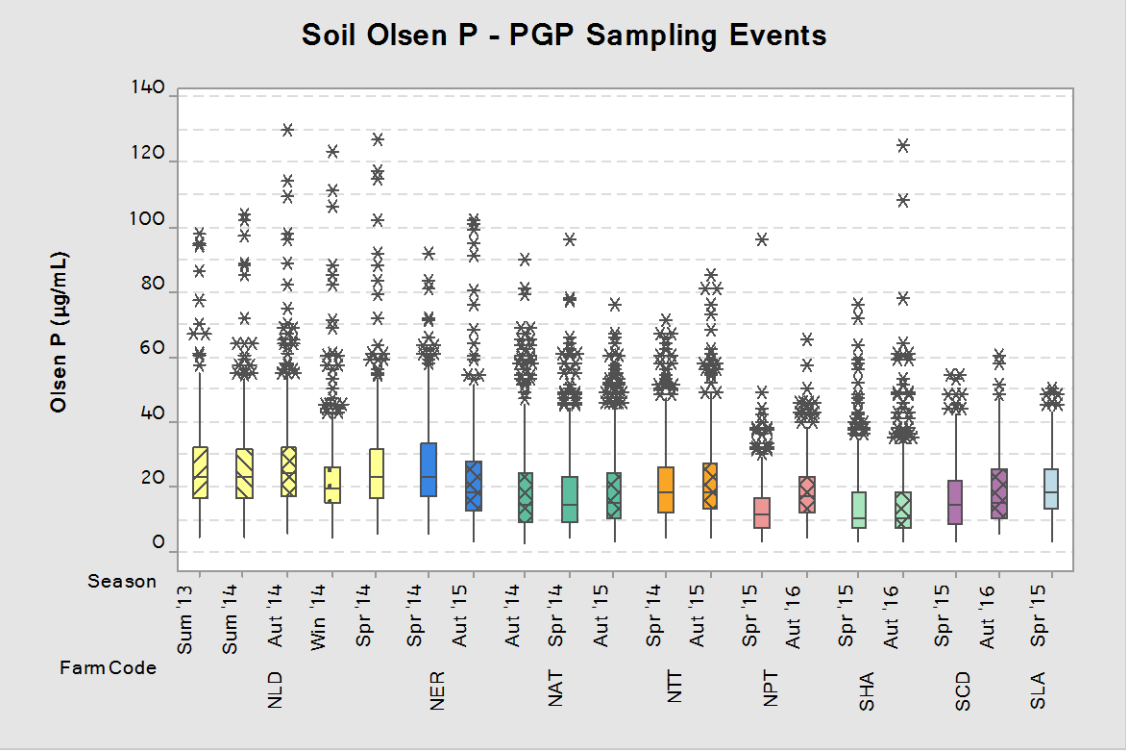


Figure 4-9: Box plot showing the range of soil Olsen P in samples collected at each sampling event over different farms and seasons.

Soil Olsen P has a skewed distribution as visible in the histogram presented in Figure 4-8. The highly skewed distribution is confirmed by the skewness values greater than 1 for all farms and sampling events except Lawsons in the spring, which has a skewness value of 0.86 indicating a moderately skewed distribution (Table 4-4). These high positive values indicate an asymmetric distribution with a tail extending toward more positive values. Positive kurtosis indicates a relatively peaked distribution, with all values greater than 0 indicating the distributions are leptokurtic. The distribution of soil Olsen P in the samples collected from Pati Tapu in the spring is particularly sharply peaked with an excess kurtosis value of 26.3.

Table 4-4: Descriptive statistics of soil Olsen P across farms and seasons.

		Soil Olsen P (µg/mL)										
		Mean	Std Dev	CV (%)	Min	Lower quartile	Median	Upper quartile	Max	Skewness	Excess Kurtosis	n
Limestone Downs	Sum 13	26	14	55	4	16	23	32	98	1.64	4.58	400
	Sum 14	25	14	57	4	16	23	31	104	2.08	7.16	399
	Aut 14	27	16	59	5	17	24	32	130	2.45	9.28	398
	Win 14	23	15	64	4	15	19	26	123	2.97	13.5	392
	Spr 14	26	16	62	5	16	23	31	127	2.58	10.3	375
Erewhon	Spr 14	26	14	52	5	17	23	33	92	1.38	2.72	400
	Aut 15	22	15	67	3	13	18	27	102	2.29	7.84	384
Ohorea	Aut 14	19	15	77	2	9	15	23	90	1.85	3.63	400
	Spr 14	19	14	76	4	9	14	23	96	1.82	4.30	400
	Aut 15	19	13	68	3	10	15	24	76	1.56	2.21	398
Tautane	Spr 14	21	13	60	4	12	18	26	71	1.47	2.15	400
	Aut 15	22	13	62	4	13	18	27	85	1.85	4.20	400
Pati Tapu	Spr 15	13	8	66	3	7	11	16	96	3.62	26.3	400
	Aut 16	19	9	50	4	12	17	23	65	1.37	2.54	390
Harwoods	Spr 15	15	11	77	3	7	10	18	76	2.23	6.15	346
	Aut 16	15	15	94	3	7	10	18	125	3.17	15.0	347
Cleardale	Spr 15	17	11	67	3	8	14	21	54	1.27	1.13	280
	Aut 16	19	12	64	5	10	15	25	60	1.13	0.67	210
Lawsons	Spr 15	20	9	45	3	13	18	25	50	0.86	0.60	399
All	All	21	14	67	2	11	17	27	130	3.11	7.25	7118
	Aut	21	14	69	2	11	17	26	130	2.12	7.31	2927
	Spr	20	13	67	3	10	16	25	127	1.98	6.85	3000

The soil Olsen P at each individual plot from the spring and autumn sampling events were compared for each farm (Figure 4-10). The correlation between spring and autumn soil Olsen P ranges from R^2 0.42-0.84 with the weakest relationship at Pati Tapu and strongest at Harwoods. RMSE varied from 4.91 at Harwoods to 10.83 at Limestone Downs. The scatter plots show that the variation between spring and autumn soil Olsen P measurements at the same sample location were proportional to the mean. As Olsen P increased, the variation between spring and autumn values increased.

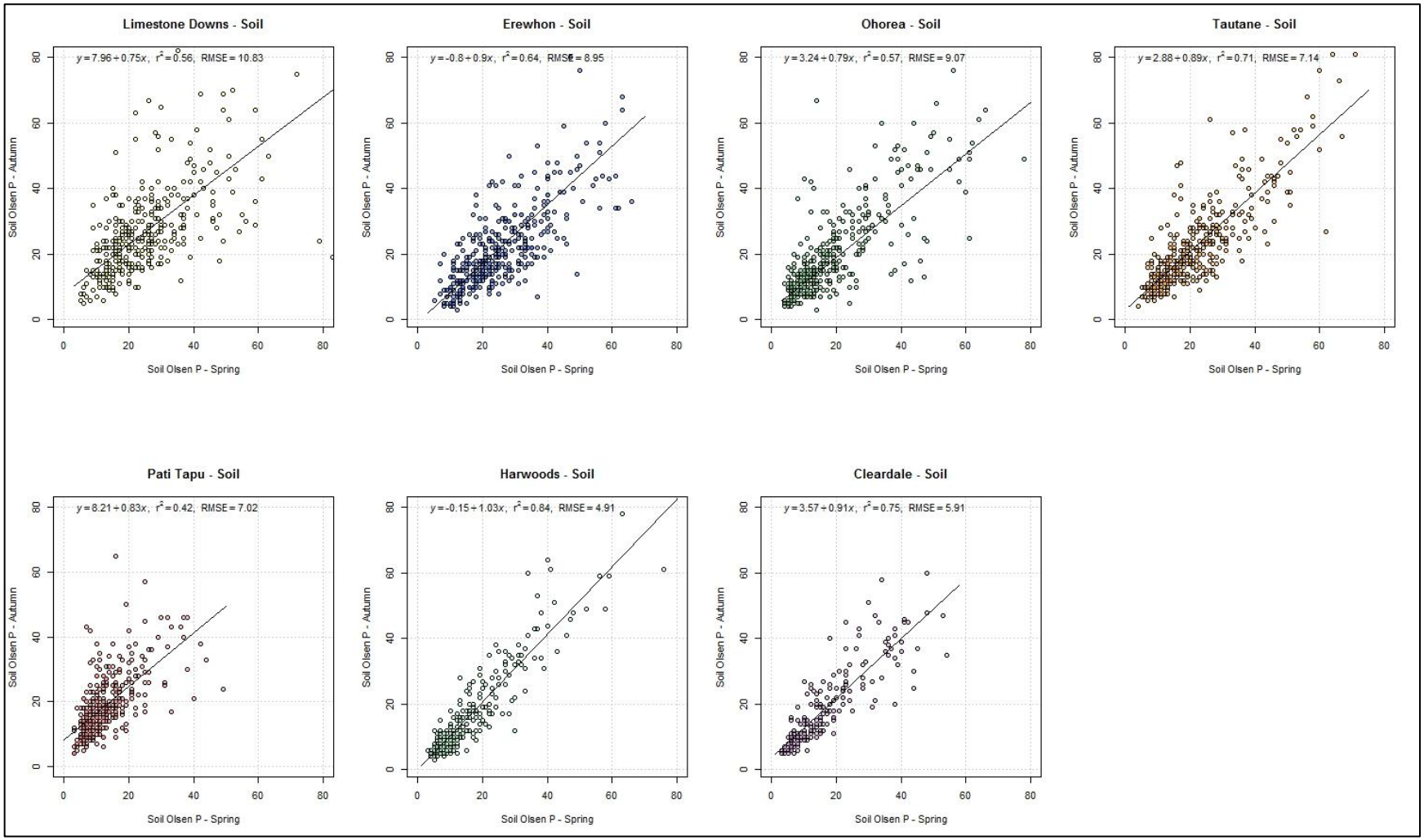


Figure 4-10: Soil Olsen P in spring and autumn for each trial farms (except Lawsons, which was only sampled in spring). Fertiliser applied to all sites at Ohorea and Pati Tapu between sampling events, and few sites at Harwoods and Erewhon.

4.3.3 Exploratory analysis to predict soil phosphate availability from mixed pasture leaf tissue using simple plant indices

4.3.3.1 Plant phosphorus indices to soil phosphorus relationship

The amount of variation in soil Olsen P explained using plant indices varied between farms, season and index used. The level of explanation ranged from an R^2 of 0.01 at Pati Tapu with combined seasonal data using the concentration of P in the leaf tissue, to an R^2 of 0.56 at Cleardale in the spring also using leaf P concentration (Table 4-5).

Table 4-5: Correlation between pasture P indices and log soil Olsen P, over the eight trial farms, over different seasons.

			P%		**PNI**		**PNI_c**		**P:N**	
Farm	Season	n	R^2 - Adj		R^2 - Adj		R^2 - Adj		R^2 - Adj	
All	Both	5358	**0.13**	***	**0.13**	***	0.12	***	0.07	***
	Spring	2921	0.21	***	**0.24**	***	0.21	***	0.12	***
	Autumn	2437	0.12	***	0.12	***	0.12	***	0.12	***
All – Grasses, herbs and weeds (all samples with greater then trace amounts of clover were removed)	Both	3430	**0.17**	***	0.16	***	NA		0.07	***
	Spring	2089	**0.26**	***	**0.26**	***	NA		0.12	***
	Autumn	1341	**0.14**	***	0.12	***	NA		0.04	***
NLD	Both	762	0.05	***	**0.06**	***	0.05	***	0.04	***
	Spring	365	**0.20**	***	0.16	***	0.14	***	0.06	***
	Autumn	397	0.05	***	**0.09**	***	0.08	***	0.05	***
NER	Both	740	0.26	***	**0.31**	***	0.27	***	0.13	***
	Spring	399	0.31	***	**0.39**	***	0.32	***	0.21	***
	Autumn	341	0.20	***	**0.21**	***	0.18	***	0.05	***
NAT	Both	785	**0.21**	***	0.14	***	0.13	***	0.04	***
	Spring	395	**0.33**	***	0.16	***	0.16	***	0.03	***
	Autumn	390	**0.19**	***	0.14	***	0.13	***	0.07	***
NTT	Both	792	**0.22**	***	0.20	***	0.18	***	0.05	***
	Spring	399	0.35	***	**0.44**	***	0.34	***	0.12	***
	Autumn	393	0.35	***	**0.47**	***	0.24	***	0.02	**
NPT	Both	784	0.01	*	0.04	***	0.03	***	**0.10**	***
	Spring	394	0.29	***	**0.32**	***	0.29	***	0.20	***
	Autumn	390	0.12	***	**0.17**	***	0.16	***	0.12	***
SHA	Both	683	0.15	***	**0.17**	***	0.16	***	0.13	***
	Spring	338	0.21	***	**0.29**	***	0.26	***	0.22	***
	Autumn	345	**0.12**	***	0.11	***	0.11	***	0.08	***
SCD	Both	457	**0.21**	***	0.19	***	0.16	***	0.10	***
	Spring	276	**0.56**	***	0.47	***	0.40	***	0.17	***
	Autumn	181	**0.42**	***	0.41	***	0.41	***	0.25	***
SLA	Spring	355	0.14	***	**0.20**	***	0.19	***	0.17	***

Level of significance of predictor: < 0.001 '***', 0.001 '**', 0.01 '*', 0.05 '.'

A summary of the relationship between soil Olsen P and a range of plant P indices are presented in Table 4-5. Plant P concentration and all plant P indices were positively related to soil Olsen P. Soil Olsen P was more strongly correlated to leaf tissue P concentration and PNI than to PNIc and P:N ratios. The direct relationship between soil Olsen P and plant tissue P concentration is shown in a series of scatter plots in Figure 4-11 and Figure 4-12. For Ohorea and Cleardale, leaf tissue P concentration gave a stronger correlation, and for Erewhon, Tautane and Pati Tapu it was the PNI. The correlation when all seasons and farms data were combined was low, with an R^2 of 0.13, using either the P concentration or the PNI.

Despite making an adjustment for the clover content in the sample, the PNI_c gave a similar, though always weaker, correlation than PNI. The only time the P:N ratio gave the stronger correlation was for the combined seasonal data at Pati Tapu. However the correlation was still very low, R^2 = 0.10. Otherwise, P:N ratio almost always gave the weakest correlation. Plant indices were generally more strongly correlated to soil Olsen P in spring than autumn and were usually stronger when the seasons were not combined.

The N and P concentration in the spring leaf tissue in relation to the optimal P concentration (Duru & Thélier Huché, 1997), as classified as satisfactory, excessive, and risk (Salette & Huché, 1991), are shown in Figure 4-13. At low soil Olsen P (0-5 µg/mL) the majority of the points are below the optimal line. In the lower row of scatter plots containing soil Olsen P of 20-25, 25-30, 30-50 and >35 µg/mL, the majority of the points are above optimal, and by an Olsen P of >35 µg/mL the majority of the points are considered in excess. However for the mid-range Olsen P values, the points fall within all categories.

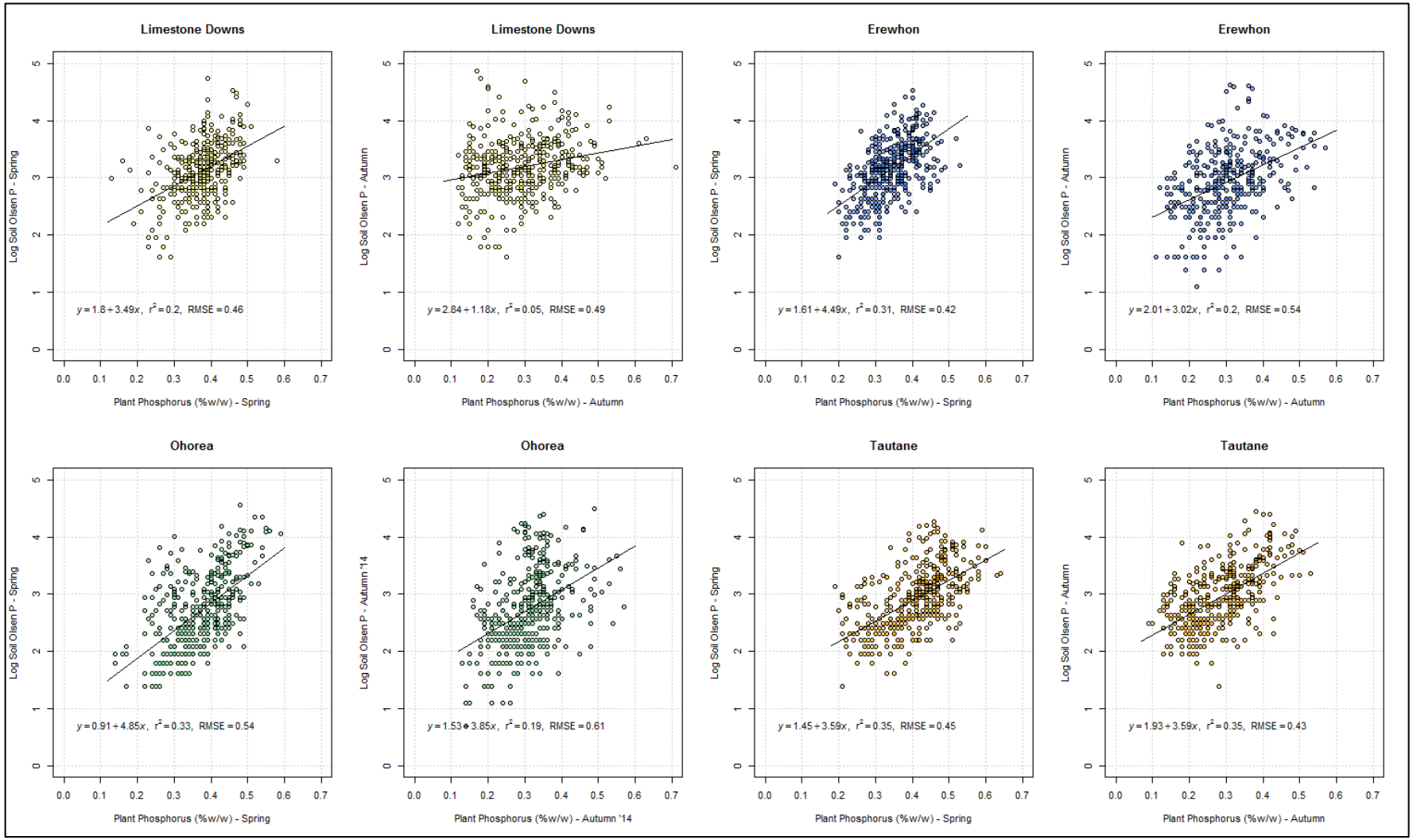


Figure 4-11: Relationship between plant P uptake (leaf tissue phosphorus % w/w) and available phosphate (soil Olsen P µg/mL) over spring and autumn at Limestone Downs, Erewhon, Ohorea and Tautane hill country farms.

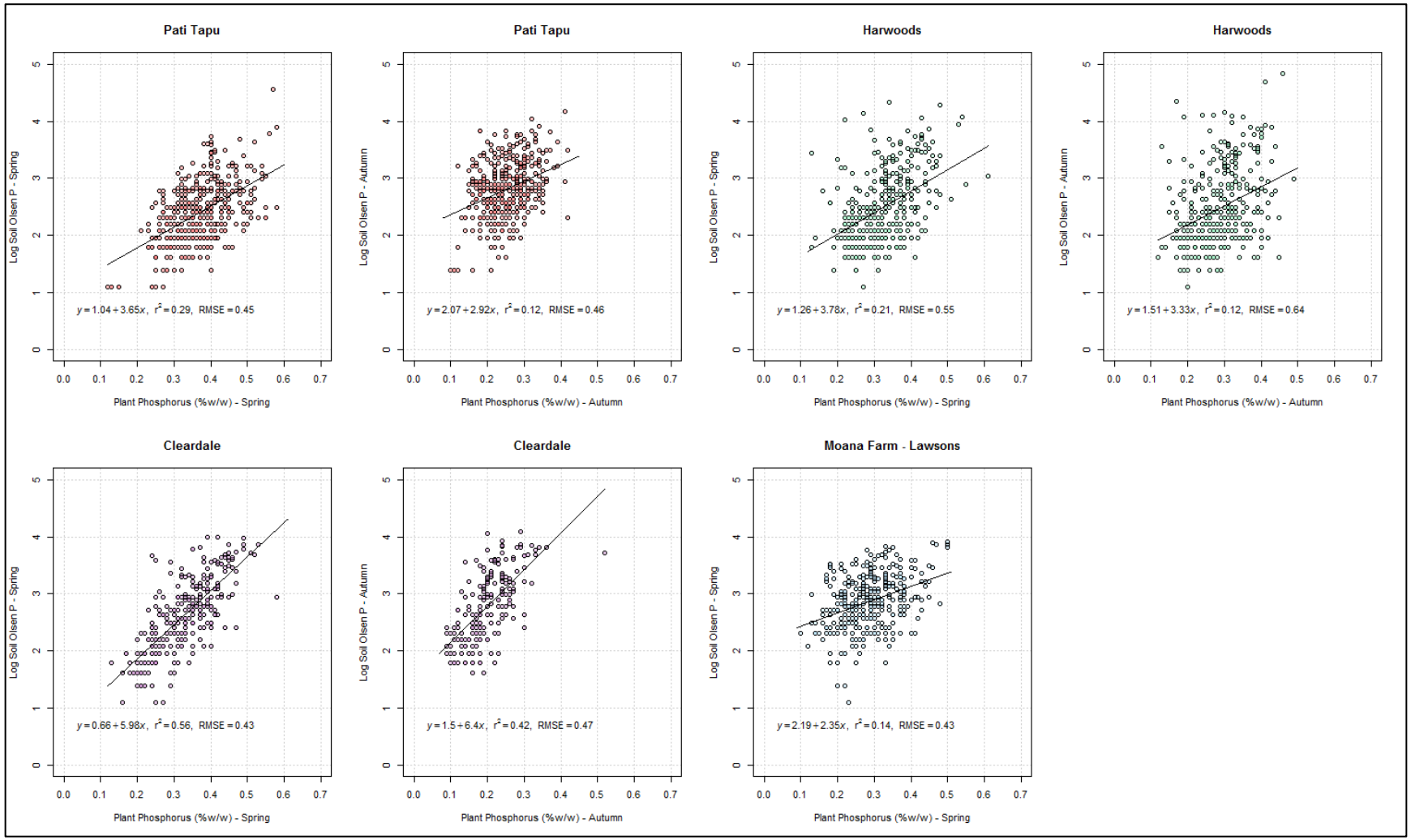


Figure 4-12: Relationship between plant phosphorus uptake (leaf tissue phosphorus % w/w) and available phosphate (soil Olsen P µg/mL) over spring and autumn at Pati Tapu, Harwoods, Cleardale and Moana Farm hill country farms.

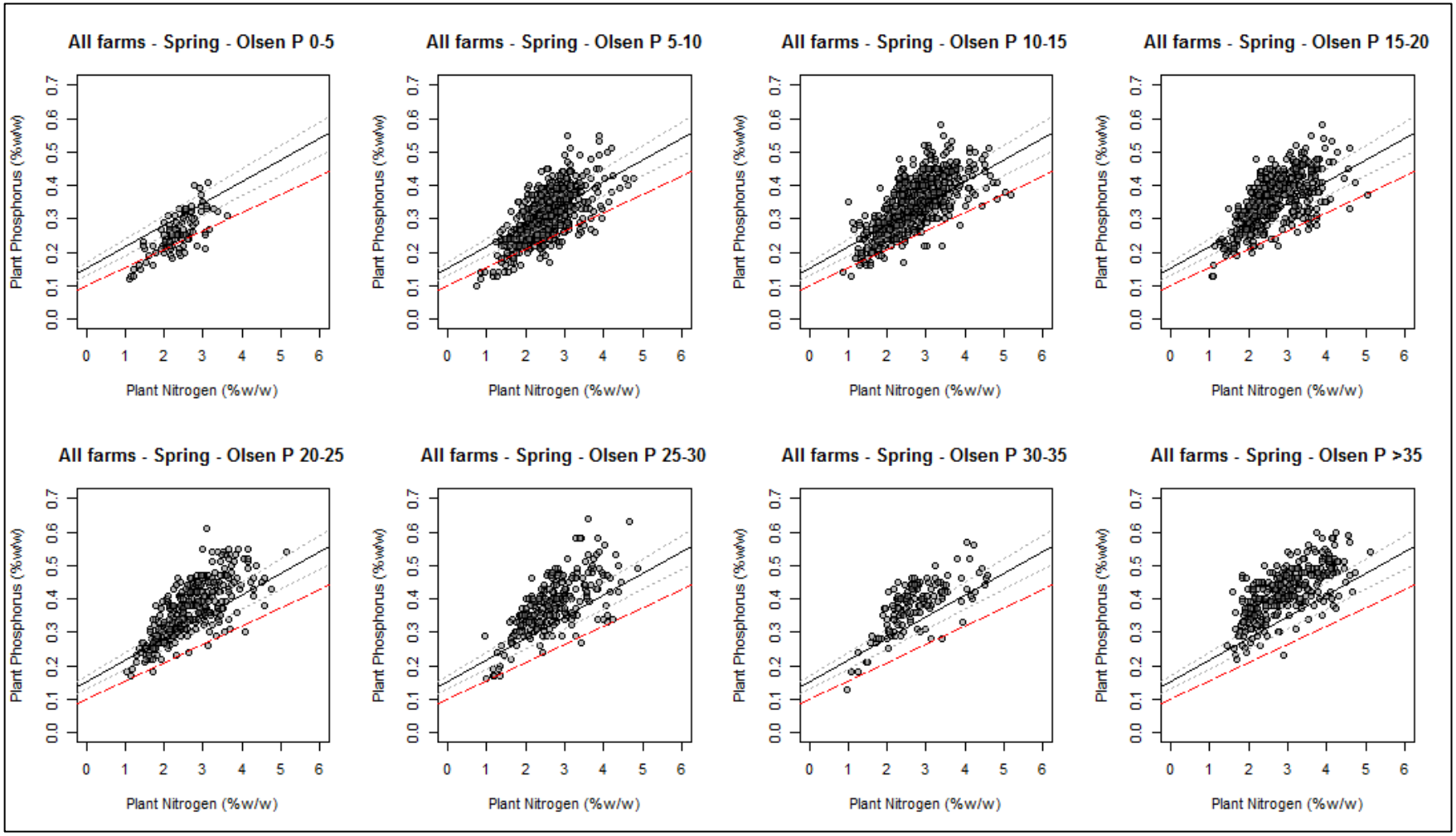


Figure 4-13: N:P nutrient concentration in the leaf tissue for the spring sampling. nitrogen and phosphorus content in relation to the: optimal phosphorus concentration (black line) (Duru & Thélier Huché, 1997); satisfactory (between grey dashed lines); excessive (above upper grey dashed line), risk (between lower grey dashed line and red dashed line); and insufficient (below red dashed line) (Salette & Huché, 1991).

4.4 Discussion

4.4.1 Phosphorus concentration in leaf tissue samples

RANGE OF LEAF TISSUE PHOSPHORUS CONCENTRATION

A widespread and expected range in pasture P concentration of 0.09-0.71 % w/w was observed in the leaf tissue samples collected within the sampling events and covered the majority of concentrations reported in the literature. Three studies reviewed reported P nutrient concentrations greater than those measured in the dataset presented here. This included the safe excess range of 0.4-0.8 % reported by McNaught (1969) who intentionally sought high P concentrations to identify the level at which mixed pasture was able to tolerate excess nutrient. They defined this as above the level required for normal function and growth, but without impairing growth and function through toxicity. Secondly, the range found of up to 0.99 % by Smith and Cornforth (1982) whose samples consisted of predominantly young leaf tissue. Young leaf tissue is expected to contain higher concentrations of P than older leaves and was not separated out in our dataset. Lastly, the P concentration of a partially unfolded young clover leaf as reported by Wilman et al. (1994) of 0.75 %. All other ranges stated in the reviewed literature for both mixed and single species samples, were within the range measured in this dataset.

The direct comparability of studies reporting nutrient concentration in pasture leaf tissue is difficult as the conditions and techniques used to collect the leaf tissue samples varies significantly, and is in some cases not stated or unknown. The samples within the current study were unsorted and cut to grazing height (2 cm) from within a 0.5 x 0.5 m quadrat. However, reported pasture nutrient concentration in the literature is often from: a particular species, growth stage and part of the plant (Wilman et al., 1994); mixed species samples (McNaught, 1969; Smith & Cornforth, 1982; Wells, 1970); different seasons, when the plants are at a different age or stage of maturity (Wilman et al., 1994); grown in pot trials (Smith et al., 1985) or under field conditions (Knowles & Grace, 2014); from only one or few sites, and often with very small sample sizes; under different trial conditions, for example under dung and urine (Joblin & Keogh, 1979) or differing fertiliser treatments; sampling technique including cut (Saunders, 1984) or plucked (Wells, 1969); and from different sized plots. The specified concentration including ranges found, means, optimal or critical levels (McNaught, 1969, 1970; Smith et al., 1985) etc. as summarised in Table 4-1 all differ. This makes the interpretation and comparison of studies difficult and it can only be concluded that the variation apparent in the dataset was realistic and encompassed a significant range of pastures likely to be encountered in New Zealand hill country.

LEAF TISSUE PHOSPHORUS CONCENTRATION OVER SEASONS AND ACROSS FARMS

Phosphorus concentration in the leaf tissue varies seasonally. This is to be expected and trends followed are those reported by other studies. Highest P nutrient concentrations were in the winter sampling and lowest in the summer at Limestone Downs. Leaf tissue P concentration followed the same seasonal trends as shown by other studies (Gillingham & During, 1973; Saunders & Metson, 1971; Walsh & Birrell, 1987). Burkitt et al. (2010) found that P concentration in pasture was highest in the autumn and winter, when growth rates were the slowest. In their work pasture was harvested at optimal grazing time, based on ryegrass leaf stage. Therefore the samples they collected contained only fresh green material. In contrast, autumn samples collected in our dataset were lower than spring, most likely because they contained considerable amounts of dead material, lowering the measured concentrations.

Phosphorus concentration in the leaf tissue is only moderately correlated between the spring and autumn sampling events, with the seasonal changes in pasture the most probable explanation. Nutrient concentration is known to change with season and climate, due to the changes in plant maturity (McNaught, 1973). However species composition and growth cycle also change with season (Fulkerson et al., 1998). This was particularly evident with the changes in sward dominance of ryegrass and kikuyu over different seasons at Limestone Downs. The seasonal variation in botanical composition and structure is different even at paddock scale (Cosgrove, Betteridge, Thomas, & Corson, 1998). Species can affect nutrient content in pastures (Schlegel et al., 2016; Wilman & Derrick, 1994) making the effect of seasonality highly complex and dynamic. Whelan and McBratney (2000) state that careful analysis of crop data that varies greatly on a temporal scale is required to ensure that temporal variability is accounted for, as it is often greater than the spatial variability. These reasons could provide partial explanation for the moderate to weak correlation between spring and autumn P concentrations in the leaf tissue at each plot. The two most weakly correlated farms, Pati Tapu and Ohorea, were the only two farms to have received fertiliser applications over the whole farm between the sampling events, likely to have further affected leaf tissue concentrations.

CRITICAL NUTRIENT CONCENTRATIONS

Critical nutrient concentrations have been established to identify nutrient deficiencies in pasture plants. However they are difficult to relate directly to the data collected within this research. Critical nutrient concentrations are usually specific to a particular pasture species (Butler & Bailey, 1973; Grant, Flaten, Tomasiewicz, & Sheppard, 2001; McNaught, 1970). For nutrient deficiency diagnostics, clover only samples are generally preferred to grasses, as clover is not complicated by N deficiencies (McNaught, 1970). However Mackay, Saggar,

Trolove, and Lambert (1995) found a strong correlation (r=0.92) between P concentration in the leaf tissue of clover-only and mixed pasture samples, which held over a range of soil fertility levels and during summer, autumn, and winter. They suggested that either sample would provide very similar information. New Zealand literature especially tends to focus on ryegrass and white clover (Crush & Hunt, 1992). However the results of the botanical composition (Appendix A) indicate a much more diverse pasture composition than ryegrass and white clover present across these hill country farms. Mixed pasture leaf tissue samples have been traditionally collected in terms of animal dietary requirements (Knowles & Grace, 2014) and are seldom used for identifying plant nutrient deficiencies where they are generally supplementary to soil tests (Cornforth, 1984b) in agricultural systems.

A particular growth stage is specified for which the critical values have been established (Grant et al., 2001). The sensitivity and ease of recognition of the youngest fully expanded leaf means it is often used (Cornforth, 1984b). Critical nutrient concentrations established therefore do not apply to the data collected. The specific plant tissue criteria limits the confounding influences that may supervene in mixed swards (Butler & Bailey, 1973) that make them difficult to interpret (Whitehead, 2000). Pasture nutrient concentration in the leaf tissue are also affected by: limited physical conditions such as temperature or drought (Cornforth, 1984b; McNaught, 1970); changes as a plant develops and matures (McNaught, 1970); growing conditions; and concentrations of other nutrients in the tissue (Grant et al., 2001), all of which were situations encountered during data collection.

Any state of pasture on a commercial hill country farm needs to be covered for the approach to be successful. This is because the AisaFENIX imaging system measures reflectance of the pasture canopy in its state at the time of image capture and will provide pasture biochemical and biophysical information for model inputs for whole farm analysis. Figure 4-3 gave examples of the range of pasture states at the time of sampling. Many of the influences on nutrient concentration such as botanical composition, stage of maturity and regrowth, and the magnitude of their effect are unable to be quantified given the data collected, and are outside the scope of the thesis. This variation in pasture is evident in the photographs of the plots and it is acknowledged that these factors are likely important, but understanding this effect is outside the scope of the thesis.

DEAD VEGETATION FRACTION

The dead vegetation fraction in the samples collected had an effect on the leaf tissue concentration measured via wet chemistry analysis. This was one cause of variation in leaf

tissue that was quantified and able to be analysed. As the dead vegetation fraction in the samples increases, the P concentration in the leaf tissue samples decreases and the variation in P concentration between samples decreases. Phosphorus concentration in leaf tissue decreases with the age of leaf material (Schlegel et al., 2016; Wilman et al., 1994) and is known to be very low in dead leaf tissue (Wilman et al., 1994). As dead vegetation showed no correlation with soil Olsen P and was strongly correlated to leaf tissue P concentration, there are areas that were low in leaf tissue P concentration due to the high dead vegetation content, and not necessarily due to low soil P availability such as dry areas.

4.4.2 Soil Olsen P

RANGE IN SOIL OLSEN P

The range in soil Olsen P estimates from 2 to 130 µg/mL covered a wide range of soil fertility, similar to the range of 4.3-130 µg/mL measured across a grazed field extensively sampled by Fu et al. (2013), with 396 samples collected on a 15m grid. Low fertility sheep and beef farms are considered <20 µg/mL and high is generally over >30 µg/mL. The range of soil Olsen P reported by Sparling and Schipper (2002a) across sheep and beef farms was narrower than in the present research, being approximately 5-50 µg/mL. The full extent of variation is not realised in soil tests results unless adequate soil sampling is undertaken (McCormick et al., 2009). Soil testing methodology often aims at reducing variability (Morton et al., 2000). The CV in the current study for soil Olsen P was lower than the 87.4% reported by Fu et al. (2013) and greater than those reported by Gillingham (1982) of 25 to 49% on steep land areas. The CV for soil Olsen P (67% for all farms and sampling events) was much greater than the CV for P concentration in the leaf tissue (29%).

POTENTIAL TO IMPROVE PRODUCTION THROUGH INCREASED SOIL FERTILITY

The soil Olsen P test results across the eight farms suggested there was still plenty of potential to increase pasture production through the increase in soil available phosphate, as previously reported in the literature. Wheeler et al. (2004) compared approximately 118,000 soil test results spanning 14 years from 1988-2001 for sheep and beef farms in New Zealand on different soil groups. Samples collated between 1988-1996 and then from 1997-2001 identified 78% and 65% of sites respectively on sedimentary soils below the range for near maximum pasture production (20-25 µg/mL) and 71% and 63% on volcanic soils (20-30 µg/mL - range for near maximum pasture production) respectively for the same time periods. Samples collected across the eight commercial farms between 2013-2016, identify 61% of sites in the spring sampling event, and 60% in the autumn, below the range for near maximum pasture production on both sedimentary and volcanic soils (<20 µg/mL). Approximately 20% of

samples were classified as above the upper limit, although the upper limit for sedimentary soils used by Wheeler et al. (2004) was 25 µg/mL and the values stated in Table 4-3 use the upper limit of 30 as defined by Morton and Roberts (2009). Nevertheless, both show the potential for fertiliser inputs to be reduced on some areas without loss of pasture productivity.

DISTRIBUTION OF SOIL OLSEN P

Soil Olsen P was highly positively skewed as grazed agricultural fields are usually log normally distributed. Grazed agricultural areas show positively skewed distributions (Fu et al., 2013; McCormick et al., 2009; Wheeler et al., 2004) most likely due to the effect of nutrient redistribution by the grazing animals (Rowarth et al., 1988). These have been reported to be normally distributed in continually cropped fields (Fu et al., 2013). The median value for soil Olsen P across the entire dataset is 17 µg/mL, compared to a mean value of 21 µg/mL and a skewness value of 3.11. Interpretation of soil test results are often based on average values and with highly skewed distributions, this often misrepresents the situation.

LEAF TISSUE PHOSPHORUS CONCENTRATION OVER SEASONS AND ACROSS FARMS

While soil Olsen P showed temporal variation, there was no seasonal trend across farms and seasons. Large temporal variation is known to exist in soil Olsen P measurements (Friesen, Blair, & Duncan, 1985; Roberts, 1987) and is of concern when attempting to decide appropriate fertiliser programmes (Friesen et al., 1985). Roberts (1987) observed large temporal variation but no seasonal trend in soil Olsen P results on two sites, where 30 cores were collected from a 40 x 50m plot. It is this known temporal variation, along with large spatial variation that means Friesen et al. (1985) suggest that changes in soil are more easily detected in small plots. Despite the amount of phosphate in a given volume of soil having been regarded as the most stable soil fertility factor (Jeffrey, 1988), there was still great variation between the estimates of soil Olsen P sampled from the same plot in autumn and spring in the current study. The greatest difference between spring and autumn sampling events was at Pati Tapu. This is expected given the generally low soil fertility status of the farm and the fertiliser application that occurred between these events. The correlation between spring and autumn soil Olsen P across the different farms, excluding Pati Tapu, ranged from 0.56 to 0.84 with RMSE from 4.9 to 10.8. However the variation was heteroskedastic, meaning it increases as soil Olsen P increases. The large variation in soil Olsen P estimates from the same plots approximately six months apart highlights the difficulty in predicting exact values, as the variation suggests that the true value lies within a large range.

4.4.3 Exploratory analysis to predict soil Olsen P from mixed pasture leaf tissue, using simple plant indices

Positive relationships between plant P indicators and soil Olsen P were observed. The relationship between plant indices and soil phosphate were not as strong as has been published in other studies. However other studies were generally on a much smaller scale, on one or a few sites. With the spring and autumn samples combined, the dataset includes just under 6,000 samples from 0.5m x 0.5m quadrats, which was a much larger dataset than reported in the literature. The strongest correlation between herbage and soil was on a single farm within a season. As data was combined, the relationship weakened. Rowarth and Gillingham (1990) conducted a ryegrass pot trial that resulted in herbage P and soil Olsen P highly correlated (r^2 = 0.96). However the sample size was 15, a pure sward and controlled environmental conditions. Three sites analysed separately contained only 12 samples per site in a study carried out by Burkitt et al. (2010) who reported R^2 values of 0.50, 0.41 and 0.41 between Olsen P and P concentration in the plant tissue. In contrast no correlation between soil Olsen P and plant P concentration was found by Roberts (1987), although they used 30 cores bulked and pasture cuts from within 40 x 50m site. Given the size of the plot and the variation known to exist in soil and plant P over short distances, as Friesen et al. (1985) state, smaller plots are more appropriate for detecting these changes. Acknowledgement has also been made that the number of sites is important to cover a range of different pasture types, soil groups, management intensities, environmental conditions and a wide range of soil fertility (Kawamura et al., 2011; Liebisch, 2011). This highlights the importance of sample support to appropriately capture variation and sample size, to cover a wide range of pasture and farm types.

The analysis of mixed pasture samples was a likely cause of weaker levels of explanation using plant indices. Many studies have used nutrient concentration in single species such as ryegrass (Rowarth & Gillingham, 1990) or clover (Morton, Smith, et al., 1998) or the grass only fraction (Liebisch et al., 2013) to remove variation introduced to due species composition. Consequently they achieved stronger relationships between herbage and soil than found in this study. The information collected on dominant species was insufficient to account for variation in plant nutrient concentration due to species composition. This would have involved dissection of samples which is time consuming for such large sample numbers. The use of remote sensing provides an estimate of the pasture canopy nutrient concentration irrespective of species composition. The use of single species or adjustments based on species composition

is therefore beyond the practical application given the knowledge and technology at this stage. A model developed using such information would not be able to be applied over large areas.

Plant nutrient indices were more strongly correlated to soil Olsen P in spring than autumn and the relationship weakened considerably when seasons were combined. Pasture cover is more even in spring than other seasons due to set stocking of ewes during lambing. In autumn, large mobs of breeding ewes are rotated around paddocks, rotation grazing results in a wide range of pasture cover compare to set stocking. The dead vegetation content in the sward is greater in autumn than spring (Betteridge et al., 2008). Factors such as these may partially explain seasonal difference. The majority of studies using plant indices to assess soil nutrient status have been conducted in the spring only.

LEAF TISSUE PHOSPHORUS CONCENTRATION

Although all farms and seasons resulted in a positive correlation between leaf tissue P concentration and soil Olsen P, there was a vast range in the level of explanation. The strongest relationship was at Cleardale (R^2 = 0.56 in spring and 0.42 in autumn). Figure 4-3 shows the difference in plots with the median value for P concentration in the leaf tissue of 0.31, but with estimated soil Olsen P ranging from 8-65 µg/mL. This highlights the need for more information other than solely plant P concentration to account for the variation. Plant models that focus on the uptake of nutrients in the rhizosphere are difficult to scale up to whole plant and agroecosystem scales (Hinsinger et al., 2011). This is an essential interaction in this approach but is not well understood, and complicated by many other influential factors. In their study Kawamura et al. (2011) suggested that it would be possible to use plant indices to classify the underlying soil into low, moderate, and high levels of soil P, but that more detailed predictions might be difficult. Liebisch (2011) suggested defining deficient, sufficient and surplus categories should be enough to inform fertiliser applications.

PNI AND PNIC

The level of explanation gained using PNI to predict soil Olsen P varied across sites and season, but was always positively correlated. Garnier et al. (2007), Duru and Thélier Huché (1997) and Jouany et al. (2002) also found positive correlations, although the latter two studies found stronger relationships with measures of soil phosphate other than with Olsen P. Although similar levels of explanation were achieved using leaf tissue P concentration or PNI, PNI appeared to give a better explanation than leaf tissue P concentration for farms which used urea.

The plant index PNIc, which used an adjustment for clover content at each site, did not improve the ability to determine the soil P status. The legume content of pasture is known to have an effect on plant nutrient indices that use N concentration in the leaf tissue. Liebisch et al. (2013) used and recommended to analyse only the grass fraction. In contrast, Jouany et al. (2004) developed the PNIc to account for the higher N content in the clover leaf tissue. Despite the percentage of clover in the sample being estimated and used to calculate the PNIc, it did not demonstrate any improvement in the level of explanation on any farm or season compared to PNI. In hill pastures, clovers are naturalised plants from those sown 50-100 years ago with a prostrate habit. Their stolons remain close to the ground which enables them to handle hard grazing (White & Hodgson, 1999). This also means that the clover cut during the sampling process may be under represented in the leaf tissue sample compared to that estimated in the sward. The use of urea on some of the farms will also affect the clover content and the N content of the pasture and plant indices. Although urea is used on some of the trial farms, this data was not collected.

P:N RATIO

The P:N ratio did not achieve as high level of explanation compared to leaf tissue P concentration or PNI. P:N ratios have more commonly been used on clover only samples (Morton, Sinclair, et al., 1998). Nutrient ratios were anticipated to be more useful in situations where the age and maturity of pasture varied, or to allow appropriate analysis of pasture at any time (McNaught, 1970). N:P ratios were shown to have no seasonal pattern or effect due to cutting frequency by del Pino Machado (1994) showing promise that they could be used under a wide range of pasture conditions. Nutrient ratio of P:N for clover only samples in New Zealand pastures was successful in assessing P deficiency and determining a fertiliser response (Morton, Smith, et al., 1998). However, the results on mixed pasture samples in our study show less potential than P concentration or PNI. To use highly sensitive differences in nutrient concentration in this type of approach must be used carefully when replaced with estimates derived from hyperspectral imagery, as the error in these estimates may be similar or greater than the differences in N and P.

4.4.4 The use of plant tissue to determine soil nutrient status

The heavy reliance on leaf tissue P concentration of simple plant indices is not only limited by the complexity from variation in the leaf tissue concentration itself as previously outlined throughout this thesis, but also in the phosphate effectively sampled in a soil core vs. via a plant and the response of pasture plants and plant communities to the availability of phosphate in the soil.

EFFECTIVE SOIL SAMPLING SUPPORT: SOIL CORES VS. LEAF TISSUE

Phosphate in the soil measured via soil cores is different to that expressed through the plant leaf tissue. Theoretically, with all other factors causing variation in P concentration in the leaf tissue aside, the two approaches are different measurements. Soil cores are collected within a quadrat and analysed using the traditional Olsen P test in the laboratory. This estimates the potentially available or labile P in the soil solution from a subsample of the bulked sample, from the total volume of the nine cylindrical cores taken to a depth of 7.5 cm. The leaf tissue P concentration is a measure of the previous uptake of phosphate ions from the soil solution within the root zone of those plants. This is related to soil moisture, soil solution P concentration, the volume of soil and distribution within which that particular plants roots have explored, and will vary with root architecture, mass, length, hairs and mycorrhizal associations, see Figure 4-14.

Figure 4-14: Varied rooting depth and architecture of pasture plant roots, in comparison to traditional soil sampling core collected to 7.5 cm.

Uptake of phosphate from the soil by roots of pasture species is predominantly from within the top 7.5 cm of soil (Gillingham, Tillman, Gregg, & Syers, 1980; Nguyen & Goh, 1992; Rowarth & Gillingham, 1990), with the majority of available phosphate (Rowarth & Gillingham, 1990) and uptake (Gillingham et al., 1980) occurring within the top 0-3 cm. It makes sense then that the bulk of roots mass is also reported to be in the top 7.5 cm (Nguyen & Goh, 1992) to 10 cm (Barker, Zhang, & Mackay, 1988). The proportion of plant available P uptake decreases

down the soil profile and compared to other nutrients, is the most concentrated in the top soil to 20 cm when considering the soil profile to a depth of 100 cm (Jobbágy & Jackson, 2001). Significant P uptake from depths greater than 30 cm is believed to be unlikely (Gillingham et al., 1980). Pasture roots are capable of reaching greater depths where they are able to penetrate the soil (Molloy, 1998). Nutrient uptake from greater depths is important under low fertility, under low soil moisture (Gillingham et al., 1980).

Given the traditional sampling methodology of collecting soil cores to a depth of 7.5cm, leaf tissue nutrient obtains different information. The results presented here, as Liebisch (2011) also reported, found that plant P concentration can indicate surplus P even on soil that was only deemed 'sufficient' in P. They suggest that soil tests do not account for all available P and soil depths. There may be an advantage in using leaf tissue, with all other influences to nutrient concentration aside, in that the plant effectively adjusts soil sampling according to root exploration which will be a factor of soil condition and a reflection on what has been available to the plant from all sources and forms of soil P. The disadvantage, in terms of useful information to guide fertiliser decisions, is that leaf tissue is effectively a history and not a measure for estimating phosphate availability longer term as provided through traditional soil core analysis. Cornforth, Sinclair, and Rowarth (1993) suggest that leaf tissue concentration may play a role in assessing fertiliser policies to maintain an optimal nutrient balance, rather than deciding rates to apply. However, if P concentration in the leaf tissue drops, then it would be a good indication that fertiliser P should be applied.

PLANT RESPONSE TO SOIL PHOSPHORUS AVAILABILITY

Changes in leaf tissue P concentration are one plant response to soil phosphate availability. Pasture yield, root:shoot ratios, individual plants and plant communities also respond to differing levels of soil phosphate availability. These other responses can make the interpretation of leaf tissue P concentration in relation to soil phosphate availability problematic.

Pasture plants respond and use strategies to adapt to soil phosphate availability including:

- Changes in growth rate with slow growth at low P availability (Loneragan & Asher, 1967) and an increase as soil phosphate increases, to a point where yield plateaus (Edmeades et al., 2006; McNaught, 1973; Morton, Smith, & Metherell, 1999; Ozanne & Shaw, 1967). Maximum growth of plants is achieved at a wide range of P concentration and the concentration which gave highest yields in some species produced severe necrosis in others (Asher & Loneragan, 1967). At the other end, when the supply of nutrient is slightly

inadequate for growth, given current environmental conditions, plants can adjust their growth rate to match nutrient supply and do not necessarily display typical visual deficiency symptoms (Taiz & Zeiger, 2014). Another complication is the build-up of nutrient when growth is slow, in response to climatic conditions rather than nutrient availability (Burkitt et al., 2010), or a dilution in short bursts of rapid growth (Cornforth, 1984b) which can vary significantly over a hill country farm. This results in large differences in growth rates due to the complex terrain, making the interpretation of nutrient concentration in the leaf complicated.

- An increase in leaf tissue P concentration (McNaught, 1973) from deficiency, increasing through optimal to luxury and eventually toxic levels which are species dependent (Loneragan & Asher, 1967). Visual symptoms of crop plants under moderate P deficiency generally do not have easily identifiable characteristics for field diagnosis (Grant et al., 2001). Andrew (1960) found no correlation between visual symptoms of deficiency and leaf tissue P concentration in fully emerged green leaves of white clover, and stated that visual signs are only able to diagnose acute deficiencies. In their trial the lowest leaf tissue P concentration was 0.12 %. The lowest concentration measured in the database presented in this thesis was 0.09 % w/w. These low nutrient concentrations are the result of high dead vegetation content in the samples, rather than severe nutrient deficiency. When leaf tissue nutrient appears inadequate due to drought or advancing maturity for example, it can be difficult to positively identify deficiencies (Cornforth, 1984b). The leaf tissue concentration at which growth slows and necrosis in leaves develops due to toxicity, is species dependent but has been found to be around 0.9 % (Loneragan & Asher, 1967) to 1.0 % (Asher & Loneragan, 1967). The maximum leaf tissue concentration in the dataset was 0.71 %. This is within the safe excess range of 0.4-0.8 % for mixed pasture defined by (McNaught, 1969). No symptoms of severe deficiency or toxicity were noted as identified with the naked eye. The interpretation of leaf tissue concentration alone can be limited due to the other confounding factors.
- Plants can alter their root:shoot ratio and keep the majority of P in the roots (Loneragan & Asher, 1967). Root production can be maintained at the expensive of shoot growth which is greatly reduced or even ceased (Andrew, 1960; Atkinson, 1973; Hill, Simpson, Moore, & Chapman, 2006; Loneragan & Asher, 1967; Troughton, 1977) when phosphate availability in the soil is low. Extending their root architecture through decreasing root diameter and increasing root length (Hill et al., 2006; Troughton, 1977) enables plants to explore more of the soil and reach new soil reserves of P. This is important especially for poorly mobile nutrients such as P (Hinsinger et al., 2011). Some studies have even shown the transfer of P

from the shoots back down to the roots, resulting in a decrease in shoot P concentration (Loneragan & Asher, 1967). It is known that the root biomass is much greater on low fertility soils than high fertility sites (Nguyen & Goh, 1992) and can be as much as double the root mass (Tate et al., 1991). This interaction cannot be identified using this approach. Essentially how hard the plant has to work to take up sufficient phosphate from the soil is not evident, and a plant may have twice the root system of another to maintain shoot growth, but with additional P applied may not require such an extensive root system.

- Increasing the availability of phosphate by lowering the concentration at the root surface and thus increasing the concentration gradient when phosphate availability is low (Barrow, 1975a). Again a species dependent response and one that cannot be detected using simple plant indices.

A summary of the response of pasture plants to soil P availability in terms of P concentration in the leaf tissue and growth rate of root and shoots is represented in Figure 4-15. The steepness of slopes, key turning points, maximum growth rate, and P concentration would be species dependent.

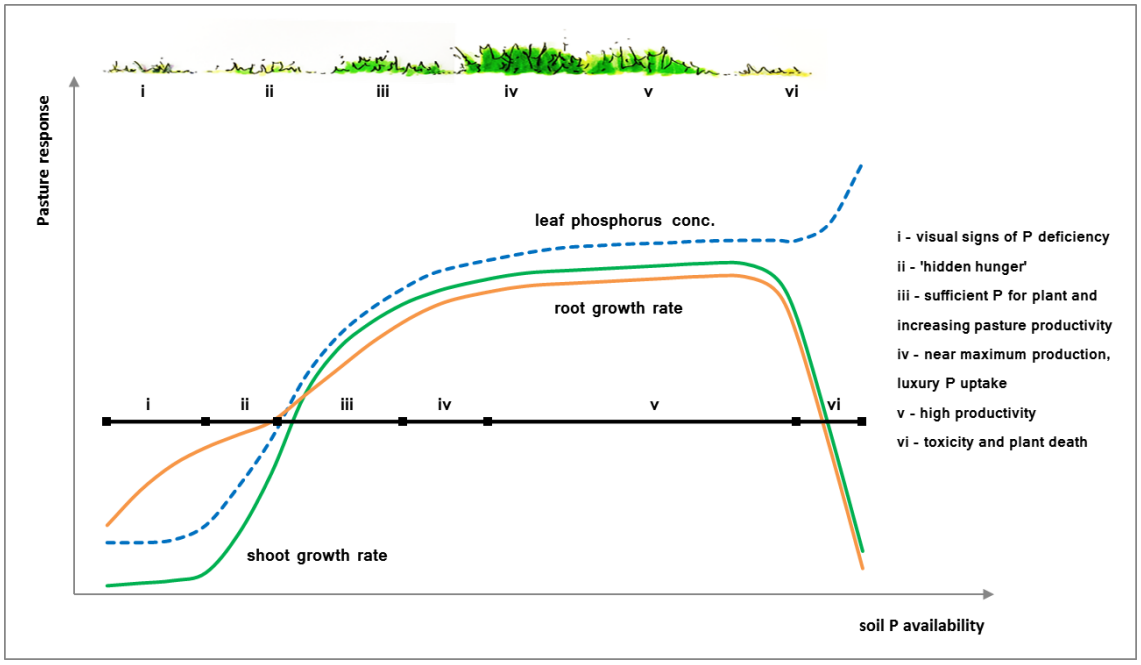


Figure 4-15: Schematic of pasture response to increasing phosphate availability in the soil, in relation to leaf tissue nutrient concentration and pasture growth.

Sufficient P in the leaf tissue alone does not necessary mean that soil P is adequate, as plants may have responded or employed strategies described above to increase P uptake and ensure adequate P is reaching the leaf tissue. It is these strategies and information that cannot be gained from leaf tissue concentration alone, and is a limitation to nutrient indices. For

example, leaf tissue P may be adequate but the plant may have had to put more energy into growing a larger root system to acquire sufficient P. Models are better at predicting nutrient uptake of poorly mobile nutrients in nutrient-rich conditions and underestimate the actual acquisition in nutrient-poor conditions (Hinsinger et al., 2011). This is most likely because they are not accounting for strategies used by plants.

4.5 Conclusion

An extensive field study achieved the capture of a diverse range of hill country environments resulting in a wide and complete range of leaf tissue nutrient concentration and soil Olsen P. The range highlighted both the variation within a farm and, in the case of soil Olsen P, the likely potential for any hill country farm to lift productivity through increasing soil fertility with 60% of sites under target Olsen P. The coefficient of variation for soil Olsen P was much greater than for P concentration in the leaf tissue. However, the distribution of leaf tissue nutrient concentrations at each sampling event varies temporally much more than soil Olsen P. This shows while soil Olsen P varies greatly, temporal variation was much greater in leaf tissue than in soil. It is essential that this variation is accounted for appropriately, as it is often so with crop data, the temporal variability is greater than the spatial variation.

Simple plant indices are of some, but limited, use. Plant P concentration and PNI were more strongly correlated to soil Olsen P than PNIc and P:N ratio. Many sources of variation in leaf tissue concentration are likely to affect this relationship, which is why most researchers use a single species and growth stage for such analysis. For the end goal of the project to be achieved, a method must be used that is successful on a mixed pasture sward.

Plant nutrition is not just about plant physiology, it is also about the transport of nutrients through the soil to the rhizosphere, particularly for poorly mobile nutrients such as P. Individual plants and pasture communities respond in different ways to differing levels of phosphate availability, one response of which, is a change in leaf tissue P concentration. However leaf tissue P concentration is a measure of previous uptake by the plant root and transport to the leaf tissue, while soil phosphate tests are aimed at providing an indication of current and readily available phosphate for the season ahead. These are essentially two different measures and although leaf tissue P concentration can provide some indication of soil fertility status, more information is required to improve the prediction of soil phosphate status.

5

5 Exploratory analysis to predict soil Olsen P in hill country using nutrient concentration of leaf tissue of mixed pasture, topographical and farm management factors

5.1 Introduction

Traditional approaches to phosphate fertiliser recommendations have involved soil testing, which in New Zealand has been the Olsen phosphate test. This test measures the potentially available phosphate for plants to give an indication of whether fertiliser would increase growth for the coming seasons. Leaf tissue P concentration and P based plant indices (Duru & Thélier Huché, 1997; Jouany et al., 2004; Liebisch et al., 2013) are useful in explaining some of the variation in soil phosphate (Chapter 4).

Hill country farms are highly variable. Regional and local scale influences, along with microclimate or microtopography result in a range of climatic and soil conditions, not only within farms but within paddocks. Farm management also adds to the diversity and complexity of hill country farms, with differing knowledge, personal preferences for stock classes or fertiliser products. For example, restrictions due to pasture growth or markets, and advice all play a part. The overall aim of the project was to create a model to estimate soil fertility that

could be implemented on commercial hill country properties outside of those included in the dataset. Any model developed must be robust and transferable, even under differing environmental conditions and management systems.

Any analysis of the soil-plant-animal system is complex, dynamic, varied, conditional and interrelated. When attempting to interpret real world situations there are many unmeasured or unmeasurable factors, that causation can be difficult to identify (Dorrough et al., 2011). Variations in nutrient concentrations are due to many factors. Agricultural experiments in relation to concentrations of nutrients in leaf tissue and supply of nutrients from the soil, often attempt to provide non-limiting conditions for growth, except the nutrient of interest, to eliminate this complication. Nutrient concentrations are often referred to in relation to a specific pasture species and plant part. However, pasture in hill country is a mixed sward. The magnitude of the effect on the leaf tissue nutrient concentration as a result of different factors is difficult to determine.

The inclusion of factors such as other plant nutrients, topography, and management factors, was the first exploratory step in identifying other important predictors. This step was possible because of the large number of variables collected within the sampling campaign, and subsequently available as inputs into a model.

This chapter aims to:

- Use stepwise linear regression analysis as an exploratory tool for predicting soil P availability measured using soil Olsen P.
- To incorporate additional plant biophysical and biochemical parameters, topography and farm management factors, to identify consistently significant or non-significant factors across farms and/or seasons, to gain a better understanding of the relationships and identify broad scale patterns.

5.2 Methodology

5.2.1 Field sites, data collection, data collation

Pasture nutrient concentration, botanical composition and soil fertility data were collected throughout the project sampling campaign. The sampling locations were spread across eight farms within the project and are described in detail in Chapter 3. The farms were selected from regions throughout New Zealand, where hill country farming is a dominant land use.

The sampling methods used in field data collection including the collection and processing of leaf tissue and soil samples are described in the later sections of Chapter 3. The sampling sites were spread across the farms and are influenced by both regional and local scale factors. Environmental conditions and farm management practices at each of the farms are described in detail in Chapter 3.

5.2.2 Variables

A range of topographic, climatic, farm management, pasture nutrient and pasture composition factors were used as inputs for the regression analysis. The variables and associated calculations are given in the following sections, with a summary table presented at the end of the methodology section (Table 5-1).

SOIL OLSEN P (*LOGSOP*)

The natural logarithm of soil Olsen P was used, as soil Olsen P has a highly skewed distribution. The log of soil Olsen P was approximately normally distributed and used as the response variable, as has been used in the previous chapter.

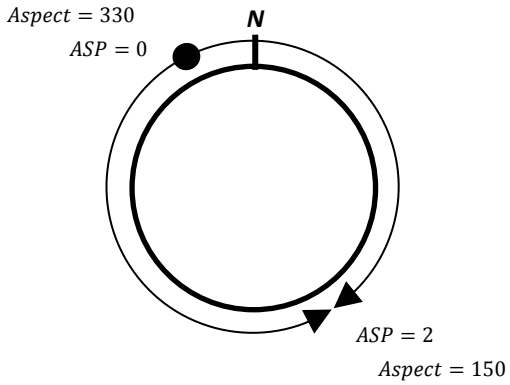
$$LogSOP_i = \mathrm{LOG}(OlsenP_i)$$

5.2.2.1 Topographical variables

The topographical inputs included: elevation, slope and aspect. Aspect is transformed to an input appropriate for linear regression.

ASPECT (*ASP*)

Aspect was converted to be included in a linear regression model. Aspect is circular, in that 0° and 360° are the same. The data was converted to be effectively a 'distance from northwest' variable, from 0 to 1: northwest to southeast, regardless of the clockwise or anticlockwise direction travelled.



$$ASP_i = 1 + \cos\left(\frac{(Aspect_i - 150) \times \pi}{180}\right)$$

Where: $Aspect$ = the measured aspect of the slope face in degrees

5.2.2.2 Climatic variables

RAINFALL (*RAIN30*)

Rainfall was measured via weather stations installed on the farms or using nearby NIWA weather stations. The accumulated total rainfall measured over the 30 days prior to the field sampling campaign was calculated.

PLANT GROWTH RATE (*PGR*)

The plant growth rate was calculated within the Ravensdown pasture growth forecaster. It was the average rate of pasture growth of the predicted growth rates during the 14 days prior to the sampling event, measured in kgDM/ha/day.

SOIL MOISTURE DEFICIT (*SMD*)

The soil moisture deficit was calculated within the Ravensdown pasture growth forecaster. It was the average soil moisture deficit during the 14 days prior to the sampling event.

5.2.2.3 Fertiliser variables

TIME SINCE THE LAST FERTILISER APPLICATION (*PFTS*)

The time elapsed (days) since the last phosphate fertiliser application prior to the field sampling campaign was calculated for each site, based on the fertiliser records collected and collated from various sources.

LAST APPLICATION OF PHOSPHATE FERTILISER (*PFLAR*)

The amount of P applied (kgP/ha) in the last fertiliser application prior to the field sampling campaign was calculated for each site, based on the fertiliser records collected and collated from various sources. The amount of P was calculated based on the product and rate applied.

ACCUMULATED TOTAL PHOSPHATE FERTILISER APPLIED (*PF3Y*)

The accumulated total P applied (kgP/ha) to each site over the 3 years prior to the field sampling campaign was calculated from the fertiliser records collected and collated from various sources.

5.2.2.4 Leaf tissue nutrient concentration

LEAF TISSUE NUTRIENT CONCENTRATION (*PLANT…*)

Leaf tissue nutrient concentration of the mixed pasture samples cut from a 0.5m x 0.5m quadrat to grazing height (2cm) was measured in the laboratory, and concentration on a % weight for weight basis was calculated.

As this thesis was part of a wider project, analysis of the relationship between predominantly pasture nutrient concentration and soil fertility presented within this thesis, and the ability to estimate pasture nutrient concentration using hyperspectral imaging were developed concurrently. The nutrients included in the analysis were chosen from those proven to be able to be predicted with a reasonable level of accuracy from hyperspectral imagery (Pullanagari et al., 2016), ensuring there would be a data source for which wet chemistry data could be substituted. At the time of the linear regression analysis this included the following nutrients: nitrogen (N), phosphorus (P), potassium (K), sulphur (S), copper (Cu), sodium (Na), manganese (Mn), zinc (Zn) and boron (B).

5.2.2.5 Pasture composition variables

Dry matter percentage, dead vegetation fraction, legume content, and NDVI were included in the regression analysis. The calculation of NDVI and botanical composition are explained in Chapter 3, sections 3.4.5 and 3.4.6 respectively.

Table 5-1: Summary of variables used in regression analysis, their definitions and units

Variable	Definition
LogSOP	Plant available phosphorus in the soil, Olsen P of soil at 0-7.5 cm depth (µg/mL; ln-transformed)
ELEV	Elevation above sea level of site (metres a.s.l.)
SLOPE	Slope angle (degrees)
ASP	Aspect of slope face (from northwest, 0-2)
RAIN30	Rainfall, 30 day average prior to the sampling event (mm)
SMD	Soil moisture deficit, average of 14 days prior to the sampling event
PGR	Predicted pasture growth rate – average of 14 days prior to sampling event (kgDM/ha/day)
PFTS	Time since the last phosphorus fertiliser application prior to sampling (days)
PFLAR	Phosphorus fertiliser - rate applied in last application prior to the sampling event (kgP/ha)
PF3Y	Accumulative total phosphorus applied in fertiliser in the 3 years prior to sampling (kgP/ha)
PLANTN	Nitrogen concentration in the leaf tissue (% w/w)
PLANTP	Phosphorus concentration in the leaf tissue (% w/w)
PLANTK	Potassium concentration in the leaf tissue (% w/w)
PLANTS	Sulphur concentration in the leaf tissue (% w/w)
PLANTCu	Copper concentration in the leaf tissue (mg/kg)
PLANTNa	Sodium concentration in the leaf tissue (% w/w)
PLANTMn	Manganese concentration in the leaf tissue (mg/kg)
PLANTZn	Zinc concentration in the leaf tissue (mg/kg)
PLANTB	Boron concentration in the leaf tissue (mg/kg)
DM%	Dry matter percentage (%)
NDVI	Vegetation index (using bands 705 and 750) related to chlorophyll content (0-1)
DeadVegFrac	Dead vegetation content in the sample derived from visual estimation (%)
LegumeFrac	Legume content in the sample derived from visual estimation (%)
SEASON	Seasonal indicator
FARM	Farm indicator (farm ID)

5.2.3 Exploratory study for predicting soil Olsen P on trial farms

As a progression from simple indices, stepwise multiple linear regression was explored. Regression techniques were used to determine the level of explanation gained to model soil P status, from plant biochemical and biophysical properties, environmental, and farm management variables.

5.2.3.1 Statistical analysis

The stepwise linear regression analysis was completed in Minitab 17. The whole dataset was split into subsets of each sampling event, containing only one season and farm. Datasets were combined by season and pooled together. Where farms and seasons were pooled, regression analyses were run with and without farm indicator variables. The average and median of the 5

plots within 1 site was calculated and used for regression analysis, as well as each of the plots individually.

All 24 variables in Table 5-1 were made available for the regression analysis. Factors were selected using stepwise multiple linear regression analysis in Minitab17 with the response variable *LogSOP* (the natural log of soil Olsen P). Factors with a p-value > 0.05 or a variance inflation factor (VIF) > 5 were subsequently removed, and the regression analysis was run again with only the significant factors. A p-value > 0.05 indicates a factor that is not significant in the model. VIF quantifies the severity of multicolinearity. A value > 5 indicates a factor that is highly correlated to another or multiple factors in the model and may not be adding any additional information. Multicolinearity in regression analysis is a major issue which can cause large differences in coefficients and may even cause signs to change.

The coefficients of standardised data and their level of significance were collated, along with the adjusted R^2 and RMSE which were also calculated. Results using individual plots, the mean or median of the 5 pegs at each site are presented.

5.3 Results

5.3.1 Stepwise linear regression analysis

The stepwise multiple linear regression analysis to estimate soil Olsen P ranged in the level of explanation for individual sampling events from an R^2 of 0.26 at Limestone Downs in the autumn using all 400 plots, to an R^2 of 0.82 at Cleardale in the spring using the median for each site. The R^2 for pooled data with all seasons and farms combined ranged from 0.37-0.44 without using farm indicator variables. The results of the stepwise multiple linear regression analysis for the individual sampling events are presented in Table 5-2, and for the data pooled across seasons and completely pooled in Table 5-3.

The results from Limestone Downs vary over the seasons with the strongest correlation in early summer with an R^2 of 0.71 using the mean of the sites. However the site median, and all 400 plots were much weaker with R^2 of 0.47 and 0.41 respectively. The weakest correlations were during the autumn sampling event with R^2 of 0.26-0.35, where few factors: leaf tissue K, Cu, Zn and B concentrations and dry matter percentage were selected. In other seasons more factors were selected and included topographical and fertiliser history as well. The results for autumn 2015 at Ohorea showed stronger correlation than in autumn 2014, but were strongest in spring with R^2 of 0.48-0.67, 0.47-0.55 and 0.67-0.79 respectively. The level of explanation was very similar in the autumn and spring regression analysis for Tautane and Pati Tapu

although different sets of factors were selected. The R^2 values were between 0.51 and 0.65 and the RMSE were slightly smaller in autumn than spring. For all other farms the reverse was true: RMSE were smaller in spring. The factors selected for the analysis of Erewhon were reasonably consistent between seasons, compared to the other farms. These included leaf tissue P and copper concentration, NDVI, legume fraction, and soil moisture deficit, with the addition of elevation and plant sodium in the autumn. Cleardale and Harwoods had the highest levels of explanation particularly in the spring. Harwoods was the only farm for leaf tissue copper concentration not to be selected at all. However it was the only farm where the three year phosphate fertiliser term was selected consistently which had a significant effect in the regression model.

For the pooled datasets, the R^2 ranged from 0.38-0.66 for the season specific models and 0.37-0.49 for completely pooled data. Leaf tissue P and copper concentrations were consistently selected across all pooled datasets. Of the topographic variables, slope appeared to be the most important and was selected more consistently than in the individual sampling event analyses, as were the fertiliser terms. Leaf tissue K concentration, NDVI and the dead vegetation fraction were consistently selected in pooled spring datasets and leaf tissue sodium and legume fraction in autumn and all seasons, with the addition of leaf tissue zinc concentration and dry matter percentage in all seasons.

The analysis was run using all of the plots individually, or the mean or the median of the 5 plots at one site. The mean almost always had the highest R^2 value, although not always the smallest RMSE. The mean or median of the 5 plots had the lowest RMSE. The number of predictors selected varied from 3-14 for the individual sampling events and from 7-18 for the pooled datasets. A larger number of predictors were selected when the regression analysis was run on the datasets containing the individual pegs rather than the average or median of the 5 plots at each site.

5.3.2 Leaf tissue nutrient concentration

Phosphorus concentration in the leaf tissue was consistently selected as a significant factor with a positive coefficient and large influence on the regression model. Copper concentration was also consistently selected in the regression analysis, however the coefficient was always negative. Nitrogen was not selected as a significant variable in most of the regression analyses. Where selected, the sign of the coefficient was inconsistent. The coefficient for leaf tissue K concentration was always positive, where selected. Potassium was often a selected factor where P is not selected or has a lesser effect in the model. Leaf tissue S concentration was not

selected in the majority of models, however where significant, the coefficient was negative, with only one exception. Sulphur was selected as a significant variable at Ohorea Station and Cleardale, but seldom on any other farm. Sodium was more commonly selected in pooled datasets than individual sampling events. The coefficient for sodium was inconsistent but generally negative, and consistently negative in pooled datasets. Manganese and Boron were not selected as a significant variable in most of the regression analyses, where selected the sign of the coefficient was inconsistent. Zinc, with the exception of Pati Tapu in the autumn, had a positive coefficient where significant.

5.3.3 Topographic variables

Of the topographic variables, slope appeared to be the most important factor. Elevation was selected in few regression models. Where selected the coefficient was generally negative. The coefficient for slope was consistently negative and selected for most of the pooled datasets. Aspect was selected in few of the regression analyses and the sign of the coefficient was inconsistent, though always positive in pooled data sets.

5.3.4 Climatic variables

The 30 day average rainfall leading into the sampling events was used only in pooled datasets as there was only one value per sampling event. Rainfall and soil moisture deficit were selected for the spring and all pooled data, except where farm indicator variables were used. Rainfall had a positive, and soil moisture deficit a negative, coefficient. Pasture growth rate was seldom selected, however consistently had a positive coefficient where included.

5.3.5 Fertiliser history

The fertiliser terms for the pooled datasets appeared to have more influence on the regression models than for individual sampling events, although less so where farm indicator variables were used. The amount of phosphate fertiliser applied for the three years prior to the sampling event had particularly strong importance at Harwoods.

5.3.6 Botanical composition

Pasture biophysical parameters were more consistent across pooled datasets with the coefficients for dry matter percentage and the dead vegetation fraction consistently positive, and NDVI and legume fraction consistently negative. The signs of the coefficient for the individual sampling events generally followed the same trends but there were some exceptions.

Table 5-2: Results of the stepwise linear regression analysis of individual sampling events

Season	Farm	Data	Adj-R-Sq (%)	RMSE	n	Max Olsen P	Min Olsen P	Constant	ELEV	SLOPE	ASP	SMD	PGR	PFTS	PFLAR	PF3Y	PLANTN	PLANTP	PLANTK	PLANTS	PLANTCu	PLANTNa	PLANTMn	PLANTZn	PLANTB	DM%	NDVI	DVF	LF	No of predictors
Early Summer 2013	NLD	All plots	**41.1**	0.41	385	98	4	3.11	0.13 ***	-0.18 ***					0.05 *		0.17 ***	0.27 ***			-0.52 ***	-0.06 *		0.24 ***		0.16 ***			-0.05 *	10
		Mean	**70.9**	0.24	77	86.8	5.6	3.11	0.12 **	-0.16 ***					0.10 **			0.19 ***	0.43 ***		-0.53 ***	0.14 **		0.30 ***		0.32 ***				9
		Median	**47.0**	0.35	77	94	6	3.10		-0.13 *				-0.13 **				0.24 ***	0.28 ***		-0.41 ***					0.17 *				6
Late Summer 2014	NLD	All plots	**46.2**	0.38	397	104	4	3.10	-0.07 *	0.08 **		0.23 ***	0.15 ***			0.10 ***	0.14 ***	0.18 ***			-0.28 ***		-0.12 ***	0.17 ***	-0.06 *	0.10 *	0.20 ***		-0.21 ***	14
		Mean	**60.5**	0.27	80	96	6.8	3.10				0.22 ***	0.13 **			0.10 **	0.16 **				-0.45 ***		-0.19 ***	0.34 ***			0.19 ***		-0.22 ***	9
		Median	**44.0**	0.34	80	97	5	3.08										0.20 **	0.23 ***		-0.38 ***			0.23 ***					-0.16 **	5
Winter 2014	NLD	All plots	**51.2**	0.27	218	123	4	3.05				x						0.28 ***			-0.22 ***	-0.07 *	-0.07 *	0.37 ***						5
		Mean	**66.7**	0.18	47	97.8	5	3.04				x						0.24 ***			-0.19 ***		-0.10 *	0.39 ***						4
		Median	**56.6**	0.21	47	88	4	3.02				x						0.30 ***			-0.21 ***	-0.11 *		0.36 ***						4
Autumn 2014	NAT	All plots	**46.9**	0.50	395	90	2	2.72		-0.11 ***	-0.14 ***				0.30 ***			0.32 ***			-0.17 ***	-0.16 ***		0.15 ***	-0.07 **				-0.06 *	9
		Mean	**50.4**	0.41	80	67	3.6	2.72			-0.14 *				0.24 ***			0.31 ***				-0.20 **		0.12 *	-0.12 *				-0.12 *	7
		Median	**54.6**	0.39	80	67	3	2.70			-0.17 **							0.22 **				-0.13 *		0.15 **	-0.16 **		0.25 ***		-0.13 *	7
	NLD	All plots	25.9	0.43	396	130	5	3.18										0.13 **	0.18 ***		-0.22 ***			0.15 ***	-0.08 **	0.10 **				6
		Mean	**34.7**	0.34	80	109.4	6.6	3.18											0.24 ***		-0.26 ***			0.20 ***	-0.09 *					4
		Median	**32.6**	0.36	80	109	6	3.17											0.32 ***		-0.26 ***			0.19 ***		0.13 *				4
Autumn 2015	NTT	All plots	**53.1**	0.36	392	85	4	2.93				0.10 **	0.06 *	x	x	-0.13 **		0.34 ***			-0.17 ***	-0.13 ***	-0.11 ***		0.08 ***		0.10 *		-0.08 ***	10
		Mean	**55.1**	0.32	80	79.2	7	2.93						x	x			0.44 ***		-0.18 *			-0.14 **						-0.11 **	4
		Median	**56.2**	0.32	80	81	6	2.93						x	x			0.42 ***			-0.20 ***	-0.11 *	-0.12 **		0.09 *					5
	NER	All plots	**47.3**	0.40	341	102	3	2.92	-0.16 ***	-0.11 ***		-0.08 **				0.07 *		0.49 ***			-0.27 ***	0.09 **					-0.17 ***		-0.11 ***	9
		Mean	**57.5**	0.32	73	97.6	4.8	2.93	-0.21 ***				0.11 *					0.57 ***			-0.30 ***	0.15 **					-0.20 **		-0.12 *	7
		Median	**49.5**	0.36	73	99	5	2.93	-0.18 **			-0.12 *						0.53 ***			-0.27 ***	0.13 *					-0.18 *		-0.12 *	7
	NAT	All plots	**48.4**	0.44	388	76	3	2.76		-0.19 ***	-0.17 ***	0.11 **				0.12 ***	0.11 **	0.37 ***		-0.35 ***		-0.10 ***		0.07 **	-0.06 *			-0.09 **	-0.10 ***	12
		Mean	**67.0**	0.29	80	56.6	4.6	2.76		-0.19 ***	-0.10 **					0.14 **	0.18 **	0.52 ***		-0.51 ***			0.11 **		-0.08 *					8
		Median	**64.6**	0.31	80	51	4	2.74		-0.12 *	-0.10 **					0.10 *		0.40 ***	0.26 **	-0.43 ***			0.13 **							7
Autumn 2016	NPT	All plots	**51.9**	0.33	386	65	4	2.80				0.10 ***	0.06 *	-0.14 ***	0.19 ***			0.30 ***				-0.14 ***	-0.05 *	-0.11 ***				0.12 ***		9
		Mean	**65.3**	0.23	78	42.6	4.4	2.80				0.08 *		-0.13 ***	0.19 ***			0.31 ***				-0.13 ***		-0.12 **				0.16 ***		7
		Median	**56.9**	0.26	78	43	4	2.81						-0.13 ***	0.20 ***			0.28 ***				-0.11 **		-0.16 ***				0.13 **		6

	SCD	All plots	**56.0**	0.30	161	60	5	2.86	0.16 ***	-0.11 **	0.13 ***			-0.30 ***				0.27 ***				-0.16 ***						0.12 **		7
	SCD	Mean	**62.3**	0.29	41	52	5.4	2.75						-0.13 *				0.51 ***		-0.20 *										3
	SCD	Median	**62.1**	0.30	41	51	5	2.75						-0.16 *				0.53 ***		-0.22 *										3
	SHA	All plots	**65.2**	0.37	333	125	3	2.43			0.10 **		0.11 **			0.38 ***	-0.20 ***	0.17 ***	0.27 ***									0.19 ***	0.09 **	8
	SHA	Mean	**73.4**	0.30	68	77.8	4.4	2.43								0.39 ***	-0.27 ***		0.37 ***									0.20 ***	0.19 **	5
	SHA	Median	**61.8**	0.36	68	61	4	2.41							0.14 *	0.40 ***						-0.24 ***								3
Spring 2014	NTT	All plots	**52.0**	0.39	385	71	4	2.86						x	x	0.08 **	-0.08 *	0.34 ***				-0.09 ***	-0.13 ***		-0.08 ***		-0.07 *			7
	NTT	Mean	**55.4**	0.33	78	65.6	6.6	2.86						x	x			0.37 ***					-0.16 ***					0.17 **		3
	NTT	Median	**50.7**	0.35	78	66	7	2.86						x	x		-0.22 **	0.42 ***				-0.08 *	-0.14 **							4
	NLD	All plots	**47.4**	0.37	370	127	5	3.13	-0.08 **			-0.06 **						0.28 ***	0.21 ***	-0.08 *	-0.18 ***	0.06 *	0.09 **	0.22 ***	-0.08 **	0.07 **				11
	NLD	Mean	**57.3**	0.29	76	110.6	6	3.15										0.21 ***	0.31 ***		-0.24 ***		0.16 **	0.23 ***		0.09 *				6
	NLD	Median	**57.7**	0.30	76	115	6	3.14										0.16 **	0.30 ***		-0.24 ***		0.12 *	0.24 ***						5
	NAT	All plots	**66.5**	0.37	384	96	4	2.68	-0.07 **	-0.17 ***				-0.06 **	0.35 ***			0.55 ***		-0.15 ***	-0.09 **			0.09 **						8
	NAT	Mean	**78.8**	0.25	80	62.8	5	2.69	-0.10 **	-0.13 **				-0.09 **	0.34 ***			0.43 ***	0.15 **	-0.18 ***										7
	NAT	Median	**76.1**	0.27	80	61	5	2.65	-0.11 **	-0.13 **					0.32 ***			0.46 ***	0.16 **	-0.17 ***							-0.12 **			7
	NER	All plots	**59.7**	0.31	389	92	5	3.14			0.06 **	-0.13 ***		0.07 **		0.10 ***		0.41 ***			-0.16 ***	-0.05 **					-0.09 ***		-0.11 ***	9
	NER	Mean	**63.6**	0.27	78	75.6	8.4	3.14				-0.09 **						0.41 ***			-0.12 *						-0.12 **		-0.13 **	5
	NER	Median	**62.1**	0.28	78	72	9	3.13				-0.11 **						0.36 ***						-0.07 *			-0.14 ***		-0.17 ***	5
Spring 2015	NPT	All plots	**54.6**	0.34	385	96	3	2.40	0.07 **	-0.12 ***	0.06 **	0.07 **		-0.05 **	0.24 ***			0.33 ***			-0.12 ***	-0.14 ***	-0.12 ***		0.08 ***	0.11 ***			-0.06 **	13
	NPT	Mean	**62.0**	0.27	77	36.4	3	2.40		-0.09 *	0.11 **				0.23 ***			0.31 ***				-0.08 *	-0.16 ***			0.21 ***				7
	NPT	Median	**58.7**	0.30	77	37	3	2.39							0.20 ***			0.32 ***					-0.11 **			0.20 ***			-0.08 *	5
	SCD	All plots	**77.6**	0.30	263	54	3	2.62	0.14 ***	0.13 ***		0.23 ***	0.27 ***	-0.19 ***	-0.15 ***			0.52 ***			-0.18 ***			0.06 **				0.11 ***		10
	SCD	Mean	**78.8**	0.25	55	44.8	3.8	2.60										0.74 ***		-0.23 **		0.10 *	0.19 ***	-0.09 *				0.14 **		6
	SCD	Median	**81.7**	0.24	55	44	4	2.59							-0.17 ***			0.64 ***			-0.27 ***	0.14 **	0.11 *					0.17 ***	0.11 *	7
	SLA	All plots	**52.5**	0.30	353	50	3	2.86	-0.08 ***	-0.06 *	0.07 *	-0.05 *		x		0.04 *		0.40 ***			-0.24 ***			0.20 ***		0.18 ***				9
	SLA	Mean	**62.1**	0.24	76	38.6	4.6	2.86						x		0.07 *		0.43 ***			-0.31 ***			0.24 ***		0.14 *				5
	SLA	Median	**56.5**	0.26	76	40	4	2.84	-0.10 **					x				0.32 ***			-0.27 ***			0.27 ***						4
	SHA	All plots	**72.6**	0.30	324	76	3	2.44				-0.20 ***				0.28 ***		0.24 ***	0.23 ***			0.12 ***	0.06 **			0.08 *	-0.15 ***	0.10 ***		9
	SHA	Mean	**80.1**	0.23	67	59.25	5	2.45				-0.17 ***				0.27 ***		0.21 ***	0.22 ***			0.13 *					-0.22 ***	0.16 **		7
	SHA	Median	**74.8**	0.26	67	58.5	5	2.45				-0.17 ***				0.25 ***			0.18 ***	0.17 **							-0.18 **	0.15 **		6

Notation: Farm — NLD: Limestone Downs, NAT: Ohorea Station, NTT: Tautane Station, NER: Erewhon Station, NPT: Pati Tapu Station, SCD: Cleardale, SHA: Harwoods, SLA: Lawsons/Moana Farms

Data — All pegs: individual pegs

Mean: calculated mean of the 5 pegs at each site

Median: calculated median of the 5 pegs at each site

Level of significance

* 0.05-0.01

** 0.01-0.001

*** < 0.001

Table 5-3: Results of the stepwise linear regression analysis of pooled datasets to predict soil Olsen P

Season	Farm		Adj-R-Sq	RMSE	n	Max Olsen P	Min Olsen P	Constant	SEASON		FARM								ELEV	SLOPE	ASP	RAIN30	SMD	PGR	PFTS	PFLAR	PF3Y	PLANTN	PLANTP	PLANTK	PLANTS	PLANTCu	PLANTNa	PLANTMn	PLANTZn	PLANTB	DM%	NDVI	DVF	LF	No of predictors
Autumn 2014/2015/2016	All farms	All plots	37.8	0.47	2792	130	2	2.83	x	x	x	x	x	x	x	x	x	x	-0.11 ***	-0.10 ***			-0.07 ***		0.05 ***	0.09 ***	0.13 ***		0.34 ***		-0.08 ***	-0.11 ***	-0.14 ***	-0.05 ***						-0.09 ***	12
		Mean	45.4	0.40	580	109	4	2.82	x	x	x	x	x	x	x	x	x	x	-0.10 ***	-0.07 **			-0.06 **		0.05 *	0.11 ***	0.12 ***		0.30 ***	0.12 ***	-0.12 **	-0.13 ***	-0.11 ***						-0.09 ***	12
		Median	44.4	0.41	580	109	3	2.81	x	x	x	x	x	x	x	x	x	x	-0.10 ***	-0.06 **			-0.06 *		0.06 *	0.10 ***	0.13 ***		0.29 ***	0.13 ***	-0.11 **	-0.14 ***	-0.10 ***						-0.09 ***	12
											NLD	NAT	NTT	NER	NPT	SCD	SLA	SHA																					
	All farms	All plots	40.3	0.46	2800	130	2	2.83	x	x	0.12 ***	-0.09 ***			-0.05 ***	0.10 ***			-0.12 ***	-0.08 ***				0.04 **			0.18 ***		0.36 ***		-0.09 ***	-0.10 ***	-0.14 ***			-0.02 *				-0.08 ***	10
		Mean	47.8	0.39	580	109	4	2.82	x	x	0.11 ***	-0.10 ***			-0.07 **	0.06 **			-0.12 ***	-0.07 **							0.17 ***		0.33 ***			-0.14 ***	-0.16 ***							-0.11 ***	7
		Median	46.8	0.40	580	109	3	2.81	x	x	0.10 ***	-0.10 ***			-0.07 **	0.07 **			-0.11 ***	-0.06 **							0.18 ***		0.34 ***			-0.15 ***	-0.13 ***							-0.11 ***	7
	All NORTH Is. farms	All plots	35.2	0.47	2298	130	2	2.88	x	x	x	x	x	x	x	x	x	x	-0.11 ***	-0.08 ***				0.05 **	0.07 ***	0.13 ***	0.12 ***		0.36 ***		-0.09 ***	-0.12 ***	-0.09 ***	-0.04 **	0.03 *					-0.09 ***	13
		Mean	41.8	0.40	471	109	4	2.89	x	x	x	x	x	x	x	x	x	x	-0.12 ***	-0.07 **					0.09 ***	0.14 ***	0.12 ***		0.32 ***			-0.15 ***	-0.11 ***							-0.11 ***	9
		Median	41.1	0.41	471	109	3	2.88	x	x	x	x	x	x	x	x	x	x	-0.12 ***	-0.07 **					0.09 ***	0.13 ***	0.13 ***		0.33 ***			-0.17 ***	-0.11 ***							-0.10 ***	9
	All SOUTH Is. farms	All plots	59.9	0.38	494	125	3	2.57	x	x	x	x	x	x	x	x	x	x		-0.09 ***	0.07 ***					-0.15 ***		0.22 ***	-0.15 ***	0.15 ***	0.32 ***		-0.10 **			0.08 **	-0.07 **		-0.27 ***			11
		Mean	65.8	0.32	109	78	4	2.55	x	x	x	x	x	x	x	x	x	x		-0.08 *	0.07 *					-0.28 **		0.17 *	-0.19 **	0.15 *	0.24 ***	-0.16 *	-0.12 *				-0.09 *		-0.28 ***			9
		Median	63.6	0.34	109	61	4	2.54	x	x	x	x	x	x	x	x	x	x				-0.39 ***																			7
Spring 2014/2015	All farms	All plots	47.6	0.44	2853	127	3	2.78	x	x	x	x	x	x	x	x	x	x	0.04 **	-0.09 ***	0.02 **	0.21 ***	-0.26 ***		-0.05 ***	0.27 ***	-0.04 **	-0.11 ***	0.35 ***	0.16 ***		-0.12 ***				0.07 ***				-0.09 ***	0.06 ***	-0.02 *	16
		Mean	50.1	0.39	587	111	3	2.78	x	x	x	x	x	x	x	x	x	x		-0.07 ***		0.27 ***	-0.28 ***			0.26 ***			0.30 ***	0.15 ***		-0.18 ***				0.07 ***			-0.14 ***	0.05 *		10
		Median	48.9	0.40	587	115	3	2.77	x	x	x	x	x	x	x	x	x	x		-0.08 ***		0.24 ***	-0.27 ***			0.24 ***		-0.13 ***	0.34 ***	0.17 ***		-0.13 ***				0.07 ***			-0.11 ***	0.05 *		11
											NLD	NAT	NTT	NER	NPT	SCD	SLA	SHA																					
	All farms	All plots	53.0	0.41	2869	127	3	2.78	x	x		-0.13 ***	-0.16 ***		-0.28 ***	-0.07 ***		-0.06 ***	-0.05 ***	-0.06 ***	0.02 **					0.12 ***	-0.06 **	0.36 ***	0.18 ***		-0.12 ***				0.06 ***				0.06 ***	-0.03 *	0.10 ***	-0.03 **	13
		Mean	57.3	0.36	587	111	3	2.78	x	x	0.24 ***	0.17 ***	0.08 ***	0.24 ***				0.10 ***	0.19 ***				-0.19 ***		0.07 *			0.32 ***	0.21 ***		-0.17 ***				0.05 *				-0.13 ***	0.10 ***		9
		Median	56.5	0.37	590	115	3	2.77	x	x	0.18 ***			0.16 ***	-0.12 ***			0.06 *	0.09 ***				-0.08 **			0.09 ***		0.31 ***	0.21 ***		-0.12 ***		0.06 **			-0.05 **		-0.14 ***	0.07 **		10
	All NORTH Is. farms	All plots	53.0	0.41	1918	127	3	2.84	x	x	x	x	x	x	x	x	x	x		-0.07 ***	0.03 **	0.17 ***	-0.18 ***	0.05 ***		0.24 ***		-0.10 ***	0.34 ***	0.12 ***	-0.07 ***	-0.05 **		-0.10 ***	0.08 ***	-0.04 **		-0.08 ***		-0.05 ***	16
		Mean	55.9	0.37	389	111	3	2.85	x	x	x	x	x	x	x	x	x	x				0.23 ***	-0.23 ***			0.30 ***			0.31 ***	0.18 ***	-0.13 ***							-0.11 ***		-0.09 ***	8
		Median	58.5	0.36	389	115	3	2.83	x	x	x	x	x	x	x	x	x	x		-0.06 *	0.04 *	0.13 ***	-0.24 ***	0.07 *		0.22 ***		-0.19 ***	0.30 ***	0.15 ***								-0.10 ***			13
	All SOUTH Is. farms	All plots	55.8	0.38	940	76	3	2.65	x	x	x	x	x	x	x	x	x	x							-0.08 ***	-0.16 ***	0.16 ***		0.37 ***	0.12 ***		-0.16 ***		0.11 ***					-0.07 ***	0.10 ***		9
		Mean	60.8	0.33	198	59	4	2.65	x	x	x	x	x	x	x	x	x	x								-0.16 ***	0.20 ***		0.37 ***	0.09 *		-0.20 ***		0.15 ***					0.16 ***		7
		Median	57.6	0.35	198	59	4	2.64	x	x	x	x	x	x	x	x	x	x								-0.17 ***	0.21 ***		0.35 ***	0.09 *		-0.19 ***		0.17 ***					0.13 ***		7
ALL FARMS/ ALL SEASONS	All farms	All plots	37.3	0.47	6645	130	2	2.85	x	x	x	x	x	x	x	x	x	x	-0.03 ***	-0.11 ***	0.01 *	0.06 ***	-0.10 ***		-0.03 **	0.15 ***	0.03 **		0.33 ***			-0.15 ***	-0.08 ***	-0.05 ***	0.09 ***					-0.08 ***	16
		Mean	42.0	0.41	1375	111	3	2.84	x	x	x	x	x	x	x	x	x	x		-0.10 ***		0.06 ***	-0.11 ***		-0.04 **	0.18 ***			0.33 ***			-0.14 ***	-0.07 ***	-0.04 *	0.08 ***				0.05 *	0.07 **	-0.10 ***	13
		Median	40.1	0.43	1375	115	3	2.83	x	x	x	x	x	x	x	x	x	x		-0.10 ***		0.06 ***	-0.11 ***		-0.04 **	0.18 ***			0.33 ***			-0.15 ***	-0.07 ***	-0.03 *	0.08 ***				0.06 *	0.05 **	-0.09 ***	13
									LSM	AUT																														
		All plots	37.6	0.47	6646	130	2	2.85	-0.03 **	0.03 ***	x	x	x	x	x	x	x	x	-0.03 ***	-0.10 ***	0.01 *	0.06 ***	-0.13 ***		-0.02 **	0.15 ***	0.03 **		0.35 ***		-0.03 **	-0.14 ***	-0.07 ***	-0.05 ***	0.08 ***				0.05 ***	-0.08 ***	17
		Mean	43.8	0.41	1372	111	3	2.84		0.12 ***	x	x	x	x	x	x	x	x		-0.08 ***		0.05 **	-0.12 ***	0.08 ***	-0.06 ***	0.18 ***			0.28 ***	0.19 ***	-0.06 **	-0.16 ***			0.08 ***			0.07 **	-0.08 ***		-0.08 ***	14
		Median	40.3	0.42	1373	115	3	2.83		0.10 ***	x	x	x	x	x	x	x	x		-0.10 ***		0.05 **	-0.12 ***	0.08 ***	-0.04 **	0.20 ***			0.35 ***			-0.15 ***	-0.08 ***		0.05 **			0.05 *	-0.05 *		-0.08 ***	13
									WIN	SPR	NLD	NAT	NTT	NER	NPT	SCD	SLA	SHA																					
		All plots	41.6	0.45	6682	130	2	2.85	-0.04 ***	-0.08 ***		-0.06 ***	-0.06 ***		-0.19 ***	-0.03 ***			-0.10 ***	-0.08 ***	0.02 *	-0.07 ***		0.02 *	-0.02 *	0.06 ***	0.11 ***	0.03 **	0.38 ***		-0.06 ***	-0.16 ***	-0.10 ***	-0.03 ***	0.08 ***				0.05 ***	0.05 ***	-0.08 ***	18
		Mean	48.9	0.39	1377	111	3	2.84	-0.06 ***	-0.06 ***	0.20 ***	-0.05 ***			-0.12 ***					-0.06 ***					-0.05 ***		0.10 ***		0.28 ***	0.15 ***		-0.17 ***	-0.07 ***		0.08 ***				0.12 ***		-0.09 ***	10
		Median	42.9	0.42	1371	115	3	2.83		-0.09 ***		-0.05 ***			-0.12 ***		0.06 ***			-0.08 ***				0.06 ***		0.14 ***	0.08 ***		0.35 ***			-0.15 ***	-0.11 ***		0.05 **			0.05 *		0.06 **	-0.08 ***	11

Notation: Farm NLD: Limestone Downs, NAT: Ohorea Station, NTT: Tautane Station, NER: Erewhon Station, NPT: Pati Tapu Station, SCD: Cleardale, SHA: Harwoods, SLA: Lawsons/Moana Farms

Data All pegs: individual pegs

Mean: calculated mean of the 5 pegs at each site

Median: calculated median of the 5 pegs at each site

Level of significance * 0.05-0.01, ** 0.01-0.001, *** < 0.001

5.4 Discussion

The stepwise multiple linear regression analysis to predict soil Olsen P provided an exploratory study which enabled so understanding of the importance and effect of different variables. Environmental data is noisy and there are many sources of variation. Hill country farming systems are dynamic, constantly changing with animal grazing, plant growth, and weather, and also seasonally with pasture species composition, plant maturity, grazing strategies and pressure, climate, and fertiliser. They are generally unique with their own landscape, farm management style and farmer preferences. All of these factors combine to create an individual system, and the importance and effect of different factors will depend on the system itself. It was necessary to understand the effect of different variables to identify broad scale patterns, and ensure the effects reflect reality in terms of known agronomic relationships, thereby avoiding the possibility of artificial relationships as can often happen with highly correlated data.

The results from the pooled datasets in the stepwise linear regression analysis gave a higher level of explanation than the simple plant P indices presented in the previous chapter, regardless of the inclusion or exclusion of farm and season indicator variables. For the pooled datasets, the R^2 ranged from 0.38 to 0.66 for the season specific models and 0.37 to 0.49 for completely pooled data. For plant P indices (P, PNI and PNI_c) the R^2 values for spring, autumn, and combined seasons were 0.21-0.24, 0.12, and 0.12-0.13 respectively. The additional factors improved the ability to predict soil Olsen P.

5.4.1 Phosphorus concentration in the leaf tissue

Phosphorus concentration in the plant leaf tissue (*PLANTP*) was the most important factor in predicting soil Olsen P. This was expected to be an important factor, as P concentration and its relationship to soil Olsen P in other studies was discussed in the previous chapter, section 4.4.3. Studies including Burkitt et al. (2010); Kawamura et al. (2011); Liebisch (2011); Loranger (2016) have shown the extent to which P in the leaf tissue can be used to identify the status of soil phosphate availability.

5.4.2 Copper concentration in the leaf tissue

Copper concentration in pasture leaf tissue (*PLANTCu*) was a significant negative factor in many of the regression analyses, but copper cycling in agriculture is not as well understood as other nutrients. Copper deficiency in New Zealand pastures is well known in relation to animal dietary requirements, and has been recognised since the early 1940's (Grace et al., 2010). However, copper in relation to plant growth is less researched, possibly as there appears to be

no significant restriction to pasture growth due to copper deficiency (Jarvis & Whitehead, 1981). In predicting soil Olsen P, the coefficient for leaf tissue copper concentration was consistently selected and always negative.

Literature has been published in relation to: copper concentration in different species (Cornforth, 1984a, 1998b; Gladstones, Loneragan, & Simmons, 1975; Harrington et al., 2006; Longhurst, Roberts, & Waller, 2004); stage of pasture maturity (Cornforth, 1984a; Fleming & Murphy, 1968; Gladstones et al., 1975; Schlegel et al., 2016); phosphate fertiliser (Cornforth, 1998b; Lambert & Grant, 1980; Murphy, Ellis Jr, & Adriano, 1981; Reuter, Robson, Loneragan, & Tranthim-Fryer, 1981); and lime applications (Cornforth, 1998b; Lambert & Grant, 1980; Murphy et al., 1981). Many studies observed a relationship between copper concentration in plant leaf tissue and the use of phosphate fertiliser, and although no definitive explanation has been given to the scientific reason for this, it appears this is the most plausible explanation for its significance in the model. Further research would be required to investigate the significance of copper.

Copper concentration is known to vary in leaf tissue, particularly between **different species**. Literature consistently reports legumes having a higher concentration of copper in the leaf tissue than grasses (Cornforth, 1998b; Gladstones et al., 1975; Metson, Gibson, Hunt, & Saunders, 1979b; Reay & Marsh, 1976; Schlegel et al., 2016). Gladstones et al. (1975) also observed that the rate of decline in copper concentration in the leaf tissue in advancing maturity was slower in legumes than grasses and herbs. Longhurst et al. (2004) observed weeds had higher copper concentration than grass and legume, but copper concentration was significantly higher in weeds on non-farmed than farmed pasture. This may be due to the use of phosphate fertiliser. Harrington et al. (2006) found copper concentration was significantly higher in chicory, narrow-leaved plantain, Californian thistle, dandelion and hairy buttercup compared to perennial ryegrass and white clover in organic dairy pasture. Of these species, only the weedy species, dandelion and hairy buttercup, were recorded often in the three most dominant species in the visual estimation. Copper concentration linked to species could highlight the greater proportion of such weedy species on areas with lower fertility: Olsen P.

Leaf tissue copper concentration has been shown to decrease with increased use of **phosphate fertiliser** in a range of plant species. The addition of phosphate fertiliser has induced copper deficiencies in: poplar (Teng & Timmer, 1990); Douglas fir and Scots pine seedlings, and poplar and willow cuttings (Smilde, 1973), wheat (Shukla & Singh, 1979), citrus (Olsen, 1972) and pasture grasses and legumes (Lambert & Grant, 1980; Reuter et al., 1981). Copper deficiency is

mentioned or included in a list of micronutrient deficiencies induced due to heavy applications of phosphate fertiliser (Cornforth, 1998b; Lambert & Grant, 1980; Murphy et al., 1981; Reuter et al., 1981) and lime (Cornforth, 1998b; Lambert & Grant, 1980; Murphy et al., 1981). In some literature it is said to occur, or is amplified, when the availability of copper is at or near deficient levels (Adriano, 1986; Cornforth, 1998b; Murphy et al., 1981). The addition of superphosphate to North Island hill pastures has resulted in an increase in soil Olsen P and a decrease in legume copper concentration in leaf tissue (Lambert & Grant, 1980). Similarly, copper deficiency was induced in subterranean clover grown in a pot trial with increasing supply of P (Reuter et al., 1981). Explanations given for the induced copper deficiency in highly fertilised crops with phosphate fertiliser is not clear. Reuter et al. (1981) stated that phosphate fertiliser encouraged growth in the plant and resulted in a dilution of copper in the leaf tissue, which was partly responsible for the observed copper deficiency. Smilde (1973) had earlier suggested that P interferes with the translocation of copper from roots to shoots. Reuter et al. (1981) also state that copper absorption was depressed but that it was not known how phosphate fertilisers depress copper absorption in plants.

The availability of soil nutrients for uptake by plants is affected by **soil pH**. Copper is known to be more readily available in more acidic soils, most readily available around pH 5.0, and decreasing through to a pH of around 5.5. The availability of P is greatest at pH 6.0-7.0, decreasing above or below this. However there does not appear to be any clear evidence of this relationship expressed through the leaf tissue, Figure 5-1. Copper concentration did not appear to be higher in the leaf tissue in plants growing in more acidic soils; neither did P concentration appear to be higher in the leaf tissue in plants growing in soils where pH allows soil phosphate to be most readily available. It is therefore unlikely that the significance of copper as a predictor is related to availability of copper in relation to pH, which would also affect the availability of soil phosphate.

The most plausible explanation that copper concentration was important in the model may be related to, in part, either the use of phosphate fertiliser or pasture species. Although no strong correlation was found between phosphate fertiliser terms in the model and leaf tissue copper concentration, the fertiliser history going back only a few years used in the fertiliser terms does not hold information on the long term fertiliser history that could date back more than 50 years. For example, fertiliser use at Pati Tapu was among the highest rates used of all the farms. However, prior to this it is known that the previous owners used very little fertiliser at all and perhaps none in some areas. This may also explain why copper was not a significant

factor at Pati Tapu when farms were analysed individually. However more research into this area is needed to understand this relationship properly.

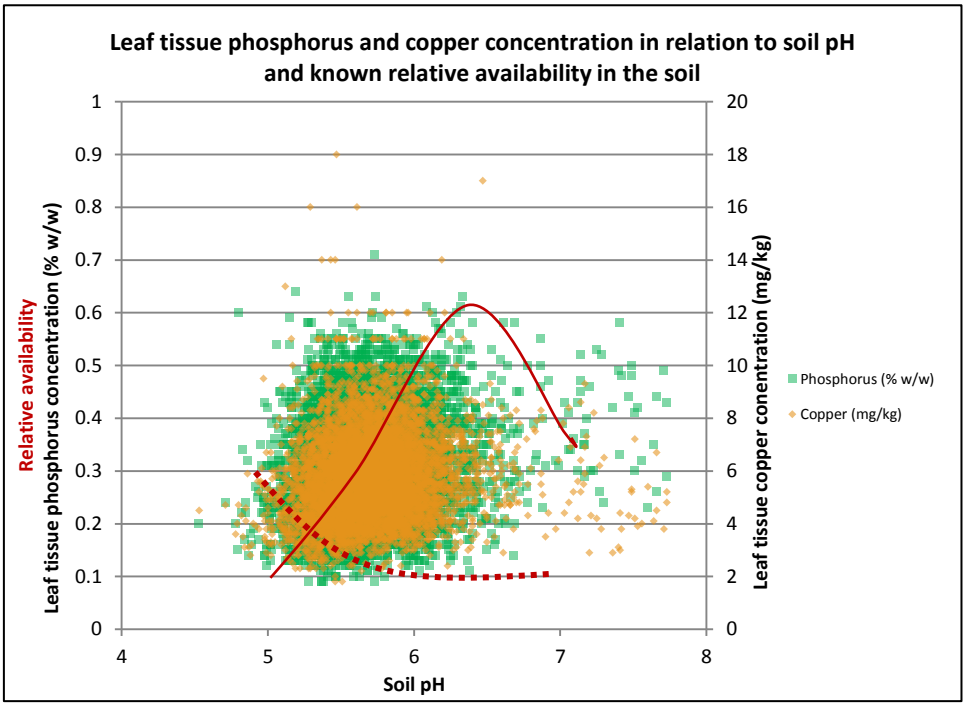


Figure 5-1: Leaf tissue phosphorus and copper concentrations compared to soil pH, with the relative availability in the soil of each nutrient (as shown in McLaren and Cameron (1996)) in relation to soil pH superimposed on the graph.

5.4.3 Other nutrients concentration in the leaf tissue

Leaf tissue P and K concentration are highly correlated. The macronutrients, N, P, K and S are known to be highly correlated in pasture leaf tissue, as were also shown by Jones and Tracy (2015). Potassium was generally selected where P was not, or when the coefficient for P was smaller. In rerunning the regression model, excluding K, it was found that P was selected and there was very little difference in the level of explanation (results not shown).

There are vast amounts of literature available relating different nutrients in pasture to different factors (seasons, species, weather, fertiliser response, grazing management, soils, stage of maturity, antagonistic and synergistic nutrient uptake, etc.). Results from such studies are often contradictory and acknowledge their site or season specific influences. To explain all possible scenarios and reasons for the selection of different nutrients in the regression analysis would be extensive. Therefore this has not been discussed in detail in this thesis.

5.4.4 Sample composition

In the regression analysis containing only one sampling event, either dry matter percentage, NDVI or the dead vegetation fraction were selected. NDVI, dry matter percentage and amount of dead material are all highly correlated, as would be expected in leaf tissue samples. The

higher the content of dead material in the sample, the greater the DM%, due to the very low water content of dead vegetation. The dead vegetation fraction and DM% are negatively correlated to NDVI. NDVI is a vegetation index that is strongly linked to chlorophyll content. As dead vegetation increases and the content of green leafy material decreases, the chlorophyll content decreases. It is this strong multicolinearity between the variables that has probably meant only one of the three was selected. In the pooled datasets, often more than one variable was selected, which may result in artificial relationships. Sample composition is important as the amount of dead material in the plant tissue sample had a significant effect on the nutrient concentration in the tissue sample, as shown in the previous chapter.

5.4.5 Topographic variables

Of the topographic variables, slope was most often included in the regression models. Soil P has been reported to decrease with increasing slope (López, Lambert, Mackay, & Valentine, 2003; Rowarth, Tillman, Gillingham, & Gregg, 1992) and the consistently negative coefficient for slope in the regression analysis supported this. Topography influences soil forming processes and has a major effect on soil depth and nutrient cycling. Steeper slopes have shallower soil through more frequent soil erosion (McLaren & Cameron, 1996), affect the movement of water downhill which carries nutrients with it (McColl & Gibson, 1979), and constantly lose P through the transfer of nutrients by grazing animals (Rowarth et al., 1992). Given current agronomic knowledge, slope is a variable that was expected to be important and negatively correlated to soil Olsen P.

The selection and results of elevation in the individual sampling events were inconsistent with coefficients both positive and negative. When data is completely pooled, elevation is forced to have the same effect on all farms. Some coastal farms such as Limestone Downs and Tautane are at a much lower altitude, and therefore have much smaller values, than Erewhon and Cleardale. Although water and nutrients, such as phosphate, are known to move downslope (McColl & Gibson, 1979) and could therefore in some way be linked to elevation, the scale at which the elevation is over is important. When the data was combined, it essentially implied that a difference in Olsen P may exist from the top of the highest mountain, to the sea. The inclusion of elevation when analysing completely pooled data needed to be revised or another approach to data analysis was required.

Most studies that examine aspect in relation to hill country focus on pasture production (Gillingham, 1973; Lambert, 1977; Radcliffe, 1982; Radcliffe & Lefever, 1981), its effect on temperature and moisture (Gillingham & Bell, 1977) and how this relates to species

composition, plant growth, and plant development (Gillingham, 1973; Gillingham & Bell, 1977). The results of pasture growth monitoring at Ohorea (results not shown) suggest that while slope has a large impact on total pasture production, aspect has a strong influence of the seasonal pattern of growth. Betteridge et al. (2008) mention seasonal differences in soil temperate and moisture between steeper north and west faces, and south and east faces, determining conditions for good or poor growth. While the inclusion of aspect was inconsistent in individual sampling events where included in pooled data, it had a positive coefficient relating higher soil Olsen P on southeast facing slopes and lower on northwest.

5.4.6 Climatic and weather data

Soil Olsen P exhibited temporal variation but no seasonal trend as found in other studies (Friesen et al., 1985; Roberts, 1987), however leaf tissue P concentration showed seasonal trends which are well reported (Burkitt et al., 2010; Gillingham & During, 1973; Saunders & Metson, 1971; Walsh & Birrell, 1987). Variables were included in an attempt to account for the variation due to the seasonal and weather effects at the time of sampling. The inclusion of such variables was not straightforward and requires further investigation.

Soil moisture deficit was more consistently selected in pooled datasets where the coefficient was negative. It was observed in this dataset that as dry matter percentage or dead vegetation content in the sample increased, the leaf tissue P concentration decreased. Fleming (1973) linked the decrease in P content to soil moisture deficit as soils dry out. It is therefore likely that soil moisture deficit was important in the analysis for the same reason, accounting for drier conditions rather than a link to soil phosphate availability.

Although the effect of weather on leaf tissue nutrient concentration, and seasonal adjustments to account for this variation is scarce in literature, it is an important effect that must be handled in a model containing plant nutrient content collected from different points in time. Seasonal adjustments were included using indicator variables, which were selected when included in pooled data. However seasons are cyclic, differ from year to year and differ for different climatic zones. From analysing a range of leaf tissue nutrients and weather variables Jones and Tracy (2015) used coefficients for the calendar month, 15 days soil moisture, and 5 day relative humidity, prior to leaf tissue harvest to adjusted for changes over the growing season in N, P, K, S or Cu on their site in Virginia, U.S.A. They found nutrient concentration increased with increasing soil moisture and decreasing relative humidity, which they suggest are linked to transpiration rates and plant nutrient uptake. Roche et al. (2009b) found that season had a stronger effect than weather on leaf tissue nutrient concentration.

However, weather explained up to 14% of the variation in leaf tissue content, with P the most strongly affected nutrient compared to other nutrients: K, S, Ca, Na, Cu, Mo, Zn, Fe, Mg, Mn. The effect of weather was over and above that explained by season and farm, its influence did however differ across seasons.

A variable containing the average rainfall in the 30 days prior to the sampling event was added but as there was only one weather station at each farm, all data entries for each sampling event had the same value. As the variable was included more often where farms indicator variables were not, it was likely that the variable was acting as an indicator variable for individual sampling events, rather than any effect due to climatic conditions. Although weather data was collected hourly at weather stations, the temporal resolution of the leaf tissue nutrient concentration measurements was such that no meaningful analysis could be completed. However this is an important area that requires further research.

5.4.7 Fertiliser history

Phosphate fertiliser has been applied to New Zealand hill country soils, to increase phosphate availability to plants and lift production for many years, and has been the subject of much research. The fertiliser records on the eight farms vary greatly from Tautane and Limestone Downs that have applied fertiliser relatively uniformly; Cleardale and Erewhon who undertake quite varied fertiliser plans; and Lawsons and Harwoods that have missed large areas of their farms each year. All scenarios are not uncommon on hill country farms and poor farm profitability is often a cause of below maintenance rates of fertiliser applied (Cosgrove & Field, 2016). This makes the inclusion of fertiliser terms in a universal model more difficult.

It is widely known that application of phosphate fertiliser increases soil P content (Lambert et al., 2014; Rowarth et al., 1992), increases pasture production (Lambert et al., 2014), increases plant P concentration (Rowarth et al., 1988; Wilman et al., 1994) and influences dominant pasture species (Wan et al., 2009). When fertiliser is withheld or applied at rates below those required for maintenance, Olsen P declines (Roberts et al., 1994). It has been stated that in modern agricultural systems fertiliser application has more influence on herbage N, P and K than the underlying soil characteristics (Fleming, 1973) to the point where fertiliser history has been used to predict soil Olsen P (McCall & Thorrold, 1991).

Generally the fertiliser terms showed the expected effect on soil Olsen P, with a decrease as time since the last application increased, and an increase as the last application rate increased and the total applied in the three years prior to the sampling event increased. The variables holding information around the last fertiliser application are related to each other in that a

large dose of phosphate fertiliser applied a short time ago will have a different effect on the soil phosphate availability than if it had been applied years prior. The variable PFTS was the time in days since the last fertiliser application was made. However it may be better for the two variables, PFTS and PFLAR to be combined into one that incorporates the time since and the application rate of the last application.

5.5 Conclusion

The stepwise multiple linear regression analysis provided a useful exploratory study to begin to understand the variables and their effect. Variables that appeared to be important in predicting soil Olsen P were: leaf tissue P and copper concentration, slope, fertiliser history, the proportion of green tissue in the sample, and seasonal information. There were, however, many differences between individual farms when sampling events were analysed separately, highlighting that each farm is a unique system, but with were general trends across all farms.

The level of explanation for pooled datasets was greater than that of simple plant indices presented in the previous chapter. Levels of explanation are thought to be realistic given the observations and measurements are collected from real world situations on commercial working farms. Pooled datasets generally resulted in lower levels of explanation than can be achieved using a single sampling event. Complete pooling is known to result in under fitting. While the analysis using individual sampling events gains a higher level of explanation, the regression models use a unique set of variables and coefficients that would likely perform poorly if used on another farm or season. An approach is required where farms can be used to share information and inform general relationships across farms and seasons while accepting their uniqueness. Partial pooling is a technique that allows sharing of information across the dataset and was the next step taken in the following chapter, Chapter 6, through a hierarchical modelling approach.

6

6 Bayesian hierarchical modelling for the prediction of soil Olsen P across hill country farms

6.1 Introduction

The ultimate outcome of the research project would be to develop a model allowing predictions of soil Olsen P over any hill country farm in New Zealand to be made with a known level of uncertainty. The current technique for soil testing hill country farms involves bulking nine soil cores along 100m transects to obtain an average value for soil Olsen P. This information is spatially sparse and of limited use. The ability to use patterns in plant biochemical characteristics and ancillary data to estimate and then map the availability of phosphate in the soil across an entire hill country farm would provide enormous amounts of information. This could then be made available for farmers and fertiliser reps to base decisions around the best rate, product and placement of phosphate fertiliser. To rely heavily on the use of pasture biochemical and biophysical parameters, to create a model to infer underlying soil phosphate availability, that performs well across wide temporal and spatial scales, proved challenging.

Some research on local scale agricultural systems has shown vegetation characteristics reflect soil properties. To use this approach requires a good understanding of soil-plant interactions (Kawamura et al., 2011). The botanical composition of pasture (López et al., 2006; Wan et al., 2009), the morphology (Atkinson, 1973) and physiological characteristics (Kawamura et al., 2011; Liebisch, 2011) are known to vary with phosphate availability. Botanical composition, and plant physiological, phenological and morphological characteristics – including leaf tissue P concentration – vary with season, climate, soils, grazing, and farm management.

Simple experiments used to gain an understanding of complex environmental systems can often fail to apply to real world situations. Scaling up to conditions outside of those included in the dataset can be problematic, as important variables and processes happening at different scales may be missed. To attempt to include the complexity of such systems can lead to complicated models that are over fitted and have poor predictive power (Clark, 2005). Finding a relationship between primarily leaf tissue P concentration of heterogeneous pasture and soil phosphate availability over a wide spatial and temporal scale, with such a low signal to noise ratio, is a challenge few papers describe.

In the previous Chapter, the eight commercial hill country farms were analysed individually or the whole data set was pooled together as initial exploratory data analysis. Data collected from multiple sites were analysed separately (no pooling), or analysed altogether with no discrimination between sites (complete pooling), these approaches can lead to over fitting or under fitting of the data respectively. Hierarchical or multilevel modelling fits such datasets more appropriately as the estimates of population parameters allow for more accurate predictions over new sites (Gelman et al., 2013) or in this case, farms. A Bayesian approach to hierarchical multiple linear regression was used. In using hierarchical or multilevel modelling, it was intended that the broad scale patterns of the effects of the included variables on soil Olsen P would be identified. Models were validated using a leave-one-out-cross-validation.

This chapter aims to:

- Develop a Bayesian hierarchical multiple linear regression model to estimate soil Olsen P using the data collected at each site across the eight commercial farms.
- Validate the Bayesian hierarchical multiple linear regression model across the eight commercial farms using a leave-one-out-cross-validation.
- Discuss and highlight the realities, challenges and limitations of the data, model and the concept of this approach to predicting soil Olsen P.

6.2 Background

HIERARCHICAL MODELLING

Data collected at plot scale is increasingly being used to inform regional research and policy, particularly in ecology. This approach becomes even more challenging when analysing highly spatially variable elements such as soil properties (Kaye et al., 2008). Previous research attempting to find a direct relationship between leaf tissue P concentration and soil P availability were predominately on one site (Jones & Tracy, 2014; Kawamura et al., 2011; Rowarth & Gillingham, 1990) or multiple sites where sites were analysed independently (Burkitt et al., 2010; del Pino Machado, 1994; Roberts, 1987). Randomly sampling the entire area of New Zealand hill country is impractical. Therefore eight farms were chosen from different geographical areas, where land use was dominated by hill country farming. This sampling technique made data collection feasible, but results in clustered sampling within the population we are ultimately attempting to represent. Analysing and interpreting data collected using this type of clustered sampling must be treated appropriately. Clustered data is common in many datasets but its structure is often ignored in analysis. Three options can be taken when analysing clustered data (McElreath, 2016) and the implications of this in the dataset are:

- No pooling: this is when data from each cluster is kept separate. It assumes nothing can be learnt from one farm that can inform or improve our knowledge of another farm. (However, we know observations made on one farm can provide important information to improve our understanding on farms not yet visited.) A no pooling approach generally results in over fitting, especially in groups with smaller sample numbers as there is less data to inform estimates and the associated error is high.
- Complete pooling: this is when all data is pooled together. The population of farms is said to be invariant and all farms are considered identical, which is known to be false. Complete pooling results in under fitting, as it produces one coefficient for each variable for all farms.
- Partial pooling: this approach allows information to essentially be borrowed across farms to improve estimates of each farm, while recognising that the farms are individual. Predictions made on clusters outside of the dataset are also improved using partial pooling.

The approach taken was to use Bayesian hierarchical linear regression. Hierarchical models can be constructed relatively simply to account for processes operating at different scales (Qian,

Cuffney, Alameddine, McMahon, & Reckhow, 2010) and incorporate highly complex spatio-temporal problems (Clark, 2005).

BAYESIAN APPROACH

The Bayesian approach to statistics differs significantly from frequentist statistics in which the parameters are said to be fixed and unknown. In a Bayesian approach, parameters are treated as random variables whose probability distribution is used to quantify them along with their uncertainty. Bayesian inference has been used extensively in the medical sciences and is becoming a more popular approach in environmental sciences (Aguilera, Fernández, Fernández, Rumí, & Salmerón, 2011a; Chen & Pollino, 2012; Uusitalo, 2007). In environmental sciences in particular, it is rare to obtain exact or definitive answers, however it is possible to understand which outcomes are more or less plausible (Brewer, 2015). Bayesian inference works on the basis of reallocating probability based on plausibility.

The advantages of taking this Bayesian hierarchical regression approach to modelling:

- Soil Olsen P is itself an estimate, that is the value of the measured soil Olsen P from the soil cores collected is an estimate rather than the actual value.
- Appropriately modelling missing data allowing all of the information collected to be used without the missing cases bearing any influence on the results. The database amalgamates data from many different sources (RTK GPS, slope and aspect, fertiliser records, wet chemistry analysis for plant tissue and soil, and plant indices derived from proximal sensing). Although only a small percentage of these were missing in each dataset, it was not the same sample point in every dataset. Many modelling techniques use complete cases only, and therefore lose data and information. In modelling missing data for the variables used in this chapter, 297 samples or 5% of the data was retained that may otherwise have been lost.
- A hierarchical approach reduces over fitting because the correlation in the parameters means that the n (number of farms) slope parameters are not entirely free. A hierarchical or multilevel approach pools information across different clusters, in this case farms. The properties of these clusters come from a population – all the hill country farms in NZ. The parameters, which are treated as random variables, can be correlated across farms. So the effect of one variable across all farms must come from some known distribution, this means that the effect of slope on Olsen P, for example, should be correlated across farms. It is also possible to reduce or restrict the variation across a parameter where it is believed it should have a similar effect at all locations.

- Imbalance in sampling: this approach automatically copes with farms being sampled more times than others, and for some farms having more sites than others. It prevents clusters/farms with more samples from unfairly dominating.
- The modelling undertaken is a real world situation, not a designed experiment. It is an advantage to see exactly how the variables are influencing the model and how and why farms are different. This gives a better understanding of the effects of different variables in the model, the ability to identify missing variables, and modify inputs to ensure they make agronomic sense on a range of different farming systems.
- Random and fixed effects can be modelled in different ways. This is particularly important for this dataset given there is a low signal to noise ratio.
- Improved predictions on new sites, and provides information around uncertainty. The posterior distribution for predicted levels of soil fertility can be stated with their uncertainty.

6.3 Methodology

6.3.1 Study sites and data

The field study sites, site selection, fieldwork methodologies and database development are outlined in detail in Chapter 3. An extensive database was developed collecting data from eight commercial farms throughout the North and South Island of New Zealand. The dataset used for model development included the autumn and spring sampling events only, as the winter and summer sampling occurred only at Limestone Downs.

6.3.2 Variables: calculations and inputs

A total of 14 variables were used in the model and are summarised in Table 6-2. Transformations and calculations were used to derive values for some of the model inputs additional to those described in Chapters 3 and 4 and are outlined as follows:

SOIL ORDER

Soil order was incorporated into the database as defined by the 15 orders described by Hewitt (2010) in the New Zealand Soil Classification (NZSC). Eight of the 15 orders were covered across the 606 sites. Soil order is the highest level in the NZSC.

FERTILISER TERMS

The average amount of P applied annually in fertiliser was calculated. Fertiliser records were collected for each farm going back as far as they were still deemed accurate; this was at least

three years on all farms. The date, rate, product applied and location on the farm were collated. For each site and fertiliser application, kilograms of P were calculated based on the product and rate.

The average annual kilograms of P applied were calculated for each site:

$PFAA_i$ is the annual average rate of P in fertiliser applied in kgP/ha/year at plot *i*

The last application at plot *i* was based on the rate and time passed since the application was made and calculated as:

$$PFLA_i = \left(\frac{t_i}{r_i}\right)$$

where: t_i is the time in days since the last application and r_i is the rate of P in the fertiliser in kgP/ha

STOCK UNITS (SUSSL)

Stock units were calculated as the stock units run in each paddock over the lambing period. From the end of winter to summer ewes are set stocked for lambing with some cattle run amongst them. It is over this period that the highest rate of pasture production occurs in the yearly cycle (Gillingham, 1980; Radcliffe, 1974). Calculations were based on relative feed requirements for different classes of stock. To adjust ewe numbers for the number of lambs carried, the percentage increase in the dietary requirements of single bearing compared to twin bearing ewes (B+LNZ, 2017a, 2017b) was estimated. This variable was used as a relative level of production over different areas of the farm and between farms. Where cattle were run with ewes, farmers provided additional information in stock units.

Table 6-1: Conversion of ewes and hoggets at lambing to stock units

Stock class	Ewe				2 Tooth		Hogget	
Bearing	Single	Single/twin	Twin	Triplet	Single	Twin	Single	Twin
Stock units	1	1.2	1.4	2	1	1.4	1	1.1

LEAF TISSUE NUTRIENTS

Leaf tissue P concentration was used as the most strongly correlated nutrient to soil Olsen P. However to avoid issues with multicolinearity in the data, not all other leaf tissue nutrients

available in the dataset were used in the analysis. To build up the model gradually, only one other nutrient was selected to include in this modelling. Calcium was selected as it was the least correlated to plant P concentration, which was also found by (Jones & Tracy, 2015), to minimise the effects of multicolinearity. Calcium was excluded from analysis in previous chapters as at that stage results showed it was unlikely that calcium concentration could be accurately estimated from hyperspectral imagery. This would mean predictions would not be able to be made across whole farms. Alternatively leaf tissue copper concentration was used as it was identified in the previous chapter as a consistently selected predictor of soil Olsen P. Copper was also less correlated to P than other nutrients such as N, K and S, minimising multicolinearity affects.

MISSING LEAF TISSUE DATA

Data for each plant nutrient, in each survey, were modelled in Minitab® 17 using lognormal, gamma and weibull distributions to estimate their parameters. These distributions were used as they are positive and modelled missing data values must always be positive, negative values of leaf tissue nutrient concentration are not possible. The different distributions were used to model the missing values in WinBUGS. The Deviance Information Criterion (DIC) statistic was used to determine which distribution provided the best fit for the model. In the final model, the distributions were parameterised within the model itself.

Gamma distribution

- parameterised by a and b.
- a = shape and b = rate
- in WinBUGS the gamma distribution is parameterised by the shape and scale, where scale = 1/b
- Missing data estimated using a gamma distribution: Leaf tissue P and Cu concentration

Lognormal distribution

- Missing data estimated using a lognormal distribution: Leaf tissue Ca concentration

Weibull distribution

- Missing data estimated using a weibull distribution: NDVI

Table 6-2: Variables used in the model, their definitions and units

Variable	Definition
LogSOP	Plant available phosphorus in the soil, Olsen P of soil at 0-7.5 cm depth (µg/mL; log-transformed)
ELEV	Elevation above sea level of site (metres a.s.l.)
SLOPE	Slope angle (degrees)
ASP	Aspect of slope face (from northwest, 0-2)
SACT	Cross term for *SLOPE* and *ASP*
SOIL	Soil order indicator variables: *SOILB* is 1 if brown soils; *SOILE* is 1 if melanic soils; *SOILG* is 1 if gley soils; *SOILL* is 1 if allophanic soils; *SOILM* is 1 if pumice soils; *SOILP* is 1 if pallic soils; *SOILR* is 1 if recent soils; *SOILN* is 1 if granular soils.
PFAA	Annual average phosphorus applied in fertiliser (kgP/ha/yr)
PFLA	Phosphorus applied in last fertiliser application prior to the sampling event (days/(kgP/ha))
SUSSL	Set stocking rate over lambing period: including sheep and cattle (su/ha)
AUT	Season indicator: 0 if spring sampling; 1 if autumn sampling
PGR	Predicted pasture growth rate – average of 14 days prior to sampling event (kgDM/ha/day)
PLANTP	Phosphorus concentration in the leaf tissue (% w/w)
PLANTCA	Calcium concentration in the leaf tissue (% w/w)
PLANTCU	Copper concentration in the leaf tissue (mg/kg)
NDVI	Vegetation index (using bands 705 and 750) related to chlorophyll content (0-1)

6.3.3 Model development

DESCRIPTION OF HIERARCHICAL MODELS

In creating the model, the local and regional relationships that govern the system need to be appropriately incorporated into a hierarchical structure. Some variables are likely to have a similar effect regardless of the location of the farm, while others will vary between farms as they are influenced by regional processes or specific farm practices. Hierarchical linear regression was used where the effects of some parameters were allowed to vary between farms. Different hierarchical structures were tried to determine which most appropriately fit the data.

The model was structured using the probability distribution centric convention rather than an error term and with varying effects as below (full model description provided in section 6.4.1):

$$LogSOP_i \sim Normal(f_i, \tau_i)$$

$$f_i = \alpha_F + \beta_F x_i$$

Where $LogSOP_i$ (the log of soil Olsen P of plot *i*, where *i* is a unique identifier for each plot within each site on a particular farm) is normally distributed with a mean f_i and precision τ_i. The $LogSOP_i$ is modelled against variables, x_i, measured on the same plots. Where a farm intercept was used, the intercept was α_F. The slope, β_F, was allowed to vary across farms (*F*). However the hierarchical structure means that these are correlated across farms and must be drawn from a distribution common to all slopes across farms. These common distributions are known as hyperparameters.

Hyperparameters are used to restrict the coefficients for individual farms, meaning the slope effects between farms are correlated, not as strongly as within a farm, but they come from some known population. This borrowing of information across farms, improves the estimation of parameters on farms with fewer observations, a concept known as shrinkage. This is particularly important in analysing datasets such as this given the imbalance in the number of samples collected from the different farms and in different seasons. In this way, a hierarchical approach reduces over fitting because the correlation in the parameters means that, in our case the eight farms, slope parameters are not entirely free. This also reduces under fitting which is the case of complete pooling.

The principles explained here for simple regression can be extended to multiple regression which was the case for the models presented in this chapter. Farm intercepts were replaced by soil order to allow estimates to be made on new sites.

CONSTRUCTION OF THE BAYESIAN HIERARCHICAL MODELS

A hierarchical model was used to model soil Olsen P, implemented with a Bayesian approach. The models were built and run using WinBUGS software (Lunn, Thomas, Best, & Spiegelhalter, 2000). The WinBUGS software package allows the implementation of the computationally complex Markov Chain Monte Carlo (MCMC) iteration technique to be constructed relatively simply (Clark, 2005). WinBUGS uses the Metropolis-Hastings algorithm and Gibbs sampler for Bayesian inference. As a laymen's explanation of the technique, a random set of coefficients are drawn and it is decided if this is plausible given the data we have. This is essentially

decided by the Metropolis-Hastings algorithm. Except continually drawing random sets of coefficients is inefficient as the majority would not be plausible and would be disregarded, so the Gibbs sampler restricts the steps and means that more plausible draws are made. Each plausible outcome is essentially kept and forms the Markov chain and in turn the posterior distribution. Non-informative prior distributions were used, and the initial part of the Markov chain removed as the burn-in period as this is not representative of the posterior distribution.

For the simpler models using only plant tissue or physical variables, 50,000 iterations were run with a thinning interval of 10 and a burn-in period of 10,000. The more complex models were run for 100,000 iterations with a thinning interval of 10 and a burn-in period of 15,000.

MCMC chains were checked to ensure convergence had been achieved. Generated values are plotted against iterations in a trace plot which were used to observe the MCMC chains. Chains must not show strong periodicities and trends, but be well mixed with an appropriate burn-in period, for example Figure 6-1. Autocorrelation plots were checked to ensure values were not linearly dependent on past values. The posterior distributions were checked to ensure they were approximately normally distributed and not centred over zero to indicate a significant model input, as seen in the coefficients in Figure 6-2. Values for the monitored hyper/parameters were drawn from the resultant posterior distributions.

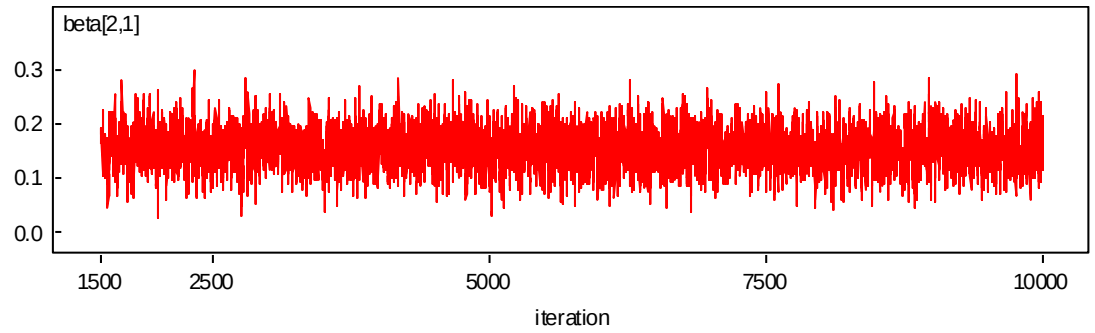


Figure 6-1: Example of a stable, well-mixed chain with the burn-in period removed as observed in a trace plot.

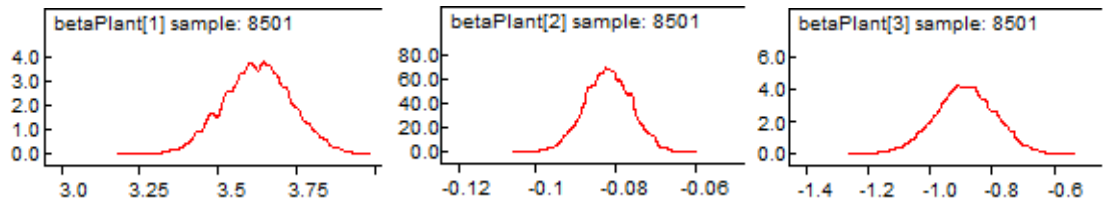


Figure 6-2: Examples of posterior distributions for coefficients, showing significant distribution: not centred on 0.

MODEL SELECTION

After a large number of iterations and an appropriate burn-in period and thinning interval are established in order to leave approximately independent and identically distributed data,

models can be compared using the Deviance Information Criterion (DIC) statistic (Spiegelhalter, Best, Carlin, & Van Der Linde, 2002). DIC is a measure of both model complexity and fit, a smaller value indicating a better fit. There are a number of ways in which a model to estimate soil Olsen P can be structured using the different variables and hierarchical structure.

MODEL ASSESSMENT AND PERFORMANCE

The different models were run within WinBUGS. The coefficients were tracked and the mean of the posterior distribution for each parameter was reported. The step function was used to identify the important variables and their effect in the model. This function gives the probability the coefficient > 0. If the coefficient is highly likely to be positive the probability is close to one, if the coefficient is negative the probability is close to 0 and a probability of 0.5 the coefficient is likely to have very little, if any, effect in the model.

To assess the level of error in the selected models, the standard deviation around Olsen P was calculated and compared between the different models.

$$Std.dev.LogSOP = \sigma = \sqrt{1/_{tau}}$$

$$Std.dev.Olsen\ P = \sqrt{e^{2\mu+\sigma^2}(e^{\sigma^2} - 1)}$$

Where: $\mu = mean\ of\ LogSOP$ and $\sigma = std.dev.LogSOP$

Standard deviation around *LogSOP* was compared between the physical only, plant biochemical and biophysical, and the combined models.

To ensure there is no bias in the dataset or model, the dataset was randomly split in half. In Minitab17, a Bernoulli distribution was used with a probability of 0.5 to generate values of 0 or 1. A linear regression analysis was performed on half of the dataset and the residuals calculated. The resulting coefficients were used to calculate estimates of *LogSOP* on the second half of the data and the residuals calculated. Histograms of the residuals from each half were checked, to ensure there is no bias in the dataset.

6.3.4 Model Validation: Leave-out-out-cross-validation

A leave-one-out-cross-validation was used to validate the model. Each farm was left out of the final model in turn, and the model run. *LogSOP* was monitored to track the estimates over the farm, which was treated as an independent dataset. The model was run for 100,000 iterations with a thinning interval of 10 and a burn-in period of 15,000. Predicted and actual values were

compared and the residuals calculated using the mean of the predicted posterior distribution for soil Olsen P. To evaluate the predicted values against the status quo, the average of all Olsen P soil tests results were graphed. Although the methodologies used to collect the soil samples differs from the traditional soil sampling technique used by fertiliser reps, the results of this dataset will provide a more representative average. This was intended to compare the predicted values of the Bayesian hierarchical model against the most risk adverse and simplest approach that is used traditionally and leads to blanket application of fertilisers.

6.4 Results

6.4.1 Model development

All eight farms were combined into hierarchical models that contained only physical variables, only plant biochemical and biophysical variables and then a final model that incorporated all variables. The spring and autumn sampling events, except Lawsons which was sampled in the spring only, were used. Within these, a number of different model structures were tested, Table 6-3.

The intercept was initially incorporated as varying by farm. However this was changed to use the soil order as the intercept, given the effect of soil order should theoretically be the same across all farms. This also allows estimates to be made in a leave-one-out-cross-validation and on farms outside the dataset. The soil order term was tested using different structures for the hyperparameters, as either fully, restricted or non-hierarchical where β*Soil* is the coefficient for soil order *S* on farm *F*.

Fully hierarchical:

$$\beta Soil_{s,F} \sim Normal(\mu_s, \tau_s)$$

$$\mu_s \sim Normal(0, 0.000001)$$

$$\tau_s = {}^{1}/_{\sigma_s^2}$$

$$\sigma_s \sim Uniform(0, 10)$$

Restricted hierarchical (this narrows the distribution of the hyperparameter, essentially forcing the effect of soil order to be strongly correlated across farms):

$$\beta Soil_{s,F} \sim Normal(\mu_s, \tau_s)$$

$$\mu_s \sim Normal(0, 0.000001)$$

$$\tau_s = {}^{1}/_{\sigma_s^2}$$

$$\sigma_s = 0.05$$

Non-hierarchical:

$$\beta Soil_s \sim Normal(0, 0.000001)$$

Topographic variables: *SLOPE*, *ASP*, *SACT* and *ELEV* were fully hierarchical by farm across all models. This allowed the effect of topographic factors to vary across farms. The management variables: *PFAA*, *PFLA* and *SUSSL* were also fully hierarchical by farm across all models. The coefficients for *PFAA* were forced to be positive, confirming that the addition of phosphate fertiliser increased soil Olsen P, and *SUSSL* was forced to be negative due to permanent nutrient removal. The plant biochemical and biophysical factors, *PLANTP*, *PLANTCA* or *PLANTCU,* and *NDVI* were included as non-hierarchical parameters having the same effect, irrespective of location. *PGR* and *AUT* were also included as fully hierarchical terms.

A cross-classification structure was also analysed. Cross-classified multilevel models can be used when there is more than one type of cluster within the same model. The effect of plant biophysical and biochemical factors were correlated across seasons, while other factors such as topographic and farm management variables were correlated across farms.

A model that used only the plant nutrient data has been compared to two others, a model using only topographic, soil and farm management data, and other models that combined all variables. The DIC's for the combined models were lowest, between 5895 and 6587 using calcium or copper as the second plant nutrient and a range of different model structures. The DIC's were higher for the topographical, soil and farm management only model: 7554 and highest for plant only: 8101 and 8210 using calcium or copper respectively (Table 6-3). The residual error in these models show a significant decrease when all the data was combined (Figure 6-3). The models using calcium as the second leaf tissue nutrient resulted in slightly better model fits and lower residual errors than the same model structures using copper. Both the plant leaf tissue properties, and the topographical and management data had an important contribution and subsequent modelling focused on using all variables.

Table 6-3: Comparison of model inputs, showing the difference in model structure and performance, as indicated by the DIC for models including plant calcium and copper

				Physical												Plant				
				Soil	Topographic				Seasonal		Management					Chemical		Phys		
Model	Model	Alpha	Farm Term	SOIL	SLOPE	ASP	SACT	ELEV	AUT	PGR	PFAA	PFLA	SUSSL	P Fert -PFAA / SUSSL	PLANTP	PLANTCA or PLANTCU	NDVI	Calcium DIC	Copper DIC
Plant_01	Plant only - common intercept	a													N-h	N-h	N-h	8537	8855
Plant_02	Plant only - with farm intercept		a												N-h	N-h	N-h	8101	8210
Phys_01	Physical only - soil intercept			H-r	H (f)	H (f)	H (f)	H (f)	H (f)		H (+)	H (f)	H (-)					7554	7554
All_01	All - soil restricted hierarchical by farm			H-r	H (f)	H (f)	H (f)	H (f)	H (f)	H (f)	H (+)	H (f)	H (-)		N-h	N-h	N-h	5998	6194
All_02	All - soil fully hierarchical by farm			H	H (f)	H (f)	H (f)	H (f)	H (f)	H (f)	H (+)	H (f)	H (-)		N-h	N-h	N-h	5895	6007
All_03	**All - soil non-hierarchical**			**N-h**	**H (f)**	**H (f)**	**H (f)**	**H (f)**	**H (f)**	**H (f)**	**H (+)**	**H (f)**	**H (-)**		**N-h**	**N-h**	**N-h**	**6088**	**6285**
All_04	All - soil non-hierarchical, with farm intercept		a	N-h	H (f)	H (f)	H (f)	H (f)	H (f)	H (f)	H (+)	H (f)	H (-)		N-h	N-h	N-h	5975	6188
All_05	All - All_03 - no PGR			N-h	H (f)	H (f)	H (f)	H (f)	H (f)		H (+)	H (f)	H (-)		N-h	N-h	N-h	6140	6311
All_06	All - All_03 - no Autumn			N-h	H (f)	H (f)	H (f)	H (f)		H (f)	H (+)	H (f)	H (-)		N-h	N-h	N-h	6147	6299
All_07	All - All_03 - no PGR or autumn			N-h	H (f)	H (f)	H (f)	H (f)			H (+)	H (f)	H (-)		N-h	N-h	N-h	6431	6587
All_08	All - All_03 - PGR non-hierarchical			N-h	H (f)	H (f)	H (f)	H (f)	H (f)	N-h	H (+)	H (f)	H (-)		N-h	N-h	N-h	6190	6315
All_09	All - All_03 - no slope/aspect cross term			N-h	H (f)	H (f)		H (f)	H (f)	H (f)	H (+)	H (f)	H (-)		N-h	N-h	N-h	6117	6322
All_10	All - All_03 - Remove yearly ave P applied and SU			N-h	H (f)	H (f)	H (f)	H (f)	H (f)	H (f)		H (f)			N-h	N-h	N-h	6312	6423
All_11	All - All_03 - P fertiliser Yr Ave/SU			**N-h**	**H (f)**	**H (f)**	**H (f)**	**H (f)**	**H (f)**	**H (f)**		**H (f)**		**H (f)**	**N-h**	**N-h**	**N-h**	**6074**	**6239**
All_12	All - All_03 - No management terms			N-h	H (f)	H (f)	H (f)	H (f)	H (f)	H (f)					N-h	N-h	N-h	6553	6727
All_13	All - All_03 - Plant terms hierarchical by season			**N-h**	**H (f)**	**H (f)**	**H (f)**	**H (f)**	**H (f)**	**H (f)**	**H (+)**	**H (f)**	**H (-)**		**H (s)**	**H (s)**	**H (s)**	**6076**	**6196**
All_14	All - All_03 - Plant terms and PGR hierarchical by season			N-h	H (f)	H (f)	H (f)	H (f)	H (f)	**H (s)**	H (+)	H (f)	H (-)		H (s)	H (s)	H (s)	6123	6307
All_15	All - All_03 - Plant terms hierarchical by season, PGR non-h			N-h	H (f)	H (f)	H (f)	H (f)	H (f)	**N-h**	H (+)	H (f)	H (-)		H (s)	H (s)	H (s)	6134	6301

Notation: N-h = Non – hierarchical; H (f) = fully hierarchical by farm; H (+) = fully hierarchical by farm - positive coefficient; H (-) = fully hierarchical by farm - negative coefficient; H-r = fully hierarchical by farm - hyperparameter s.d. = 0.05; and H (s) = fully hierarchical by season.

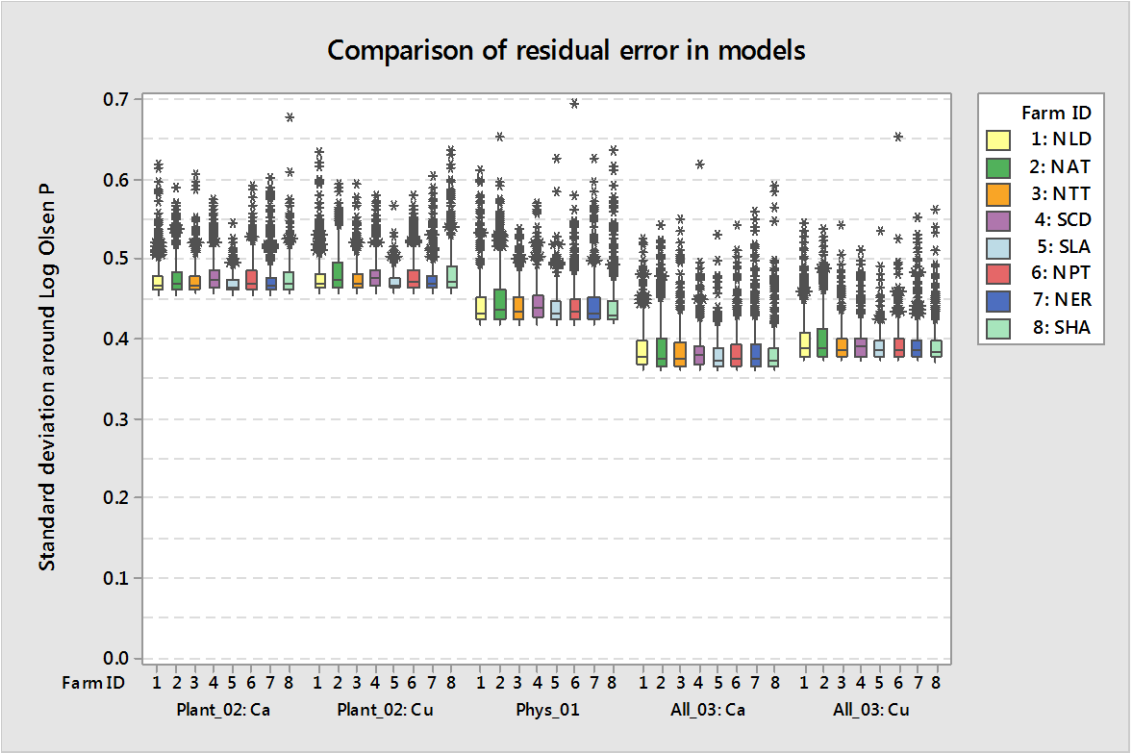


Figure 6-3: Comparison of residual error level in the models showing the reduction in residual error through combining plant biochemical and biophysical information in addition to topographical and farm management factors.

Using different structures for the hyperparameters of soil orders: the fully hierarchical, restricted hierarchical and then the non-hierarchical structure gave the best to weakest fit. However the fully hierarchical model appeared to be over fitting. As soil order theoretically should have the same effect regardless of the farm's location, the non-hierarchical model was the most appropriate structure. The results of different combinations of variables are provided in Table 6-3. The two other models with low DIC were 'All_11' using leaf tissue calcium or leaf tissue copper and 'All_13' using leaf tissue calcium or leaf tissue copper, with DIC's of 6088 and 6076 and 6285 and 6196 respectively. Model 'All_11' combined the *PLAA* and the *SUSSL* variables to essentially provide information on the amount of fertiliser applied compared to the level of productivity. 'All_13' used a cross classification structure where plant biophysical and plant biochemical parameters were correlated across seasons, in the same way the other effects were correlated across farms. The model 'All_03' was selected as although the DIC was larger, the coefficients were more consistent across farms. The model description follows.

The model 'All_03' uses topographical features, management factors and plant tissue information. A total of 15 sampling events across the eight farms are included in the model of soil Olsen P, for i = 1… N samples, where N = 5,660 (the number of samples in the dataset). $LogSOP_i$ is therefore the natural logarithm of the measured soil Olsen P of the i-th sample defined by a sample taken in a particular season at the individual pegs or plots in the field.

LogSOP is assumed to be normally distributed with a mean f_i and a precision $\tau_{i.}$ $\beta_{(B,F)}$ is a matrix of regression coefficients where *F* = 1... *NoF*, where *NoF* is the number of farms in the dataset. $\beta Soil_{S,}$ and $\beta Plant_P$ are vectors of regression coefficients for soil order and the plant chemical and physical variables.

The summary of the hierarchical model is defined as:

$$LogSOP_i \sim Normal(f_i, \tau_i)$$

$$\begin{aligned} f_i = {} & \left(\beta_{(1,F)} \times SLOPE_i\right) + \left(\beta_{(2,F)} \times ASP_i\right) + \left(\beta_{(3,F)} \times SACT_i\right) + \left(\beta_{(4,F)} \times ELEV_i\right) - \left|\beta_{(5,F)} \times SUSSL_i\right| \\ & + \left|\beta_{(6,F)} \times PFAA_i\right| + \left(\beta_{(7,F)} \times PFLA_i\right) + \left(\beta_{(8,F)} \times AUT_i\right) + \left(\beta_{(9,F)} \times PGR_i\right) \\ & + \left(\beta Soil_{(1)} \times SOILB_i\right) + \left(\beta Soil_{(2)} \times SOILE_i\right) + \left(\beta Soil_{(3)} \times SOILG_i\right) \\ & + \left(\beta Soil_{(4)} \times SOILL_i\right) + \left(\beta Soil_{(5)} \times SOILM_i\right) + \left(\beta Soil_{(6)} \times SOILP_i\right) \\ & + \left(\beta Soil_{(7)} \times SOILR_i\right) + \left(\beta Soil_{(8)} \times SOILN_i\right) + \left(\beta Plant_1 \times PLANTP_i\right) \\ & + \left(\beta Plant_2 \times PLANTCA_i\right) + \left(\beta Plant_3 \times NDVI_i\right) \end{aligned}$$

The error term is defined as:

$$\tau_i = \frac{1}{\sigma_i^2}$$

$$\sigma_i = e^{x_i}$$

$$x_i \sim Normal(\mu_i, v)$$

$$\mu_i \sim Normal(M, w)$$

$$M \sim Normal(0, 0.000001)$$

$$v \sim Gamma(0.1, 0.1)$$

$$w \sim Gamma(0.1, 0.1)$$

The topographic and management features are hierarchical. However soil order and the plant physical and chemical properties are not, this means that these factors are having the same effect across all farms. The coefficients are defined as:

$$\beta_{(B,F)} \sim Normal(MB_B, TB_B)$$

$$MB_B \sim Normal(0, 0.000001)$$

$$TB_B = \frac{1}{SB_B^2}$$

$$SB_B \sim Uniform(0, 150)$$

$$\beta Soil_s \sim Normal(0,0.000001)$$

$$\beta Plant_P \sim Normal(0,0.000001)$$

$\beta_{(B,F)}$ is a matrix of regression coefficients where β = 1,2,3…9 for SLOPE, ASP, SACT, ELEV, SUSSL, PFAA, PFLA, AUT, PGR respectively. $\beta Soil_S$ is a vector of regression coefficients where S = 1,2,3… 8 for soil orders of Brown, Melanic, Gley, Allophanic, Pumice, Pallic, Recent and Granular respectively. $\beta Plant_P$ is a vector of regression coefficients where P = 1, 2 or 3 for leaf tissue P concentration, leaf tissue calcium or copper concentration and NDVI respectively.

A check of residuals ensured that for the models 'All_03' with calcium (Figure 6-4) and 'All_03' with copper (Figure 6-5) were approximately normally distributed around 0. The distributions of the residuals from the two halves of the data overlapped, ensuring there was no bias in the model.

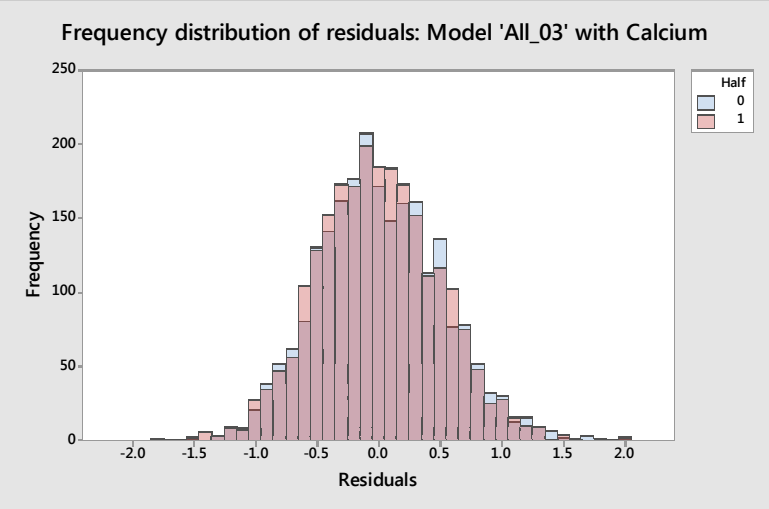


Figure 6-4: Distribution of residuals for model 'All_03' with calcium

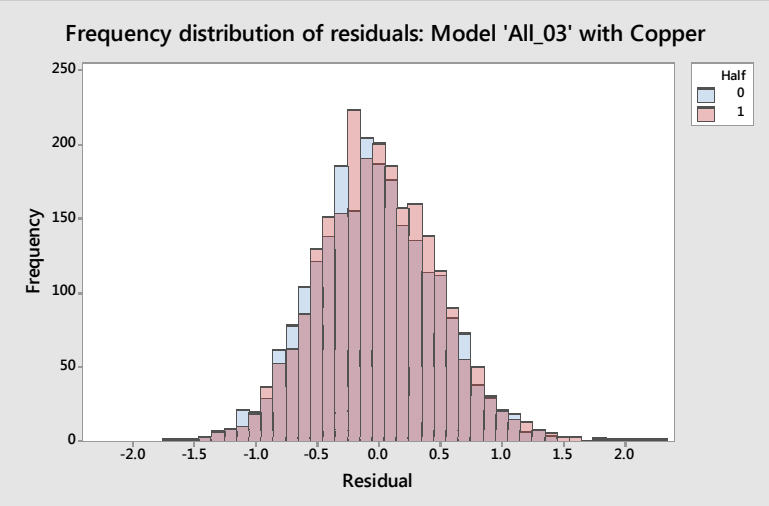


Figure 6-5: Distribution of residuals for model 'All_03' with copper

The mean of the posterior distribution of the parameters in the model 'All_03' are reported in Table 6-4 (calcium) and

Table 6-5 (copper). Figure 6-6 presents the results of the step function analysis which is the probability the coefficient > 0. The majority of variables were significant in the models. The results for model 'All_03' using either leaf tissue calcium or copper concentration are similar.

The *SLOPE*, *ASP* and *SACT* trade off against each other making their effect difficult to interpret. The coefficient for *ELEV* was negative for Ohorea, Tautane, Lawsons, Erewhon and Pati Tapu and positive for Cleardale, Harwoods, Pati Tapu when calcium was used and Limestone Downs when copper was used. *ELEV* at Limestone Downs was not significant when calcium was used. The results of the step function analysis show the topographical variables are important inputs in the model. The coefficient for *PFLA* on all farms was negative except for Erewhon and Lawsons. *PFLA* at Tautane in the model using leaf tissue calcium concentration, and *PFLA* at Ohorea in the model using copper concentration in the leaf tissue were not significant, but were significant for all other farms. The coefficient for *AUT* was always positive and significant. The coefficient was positive for *PGR* as well, with the exceptions of Cleardale and Pati Tapi. The intercepts based on soil order were from smallest to largest *SOILE*, *SOILR*, *SOILN*, *SOILB*, *SOILP*, *SOILL*, *SOILG* and *SOILM* for the model using leaf tissue calcium and only *SOILL* and *SOILG* are switched in the model using leaf tissue copper concentration. For both models *PLANTP* had a positive coefficient and *PLANTCA* or *PLANTCU* and *NDVI* negative. All leaf tissue variables were significant in the models.

Table 6-4: Coefficients for model 'All_03' using plant calcium concentration

All_03	NLD	NAT	NTT	SCD	SLA	NPT	NER	SHA
SLOPE	0.0184	-0.0255	-0.0087	-0.0187	-0.0031	0.0000	-0.0192	0.0048
ASP	0.2417	-0.1370	-0.0157	0.2838	-0.0910	-0.0218	-0.1187	0.1164
SACT	-0.0125	0.0048	-0.0025	0.0015	0.0075	0.0011	0.0146	-0.0045
ELEV	0.0000	-0.0005	-0.0007	0.0009	-0.0008	0.0001	-0.0004	0.0001
SUSSL	-0.0650	-0.0041	-0.0011	-0.0090	-0.0066	-0.0077	-0.0017	-0.0089
PFAA	0.0122	0.0057	0.0034	0.0009	0.0131	0.0132	0.0061	0.0325
PFLA	-0.0054	-0.0014	-0.0032	-0.0079	0.0073	-0.0268	0.0036	-0.0163
AUT	0.3511	0.3773	0.3389	0.3889	0.3228	0.2827	0.2200	0.3055
PGR	0.0049	0.0086	0.0024	-0.0022	0.0063	-0.0072	0.0116	0.0072
All farms	SOILB	SOILE	SOILG	SOILL	SOILM	SOILP	SOILR	SOILN
	2.542	2.026	2.742	2.727	2.765	2.715	2.442	2.522
	PLANTP	PLANTCA	NDVI					
	3.448	-0.8305	-1.176					

Table 6-5: Coefficients for model 'All_03' using plant copper concentration

All_03	NLD	NAT	NTT	SCD	SLA	NPT	NER	SHA
SLOPE	0.0155	-0.0295	-0.0080	-0.0186	-0.0009	-0.0020	-0.0244	0.0039
ASP	0.1555	-0.1097	0.0287	0.2371	-0.0667	-0.0126	-0.1098	0.1109
SACT	-0.0117	0.0043	-0.0036	0.0019	0.0066	0.0009	0.0141	-0.0087
ELEV	0.0006	-0.0005	-0.0005	0.0008	-0.0007	-0.0004	-0.0004	0.0001
SUSSL	-0.0795	-0.0044	-0.0015	-0.0087	-0.0099	-0.0065	-0.0017	-0.0082
PFAA	0.0197	0.0157	0.0030	0.0011	0.0108	0.0095	0.0074	0.0326
PFLA	-0.0030	0.0001	-0.0050	-0.0061	0.0099	-0.0253	0.0051	-0.0203
AUT	0.3806	0.3957	0.3826	0.3948	0.3633	0.3202	0.2903	0.3809
PGR	0.0048	0.0079	0.0026	-0.0022	0.0025	-0.0027	0.0111	0.0050
All farms	SOILB	SOILE	SOILG	SOILL	SOILM	SOILP	SOILR	SOILN
	2.425	1.946	2.592	2.603	2.653	2.558	2.313	2.408
	PLANTP	PLANTCU	NDVI					
	3.761	-0.0930	-0.9114					

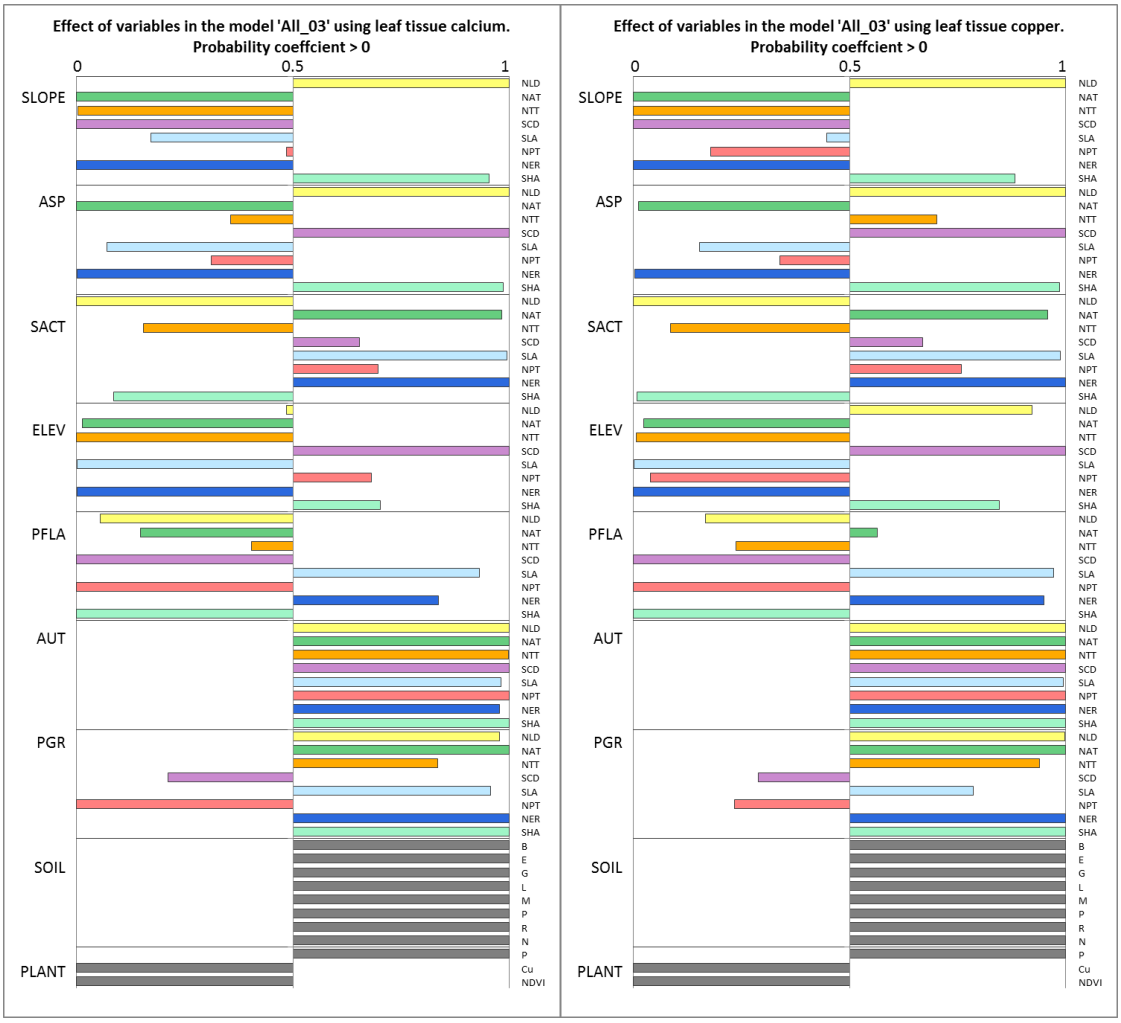


Figure 6-6: Proability of the coefficients in the model > 0 for the model 'All_03'using leaf tissue calcium (left) and leaf tissue copper (right) concentrations. Coeffcient specified primary y axis and farm, soil order or plant biophysical or biochemical paramter on the secondary y axis.

6.4.2 Model Validation: Leave-out-out-cross-validation

A leave-one-out-cross-validation was used to assess the ability of the model to estimate soil Olsen P on each farm using only data from the remaining seven farms. Harwoods (SHA) was included as data to inform predictions on other farms. However the dominance of Melanic soils on this property, and given these soils do not occur on any of the other farms, there was no knowledge of this particular soil order in the data set and it was not possible to make reasonable predictions using this model. The performance of the models to predict soil Olsen P are reported in Table 6-6 which gives a summary of the R^2 and RMSE for the models 'All_03', using leaf tissue copper and calcium concentration and for the autumn and spring sampling events.

The relationships between actual and predicted soil Olsen P across farms and season were between R^2 of 0.09 and 0.42. The best results were in the leave-one-out-cross-validation in the spring using plant calcium for Ohorea (NAT), with an R^2 of 0.42 when the actual and predicted values were compared. There was little difference in the performance of the two models using either calcium or copper leaf tissue concentration, though calcium was generally slightly better. Tautane was the only farm to differ, with the model using copper performing slightly better, R^2 0.26 and 0.25 compared to calcium 0.21 and 0.19. The predictions at Erewhon in the spring were better than in the autumn, this was also true, but to a lesser extent, at Ohorea, Pati Tapu, Tautane and Limestone Downs. The results for the leave-one-out-cross-validation showed that predictions at Limestone Downs using the other seven farms, was not as successful, compared to leaving out any of the other farms.

Table 6-6: Results for the leave-one-out-cross-validation across the eight trial farms

	Leave one out cross validation							
	Model: All_03 with Calcium				**Model: All_03 with Copper**			
	Spring		**Autumn**		**Spring**		**Autumn**	
	R^2	RMSE	**R^2**	RMSE	**R^2**	RMSE	**R^2**	RMSE
NLD	**0.09***	16.8*	**0.02***	21.2*	**0.04***	18.1*	**0.01***	21.6*
NER	**0.23****	13.5**	**0.08****	14.8**	**0.19****	13.6**	**0.09****	14.7**
NAT	**0.42**	11.2	**0.21**	13.1	**0.34**	12.8	**0.19**	11.8
NTT	**0.21**	12.1	**0.19**	12.1	**0.26**	11	**0.25**	11.6
NPT	**0.30**	11.7	**0.26**	8.2	**0.33**	10.5	**0.2**	9.1
SHA	**NA**	NA	**NA**	NA	**NA**	NA	**NA**	NA
SCD	**0.28**	11.7	**0.31*****	14.9***	**0.31**	12.3	**0.29*****	15.5***
SLA	**0.23**	10.0			**0.24**	10.1		

* excluded sites on granular soils

** excludes sites on pumice soils

*** reduced sampling event

The actual soil Olsen P estimates vs. the predicted values from the leave-one-out-cross-validation are compared for each farm separately in Figures 6-7 to 6-13. The average value for spring (◆) and autumn (□) were used as an example of the current approach of using a single value for soil Olsen P which is currently used for blanket fertiliser applications. This means only one value – the average – is used for all of the predicted values. The mean of the predicted posterior distribution from the Bayesian hierarchical model ('All_03' using leaf tissue copper concentration) for spring (◆) and autumn (□) are graphed as a comparison of the current and proposed approach.

In all cases, the predicted values from the hierarchical model were more strongly correlated to the actual values measured at the plots, than the averaged single value for all plots. However soil Olsen P was seldom predicted above 40 µg/mL. Predicted values had a narrower range and were lower in general than the actual values. Cleardale and Lawsons were particularly affected. All relationships between actual and predicted values from the hierarchical model were positive, though none were close to the ideal result of a slope of 1, due to the lower predicted values. However using the average value for the data (to demonstrate the blanket approach) showed no relationship at all, as there is only one predicted value.

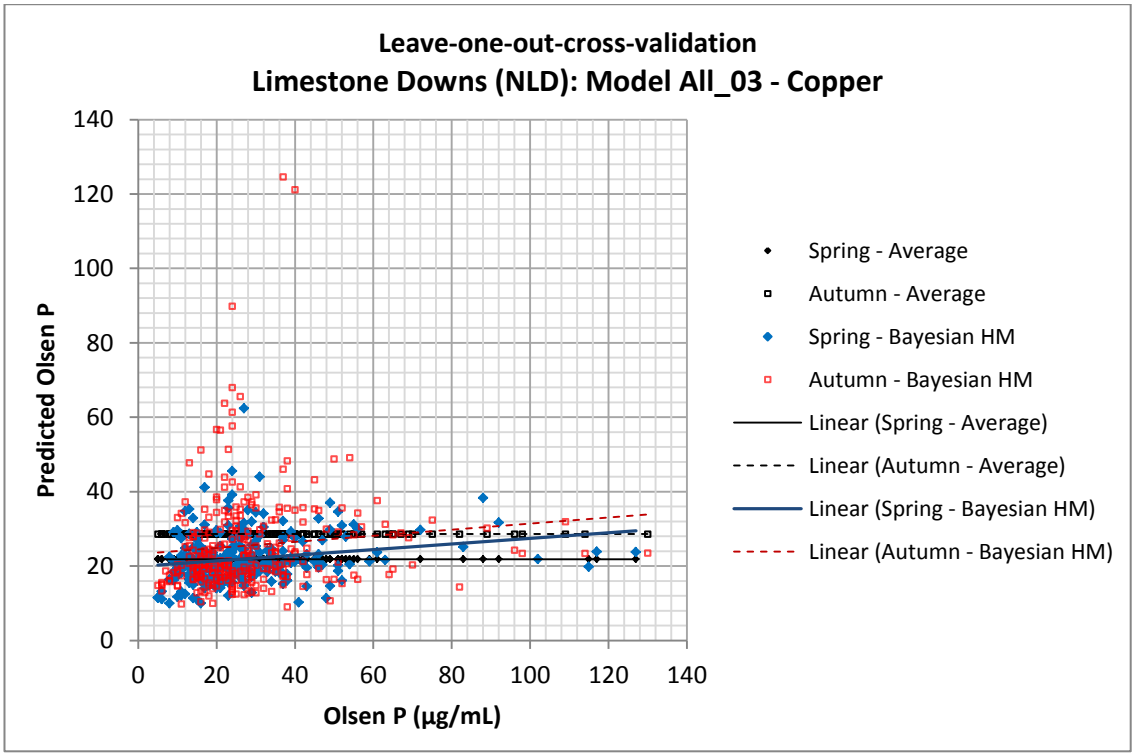


Figure 6-7: Predicted and actual soil Olsen P; results of the leave-one-out-cross-validation for Limestone Downs (NLD) for the model 'All_03' using leaf tissue copper concentration for ◆– spring and □ – autumn using the Bayesian Hierarchical Model and ◆– spring and □ – autumn using an average value.

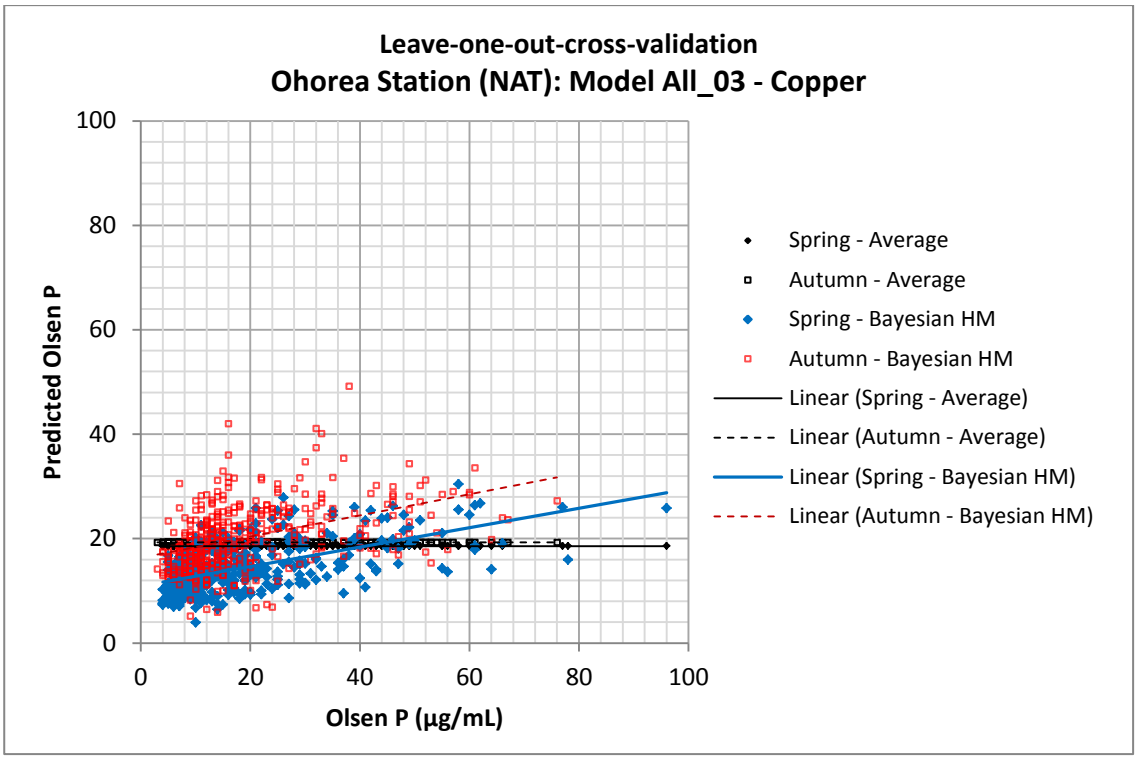


Figure 6-8: Predicted and actual soil Olsen P; results of the leave-one-out-cross-validation for Ohorea Station (NAT) for the model 'All_03' using leaf tissue copper concentration for ◆– spring and □ – autumn using the Bayesian Hierarchical Model and ◆– spring and □ – autumn using an average value.

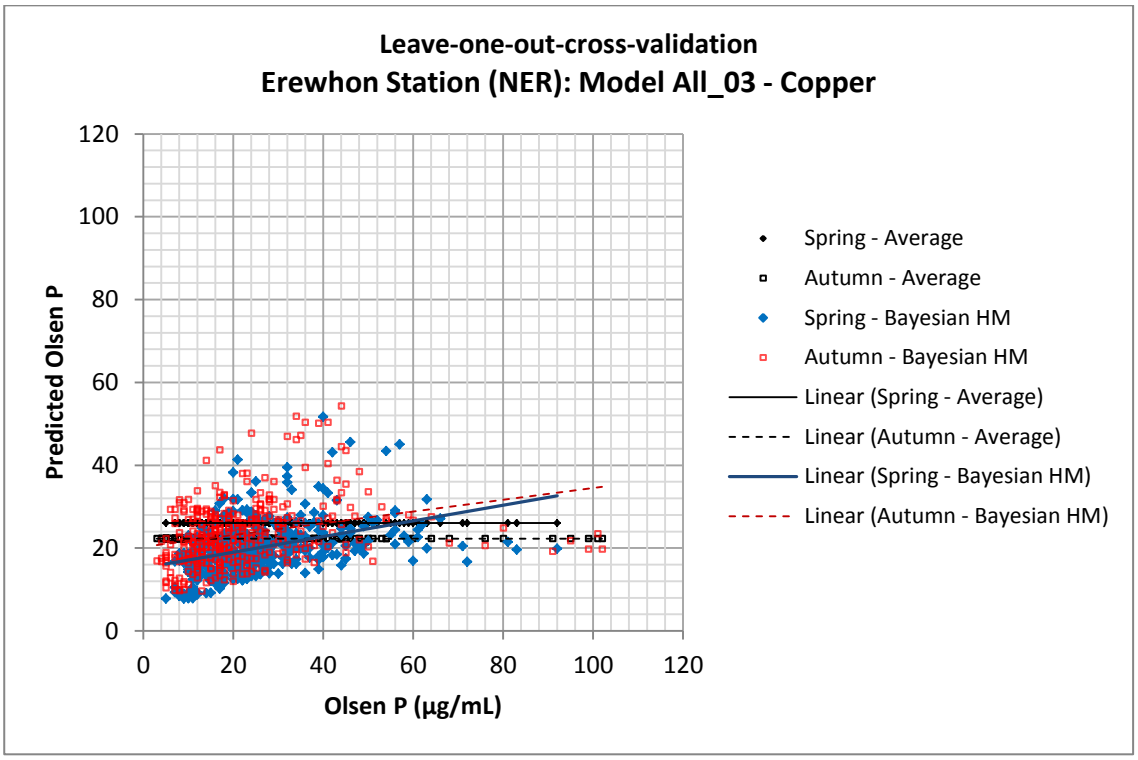


Figure 6-9: Predicted and actual soil Olsen P; results of the leave-one-out-cross-validation for Erewhon Station (NAT) for the model 'All_03' using leaf tissue copper concentration for ◆– spring and □ – autumn using the Bayesian Hierarchical Model and ◆– spring and □ – autumn using an average value.

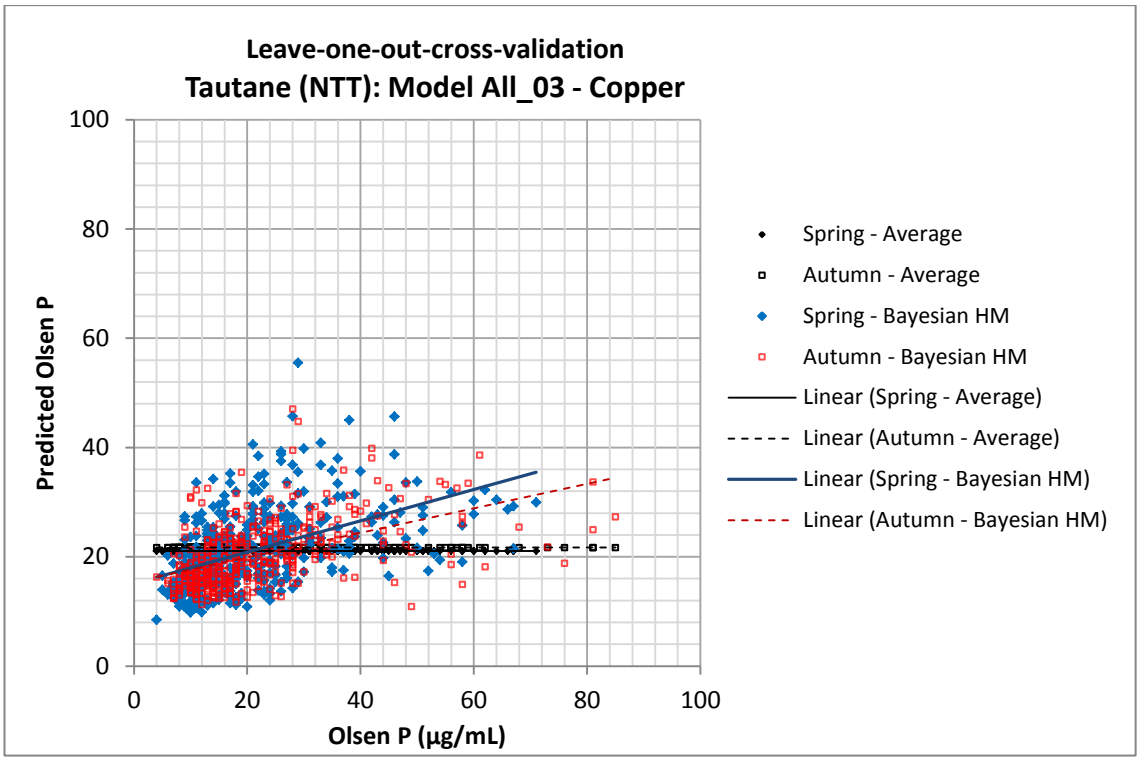


Figure 6-10: Predicted and actual soil Olsen P; results of the leave-one-out-cross-validation for Tautane (NTT) for the model 'All_03' using leaf tissue copper concentration for ◆– spring and □ – autumn using the Bayesian Hierarchical Model and ◆– spring and □ – autumn using an average value.

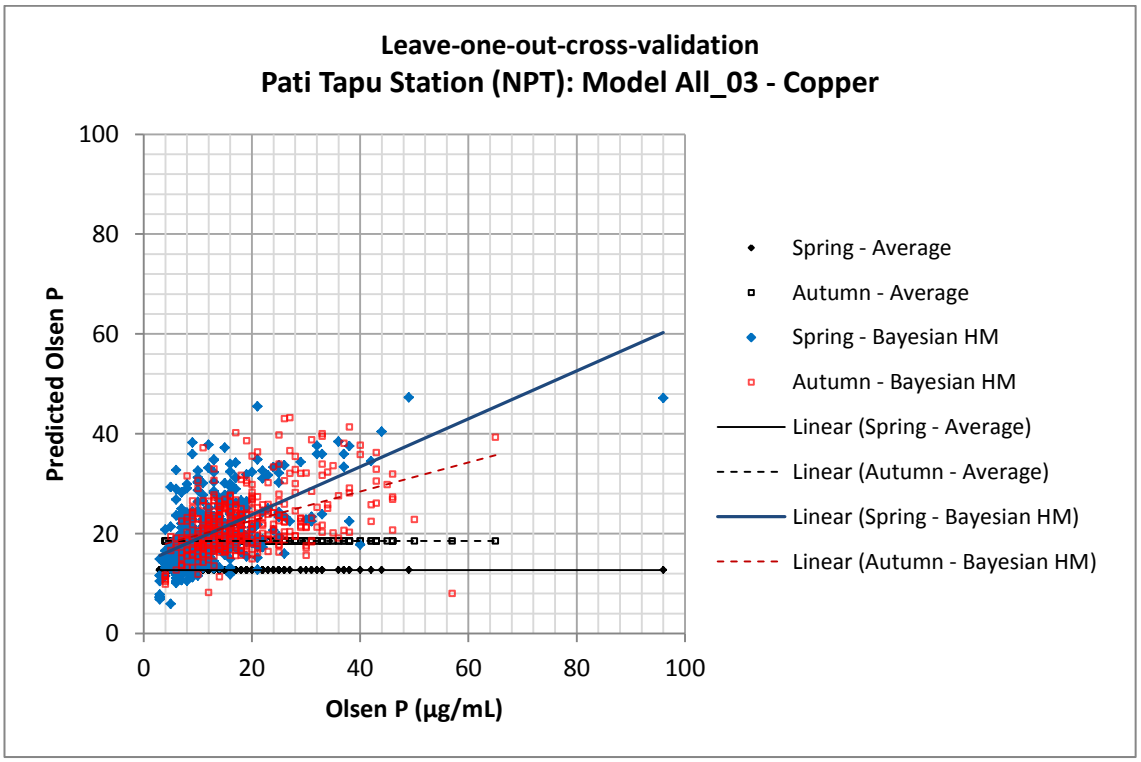


Figure 6-11: Predicted and actual soil Olsen P; results of the leave-one-out-cross-validation for Patitapu (NPT) for the model 'All_03' using leaf tissue copper concentration for ◆– spring and □ – autumn using the Bayesian Hierarchical Model and ◆– spring and □ – autumn using an average value.

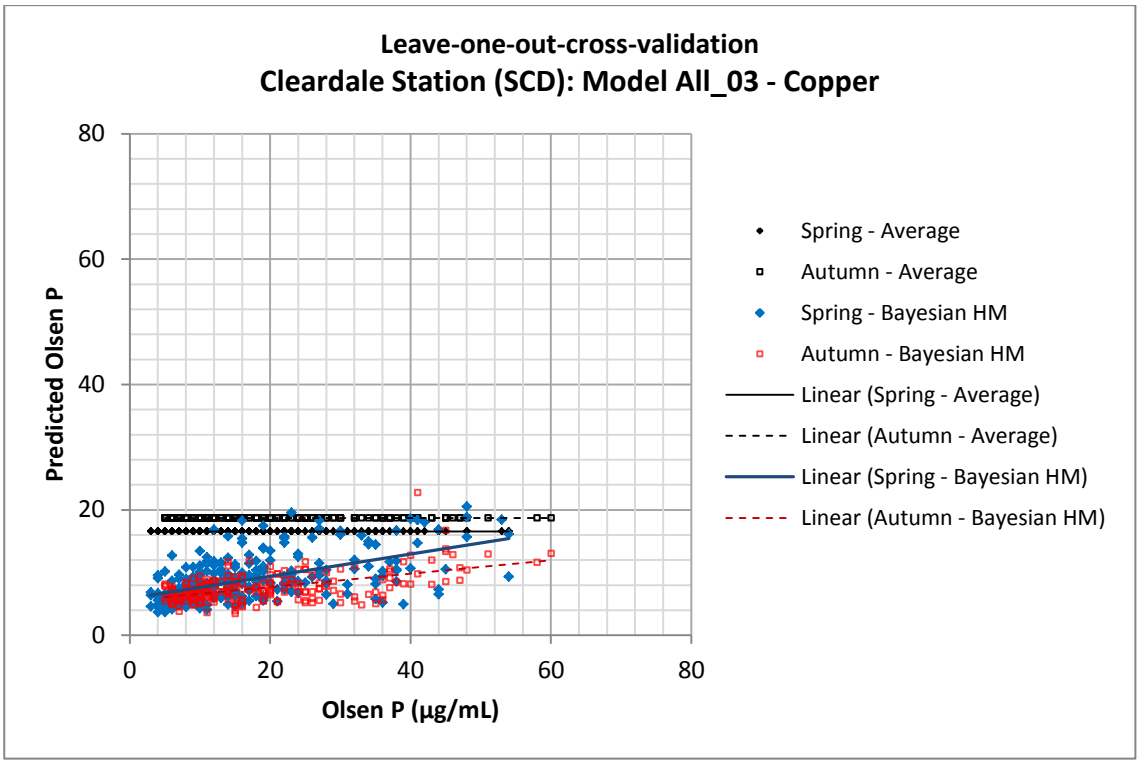


Figure 6-12: Predicted and actual soil Olsen P; results of the leave-one-out-cross-validation for Cleardale (SCD) for the model 'All_03' using leaf tissue copper concentration for ◆– spring and □ – autumn using the Bayesian Hierarchical Model and ◆– spring and □ – autumn using an average value.

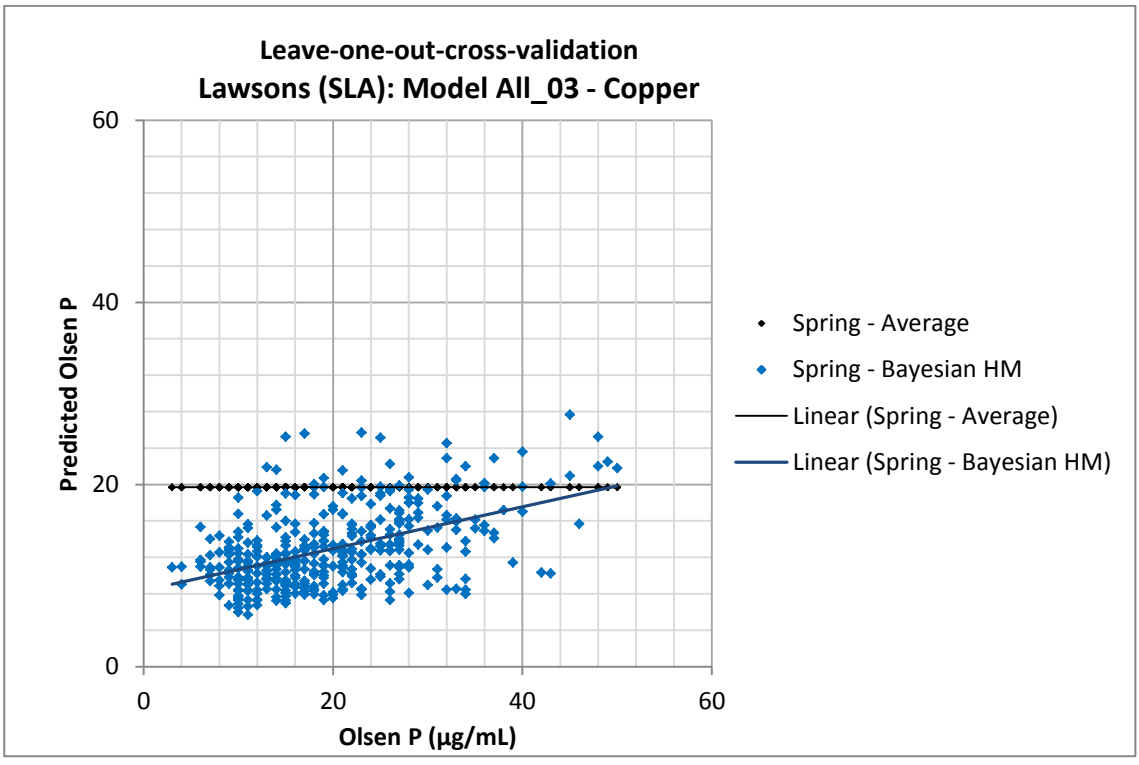


Figure 6-13: Predicted and actual soil Olsen P; results of the leave-one-out-cross-validation for Lawsons (SLA) for the model 'All_03' using leaf tissue copper concentration for ◆– spring using the Bayesian Hierarchical Model and ◆– spring using an average value.

6.5 Discussion

6.5.1 Model development, comparison and performance

Models using a combination of both physical and plant factors were a better fit than models using only plant or only physical factors. A significant reduction in the DIC and in residual errors confirmed that a combined model outperformed either of the simpler models. These results led to the development and comparison of fifteen different models using different structures and combinations of inputs, from both the physical and plant variables.

The model 'All_03' was selected as the best model and the model was used for a leave-one-out-cross-validation. This model had one of the lowest DIC values. Compared to other models, 'All_03' showed more consistency in the signs of coefficients across farms, which is important for the identification of broad scale patterns.

In the model developed using farm indicator variables ('All_04'), the DIC was lower and the coefficients were more consistent across the eight farms (results not shown) than the model selected. The anomalies between farms were more easily explained in agronomic terms. However the inclusion of farm indicator variables would restrict the model to making predictions only on these eight farms. Although the models were not applied to any farms outside of this dataset within this thesis, it was the goal of the wider project.

The models using leaf tissue calcium concentration had a lower DIC and smaller residual errors than the same model structures using copper. The difference in DIC for the combined models was between 100 and 200. Although the models using calcium provided a better model fit, the ability to estimate either nutrient using the AisaFENIX imaging system must also be considered. If there is a significant difference in the predictions of leaf tissue copper and calcium from hyperspectral imaging, this may introduce a bigger error than that evident between the models. Current results from other components of the project show that copper concentration in the leaf tissue can be more accurately estimated from the hyperspectral imagery than calcium.

The use of cross classification, where plant biochemical and biophysical factors were hierarchical across seasons ('All_13'), made a significant improvement in the model fit for copper, but made little difference to the model including calcium concentration in the leaf tissue. The DIC decreased by 89 and 12 respectively. If a model using copper rather than calcium is preferred, cross classification may be worth further investigation

6.5.2 Physical factors

SOIL INFORMATION

Soil orders rather than farm indicator variables provided intercepts for the models to allow predictions to be made on farms outside the dataset. The effect of each soil order on soil Olsen P was structured in the final model as common to all farms. Fully and restricted hierarchical structures were tried, however a non-hierarchical structure was used. Although the hierarchical structures improved the model performance the coefficients for the soil order terms were not consistent across farms, indicating that they were over fitting. As categories for soil order were developed in the NZSC system as a national scale classification, it made most agronomic sense and aimed to identify broad scale patterns through the use of a common effect across all farms. Soil information is important in understanding the way in which soils influence the availability P through storing and replenishing P once it is removed via plant roots, and the amount of applied phosphate in fertiliser that is fixed or lost to the soil (McLaren & Cameron, 1996).

The mean of the posterior distributions of the coefficients were from largest to least: pumice, allophanic /gley, pallic, brown, granular, recent and melanic. However, pumice was represented by only 5 sites on a river flat at Erewhon and so are not representative of pumice soils nationally.

TOPOGRAPHIC VARIABLES: SLOPE, ASPECT, AND ELEVATION

Slope, aspect and their cross term were important factors in the model. The interpretation of these factors was complicated due to the inclusion of the cross term. The coefficients were inconsistent across farms, including their signs, as they were trading off against each other. The DIC's for the models without the slope/aspect cross term were 6117 using calcium as the second leaf tissue nutrient and 6088 with the cross term included and, 6322 and 6285 for the models using copper instead of calcium. As slope decreases, it is expected that the influence of aspect would reduce. Management units for fertiliser applications have been defined on slope categories alone, e.g. Morton et al. (2016). The other management factors and inclusion of leaf biochemical and biophysical variables were making a significant contribution and significantly reduced the residual error in the model.

The coefficients for elevation vary between farms. The effect of the variables in the model was not only due to the affect they have in the landscape but also the position of the sites within these landscapes. The contour of farms such as Tautane and Lawsons was dominated by hill country with steeper slopes at higher elevations and flats on the lowest parts of the farms and

in the valley floors. In contrast, the coefficient for elevation at Cleardale was positive whether calcium or copper were used. The lower flats at Cleardale alongside the Rakaia River are shallow, very stony recent alluvial soils and therefore lower soil Olsen P compared to the upper more developed terraces.

The structure of the hierarchical model meant that the effect of elevation, varied across farms. The inclusion of elevation in this way was more appropriate than in complete pooling approaches where elevation has the same effect across all farms. This essentially means that soil Olsen P is expected to vary from the highest farmed areas, to coastal areas. The scale at which elevation is assessed is important. Water and nutrients, including phosphate, move downslope but they move over only relatively short distances (McColl & Gibson, 1979), except in the case of surface runoff. Elevation was included in the analysis, but landscape elements may be a more appropriate variable to use in models but requires further investigation.

The different factors in the model are influenced by general trends across farms but are also influenced by the location of the sites. For example if a farm has a large area of fertile river flats on the lowest areas of the farm, there could be trade-off between variables such as soil order, elevation and slope (Figure 6-14). At Lawsons, the area classified as Pallic soils was also the locations of sites on flats and the lowest elevation on the farm. Factors such as soils, slope and elevation are likely to hold similar information in many cases, as topography greatly influences soil forming properties.

FERTILISER HISTORY

Fertiliser history contained important information for predicting soil Olsen P. The average annual phosphate fertiliser application (*PFAA*) was forced to have a positive coefficient in the model as the addition of phosphate fertiliser should increase soil phosphate. However the level of production on that piece of land affects whether soil Olsen P builds over time, or is taken up by plants (Morton et al., 1999; Rowarth & Gillingham, 1990).

The coefficient for the last fertiliser application (*PFLA*) was negative for all farms except Erewhon and Lawsons. It was most logical for the coefficient to be negative as more recent fertiliser applications containing high rates of P would have a higher soil Olsen P than areas that received low rates of phosphate fertiliser, some time ago. The fertiliser records

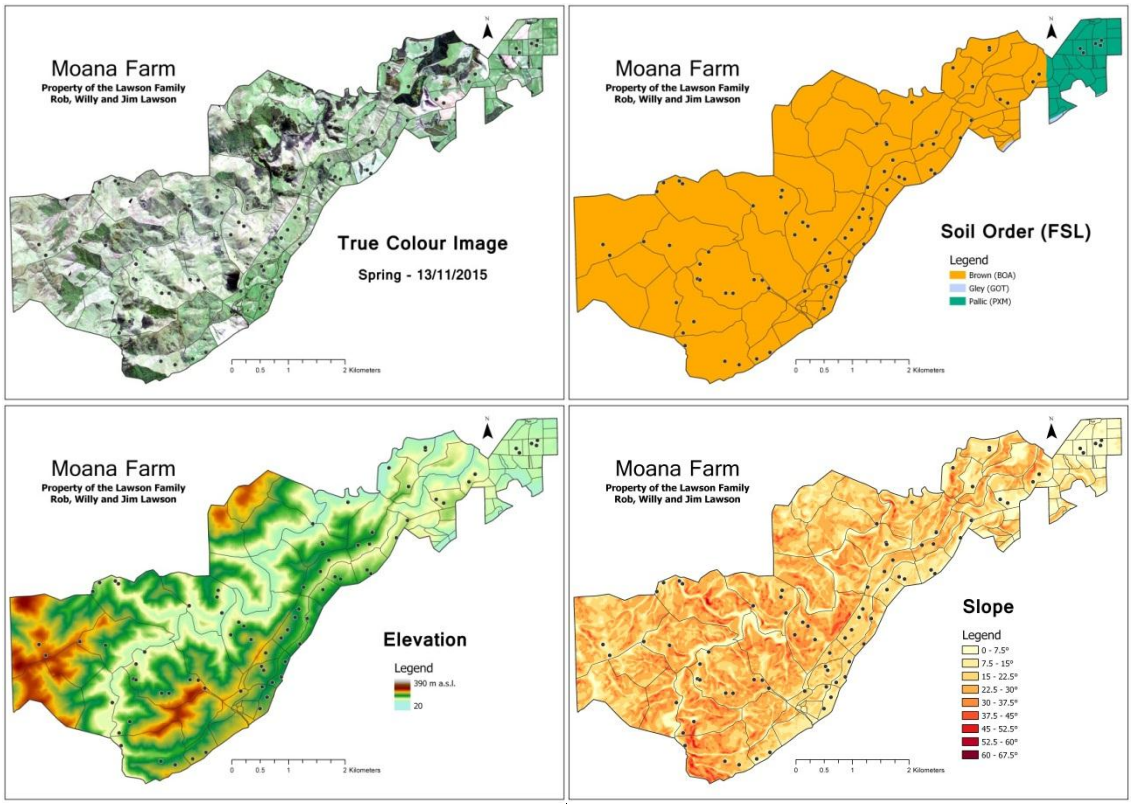


Figure 6-14: Lawons/Moana farm showing a true colour image (top left), soil order (top right), elevation (bottom left) and slope (bottom right) over the property.

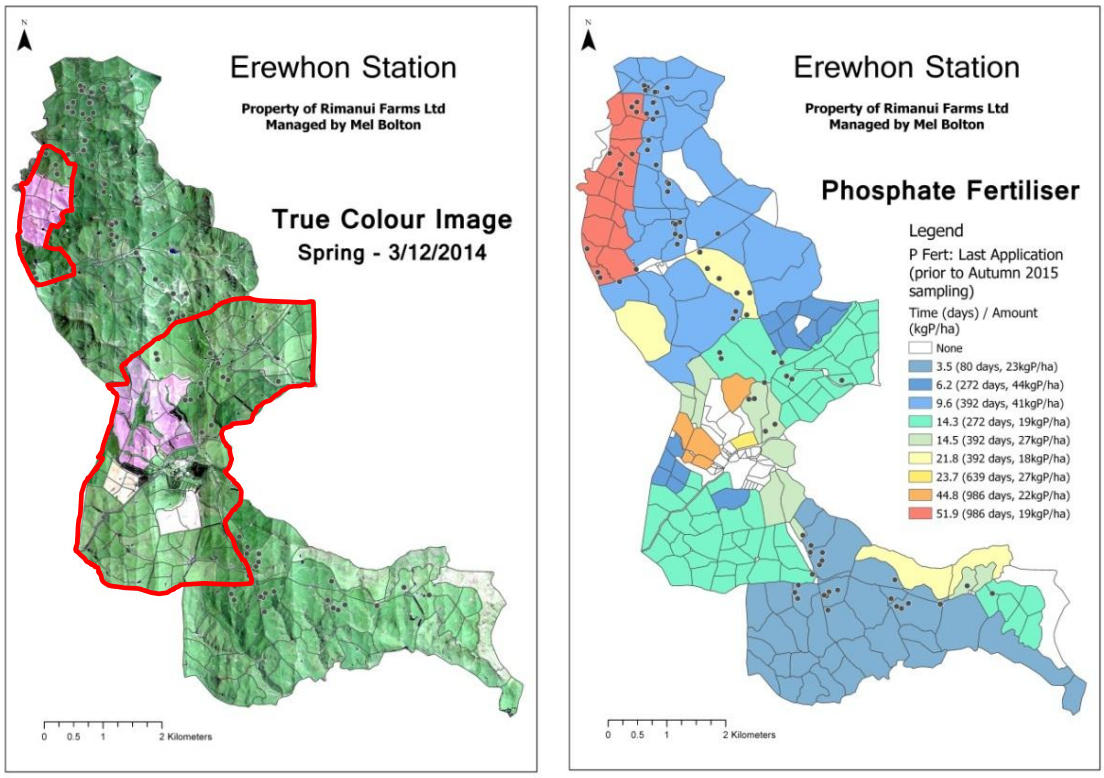


Figure 6-15: Erewhon Stations, a true colour image with flats and easy hills which have undergone extensive regrassing and cropping outlined in red (left) and the last fertiliser application prior to the autumn 2015 sampling.

at Erewhon were thought to be incomplete (see Chapter 3). Fertiliser has been spread on easier hill and flats by truck. Often only small areas were fertilised at one time, with different products, and records for small jobs such as these are often missed. The most recent fertiliser application prior to sampling was also to the steep, low producing areas (Figure 6-15). As a result, the fertiliser variables for Erewhon may not be accurate and cause false relationships.

The variables: *PLAA*, *PFLA* and *SUSSL* for Lawsons were highly correlated (Figure 6-16). The blocks defined for fertiliser have been used continuously over the years, and therefore sites fall into the same groups within each variable. Although the stocking rates are defined by slightly different geographic boundaries, they are very similar. These small differences may be causing artificial relationships between the variables.

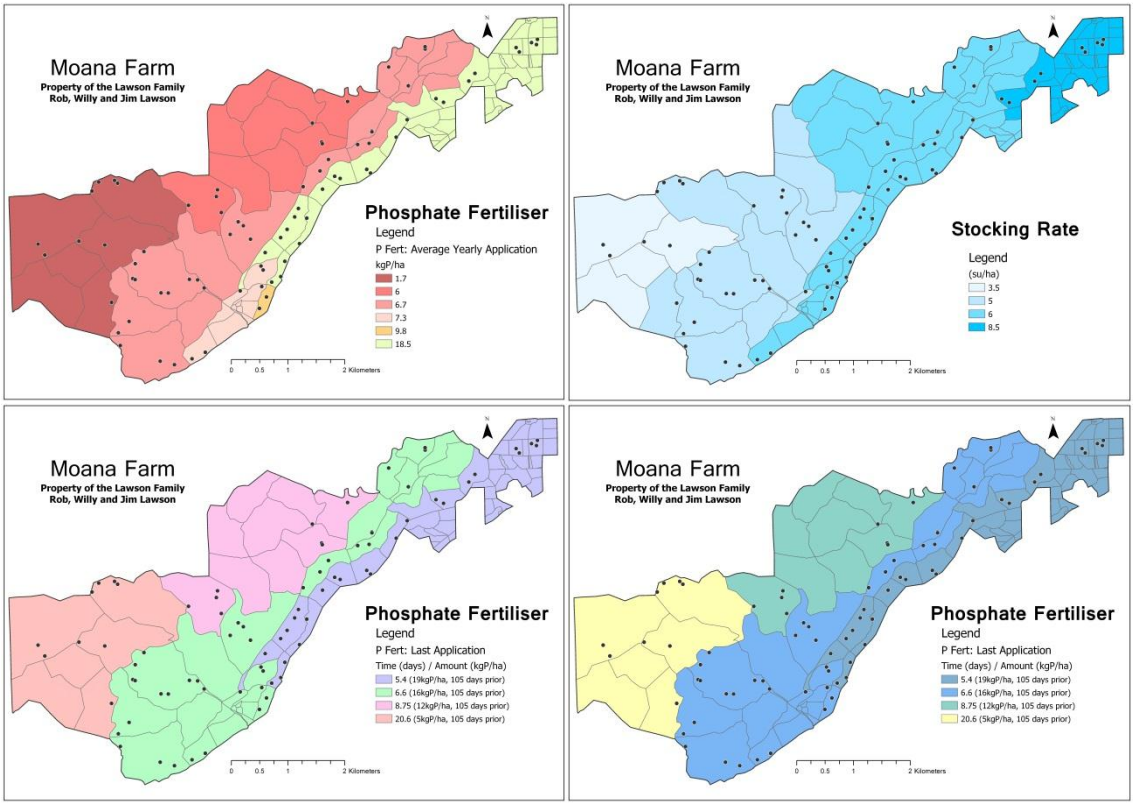


Figure 6-16: Farm management variables at Lawsons/Moana Farm. The average (top left) and last (bottom row) application of phosphate fertiliser prior to sampling and set stocking rates at lambing (top right) are mapped.

When leaf tissue calcium concentration was used, the coefficient for *PLFA* at Tautane had no significant effect. Tautane generally apply fertiliser as blanket applications (Figure 6-17). If fertiliser has been applied evenly across the whole property, in theory, it should not contribute to variation in soil Olsen P across the farm. As the last application prior to the sampling events was a blanket application, the value for *PFLA* is 12.8 for all sites in spring and 23.2 in autumn.

Commercial farms have different approaches to their fertiliser programmes. Incorporating this information into a model was not straight forward and requires some further improvements.

The procedures and accuracy of keeping fertiliser records also needs to be addressed if this is a variable that is to be included. The automation of consistent fertiliser records going forward would be essential.

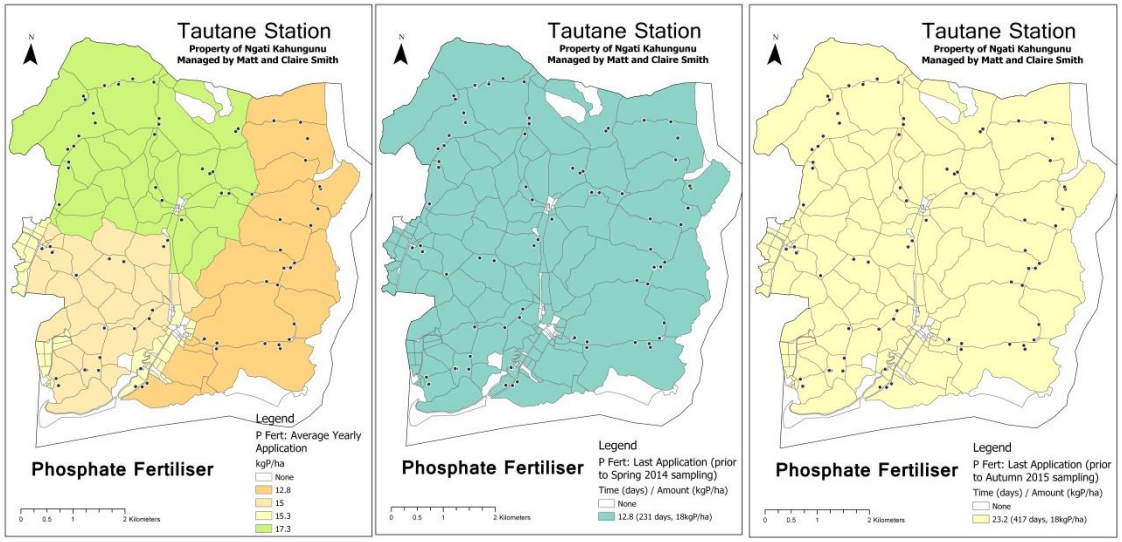


Figure 6-17: Fertiliser variables at Tautane Station, *PLAA* (left) and *PFLA* for spring (centre) and autumn (right).

STOCKING RATE

Set stocking rate at lambing was a significant variable in the model. The level of productivity of areas within a farm and between farms is difficult to quantify. The use of stock units, especially in analysis comparing different farms, often leads to misinterpretation as it is applied differently on each farm (Parker, 1998). Many studies have tried to model or estimate levels of productivity using animal intake where class, breed, weight gain, productivity etc. are used to calculate feed demands and therefore productivity and nutrient removal. Set stocking at lambing was selected as a measure of productivity as much of the years pasture growth occurs during this period. Gillingham (1980) measured the seasonal growth pattern of pasture across different stratum and found approximately ⅔'s to ¾'s of total annual growth on each stratum occurred within spring and summer. Set stocking for lambing is an allocation of stock in each area of the farm from prelamb to weaning and a figure already recorded by farmers. This provided an indication of the level of productivity within the farm. The hierarchical structure allowed for the effect to vary between farms, as stock units will not be equal across farms, but the effect must be correlated across farms.

6.5.3 Plant factors

The inclusion of plant biophysical and biochemical variables reduced the residual error in the model significantly. Leaf tissue P concentration (*PlantP*), either calcium (*PlantCa*) or copper (*PlantCu*) concentration and the vegetation index (*NDVI*) were included in the final model. Although 13 different nutrients were measured, a reduction in the number of plant

biochemical and biophysical variables was necessary to avoid the adverse effects of multicolinearity which would likely lead to severe overfitting. Calcium was originally selected as a second nutrient to incorporate in the model as it was least correlated with leaf tissue P concentration. A second set of models were run using leaf tissue copper concentration as copper was identified as an important factor in the stepwise linear regression analysis and it was unknown if calcium could be predicted at that time from hyperspectral imagery.

The first stage of the project required the development and validation of estimates of pasture nutrient concentration from hyperspectral imaging. Pasture canopy spectra from the visible (VIS), near infrared (NIR) and short wave infrared (SWIR) regions were used to develop robust algorithms using cut pasture samples analysed in the laboratory. As the project developed, the increasing number of samples in the database, the addition of new farms, and the progression and development of more robust algorithms determined which nutrients were able to be predicted from hyperspectral imaging and with what level of accuracy. It was important to include only nutrients that can be predicted using hyperspectral imagery as this provides the substitute data for wet chemistry analysis in the model. However as multiple parts of the project were being developed simultaneously, this information became available as the project progressed. Copper was able to be predicted more accurately than calcium using the AisaFENIX imaging system and would therefore be able to be used as a model input when applied over whole farms or new locations.

LEAF TISSUE PHOSPHORUS CONCENTRATION

Leaf tissue P concentration was included as it had the highest correlation to soil Olsen P which was expected. Leaf tissue P concentration was positively correlated to soil Olsen P which was expected, and also shown in other studies. The relationship between soil P and leaf tissue P concentration has been discussed throughout the previous chapters in this thesis.

LEAF TISSUE CALCIUM CONCENTRATION

Calcium concentration was a significant term in the model with a negative coefficient for the term *PlantCa.* Calcium concentration in the leaf tissue is most commonly linked to the age of the leaves and species in the literature. The low mobility of calcium in the leaf tissue means it is not readily moved from old to new leaves (Whitehead, 2000) and calcium accumulates in tissue of older leaves (Loneragan & Snowball, 1969). Calcium is not mobilised even when grown in deficient conditions (Loneragan & Snowball, 1969), though calcium deficiency in pasture plants is rare, and concentration in the leaf tissue is usually 2 or 3 fold above the plants needs (McNaught, 1973). Leaf tissue calcium concentration increases in leaves of

ryegrass (Fulkerson et al., 1998; Wilman et al., 1994), cocksfoot (Rawnsley, Donaghy, Fulkerson, & Lane, 2002) and white clover (Wilman et al., 1994) as they age. Leaf tissue calcium concentration increased 5 fold in ryegrass and white clover over four growth stages, while P concentration decreased to about two thirds (Wilman et al., 1994). These studies suggest that there is a strong relationship between calcium concentration and age of the leaf tissue. Leaf tissue age was not recorded at the time of sampling.

Calcium concentration is consistently reported to vary significantly between species. The concentration of calcium in leaf tissue of clover is widely known to be greater than in grasses (McNaught, 1970; Metson & Saunders, 1978; Wells, 1969; Wilman et al., 1994). The critical range for maximum growth is reported to be higher in white clover than ryegrass (McNaught, 1970) and more broadly reported as higher in legumes and herbs than in grasses and cereals by Loneragan and Snowball (1969). At luxury levels, calcium accumulated in the tops of legumes and herbs to much higher levels than grasses and cereals (Loneragan & Snowball, 1969). Calcium concentration was found to be significantly greater in narrow-leaved plantain and Californian thistle (Harrington et al., 2006), and dandelion and plantain (Wilman & Derrick, 1994) compared to other pasture species. While Californian thistle and plantain are classified as high fertility dicotyledons, species such as catsear and hawkbit are classified as low fertility species and all are classified under low herbage accumulation hill country species (López et al., 2006). It is difficult to link calcium concentration to a particular species abundance and species to soil fertility within this study.

Calcium uptake by plants is mainly through mass flow and competes with the other cations, Mg, K and Na (Whitehead, 2000). Calcium concentration in the leaf tissue is linearly related to the logarithm of the solution concentration in which they were grown (Loneragan & Snowball, 1969). Calcium is the dominant cation in the soil solution in non-acidic soils (Whitehead, 2000) and leaf tissue calcium concentration has been shown to increase on limed soils (Edmeades, Smart, Wheeler, & Rys, 1983). In alkaline soils calcium availability is high, and P is low with phosphate in the soil solution rapidly absorbed as calcium phosphate (Parfitt, 1979) due to precipitation reactions. There are multiple reported agronomic reasons for differences in leaf tissue calcium concentration in pasture. However, the reason for the significance of calcium concentration in the leaf tissue in this model cannot be defined fully explained.

COPPER CONCENTRATION IN PASTURE

Copper concentration was used as a second nutrient with leaf tissue P concentration in the models in place of calcium concentration. The residual error levels for the models where

copper concentration was used instead of calcium were slightly larger. The agronomic significance of copper concentration is discussed in the previous chapter, section 5.4.2.

NDVI, DRY MATTER PERCENTAGE AND DEAD VEGETATION FRACTION

As expected in leaf tissue samples, NDVI, dry matter percentage (DM%) and amount of dead material were all highly correlated (Table 6-7). The higher the dead material content in the sample the greater the DM% due to the very low water content of dead vegetation. A pearsons coefficient of correlation value of 0.635 was obtained for the spring and autumn combined dataset. The dead vegetation fraction and DM% were negatively correlated to NDVI, pearsons coefficient of correlation values of -0.634 and -0.754 respectively. To reduce the issues of multicolinearity in the model, only NDVI was included.

Table 6-7: Pearsons coefficient of correlation for all farms in spring and autumn combined

	Dry matter %	NDVI
NDVI	-0.754 0.000	Pearson correlation p-value
Dead vegetation fraction	0.635 0.000	-0.634 0.000

The dead vegetation fraction for each sample was acquired using a less consistent technique and was likely to have a much higher measurement error than NDVI and DM%. The dead vegetation fraction was determined using a visual estimation technique by an expert; no dissections were used to validate the accuracy of these visual estimations. The DM% was measured using a subsample weighed and dried in the laboratory and NDVI was derived from the canopy reflectance measurement obtained using the consistently calibrated ASD FieldSpec Pro and CAPP in field. These techniques are more consistent across farms and between sampling seasons.

NDVI measurements calculated from the ASD FieldSpec Pro and the AisaFENIX imaging system are derived from spectra collected using the same fundamental principles of measuring canopy reflectance. The AisaFENIX hyperspectral imaging system does not penetrate the surface, it measures canopy reflectance only. In pastures, dead material accumulates at the base of the sward. This visual estimation technique was used to estimate the dead vegetation fraction in the sward. It involved the expert observing right to the base of the sward to include all above ground plant material in the estimation. Dry matter percentage is calculated from the cut sample, which includes all leaf tissue to just above ground level. This may cause discrepancies when pasture covers are high.

NDVI does however, have limitations. Bare soil affects NDVI. Figure 6-18 highlights examples of sites where the NDVI is low, but this was due to the large percentage of bare soil evident. Although the majority of sites did not have large areas of bare soil exposed, it was not uncommon and it is important to be aware of this limitation. Suzuki et al. (2012) used NDVI as a threshold in their image analysis to determine plants from bare ground and dead material. An NDVI threshold could similarly be used as a step in image processing.

Figure 6-18: Examples of where there are limitations for using NDVI due to high percentage of bare soil visible, paddocks that have been grazed very hard (left), in very dry conditions (centre) and newly sown pasture that have not yet reached canopy closure (right).

Results suggested that NDVI accounts for the variation in P concentration in the leaf tissue sample due to the variation in the dead vegetation fraction, rather than being predominately due to the low availability of nutrient in the soil. NDVI showed no direct relationship to soil Olsen P (R^2 = 0.00), but was a significant factor in the model. NDVI was correlated to the amount of dead material in the sample (R^2 = 0.63), and correlated to leaf tissue P concentration (R^2 = 0.42). The coefficient for NDVI was consistently significant and always negative in all 17 model structures trialled. Nutrient concentration in the sward decreases as dry matter increases due to a dilution effect (Jones & Tracy, 2015). Phosphorus concentration in leaf tissue is known to decrease with advancing maturity in pasture species (Schlegel et al., 2016) and at very low concentrations in dead material (Wilman et al., 1994).

Dead vegetation in a pasture sward is generally greater in summer and autumn (Figure 6-19) with the gradual maturation and death of reproductive stems and dead material accumulates when the senescence rate rises at high temperatures over the summer months, but soil moisture limits material being broken down (Woodward, 1998). Spring set stocking and high feed demand compared to autumn rotational grazing management results in a more uniform pasture cover over the farm and less dead vegetation in the sward. Dead vegetation in a pasture sward is inevitable, therefore it is something that needs to be taken into account. A better understanding of the effect of dead vegetation, leaf and flower spikes, on the spectral signature and the subsequent prediction of leaf tissue nutrient concentration would be useful.

Figure 6-19: Examples of samples in spring (top) and autumn (bottom) showing variation in the dead vegetation fraction.

Most vegetation indices are developed on one or a few, often related, species and generally do not perform well on other species (Sims & Gamon, 2002). The performance of spectral indices on other species depends upon the species and their leaf structure (Sims & Gamon, 2002). A vegetation index for detecting senescent leaf material may be more appropriate or a new index that is developed for mixed pasture could improve results.

6.5.4 Model Validation: Leave-one-out-cross-validation

To assess the performance of the Bayesian hierarchical multiple linear regression model, a comparison between the new approach and the status quo needed to be made. As no traditional soil sampling was carried out at the same time as the field sampling campaign, an average of the measured soil Olsen P was used to represent a blanket fertiliser approach. It is accepted that this did not represent exactly the traditional methodology used, but the average value from the dataset (n=3,600 soil cores) will be more representative of the farm than the average collected using the traditional approach (e.g. if 12 transects are collected across a farm n = 108 soil cores). It is accepted that a uniform fertiliser application is the simplest and most risk adverse approach, and is used as a benchmark.

The predictions of soil Olsen P from the Bayesian hierarchical regression model on any of the seven farms used in the leave-one-out-cross-validation were positively correlated to the actual values of soil Olsen P. The predictions were also more strongly correlated to the actual values of soil Olsen P, than the uniform benchmark. Therefore they are an improvement on the current information provided from soil testing, to inform fertiliser. This suggests that the new approach provides a more accurate representation of the current soil fertility status on farm.

A comparison between the actual and predicted values for soil Olsen P across the different farms and season using the Bayesian hierarchical model were typically around R^2 of 0.2 - 0.4. Given the variation that exists in natural systems, and in particular in a hill country environment, these results appear realistic.

The leave-one-out-cross validation suggests that Limestone Downs is the most different from the other farms in the dataset. The model was unable to use the information on other farms to accurately inform what is happening at Limestone Downs. The most obvious difference between Limestone Downs and the other farms in the dataset is the dominance of kikuyu. The more temperate climate results in the presence of C4 plants. However the abundance of kikuyu was much greater in autumn than spring and neither season gave strong relationships.

The range in predicted soil Olsen P was much narrower than the range for the actual values measured. For example, the range in predicted values for soil Olsen P at Tautane (NTT) (model 'All_03' using plant copper) was approximately 10 and 40 µg/mL, a much narrower range than the actual values of predominately between 4 and 70 µg/mL. This discrepancy was even greater in the leave-one-out-cross-validation of Cleardale (SCD) (model 'All_03' using plant copper) where predicted values were approximately 4 to 20 µg/mL and actual values around 2 and 60 µg/mL. The ability to predict extremely high and low soil nutrient status may be difficult. Extremely high values of soil Olsen P are likely to be a result of animal dung. Dung deposits throughout grazed pastures result in concentrated areas of nutrient in the soil and are a major cause of spatial heterogeneity (Jones & Tracy, 2014). In areas of low P in the soil, pasture plants often still have adequate concentrations in the leaf tissue. The strategies employed by pasture plants to cope with low soil P conditions have been discussed in previous chapters.

6.6 Conclusion

There are many advantages of using a hierarchical modelling approach. The use of a Bayesian hierarchical model allowed the data clustered on farms within the hill country environment to

be appropriately analysed. A hierarchical approach accounts for processes acting on different scales and for fixed and random effects. Through modelling missing data, the maximum amount of information was able to be gained from the data collected. There were many and are still many additional models to explore, both in the variables used and the structure of the model. A model incorporating topographic, farm management, plant biochemical and plant biophysical information resulted in a model with the best fit and lowest residual error. The leave-one-out-cross-validation provided evidence that using a Bayesian hierarchical model would provide a more accurate representation of the soil phosphate availability on hill country farms.

7

7 Predictive soil mapping – soil Olsen P

7.1 Introduction

Through the prediction of plant functional groups based on climate and soil properties on a global scale, Prentice et al. (1992) highlight the way in which patterns in vegetation strongly reflect environmental conditions. A range of patterns in botanical composition, physiology, and canopy architecture, for example, can potentially reflect changes in environmental conditions (Kooistra et al., 2004). These patterns can be captured through remote sensing of vegetation (Kawamura et al., 2011; Schmidtlein, 2005). As the area of interest decreases to regional and local fine scale analysis, the changes in vegetation patterns become relatively more subtle. The vast contrast of distinct vegetation types are easily identified through multispectral remote sensing (Dymond, Page, & Brown, 1996). Although more subtle, changes need to be identified within regional or local scale grasslands, which is possible through hyperspectral sensing (Yule, Pullanagari, & Kereszturi, 2016).

Patterns in natural vegetation reflect more distinctly the patterns in the environment. Highly managed landscapes include a level of complexity where they are modified by human activity which can have a significant and long lasting effect. In a global study of the relationship between leaf traits and soil fertility, including 474 species but excluding crops and plantation

forestry, 48% of the variation in leaf P was explained by soil P availability (Ordoñez et al., 2009). Prentice et al. (1992) were unable to predict plant functional groups based on climate and soil properties alone where intensive agriculture had overridden natural patterns. Vegetation patterns can be affected by the history of the landscape through human interaction and disturbance; much of this history of landscapes will remain unknown (Motzkin, Wilson, Foster, & Allen, 1999).

There are many approaches to mapping soil properties. Predictive soil mapping (PSM) is the use of a statistical or numerical model that is developed using environmental variables and their relationship with soil properties. This is then applied across spatial data to create a map of a predicted soil property (Scull, Franklin, Chadwick, & McArthur, 2003). The approach was referred to as "environmental correlation" by McKenzie and Ryan (1999). One of the aims of PSM is to represent the continuous nature of soil properties across the landscape better (Scull et al., 2003).

Improving nutrient use efficiency requires information on the current nutrient status of the soil. A major barrier for the implementation of site specific nutrient management is the lack of accurate maps of soil properties of an appropriate scale to provide the basis on which management decisions can be made (Frogbrook & Oliver, 2007). Detailed soil information of any kind is scarce (Viscarra Rossel et al., 2010). To measure soil properties directly is difficult (Minasny et al., 2011) and the extent to which they can be observed through their influence on the other environmental variables is limited (McKenzie & Ryan, 1999).

Currently, the most important piece of information used to make decisions around the application of superphosphate or other phosphate fertiliser products in hill country is soil Olsen P results from laboratory testing of soil cores, collected along transects across the farm. The most risk averse option for improving P status is to blanket apply fertiliser at the same rate across a whole farm (Whelan & McBratney, 2000). Site specific nutrient management essentially aims to reduce the variation in soil phosphate by applying fertiliser to areas below the optimal level, and withholding fertiliser (and mining areas) where phosphate availability is above optimal (Bowie & Venter, 2017). As a farm is divided up into smaller blocks managed separately, it is important that decisions are based on accurate soil data. The risk is that if decisions are based on misinformation, the outcomes can have results inferior to those of a blanket approach.

The models developed in the previous chapters are based on point data containing the laboratory analysis of samples collected at the permanently marked sites. To predict over a

whole farm, input data must come from another source. Destructive leaf tissue analysis and other in field data measurements, and their collection at all locations, was not practical. Inputs were derived from alternate sources and used in the model. Although there was no opportunity to validate a map created of predicted soil Olsen P within this thesis, it was felt important to show the output of such models. Some of the model inputs used in the previous chapter were unable to be obtained for the full spatial extent of the farm at the time this work was completed. Models created using the same methodology as the previous chapter were used with fewer inputs to predict soil Olsen P across the whole farm. The software limitations meant that for the fully hierarchical model, given the size of the input data set and the complexity of the model, only a subset of the farm and a model based on a single farm was used.

This chapter aims to:

- create a data cube containing layers of input variables used in the regression model to predict soil Olsen P.
- use the coefficients of the Bayesian hierarchical linear regression model to make predictions, incorporating layers of the input variables created and stored within a GIS, across one of the commercial farms, Ohorea Station, as an example.
- use a Bayesian linear regression model, incorporating a subset of the layers of the input variables created and stored within a GIS, from Ohorea Station to make predictions of the underlying soil Olsen P, and the associated uncertainty of the predictions.

7.2 Methodology

7.2.1 Mapping of soil nutrients

All models were developed using the most accurate data available which incorporated the in situ measurements and wet chemistry analysis of leaf tissue from the laboratory. However, to make estimates across a wider area or whole farm, easily accessible data with full spatial coverage needed to be sourced. Data used for estimates over the farm are summarised in Table 7-1. This data was derived primarily from DEM's and hyperspectral imagery.

Table 7-1: Variables and data source of model inputs for estimates of soil Olsen P across Ohorea Station to create maps of soil nutrient stauts.

Variable	Source	Type	Resolution
ELEV	Derived from LINZ Digital Elevation Model (DEM)	Raster	8m
SLOPE	Calculated from LINZ Digital Elevation Model (DEM) in ArcGIS 10.3	Raster	8m
ASP	Calculated from LINZ Digital Elevation Model (DEM) in ArcGIS 10.3	Raster	8m
SACT	Calculated from *SLOPE* and *ASP* layers	Raster	8m
SOIL	Fundamental Soils Layer	Polygon	Landscape
PFAA	Digitised data from farm/fert records	Polygon	Paddock
PFLA	Digitised data from farm/fert records	Polygon	Paddock
SUSSL	Digitised data from farm records	Polygon	Paddock
AUT		Index	NA
PLANTP	Estimate from AisaFENIX hyperspectral imaging system	Raster	1m
NDVI	Estimate from AisaFENIX hyperspectral imaging system	Raster	1m

Layers for input variables were created, collated and stored within a GIS. Layers for each covariate were created using ArcGIS Pro software. The LINZ 8m DEM was used to obtain elevation and derive slope, aspect and the slope/aspect cross term. Slope and aspect were calculated using the "Slope" and "Aspect" tools from the "Spatial Analyst Tools" in ArcGIS Pro. The "raster calculator" was then used to calculate the *ASP* term as described in previous chapters and the slope/aspect cross term, *SACT*. The soils layer was obtained from the New Zealand Fundamental Soils dataset. The farm management terms were digitised from farm and fertiliser records as detailed in previous chapters. The leaf tissue P concentrations were estimates derived from the AisaFENIX hyperspectral imaging system as processed and calculated by Pullanagari et al. (2016) within the same wider project.

Not all layers used in the model developed in Chapter 6 could be obtained at the time this analysis was carried out. The predicted pasture growth rate (which needed to be provided from the Ravensdown Pasture Growth model), leaf tissue calcium concentration (which could not be predicted accurately with the AsiaFENIX hyperspectral imaging system), and leaf tissue copper concentration (which was unavailable as a layer covering the whole farm at that time) were not able to be incorporated. Therefore the model developed in Chapter 6 was unable to be used to make predictions in different areas of the farms. As many areas of the project were developed simultaneously and continued to be developed, it was difficult to determine in advance which variables would be available as full spatial layers within the scope of this thesis.

7.2.2 Ohorea station: example of whole farm estimates from hierarchical model

A hierarchical linear regression model was developed using all eight farms. The same methodology was followed as the model development in Chapter 6, but without the variables *PGR* and neither *PLANTCA* nor *PLANTCU*. The model was run within the WinBUGS software package using non-informative priors for 100,000 iterations with a thinning interval of 10 and a burn-in period of 15,000. The mean of the posterior distributions of the coefficients from this model for Ohorea Station were used to make estimates of soil Olsen P across the whole farm.. The "raster calculator" tool in ArcGIS Pro was used to calculate the predicted values, and the resulting raster data layer with a 1m resolution was used to display the predicted soil Olsen P across the entire farm. A mask was provided to remove all non-pasture surfaces from the image.

7.2.3 Ohorea station subset: estimates and uncertainty

A subset of the data from Ohorea Station was used to demonstrate the output of a model where the posterior predictive distribution can be used to estimate soil Olsen P along with the uncertainty. Due to the computational complexity of the hierarchical model and the large amounts of data in one farm, estimates along with their uncertainty were unable to be computed. Therefore, a 5 hectare subset of the data at Ohorea Station (Figure 7-1) and a linear regression model using data from only Ohorea Station, were used to reduce the computational complexity and allow estimates to be made with their associated uncertainty across a subset of the farm.

To create prediction maps of soil Olsen P, layers for each covariate were created within a GIS, ArcGIS Pro, with identical x and y extents and pixel size. The raster data was then transformed into matrices. A linear regression model using only the data from Ohorea was developed with non-informative priors and the model was run for 50,000 iterations with a thinning interval of 10 and a burn-in period of 15,000 within the WinBUGS software package. Through Bayesian inference, we can use the posterior distribution of the parameters to predict soil nutrient status at a new location with a known level of uncertainty – a posterior predictive distribution. Three maps were created: the mean of the posterior predictive distribution of soil Olsen P, and the 10th and 90th quantiles.

The 10th and 90th quantiles were calculated for soil Olsen P as below:

$$10th\ quantile\ of\ Olsen\ P = e^{LogSOP - 1.645 \times std.dev.LogSOP}$$

$$90th\ quantile\ of\ Olsen\ P = e^{LogSOP + 1.645 \times std.dev.LogSOP}$$

These two examples allowed initial steps towards predictive soil mapping of soil nutrients to be demonstrated and the amount of information that can potentially be gained, and type of information that this approach could provide, illustrated.

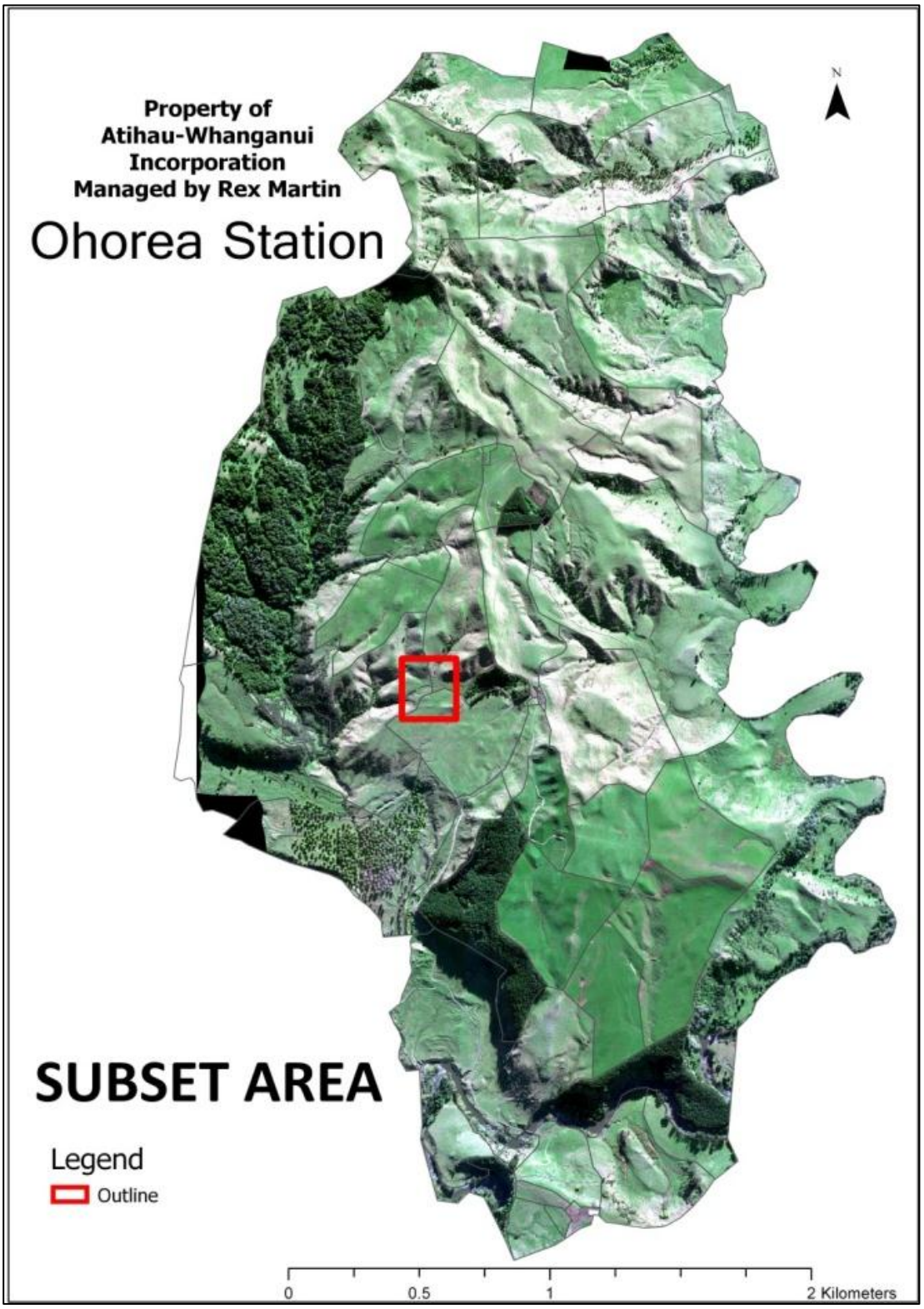


Figure 7-1: True colour image of Ohorea Station, with an outline of the 5 ha area used for the subset of data.

7.3 Results

7.3.1 Ohorea station: whole farm example from hierarchical model

The spring and autumn sampling events across the eight farms were combined into one hierarchical model. The model used topographical features, management factors and plant tissue information. The model of soil Olsen P, for i = 1… N samples, where N is the number of samples in the dataset, where N = 5,660. $LOGOlsenP_i$ is therefore the natural logarithm of the measured soil Olsen P of the i-th sample defined by a sample taken in a particular season at the individual plots in the field. *LOGOlsenP* is assumed to be normally distributed with a mean f_i and a precision τ_i. $\beta_{(B,F)}$ is a matrix of regression coefficients where F = 1... *NoF*, where *NoF* is the number of farms in the dataset. $\beta Soil_{(S),}$ and $\beta Plant_P$ are vectors of regression coefficients for soil order and the plant chemical and physical variables.

The hierarchical model used was defined as:

$$LOGOlsenP_i \sim N(f_i, \tau_i)$$

$$\begin{aligned} f_i = {} & (\beta_{(1,F)} \times SLOPE_i) + (\beta_{(2,F)} \times ASP_i) + (\beta_{(3,F)} \times SACT_i) + (\beta_{(4,F)} \times ELEV_i) \\ & - |\beta_{(5,F)} \times SUSSL_i| + |\beta_{(6,F)} \times PFAA_i| + (\beta_{(7,F)} \times PFLA_i) + (\beta_{(8,F)} \times AUT_i) \\ & + (\beta Soil_1 \times SOILB_i) + (\beta Soil_2 \times SOILE_i) + (\beta Soil_3 \times SOILG_i) \\ & + (\beta Soil_4 \times SOILL_i) + (\beta Soil_5 \times SOILM_i) + (\beta Soil_6 \times SOILP_i) \\ & + (\beta Soil_7 \times SOILR_i) + (\beta Soil_8 \times SOILN_i) + (\beta Plant_1 \times PLANTP_i) \\ & + (\beta Plant_2 \times NDVI_i) \end{aligned}$$

The error term is defined as:

$$\tau_i = \frac{1}{\sigma_i^2}$$

$$\sigma_i = e^{x_i}$$

$$x_i \sim Normal(\mu_i, v)$$

$$\mu_i \sim Normal(M, w)$$

$$M \sim Normal(0, 0.000001)$$

$$v \sim Gamma(0.1, 0.1)$$

$$w \sim Gamma(0.1, 0.1)$$

The topographic and management features were hierarchical. However soil order and the plant physical and chemical properties were not. This meant that these factors are having the same effect across all farms. The coefficients are defined as:

$$\beta_{(B,F)} \sim Normal(MB_B, TB_B)$$

$$MB_B \sim Normal(0, 0.000001)$$

$$TB_B = \frac{1}{SB_B^2}$$

$$SB_B \sim Uniform(0, 150)$$

$$\beta Soil_s \sim Normal(0, 0.000001)$$

$$\beta Plant_P \sim Normal(0, 0.000001)$$

$\beta_{(B,F)}$ is a matrix of regression coefficients where β = 1,2,3…8 for SLOPE, ASP, SACT, ELEV, SUSSL, PFAA, PFLA, AUT respectively. $\beta Soil_S$ is a vector of regression coefficients where S = 1,2,3… 8 for soil orders of Brown, Melanic, Gley, Allophanic, Pumice, Pallic, Recent and Granular respectively. $\beta Plant_P$ is a vector of regression coefficients where P = 1 or 2 for leaf tissue P concentration and NDVI respectively.

The model was used to estimate soil Olsen P over all of the pasture areas of Ohorea Station to create a map of predicted available P in the soil. The DIC for this model was 6,730, significantly greater than the hierarchical model developed using pasture growth rate and plant calcium or copper concentration with DIC values of 6088 and 6285 respectively. A difference greater than 10 is considered significant. The coefficients from this hierarchical model were used to estimate soil Olsen P at Ohorea Station in the autumn of 2014 using the following equation:

$$\begin{aligned} OlsenP_i = \exp\big(& (-0.0193 * SLOPE_i) + (-0.04348 * ASP_i) + (-0.003644 * SACT_i) \\ & + (-0.0007848 * ELEV_i) - (0.003417 * SUSSL_i) + (0.01712 * PFAA_i) \\ & + (-0.0005758 * PFLA_i) + (0.1001 * AUT_i) + (2.431 * SOILB_i) \\ & + (2.617 * SOILL_i) + (2.369 * SOILR_i) + (3.227 * PLANTP) \\ & + (-1.001 * NDVI_i)\big) \end{aligned}$$

A map of predicted soil Olsen P is presented in Figure 7-2. A true colour image at the time of the survey and the predicted Olsen P with non-pasture areas masked out are shown for comparison. The predicted Olsen P over the whole property ranged from 3 – 56 µg/mL.

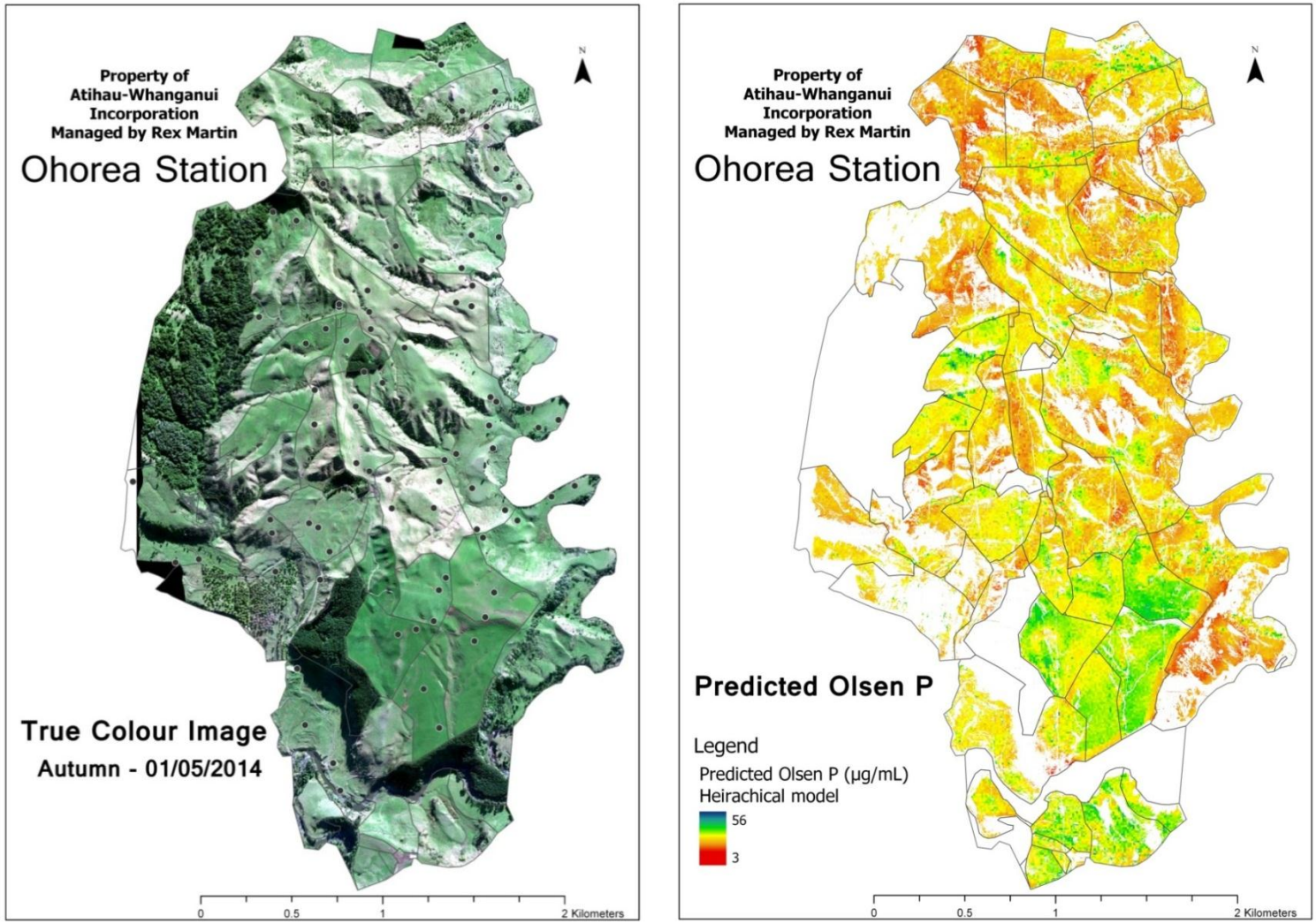


Figure 7-2: True colour image of Ohorea Station in autumn 2014 (left) and predicted soil Olsen P calculated by extrapolating over the farm using the hierarchical model (right).

7.3.2 Ohorea station subset: predictions and uncertainty

The spring and autumn 2014 sampling events from Ohorea Station were combined into one model. The model used topographical features, management factors and plant tissue information. The model of soil Olsen P, for *i* = 1… *N* samples, where *N* is the number of samples in the dataset, N = 800. $LOGOlsenP_i$ is therefore the natural logarithm of the measured soil Olsen P of the *i*-th sample defined by a sample taken in a particular season at the individual plots in the field. *LOGOlsenP* is assumed to be normally distributed with a mean f_i and a precision τ_i. β_B, $\beta Soil_S$, and $\beta Plant_P$ are vectors of regression coefficients for topographic and management factors, soil order and the plant chemical and physical variables.

The model used was defined as:

$$LOGOlsenP_i \sim Normal(f_i, \tau_i)$$

$$\begin{aligned} f_i = \alpha + (\beta_1 \times SLOPE_i) + (\beta_2 \times ASP_i) + (\beta_3 \times SACT_i) + (\beta_4 \times ELEV_i) - |\beta_5 \times SUSSL_i| \\ + |\beta_6 \times PFAA_i| + (\beta_7 \times PFLA_i) + (\beta_8 \times AUT_i) + (\beta Soil_1 \times SOILL_i) \\ + (\beta Soil_2 \times SOILR_i) + (\beta Plant_1 \times PLANTP_i) + (\beta Plant_2 \times NDVI_i) \end{aligned}$$

$$\beta_B \sim Normal(0, 0.000001)$$

$$\beta Soil_S \sim Normal(0, 0.000001)$$

$$\beta Plant_P \sim Normal(0, 0.000001)$$

The error term is defined as:

$$\tau_i = \frac{1}{\sigma_i^2}$$

$$\sigma_i = e^{x_i}$$

$$x_i \sim Normal(\mu_i, v)$$

$$\mu_i \sim Normal(M, w)$$

$$M \sim Normal(0, 0.000001)$$

$$v \sim Gamma(0.1, 0.1)$$

$$w \sim Gamma(0.1, 0.1)$$

The maps created from the means of the posterior predictive distributions and the 10th and 90th quantiles are presented in Figure 7-3. The colour scales are the same with the extension of blue through purple from 70-110 µg/mL in the 90th quantile map.

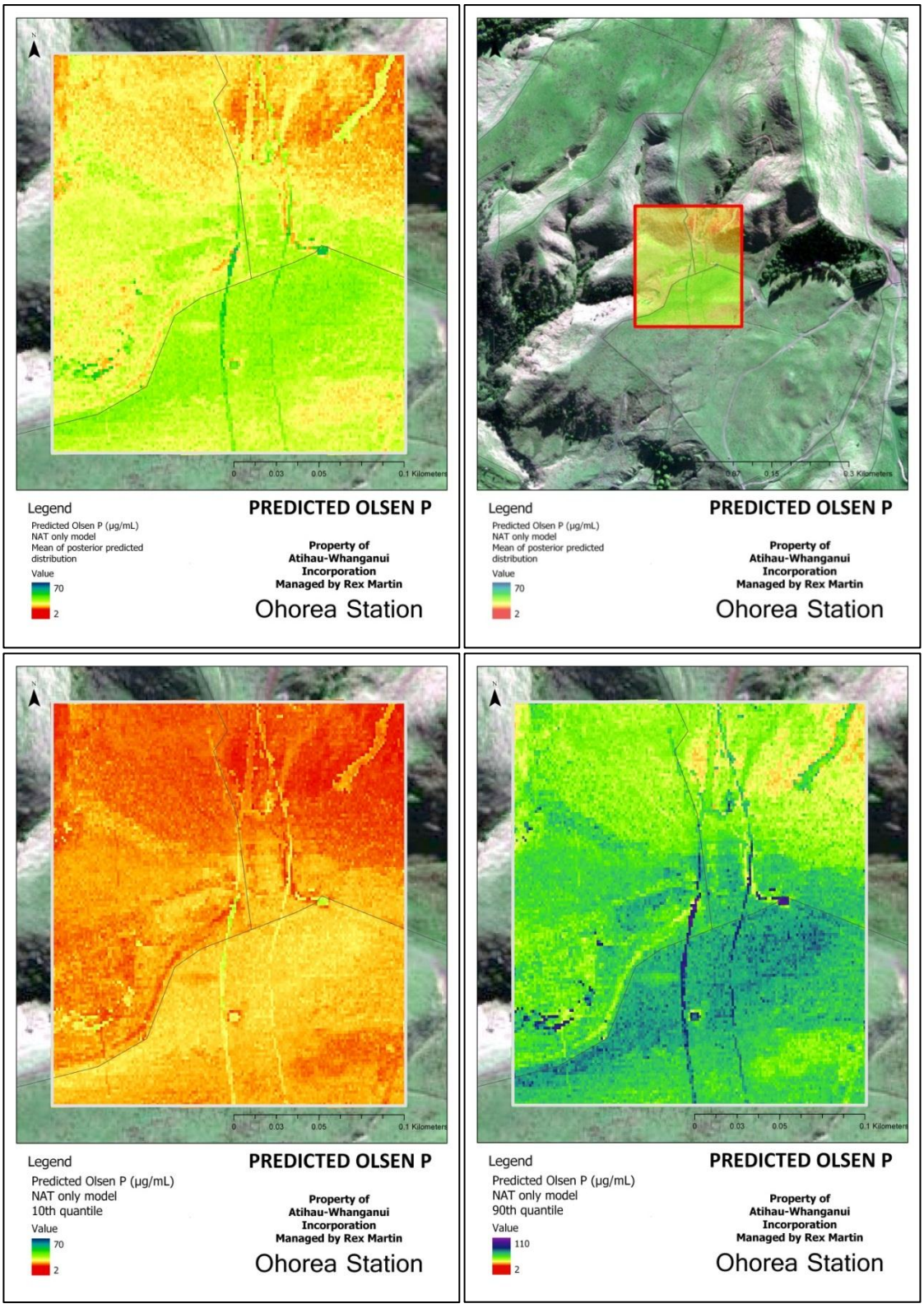


Figure 7-3: The mean of the posterior predictive distribution for soil Olsen P (top left) and within the landscape (top right), the 10th quantile (bottom left) and 90th quantile (bottom right).

7.4 Discussion

7.4.1 Predictive mapping of soil nutrients

PREDICTIVE SOIL MAPPING

The predicted values of soil Olsen P were within the range expected in hill country. For the predictions over the whole farm the values ranged from 3-56 µg/mL. The range of soil Olsen P mean values calculated from the posterior predictive distributions in the subset were 4.7-54.2 µg/mL, and for the 10^{th} quantile 2.3-27.4 µg/mL and the 90^{th} quantile 9.5-107.2 µg/mL. The range in soil Olsen P estimates from the actual dataset including all farms and seasons was 2 to 130 µg/mL. Other ranges stated in the literature were 4.3-130 µg/mL (Fu et al., 2013) and approximately 5-50 µg/mL (Sparling & Schipper, 2002a). Nutrient return via dung from grazing animals results in a small but highly concentrated area of nutrient in the soil (Fu et al., 2013; Jones & Tracy, 2014). The skewed distribution of soil Olsen P and the extremely high values are likely the result of dung (Fu et al., 2013). Although P nutrient concentration in leaf tissue has been shown to be higher in ryegrass under dung patches, 0.42-0.56 % (Joblin & Keogh, 1979), it is not much greater than normal expected concentrations in ryegrass of 0.35-0.4 %, and well within the range found in the dataset collected, 0.09-0.71 %. This could explain why the highest values of predicted soil Olsen P are much lower than the actual highest values known to exist.

Few studies have been published attempting to use predictive soil mapping to predict soil phosphate. Using environmental variables in a multiple linear regression model with a Bayesian approach was attempted for the first time, although still requires validation. The use of leaf tissue nutrient concentration, topographic and farm management variables were all important. A model developed by Moore, Gessler, Nielsen, and Peterson (1993) used stepwise linear regression to select environmental variables to predict soil P content in the top 10 cm. The model was developed based on 231 locations where measurements were made over a 5.4 ha area which had been cropped, mainly in winter wheat, for 70 years. The only variables selected were topographic variables: slope, a wetness index (surface saturation and soil moisture content) and stream power index (measure of the erosive power of overland flow), to achieve an R^2 of 0.48. McKenzie and Ryan (1999) used K concentration in the soil derived from airborne gamma radiometric remote sensing, relief, slope angle and slope curvature in regression trees and linear regression analysis to predict soil phosphate in a hardwood forest in the Bago-Maragle area in southeast Australia. Although these studies used environmental variables, they did not incorporate leaf tissue biochemical or biophysical parameters, which

were very important predictors in hill country soil phosphate modelling. PSM has predominantly been developed on agricultural land with gentle topography, but to be successful, needs to be developed and further tested over more complex terrain and in new environments (Scull et al., 2003).

PREDICTIVE MAPPING VS. INTERPOLATION

The approach of PSM of soil Olsen P through applying a model to a data cube has a major advantage over traditional and common approaches that involve interpolation or kriging of point data. The high spatial variability of soil properties has meant these techniques cannot always be implemented from point data, as has been seen in the case of soil K (Officer et al., 2006) and soil P (Kaul & Grafton, 2017) in New Zealand hill country. Studies have traditionally had only point data to work with, but the use of remote sensing and image analysis is rapidly developing. Imaging systems provide continuous data eliminating the need for interpolation or kriging. In this study, the advantage of using estimates of leaf tissue nutrient concentrations derived from hyperspectral imagery and raster data layers is that predictions of soil Olsen P could be made at every location, or more specifically, on every pixel.

The maps created, show the continuous predicted values across the landscape. A spatial pattern can be identified within the prediction maps. Lower values were on the hills and higher values on the flatter areas. A Bayesian approach had the advantage over frequentist statistics in that a level of uncertainty around the predictions made was also obtained. This provides valuable information when interpreting the results. The high level of uncertainty around the predictions is evident in the wide range in values between the 10^{th} and 90^{th} quantiles. The areas where soil Olsen P is predicted to be higher, also have greater uncertainty.

TRADITIONAL TRANSECTS VS. PREDICTIVE SOIL MAPPING

Although accuracy decreases from laboratory analysis to predictions from models based on predominantly leaf tissue nutrient concentration estimates derived from hyperspectral imagery and DEM's, continuous predictions can be made across the landscape. Predictions from PSM will never be able to match the accuracy of a single sample that is dried, sieved and homogenised in the lab. Compared to traditional transect soil sampling, PSM has grealty improved spatial resolution. It needs to be decided which approach (the traditional transect or PSM) provides a more accurate representation of the nutrient status across the farm. However, given the level of accuracy achieved to predict soil properties using lab based spectroscopy, Ben-Dor et al. (2009) believe it is only a matter of improving our knowledge, and

time, until we see similar results from image spectroscopy of bare soil. The applications and interpretation of hyperspectral imaging is expanding and improving, and it is likely that our understanding of biophysical and biochemical pasture parameters will also progress significantly over time.

Spatial datasets contain vast amounts of data. Turning that data into information involves not only the challenge of analysing a large dataset but also the computational complexity. However the information that can be derived from such data opens up huge potential beneficial applications for agriculture. A literature search by Minasny and McBratney (2016) found the size of data processed in digital soil mapping has seen a doubling of the number of pixels every two years since the 1970's. Although a subset of the data was used in this chapter to reduce the size of the dataset and the model simplified, there are ways to overcome this problem. The methodologies, development, and outputs of the model were more important to demonstrate than the ability to process data on a large scale.

7.4.2 Pasture biophysical and biochemical properties derived from hyperspectral imagery

Hyperspectral sensing can provide detailed information on plant biophysical and biochemical parameters. In grassland and pasture management, this has most often been studied in relation to forage quality parameters (Biewer, Fricke, & Wachendorf, 2009; Suzuki, Tanaka, et al., 2008). Within the wider project, the dataset has proven the ability to predict macro and micro nutrients (Pullanagari et al., 2016; Yule et al., 2015), dead vegetation fraction (Pullanagari et al., 2017), and temporal changes in leaf tissue concentration (Yule et al., 2016) using AisaFENIX hyperspectral imagery of the commercial hill country farms. The estimates of nutrient concentration, in particular P, in the leaf tissue and NDVI were very important factors in the models to predict soil Olsen P. However there are some limitations to the use of such estimates and areas which require further research and understanding.

Estimates of nutrient concentration are made on all pixels in a hyperspectral image regardless of the surface. Hill country landscapes are varied and common features such as large areas of bare soil or rocks, gravel tracks and roads, ponds and waterways, native bush or scrubland, and plantation forestry can easily be identified in an RGB image. These features have been identified in other studies using multispectral imagery (Dymond et al., 1996) and needed to be masked out. The use of 1m resolution hyperspectral imagery provided by the AisaFENIX imaging system should generate accurate masks, as these features dominate the small pixel size and have significantly different spectral properties, making them easily identifiable. These

features were removed from the Ohorea dataset to eliminate leaf tissue nutrient estimates being made on non-pasture pixels.

The interpretation of mixed pixels is more difficult. Hyperspectral images contain pixels that are a mix of both soil and plants, especially in agricultural landscapes (Lagacherie et al., 2008; Mutanga et al., 2004). Variation and inconsistencies in the target surface create noise in the data and differences in spectra that are not a result of the property of interest (Lagacherie et al., 2008), in this case leaf tissue biophysical and biochemical parameters. Dry leaf material, visible soil and rocks have a large effect on reflectance and the spectral signature (Elvidge & Zhikang, 1995; Todd, Hoffer, & Milchunas, 1998) and calculated NDVI (Elvidge & Zhikang, 1995). A percentage of all pixels in the images on any farms collected within the dataset will contain bare soil. This could be accounted for through sophisticated techniques such as spectral unmixing (Gomez et al., 2008; Guerschman et al., 2015) or more simply could be reduced using soil adjusted vegetation index (SAVI) (Elvidge & Zhikang, 1995) as an alternative to NDVI. Both could be further explored, or pixels dominated by soil could simply be ignored without major loss of information.

Hill country pastures are highly heterogeneous with two to 20 or more species typically making up the pasture sward (Kemp, Matthew, & Lucas, 2011). Approximately 23 grass species, 6 legumes, 2 herbs and 31 weed species were recorded in the three most dominant species in the plots. Most often three or fewer species contribute 80% of the total yield (Kemp et al., 2011). The occurrence and dominance in the sward depended on the farm and season; however ryegrass, browntop, white clover, Yorkshire fog and sweet vernal were the most commonly identified species, with plantain, crested dogstail, cocksfoot, kikuyu and catsear also frequently recorded. Misinterpretation could occur when estimates of leaf tissue parameters are made from spectra collected from pastures dominated by species outside the dataset, and therefore the estimates of soil Olsen P would be affected as well. There are many ways to transform a spectral signature into biophysical and biochemical parameters that have been published, however they can become less accurate outside the local study area (Dorigo et al., 2007).

In selecting sites, areas dominated by weed species were avoided. However there are some 187 plant species occurring as ‘weeds’ in New Zealand agricultural pastures and the extent of their distribution and dominance is unknown (Bourdôt et al., 2007). Some species can cover large areas, dominating the canopy, but are not desirable in the sward and are underrepresented in the pasture samples collected such as: Californian and scotch thistle

(*Cirsium arvense* and *C. vulgare*), buttercups (*Ranunculus repens*, *R. acris* and *R. sardous*), mouse-ear chickweed (*Cerastium fontanum*), hydrocotyle (*Hydrocotyle* spp.) and water pepper (*Persicaria hydropiper*). Previous work has shown the variation in nutrient concentration between species (Fulkerson et al., 1998; Harrington et al., 2006). Further work is required in this area to determine the exact effect of these species in relation to their chemical and architectural differences, and the effect on reflectance and the interpretation of the resulting spectral signature.

Hill country farms in New Zealand are based on a year-round pastoral grazing system which results in a mosaic of grazed pastures. Plant structure and leaf architecture are known to affect the spectral signature (Dorigo et al., 2007). Spectral signatures are also affected by grazed and non-grazed pastures (Numata et al., 2007; Todd et al., 1998). This affects the ability to accurately predict vegetation parameters (Kawamura et al., 2009; Mutanga et al., 2004) including calculating spectral indices (Gamon et al., 1995; Numata et al., 2007). In some of the hyperspectral images, grazing differences are evident along paddock boundaries. The effect of defoliation and regrowth on nutrient concentration and canopy reflectance is an area that requires further research.

7.4.3 Soil information

Highly detailed soil information suitable for within paddock, site specific management is scarce but would also result in an over fitted model. High level soil classification from national datasets are inaccurate and are not at an appropriate scale to identify within farm variation. Ideally, a broad soil classification, accurately mapped to capture within farm variation, would be used. There are three issues to address: detail, coverage and accuracy.

It is likely that the inclusion of detailed soil data would likely improve our ability to understand and estimate soil fertility if the system could be understood to this complex level. Detail refers to the level of the New Zealand Soil Classification (NZSC) to which the soil is mapped, from order, through groups, subgroups, family, to sibling as the most detailed level. The highest three of these levels are defined by Hewitt (2010), and family and sibling by Webb and Lilburne (2011). The inclusion of soil information from groups or more detailed levels would result in an over fitted model that could not easily be transferred to other locations. Of the 74 soil groups, few of these are represented in the data set, and less would be represented the more detailed the soil description. A model including this level of detail would be unable to predict on farms with soils classified outside of those included in the model development. Therefore, it is not appropriate to use this level of detail given the dataset and the overall objectives of the

project. Other ways of classifying soil such as those used for fertiliser recommendations (sedimentary, ash, pumice and peat) or soil texture (portion of sand, silt and clay) could alternatively be used. However accurate data would need to be sourced.

Full spatial coverage of hill country is important as the ultimate outcome is for the model to be applied to other hill country farms within New Zealand. Creating a model that relies on data that is currently unavailable would lead to significant limitations if the project was to be commercialised. The FSL was used as there is full coverage of mainland New Zealand readily available. More detailed and accurate sources, such as Smap are being developed, where spatial coverage is increasing all the time.

The accuracy of soil maps depends on the scale at which the data is collected. Accurate soil maps are scarce, as mapping soils in detail takes time and expertise. The FSL is a coarse national scale dataset. Therefore the accuracy with which the soils are classified is very low at farm scale. Prescription maps for site specific nutrient management require inputs such as appropriately scaled soil maps (Betteridge et al., 2008).

The soil orders at Limestone Downs as classified in the Fundamental Soils Layer (Figure 7-4) and on a farm scale mapping exercise (Figure 7-5) appear visually quite different from each other. Even the soil orders identified differ. In the FSL, brown soils dominate, with a large area of Allophanic soils in the north, an area of Ultic soils in the western hill area, and Recent and Gley soils in the valley floor. In the detailed farm map completed by Dr A. Palmer and his 3rd year Massey soils students over many years compared to the FSL: the areas of Gley soils are more widespread; no Ultic soils are identified; the area of Allophanic soils is much reduced and found in the east of the farm; Recent soils are identified along the coast but not the valley floor; and a large area of Granular soils is identified in the centre of the farm and on the hill in the south. For Cleardale, most of the soils in the more detailed Canterbury soils layer are classified as Brown soil. In the fundamental soils layer they are a mix of Pallic and Brown. These differences cast doubt on the accuracy of soil data and inclusion at farm scale, particularly with the fine resolution data such as that of hyperspectral imagery.

The need for greater coverage of accurate detailed soil information appropriate for farm scale use is widely recognised and is essential for site specific management. Molloy (1998) states that hill country soils are extremely difficult and costly to map in detail due to their extreme variability. However, Fraser and Vesely (2011) estimate the cost of a farm scale soil map for a 3,500 ha property would be around $10,000; or $3/ha. This would provide a map with enough information to help guide decision making around variable rate fertiliser across the farm as

well as providing information to improve predictions of soil fertility. It is likely that given the estimated cost of mapping, this could be recovered in the first year of fertiliser application, through either fertiliser savings or nutrient use efficiency. Once a detailed soil map it completed, it is a valuable resource for many years.

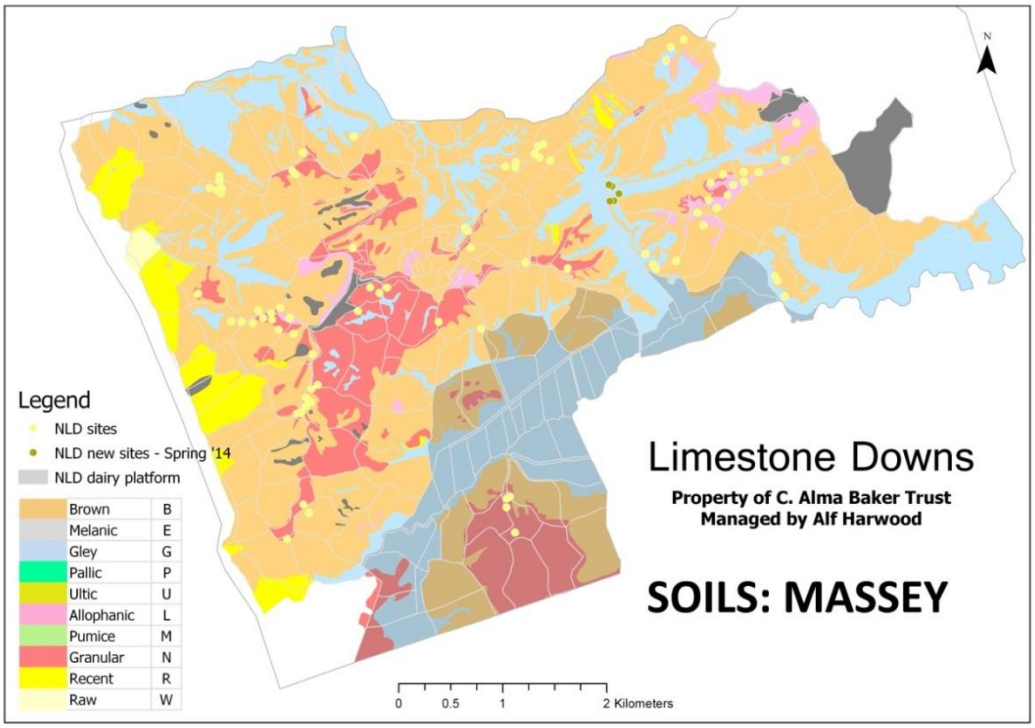


Figure 7-4: Soil orders at Limestone Downs as classified by the Fundamental Soils Layer, a national dataset

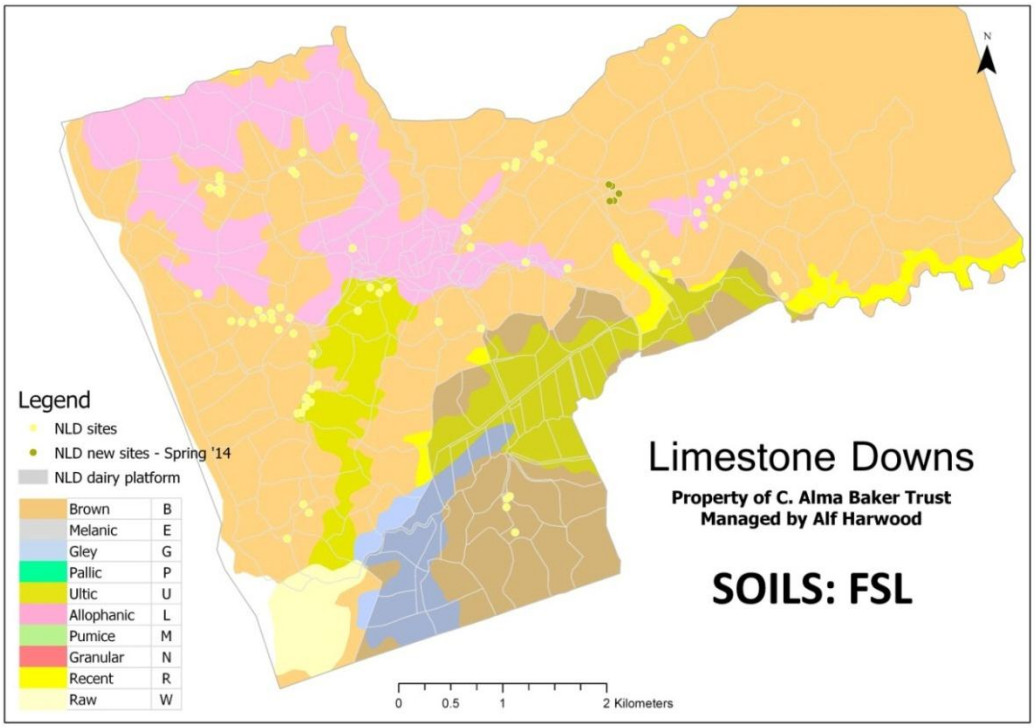


Figure 7-5: Soil orders at Limestone Downs as classified by a farm scale mapping exercise carried out by 3rd Year Massey University Soils students under the guidance of soil scientist Dr Alan Palmer

7.4.4 Topography

The topographic variables, *ELEV*, *SLOPE*, *ASP* and *SACT*, are all derived from a digital elevation model (DEM). The resolution of the national dataset is 20m, with an 8m layer calculated from this. The metadata for the DEM used states that it is suitable for cartographic visualisation only, rather than for terrain analysis. However there is no readily available national dataset with a higher resolution. A very high resolution DEM would identify micro-topographical features which may have an important, but different, effect on soil Olsen P than general landscape features. An example would be a stock track or terracette on a steep hill face. A fine scale DEM would identify the flat track of the terracette, which is known to have different soil properties, grazing behaviour, wetter, and higher levels of P (Radcliffe, 1968). However this relationship would be different to the effect of the overall slope, of the slope face. The resolution of the DEM and calculation of the topographic features needs to be understood.

A DEM with a resolution of 25-30m is acceptable on a regional or catchment scale. However it is considered not accurate enough for either paddock or farm scale (Fu & Rich, 1999, 2002; Hedley, Roudier, & Valette, 2014). The accuracy of DEM's can have a major effect on the results of the derived data layers (Costall, Williams, Gillingham, Betteridge, & Lambert, 2001; Fu & Rich, 1999; Kumar, Skidmore, & Knowles, 1997; Zhou & Liu, 2004). Errors are caused by inaccurate raw data (Kumar et al., 1997; Zhou & Liu, 2004), grid resolution (Fu & Rich, 1999; Zhou & Liu, 2004) and orientation (Zhou & Liu, 2004). The availability and accuracy of DEM's are improving (Bishop, James, Shroder, & Walsh, 2012; Dragut & Blaschke, 2006). Technologies are now available, such as LIDAR which produce a point cloud and generate more accurate DEM's (Bishop et al., 2012; Hedley et al., 2014). It is likely that a higher resolution, more accurate, DEM's with vast spatial coverage will be available in the future.

The inclusion of relief in attempting to model soil properties could be better encompassed as landscape elements. The idea of landscape elements is defining land surface based on topography, particularly position in the landscape and the curvature of the slope – both across and downslope. Terrain analysis of this kind is not often used in environmental research even when topography is a key variable (Dragut & Blaschke, 2006). Landscape elements are defined in different ways but usually include elements such as: peaks, ridges, saddles, spurs, flats, top slopes, foot slopes, concave slopes and convex slopes (Dragut & Blaschke, 2006; Radcliffe, 1982; Schmidt & Hewitt, 2004). Landscape elements could more closely represent topsoil depth, and flow of water and sediments transporting nutrients at a scale more appropriate than elevation. However deriving landscape elements from currently available DEM's did not provide an accurate or even sensible dataset. Landscape elements were derived from an 8 and

20m DEM for Pati Tapu Station (results not shown), however the classified map produced was of extremely poor quality. A higher resolution DEM may result in a more accurate data layer of landscape elements which could be incorporated. This problem has since been addressed (2018) with the introduction of a structure and motion system in the survey aircraft which provides a detailed and accurate DTM.

7.4.5 Scales and scaling

The concept of scale has multiple associations and is important to consider in any spatiotemporal data collection and analysis such as this. Soil variability is influenced by different factors acting through time and space (Lin, Wheeler, Bell, & Wilding, 2005) and at different scales (Pachepsky & Hill, 2017). Relatively little is known about scale and scaling in soil science in general (Pachepsky & Hill, 2017) with relatively few studies focusing on the spatial variability of soil properties across multiple scales (Lin et al., 2005). Predicting a highly spatially variable soil property (in this study soil Olsen P) through its relationships with environmental variables was further complicated by the range of spatial and temporal scales on which processes are happening that govern the effects of the environmental variables.

Handling data of various spatial and temporal scales is extremely complex (Bishop et al., 2012) and it is important to ensure that the scale at which data is collected accurately portrays variation so that the data captured is in fact informative (Atkinson & Tate, 2000). The uptake of nutrients from the soil is at an individual plant scale. However some of the drivers of nutrient uptake through plant growth are climatic variables, which vary on a much greater scale. The temporal resolution of sampling nutrient concentration in the leaf tissue is not often enough to assess the relationship between climate and nutrient uptake, as leaf tissue nutrient concentration is changing relatively quickly over time. From the data collected it is much easier to assess the relationship between topography and soil Olsen P at a particular sampling location. Topography does not change between two sampling events and topographic effects are therefore easier to interpret. Interpreting relationships when data and processes vary across differing time and spatial scales is difficult.

Each piece of spatial data recorded is unique to a position in space and a point in time – here a sample was collected from a plot with a specific location within a hill country property on a particular date. The use of a range of environmental variables to predict a soil property at a range of locations and at varying time points is difficult. It is important to understand the scale at which processes happen and how to link them across different scales (Pachepsky & Hill,

2017) and include them in modelling. Pachepsky and Hill (2017) outline the concept of hierarchy of scale and provide the example in agriculture as: globe, nation, region, farm, field, and plot. This is an added complexity that studies such as McKenzie and Ryan (1999) and Moore et al. (1993) involving one location and time point avoid. Field scale predictive soil mapping has been the most successful as many factors are held constant including: climate, soil parent material and time (Scull et al., 2003). This research attempts to begin to understand how to incorporate data collected across and then predict on both varying time points and locations in New Zealand hill country. The effects of some variables are in theory the same, regardless of location. And some effects will be similar but vary in different locations. Hierarchical modelling can allow for this in the structure of the model. Hierarchical modelling aims to identify broad patterns and improve predictions at different locations and time points.

Scaling in soil science is not a well-researched area (Pachepsky & Hill, 2017) but is important in terms of taking a model output and providing useful information that is easy for the end user to interpret. Soil Olsen P varies on a much finer scale than can be practically managed. The 1m resolution of the AisaFENX hyperspectral imagery means that without prior rescaling of data, the output of the model remains at this fine resolution. In soil sciences, data is often collected at fine scales, but the information it provides in terms of informing decision making and diagnostic uses in environmental management are usually on a larger scale (Pachepsky & Hill, 2017). The 1m resolution of the predicted soil Olsen P maps needs to be scaled to fit a realistic application of fertiliser at variable rates given the limitations of spread technology and cost. The results presented are not scaled as scaling after data integration is more difficult (Atkinson & Tate, 2000). Scaling is, however, essential to turn data collected, or in this case predictions, into the information (Pachepsky & Hill, 2017) needed to make informed decisions. Soil Olsen P under grazed pastures has a highly skewed distribution (Fu et al., 2013). Approaches that scale up to encompass large area averages could lead to underestimating fertiliser requirements as the use of averages of a skewed distribution can lead to misinterpretation (Officer et al., 2006). The heterogeneity or homogeneity of soil properties in an area may result in different approaches to targeted fertiliser applications. The best approach to scaling of soil properties such as Olsen P may be to provide a sliding scale tool in a user interface, rather than a predetermined rescaling procedure.

7.4.6 Spatial pattern vs. actual values of soil Olsen P

Soil Olsen P is known to be highly spatially and temporally variable (Friesen et al., 1985; Roberts, 1987). The results from this trial also show temporal variation but no seasonal pattern. The measured soil Olsen P at the same permanently marked location in the autumn

and spring show temporal variability even between samples taken within a year and within 0.5m of the previous sample (results shown in Chapter 4). The measured soil Olsen P as the result of the laboratory analysis is an estimate of the soil from within the quadrat. More precisely it is a subsample of a subsample. Nine soil cores are used to sample the quadrat and a subsample (approximately a teaspoon) is used for the laboratory analysis. It therefore raises questions around these measured values, the actual values and the level of error around this measurement – not in the laboratory test itself, but in the ability of this value to represent the available phosphate of the sampled area. Attempting to predict these exact values using laboratory results, given they are estimates of the sampled area and the temporal variation known to exist, may not be the most valuable approach.

The value in predictive soil mapping is the ability to generate continuous data across the landscape. Spatial patterns of predicted soil Olsen P could hold useful information and provide a general level of fertility which the farm holds. Other studies have suggested or categorised areas into low, medium and high; or deficient, sufficient, and surplus, levels of fertility (Kawamura et al., 2006; Kawamura et al., 2011; Liebisch, 2011) which appear to be reasonable in a highly variable system and provide sufficient information on which to base fertiliser plans. Given the spatial extent of current soil sampling methodologies, this approach provides vast amounts of information. With current spreading technology and cost of spreading, there is a limit to the minimum area and number of different rates and products that could be viably achieved. Future proofing for advances in technology should not be overlooked.

7.5 Conclusion

The aim of determining soil nutrient status on a hill country farm is to provide the farmer, farm advisor or fertiliser rep with accurate information that is representative of the farming system with which they can base their fertiliser decisions to improve nutrient use efficiency and increase production. The trade-off between the traditional methods of measuring soil Olsen P and the new predictive mapping approach could be perceived as accuracy vs. quantity. Laboratory testing of soil phosphate in the samples through the Olsen P test is very accurate for the samples sent in, whereas the new approach presented in this thesis produced estimates using a model which also highlighted the high levels of uncertainty around the predictions. However, Bramley and Janik (2005) have questioned how accurately laboratory based soil test collected in the traditional manner represent an agricultural system, due to the lack of data and how well that information translates to useful information for fertiliser recommendations. Although the estimates of soil Olsen P are made with large uncertainty, the

spatial coverage provides vast amounts of information that far outweigh the information gained from traditional soil sampling methods.

This project is the first of its kind and there is plenty of potential for the models to be improved as technology, methodologies and our understanding of the system increases over time. Modelling a highly variable soil nutrient across variable and dynamic farming systems through both time and space is complex and challenging. However this research has taken the first steps to show the potential of such undertakings. Predictive soil mapping has allowed estimates of soil Olsen P to be made continuously across the landscape that previous attempts of interpolation have not been able to achieve.

Although the maps of predicted soil Olsen P were not validated within this thesis, it is important to show that this step can be taken, and to provide an example of the potential outputs. A map with sensible spatial patterns and realistic predicted values gave the first indication that this methodology could provide valuable information. However the validation of predictions within one farm within the dataset needs to be investigated. Next, the extension of the model and the evaluation on the model's performance on a farm outside of the dataset are very important.

Validation sampling events have been completed within the wider PGP project. This has included collecting data on farms outside of the eight commercial farms presented in this thesis. Estimates of soil phosphate availability have been made using other models developed in parallel, which use different modelling techniques. Comparisons have been made between estimates of soil Olsen P generated through these models and the results from conventional transect sampling methodologies. However this data was collected outside the time frame of this thesis, and validation is therefore recommended as the next steps for the predictive soil maps presented here.

8 Overall discussion, conclusions and future work

8.1 Overall discussion

8.1.1 Hill country – a complex and dynamic system

Hill country is characteristically variable; and managing variability is the challenge of site specific nutrient management. The key elements of the agroecosystem – soil, plant, grazing animal, climate, and farmer – are interconnected by processes and relationships that are conditional on many other factors in the system. The mind map (Figure 2-2) presented in Chapter 2 provided an overview of this system and highlighted the difficulty in isolating any one relationship or interaction. 'Basic' research has attempted to eliminate variables in the hope of gaining a better understanding of one key relationship through pot and plot trials (Brougham, 1970). However, the agroecosystem is full of unmeasured or unmeasurable factors and interactions. The implications for research are that causality may be misidentified (Dorrough et al., 2011). Even the measurements made in these hill country systems are associated with great uncertainty and are often estimates rather than actual values. This does not mean that attempts to understand or model these systems should not be undertaken. It means that selecting appropriate approaches to analyse, and awareness of the complexity of, the system is essential.

Hill country is constantly changing, and processes in the system occur on differing spatial and temporal scales. Any information collected on pastures is a snap shot in time. However these snap shots are not dissimilar. In building up a database over a range of hill country farms, information learnt from the observations at any one time point improve our understanding of the system.

8.1.2 Database development

Creating a robust database was time consuming, though essential. The planning, preparation, fieldwork, data collection, data entry, checking, collating, and digitising data for the different variables across the eight farms took more time than expected. To create a multi-site, multi-seasonal dataset, with a large sample number, and a large range of variables collected within the same sample support, created the largest dataset of its kind for New Zealand hill country. As this data was also used to develop calibration equations for hyperspectral sensing a large range of pasture characteristics was required.

The stratified random sampling aimed to cover the full range of soil fertility, and a range of pasture types under differing farm management and environmental conditions. The results presented in Chapter 4 show that this was achieved. It was important to collect data across a full range of soil phosphate availability to ensure that data was not clustered around high and low fertility sites. Data collected on only two sites, identified as high and low fertility, can result in relationships appearing stronger than they are. Measured soil Olsen P presented in this thesis ranged from 2-130 µg/mL across all farms and seasons, and had a mean of 21 and median of 17 µg/mL.

Leaf tissue nutrient concentrations stated in the literature, vary greatly. The purpose of the research, and trial location, time and environmental conditions all have a major effect on the concentration reported. The range of P concentration measured in pasture covered a wide range, 0.09-0.71 % w/w. However, low P concentration in the leaf tissue did not necessarily indicate that the plants were experiencing limited P availability in the soil which complicates the objective of finding strong relationships between Olsen P and plant P.

8.1.3 Modelling approaches

Given the variability and complexity in the agroecosystem, the level of explanation achieved in data collected from commercial hill country farms, was expected to be lower than that achieved in trial pots or field plots. Single species glasshouse pot trials where conditions are much more controlled (Rowarth & Gillingham, 1990), small samples numbers (Burkitt et al., 2010), and sampling only green leaf tissue of the grass portion (Liebisch, 2011), amongst other

factors, have led to higher levels of explanation between leaf tissue P concentrations and soil phosphate availability than those presented in this thesis.

In such a complex system, Hinsinger et al. (2011) suggest that in modelling plant P, simplicity is better. Plant indices were the simplest approach to assessing P status in hill country pastures. Simple plant indices did provide a low to moderate level of explanation of soil phosphate availability. The correlation between plant indices and soil Olsen P was stronger in spring than autumn, and stronger in individual farm analysis than when farms were pooled. Of the plant indices, leaf tissue P concentration and PNI resulted in a higher level of explanation. This was unexpected as the PNI_c (Jouany et al., 2004) is adjusted for clover content and the P:N ratio was thought to be a more useful plant index as it could be used irrespective of season (McNaught, 1970). However, this was not the findings of the multi-seasonal dataset with varying clover content presented in this thesis.

Stepwise linear regression was used as an exploratory technique to introduce more factors. Variables identified as important in the stepwise linear regression analysis were: leaf tissue P and copper concentration, slope, fertiliser history and the portion of green tissue in the sample. These factors were identified as important through being consistently selected in analyses over different farms and seasons. As with plant indices, pooled datasets were not as strongly correlated to soil Olsen P as individual sampling events. Analyses of individual sampling events resulted in over fitting and pooled datasets resulted in under fitting. Multicolinearity is an issue in this data, and highly correlated variables may result in artificial relationships being identified. Although, attempts to minimise multicolinearity were made through monitoring VIF's in the regression analysis.

Researchers (Dorigo et al., 2007; Kawamura et al., 2011; Liebisch, 2011) state the importance of covering a broad range of conditions to establish a transferable relationship useful for assessing nutrient status in agroecosystems. Garnier et al. (2007) found a positive correlation between PNI and soil Olsen P at site level. Jouany et al. (2002) found a relationship between PNI and the water soluble P fraction in the top 0-5cm of soil, but the relationship did not exist at the inter-site level in either study. This was evident, to a certain degree, in the use of plant indices in Chapter 4 and the stepwise linear regression in Chapter 5. The differing environments at each farm were enough that when pooled, the level of explanation was reduced, more so for P indices than for stepwise linear regression.

A factorial design to cover all possible combinations of conditions would result in an unmanageable number of sites required to be sampled. Stratified random sampling uses

knowledge of the landscape to assist the selection of sites (Lin et al., 2005). A range of soils, topographic influences, fertiliser history, and management were covered within each farm. But sites were clustered within the population – all of New Zealand hill country. Without a full factorial design, another approach was required to maximise the use of information collected, and to handle this clustered data appropriately. Hierarchical modelling allowed data collected on the different farms to be appropriately incorporated into one model using partial pooling instead of combining multiple sites using complete pooling.

A Bayesian Hierarchical linear regression approach provided two major advantages: that partial pooling was used where information collected on the eight farms was borrowed across farms which improve estimates within and outside of these farms; and the uncertainty around the predictions was also identified. Soil variation is complex, and predictions are inevitably uncertain and this should be quantified (Heuvelink & Webster, 2001). The measurements of soil Olsen P were estimates through subsampling of soil within the quadrat and laboratory error, rather than known quantities. A hierarchical model using a combination of leaf biophysical and biochemical parameters as well as physical factors including topography, soils and farm management provided the best model fit with the lowest associated error.

Models that are strongly influenced by topographic features can lose valuable information. The approach of Morton et al. (2016) relies on topography alone. Qiu, Curtin, and Beare (2001) showed that soil samples taken on a 30-35m grid over a 10.4 ha arable paddock for soil Olsen P to a depth of 7.5 cm ranged from 14-53µg/g. The fall from the highest to lowest point in the paddock was only 2m. Soil Olsen P and contour did not exhibit the same spatial pattern. Soil fertility in arable fields is much less variable than that found in hill country as it is not affected by dung patches. This suggests that models relying heavily on topography, particularly on flats (which are important as they are the most productive areas of hill country systems), would miss valuable information around the variability within them. Flats can also be truck spread where information around spatial variability could be fully utilised, with fertiliser applied much more accurately and at a finer scale than in the hills.

The complexity of the system and the inability to measure variables exactly, mean that a highly accurate level of explanation is unrealistic. However industry people within the project are clear that the level of explanation observed is better than previously experienced. The approaches used are heavily reliant on the relationship between leaf tissue P concentration and soil Olsen P. Leaf tissue P concentration is a history of nutrient uptake, over an unknown time period. Soil Olsen P has been used in New Zealand agriculture as research has developed

a good understanding of soil Olsen P in relation to current and potentially available P to the plant. Much work has been completed in terms of likely pasture productivity response to superphosphate fertiliser based on Olsen P values (Cornforth, 1998b). Essentially leaf tissue P is a retrospective P nutrition status of the pasture, soil tests are for future nutrient management decisions (Jouany et al., 2002). Other studies have shown that plant P indices are better indicators of other measures of phosphate availability, compared to soil Olsen P. Jouany et al. (2002) found the water-soluble P fraction in the top 0-5cm of soil was more strongly correlated to plant indices than Olsen P. Soil Olsen P was the only measure of soil phosphate availability measured.

Some of the significant challenges surrounding input data were scale and multicolinearity. Data must be captured on an appropriate scale to ensure that it is informative and suitable for identifying variability (Atkinson & Tate, 2000). The resolution of the DEM and soil order were not sufficient in the surveys used within this study. Compared to a 1m resolution hyperspectral image for spatial analysis, they are not at an appropriate scale for farm analysis. There is a known discrepancy between data availability and accuracy, and requirements for agroecosystem model inputs (Dorigo et al., 2007). Multicolinearity in regression analysis was another challenge. Problems arise when input variables are highly correlated, which can cause large differences in coefficients and may even cause signs to change. Artificial relationships can also arise from small differences in highly correlated variables.

8.1.4 Interpreting leaf tissue nutrient concentration

Hill country pastures are almost constantly changing. Nutrient concentration of leaf tissue is largely controlled by two sets of processes: those that control the uptake and movement of nutrient from roots to leaf, and those that control dry matter accumulation and thus dilution of nutrients. Abiotic factors, such as drought, air temperature, and rainfall, have a strong influence on these processes. Grazing events, characterised by management strategy, stock class, and pressure, affects what leaf tissue is present for analysis. Combinations of abiotic and biotic factors are important to understand the changes in plant morphology and development, Figure 8-1. These factors make quantifying pasture difficult, as only a snap shot in time can be captured (Kallenbach, 2015). Brougham (1970) and van Dyne (1970) stated that understanding these systems requires a multidisciplinary team, a view shared 45 years on by Kallenbach (2015). Although this not yet been reached, this project attempted to make a step in this direction.

While seasonal variation within pasture nutrient concentration is widely acknowledged, quantifying and incorporating this variation in a model is difficult. It is a common issue with crop indicators, though usually crop yield is used, that temporal variation is larger in magnitude than spatial variability (Whelan & McBratney, 2000). Accounting for seasonal variation as an indicator variable, as was the case in the analysis presented in this thesis, ignores the fact that seasons are cyclic rather than discrete. A different interpretation of the leaf tissue may be needed every time a particular site is visited as, for example, a P nutrient concentration in the leaf tissue of 0.3 % w/w is not equivalent year round. Leaf tissue P concentration shows seasonal trends (Roberts, 1987; Saunders & Metson, 1971), and although Roche et al. (2009b) also found the seasonal effect was greater in magnitude than weather, the weather at the time of sampling explained up to 14% of the variation in P concentration. Jones and Tracy (2015) adjusted P concentration based on calendar month and 15 days soil moisture and 5 day relative humidity. Seasonal changes in pasture leaf tissue have been linked to air temperature (Saunders & Metson, 1971) and soil moisture (Fleming, 1973; Saunders & Metson, 1971). The temporal resolution of sampling nutrient concentration in leaf tissue in the study presented in this thesis was not sufficient to examine trends due to climatic factors which were collected hourly in this dataset. The interpretation of leaf tissue is an area that requires investigation beyond what was achieved in this thesis.

Figure 8-1: Examples of samples with different leaf architecture and morphology.

The measurement of P concentration in the leaf tissue collected from a quadrat or pixel, was the P content irrespective of whether variation was due to differences in soil phosphate availability, weather, dead vegetation content, species, stage of regrowth etc. Andrew (1960) found no correlation between visual symptoms of deficiency and leaf tissue P concentration in fully emerged green leaves of white clover and stated that visual signs are able to diagnose

only acute deficiencies. In their trial, the lowest leaf tissue P concentration was 0.12 %. The lowest concentration measured in the database presented in this thesis was 0.09 % w/w. Although low p concentration in lead tissue in the results presented in this thesis was most likely the result of high dead vegetation content in the samples, rather than severe nutrient deficiency. A value or range of P concentration expressed in leaves of pasture plants showing acute P deficiency could not be found in the literature.

An alternative approach would be to examine the spectral signature of plants with known P deficiencies, from severe deficiency symptoms that are visible to the naked eye, 'hidden hunger' (i.e. not visible), sufficient, through to surplus. Weak and spindly vegetative growth with leaves dark green and purple edges appearing on the older leaves first are all visual signs of acute P deficiency (Cornforth, 1998a). If biochemical characteristics relating to P deficiencies are evident in the spectral signature, then this may provide an alternative approach to investigate further. Nutrient deficiencies, including P, were able to be detected in lettuce using hyperspectral sensing of leaf tissue (Pacumbaba Jr & Beyl, 2011). Milton, Eiswerth, and Ager (1991) grew soybeans in nutrient solution with varying levels of P and observed reduced root and shoot biomass, and differences in spectral signatures of fully expanded leaves. However, they do acknowledge that in field situations, interpretation may be complicated by other factors.

Pasture species can influence nutrient concentration in leaf tissue samples, the extent to which depends on the species and nutrient of interest. Studies such as those conducted by Harrington et al. (2006) and Wilman and Derrick (1994) have shown the difference in nutrient concentration between a range of single species samples. The data recorded around species within this project was not intended for analysis but rather to ensure a range of pasture species were covered and to gain an insight into the extent and mix of pasture species present. The three most dominant species were recorded but no percent estimate or dissections were completed. Initial data display suggests that for particular nutrients the dominance of some species appear to have a significant effect on nutrient concentration of the sample. The distributions in Figure 8-2 display the difference in the distribution of calcium and copper concentration by the most dominant species in the mixed sward samples measured in this project, a total of 5,253 samples are represented in the figure.

Plant species differ in their ability to cope with different stress and disturbances (Grime, 1977) and therefore occupy a niche environment. Research has been conducted that identifies plant functional groups (López et al., 2006; Zhang et al., 2005) and individual species (Wan et al.,

2009) in hill country and links their presence and abundance to soil Olsen P. The identification of species in the sward could be a useful diagnostic tool for plant available P. Wan et al. (2009) found that ryegrass was most influenced by slope, browntop by soil Olsen P, and clover by annual phosphate fertiliser applications. Their results show that at an Olsen P of 10 µg/mL and 10.5° slope, ryegrass and browntop are equally competitive. The dominant species from the dataset are displayed using these criteria in Figure 8-3. The dominance of ryegrass and browntop under these criteria can be seen in this data as well.

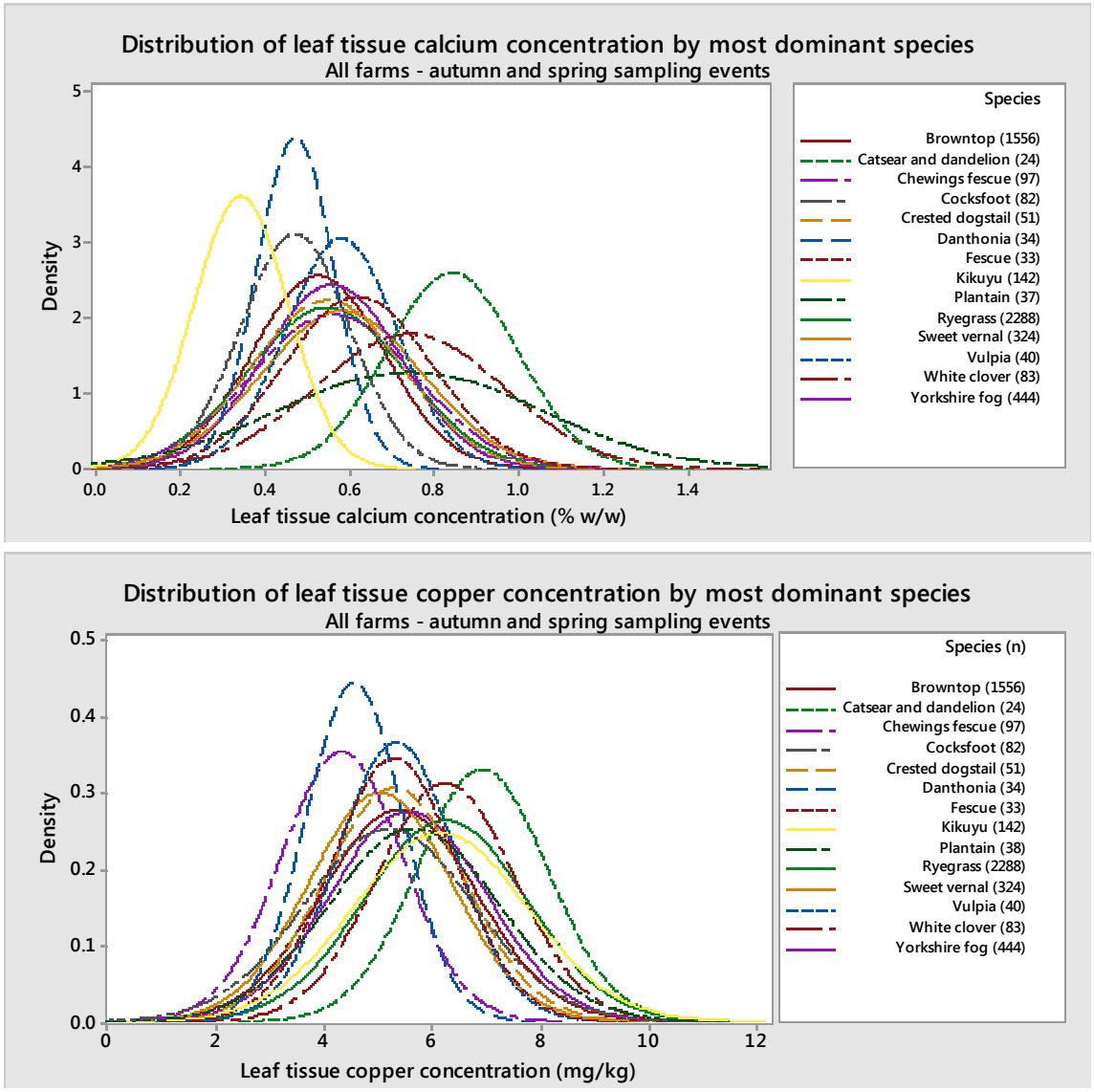


Figure 8-2: Distribution of leaf tissue calcium and copper concentration by most dominant species.

Information may not necessarily come from the most dominant species but other species in the mix as well. Figure 8-4 shows information that could potentially be gained from observing what grows alongside ryegrass when it dominates the sward, but this does not appear to hold true for browntop, Figure 8-5. Careful use and interpretation of species in the sward is

essential as botanical composition is also affected by other factors such as grazing management (Lambert et al., 1986) and topography (Grant & Brock, 1974).

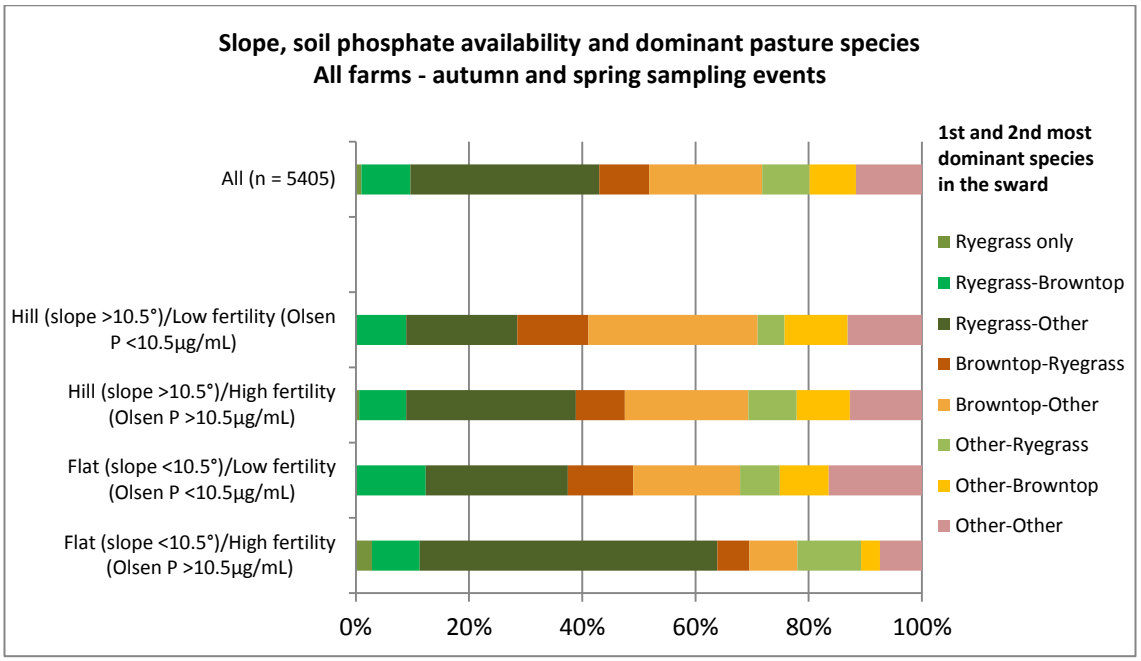


Figure 8-3: First and second most dominant species in the plots (all farms in the spring and autumn). Data split by slope and phosphate availability criteria of Wan et al. (2009), where ryegrass and browntop are equally competitive.

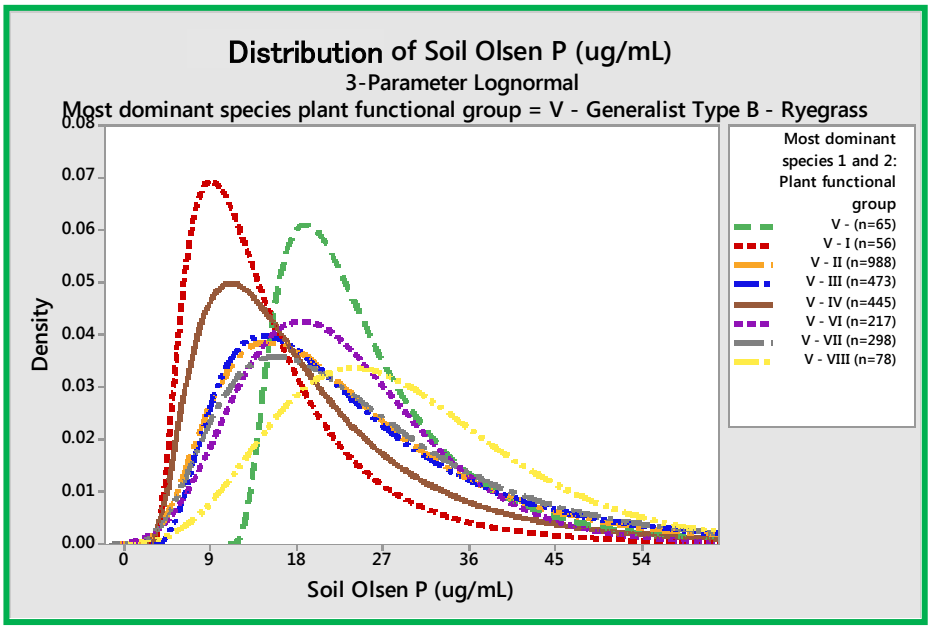


Figure 8-4: Distributions of ryegrass dominant samples grouped by plant functional group (as described by López et al. (2006) with the addition of kikuyu - VIII) of the second most dominant species. The plant functional groups used here are those described by López et al. (2006) where: group I are 'low fertility species'; II are 'medium fertility species'; III are 'high fertility grasses'; IV is generalist type A' or browntop; V is 'generalist type B' or ryegrass; VI are 'high fertility dicots'; VII are 'species with low presence'; and an additional category was added not included in their work which was VIII – kikuyu. A full list of species in each group is described in their paper.

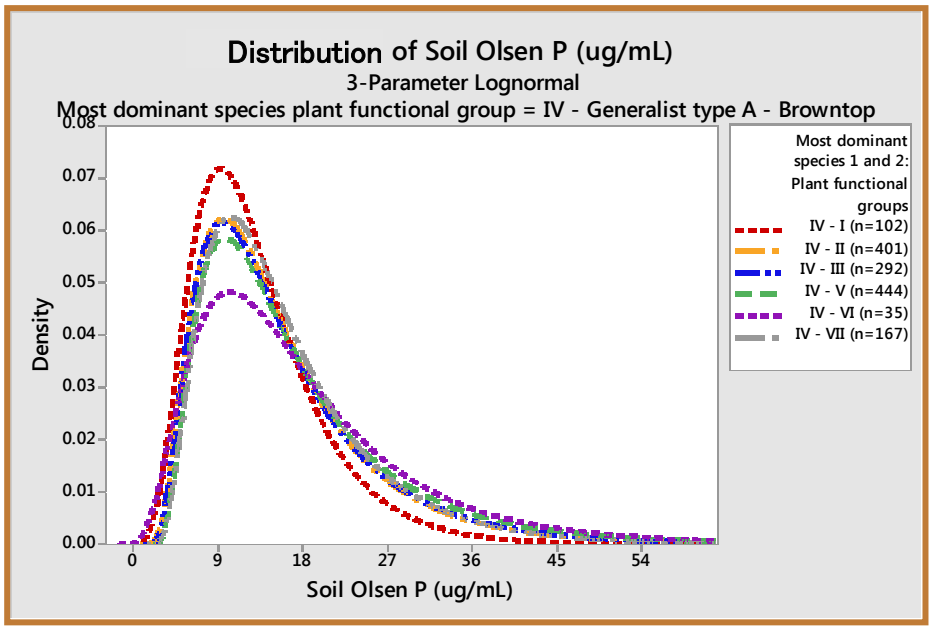


Figure 8-5: Distributions of browntop samples grouped by plant functional group (as described by López et al. (2006)) of the second most dominant species.

These analyses of species presented in Figure 8-2, Figure 8-3, Figure 8-4 and Figure 8-5 are not intended to provide a full and complete analysis, but provide an insight into potential value of information gained through species identification and abundance.

Pasture cover changes constantly as paddocks are grazed and plants regrow. Sheep and cattle graze selectively based on topography (López, Hodgson, Hedderley, Valentine, & Lambert, 2003) and species. The extent to which a pasture is grazed not only affects canopy reflectance at the time of image capture (Numata et al., 2007; Todd et al., 1998) but also regrowth of pasture. Nutrient concentration in pasture plants changes through the different stages of regrowth (Rawnsley et al., 2002; Schlegel et al., 2016; Wilman et al., 1994). An increase in leaf tissue calcium and decrease in P in cocksfoot (Rawnsley et al., 2002), perennial ryegrass (Fulkerson et al., 1998; Wilman et al., 1994), and white clover (Wilman et al., 1994) has been observed as plants regrow.

Hyperspectral imaging systems measure canopy reflectance and do not penetrate the sward. Pasture cover or height of pasture may affect the estimates of nutrient concentration in the sward particularly when the sward is long, as much of the leaf tissue will not be 'visible' to the sensor. Pastures at varying stages of regrowth are different, even to the naked eye (Figure 8-6). The only research found measuring nutrient concentration down the pasture profile was a study by Cosgrove et al. (1998). However this effect in relation to sensing is currently unknown.

Figure 8-6: Pasture at different stages of regrowth highlighting differing plant morphology and bare soil visible

8.1.5 Fertiliser recommendations

Decisions regarding fertiliser applications in hill country are currently made with very little information. The most basic, and most risk averse approach is to blanket apply fertiliser to the whole farm. A laboratory soil test is highly accurate (+\- 4 µg/mL), but not necessarily representative of the farm (Bramley & Janik, 2005). There is a trade-off between accuracy versus spatial coverage between the current and proposed approach. However evaluation of different approaches should really be around which approach provides the best information to represent the current nutrient status of the farm.

Soil Olsen P in hill country is known to be highly variable. Morton et al. (2000) and Cornforth et al. (1993) stated that soil Olsen P tests are best for monitoring long term trends. Given the soil sampled is an estimate of the quadrat, the known laboratory error, and the variability of soil Olsen P, predicting the true values is not possible. The results of the leave-one-out-cross-validation show that the models predictions are more informative than the theoretical averaged transect approach, and that trends are more appropriate as the predicted values are much lower than the actual values. Surplus concentrations in leaf tissue can occur even when soil phosphate availability is only sufficient. Liebisch (2011) recommend that even where plant P concentrations suggest supply is in excess, soil tests should be used to confirm the results before applications of phosphate fertiliser are ceased. Validating spatial patterns may be more sensible than focusing on predicting exact values. With other studies suggesting that categories of low, medium and high is sufficient information for phosphate fertiliser applications (Liebisch, 2011), this may be a sensible approach.

Scaling data is an area of much debate. The spatial resolution of the prediction maps for soil Olsen P are 1m, however this is clearly impractical for current spreading technology. This fine resolution holds much information, and it is recommended that no standard approach is set for scalling and the decision is left to the discretion of the end user. At the user interface level this could be incorperated as a sliding scale bar. Keeping the finest resolution available provides vast amounts of information, and informs decisions around how to manage areas appropriately. For example an area of large variation may be treated differently to areas of more consistent soil fertility. A mode could also be selected that follows 'rules' for the current spreading technology for example minimum polygon size and minimum distance from one side of the polygon to another, flight paths, etc. A second could include 'rules' for areas that can be truck spread. Soil Olsen P estimates will likely be incorporated into econometric modelling to determine the most effcient use of nutrients. A different approach to scaling is likely to be required in this case.

8.1.6 Pasture management: a more holistic approach

The ever expanding areas of remote sensing and GIS could provide vast amounts of information on many characteristics of pastures. Olsen P is one piece of information to consider in the development of fertiliser management plans. Although one of the major limitations to pasture growth, it is not the only limitation. Information on the status of different nutrients in the sward, or nutrient balances may provide information on what is limiting and why, for example due to synergistic or antagonistic relationships between nutrients. Liebisch (2011) advises that before phosphate fertiliser is applied to areas that are predicted to be low, other causes such as pH should be checked. Weaver and Wong (2011) found that more than 50% of samples they collected across Australian farming systems had evidence to suggest that factors other than soil phosphate were limiting yield. It may be these issues that would need to be addressed and corrected before applying phosphate fertilisers.

Pasture species could be incorporated into a fertiliser plan as species can provide information on likely soil fertility and environmental constraints. Current and desired species in the sward could be considered and shifts in species composition monitored. Although ryegrass and clover is the ultimate pasture sward in New Zealand agriculture, environmental conditions are not always suitable and as Saxby (1945) states, different species will provide the best forage under different environmental conditions. Most agricultural research is based around a ryegrass/clover sward. The application of phosphate is to increase clover production. However if clover is not present in the sward, the application of phosphate may not be the best

immediate pasture management response. Optimal or target levels for soil fertility may vary depending on species.

Ultimately fertiliser applications must improve pasture through either increased pasture growth or a shift in species composition to a higher quality sward. To increase farm profitability this pasture must be converted into an increase in products leaving the farm. In this case pasture utilisation would also be an important factor to consider. Topography and physical location in the farm may also be important here along with seasonal growth rates and microclimates. For example, if early spring growth does not meet demand, ensuring areas or warmer faces in hill country of early spring growth are not limited through nutrient availability in the soil, may help overcome this deficiency or may allow some ewes to lamb earlier so that lambs are away to slaughter earlier. Site specific nutrient management could in this way be tailored not only for the environmental conditions, but for the farmers' goals as well.

Soil Olsen P is an important piece of information to guide pasture and soil management. However opportunities arise from the vast amounts of information collected continuously across hill country farms that have not previously been available. Pasture and soil management in hill country is at the beginning of a new era. If data can be successfully turned into accurate information, farmers will have the knowledge to make more informed decisions in regards to many aspects of pasture management.

8.2 Overall conclusions

The PGP project: 'Pioneering to Precision' was the first of its kind to undertake research of this approach and magnitude. It is the beginning of a new era for nutrient management in hill country. When pioneering aerial topdressing began in the 1940's, it brought about major changes in New Zealand hill country, well informed variable rate fertiliser in hill country would be the next major leap forward for the industry. Imaging spectroscopy has opened up the opportunity to capture information on pasture biophysical and biochemical characteristics across every 0.25m^2 of a hill country farm. Spatial variation in pasture characteristics reflects variations in underlying soil properties. Understanding these relationships will be crucial to hill country nutrient management in the future.

The objective of this research was to develop a model to estimate soil Olsen P continuously across New Zealand's hill country farms. The model was to incorporate leaf tissue nutrient concentration, environmental, farm management and any other factors that could be easily obtained. The model developed needed to be easily transferred to hill country farms outside

of the dataset. These predictions of soil Olsen P would be used as the basis of variable rate fertiliser maps for aerial top dressing of phosphate fertilisers.

An extensive and robust database created has provided a valuable dataset for hill country research. A wide range of variables were measured on 3,030 plots (0.5m x 0.5m) across eight commercial hill country farms over 19 sampling events, predominantly in the spring and autumn. This is the most extensive dataset collected in New Zealand hill country with a broad range of variables collected using consistent protocols and sample support.

Bayesian hierarchical linear regression models demonstrated the significance of using plant biochemical and biophysical inputs, as well as physical factors which included topographic and farm management variables. A model combining leaf tissue P concentration, copper or calcium concentration, NDVI, topographic features, soil, fertiliser history, productivity and seasonal information were all contributing to the model and resulted in the best model fit and lowest residual error.

Hierarchical modelling has provided a more informed approach than previous methods. Few studies have attempted to use primarily leaf tissue nutrient concentrations to predict soil phosphate availability. Although the relationships described in this thesis are weaker in comparison to other well controlled experiments, they nevertheless take the farm environment into account. Current soil sampling techniques are spatially sparse and attempts to map soil properties in hill country through interpolation have been unsuccessful. Through hierarchical modelling, soil Olsen P can be estimated with a moderate level of accuracy and through predictive soil mapping can provide a great deal of spatial detail.

8.3 Recommendations for future work

The work presented in this thesis, and the project as a whole, has made a start to developing methodologies to implement well-informed variable rate fertiliser in New Zealand hill country. While models developed already improve on uniform fertiliser application, there is plenty of potential for further research to improve our knowledge in hill country and make further improvements to many different aspects of the project. Some are outlined below.

1. A better understanding of the magnitude and causes of variation in leaf tissue biophysical and biochemical properties, in particular leaf tissue P concentration, due to **climate and weather**. Monitoring of leaf tissue at the weather stations on the farms over varying time scales could provide useful information that would improve the interpretation of leaf tissue nutrient concentrations.

2. Pasture nutrient concentration has been measured regardless of the status or composition of the sward. Research around the analysis of **spectral signatures of grasses and pasture plants exhibiting P deficiencies** could be investigated.
3. **Leaf tissue copper concentration** in hill country pasture has received little attention in agricultural research. Literature refers to an identified link between the heavy use of phosphate fertilisers and copper deficiency in many plant species. Copper concentration in particular pasture species is known to vary. Further investigation to identify the cause/s and their magnitude of variation is required to understand the relationship within the soil-pasture system.
4. Further investigation is required to fully understand the major cause of variation in **leaf tissue calcium concentration** and its importance in the model. The concentration of calcium in leaf tissue of legumes and some pasture herbs is known to be greater than in grasses, and calcium builds up in leaf tissue as it ages.
5. The **effect of species on nutrient concentration of leaf tissue** samples could be investigated further. The time consuming techniques of species identification and dissections may be surpassed by hyperspectral imaging and computer image analysis. There is potential for cut leaf tissue samples to be spread over a white background. A hyperspectral image could then be taken under a bench top set up, species identified using unique spectral signatures and leaf area calculated using machine vision techniques.
6. The ability to **identify species** in a mixed sward in hill country **using a hyperspectral sensor** mounted in an aircraft requires further investigation. The ability to identify species would allow the potential for indicator species to be used, and for any effect of dominant species on measured nutrient concentrations to be accounted for. Some work has been completed such as identifying legume content (Kawamura et al., 2013) or more specifically ryegrass and white clover (Suzuki et al., 2012).
7. **Pasture cover** changes constantly as paddocks are grazed and plants regrow. A commercial hill country farm will, at any one time, have a range of different pasture covers. A better understanding of the effect of time since the **last grazing event** and the resulting plant morphology has on canopy reflectance would be beneficial. Hyperspectral sensing measures canopy reflectance and does not penetrate the sward which may have implications when pasture cover is high. The effect of stage of regrowth on nutrient concentration of a mixed pasture sward would require further investigation to determine if any regrowth stage results in inferior predictions of soil fertility or could be accounted for in a model.

8. Agricultural landscapes are a mosaic of surfaces. A limitation of continuous data collected using hyperspectral imaging is that estimates of nutrient concentration are made on **non-pasture surfaces** or **pasture species outside of the dataset**. It may be easier to identify and remove these pixels without great loss of information. Other studies have been successful in identifying pixels dominated by bare ground (Louargant et al., 2015; Suzuki et al., 2012). The effect of predictions of leaf tissue nutrient concentrations in mixed pixels requires further investigation.
9. **Plant morphology and structure** varies between species and plant development. Understanding seasonal changes in pasture is important in relation to the interpretation of remotely sensed imagery and nutrient concentrations. Mutanga et al. (2004) state that it is important to consider such effects when mapping quality in rangelands with mixed species. However this is the case for any plant biochemical or biophysical properties. For example the presence of seed head may have a significant effect on the reflectance, spectral signature, and prediction of nutrient concentration. It is important to ensure that seasonal changes in pasture do not adversely affect relationships between remotely sensed imagery and pasture parameters (Numata et al., 2007).
10. Topographic information is derived from a DEM to achieve full spatial coverage of a farm. As discussed in the previous chapter, the resolution of the DEM has a major impact on the calculated slope and aspect. The effect of **higher resolution DEM's** is worth investigating.
11. The inclusion of **landscape elements** may provide more informative information than the current topographic variables. Landscape elements would better represent soil formation and movement of nutrients through the flow of water.
12. **Soil characteristics** are undoubtedly important. As discussed in the previous chapter and in other studies, soil information is not available to the accuracy required for farm scale analysis. The fundamental soils layer is the only widely available soil data for New Zealand but may not be suitable for this purpose. Broad categories, accurately mapped, with full spatial coverage of New Zealand hill country would be ideal. The most important soil characteristics and methods of obtaining this information for inclusion in the model require further thought and investigation.
13. **Image spectroscopy of bare soil** has been used to predict a range of soil physical and chemical properties (Ben-Dor et al., 2009). Lu et al. (2013) predicted total P from hyperspectral imagery. Hill country is covered in permanent pasture, however areas of easier country are occasionally cropped and regrassed. Analysis of these areas could

provide useful information in gaining a better understanding of soil spatial variability in these landscapes. An area that was sprayed off for cropping could be analysed using hyperspectral imaging and soil phosphate availability measured. Pasture nutrient concentration prior to the paddock being sprayed out could be monitored. The nutrient concentration on resown pasture, which would be a much more uniform sward, could also be monitored.

14. **Fertiliser information** was one of the hardest pieces of data to source. Farm fertiliser records were obtained in various forms: spread sheets, emails, computer screenshots, Smart maps accounts, hand drawn maps, and flight records from spreading aircraft. Information on the same spreading event recorded in multiple forms did not always match and it is likely some applications were not recorded at all. Given that fertiliser is a sheep and beef farmers greatest expense, automated record keeping would not only provide farmers with proof of placement but an accurate record of fertiliser history. Collecting, collating and sorting fertiliser records and then digitising them was time consuming. If fertiliser history was to be used in a model that is part of a commercialised system, or for any other purpose, automated fertiliser record keeping would be essential.
15. There are many different ways in which a **model** to predict soil Olsen P can be **developed and structured**. Some of the possible areas to investigate further are: the inclusion of alternative variables such as landscape elements or a vegetation index more suited to the detection of dead vegetation; the use of cross terms could be further explored; cross classification could be further investigated to account for the data clustered by farms, and clustered by season for the pasture biophysical and biochemical parameters; and the effect of each variable and issues around multicolinearity (for example gley soils are located on the flats which may create a trade-off between the gley soil order term and slope) requires further understanding.
16. A **decision tree approach** may be an alternative to best interpret the information gathered. For example plant indices, such as NDVI, could be used to determine the state of the pasture. Specific models could then be used for different pasture states. Topography, species and other factors could also be used to split data.
17. **Model validation** is an important step. The next step is to validate the model using a similar commercial hill country farm but one outside of the first phase of model development. If the performance of the model is satisfactory, then it could be further extended to farms in different climatic regions or areas underrepresented in the data,

for example a farm on pumice soils. Identifying and validating spatial patterns may be more successful than attempting to predict absolute values.

18. There are **alternative approaches** that could be taken such as machine learning and neural networks, regression trees, and other non-linear methods. The disadvantage of many of these methods is their 'black box' structure that does not allow the user to understand the mechanics of the model and whether it is agronomically sound. Alternative approaches to predicting soil Olsen P have been undertaken within the wider project, predominantly using machine learning approaches.

9

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A

Appendix A

Summary of dominant species

The three most dominant species were identified in the plots at each sampling event. Species were identified in the field by an expert, primarily Grant Rennie of the Farm Systems team at AgResearch. A summary table was created of the raw data provided. Approximately 23 pasture grasses, 7 legumes, 2 pasture herbs, and 31 weed species were identified over a total of 19 sampling events.

		NLD Early Summer 2013			NLD Late Summer 2014			NLD Autumn 2014			NLD Winter 2014			NLD Spring 2014		
	Most abundant species	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Grasses	**Botanical name**															
Barley grass	*Critesion murinum*															
Browntop	***Agrostis capillaris***	**22**	**30**	**34**	**30**	**38**	**28**	**26**	**26**	**23**	**19**	**19**	**10**	**37**	**24**	**28**
Chewings fescue	***Festuca rubra***					**1**						**1**				
Cocksfoot	***Dactylis glomerata***		**1**	**5**	**3**	**3**	**5**	**7**	**3**	**10**		**5**	**7**	**3**	**4**	**5**
Couch	*Elytrigia repens*															
Creeping bent	*Agrostis stolonifera*															
Crested dogstail	***Cynosurus cristatus***	**19**	**32**	**6**	**17**	**22**	**24**	**7**	**12**	**14**	**20**	**26**	**36**	**1**	**6**	**17**
Danthonia	*Rytidosperma spp.*													1	2	
Indian doab	*Cynodon dactylon*															
Italian ryegrass	*Lolium multiflorum*															
Kikuyu	***Pennisetum clandestinum***	**60**	**31**	**27**	**117**	**16**	**8**	**104**	**30**	**26**	**44**	**33**	**36**	**23**	**16**	**24**
Meadow fescue	*Festuca pratensis*			1												
Paspalum	*Paspalum dilatatum*															
Phalaris	*Phalaris aquatica*															
Poa	***Poa pratensis* or *P. trivialis***		**5**	**5**					**1**	**5**	**1**	**2**	**4**		**6**	**11**
Poa annua	*Poa annua*															
Ratstail	*Sporobolus africanus*				3		1	1								
Perennial ryegrass	***Lolium perenne***	**170**	**79**	**61**	**98**	**94**	**40**	**164**	**102**	**41**	**209**	**52**	**26**	**246**	**43**	**14**
Soft brome	***Bromus hordeaceus***	**6**	**22**	**42**	**1**	**6**	**9**		**8**	**17**		**7**	**9**			**2**
Sweet vernal	***Anthoxanthum odoratum***	**61**	**52**	**46**	**35**	**46**	**52**	**7**	**21**	**25**	**21**	**24**	**20**	**22**	**15**	**29**
Tall fescue	*Schedonorus phoenix*															
Vulpia hair grass	*Vulpia spp.*															
Yorkshire fog	***Holcus lanatus***	**44**	**45**	**29**	**45**	**53**	**36**	**39**	**26**	**25**	**54**	**22**	**19**	**29**	**52**	**50**
Legume																
Alsike clover	*Trifolium hybridum*															
Lotus	*Lotus pedunculatus*		4	4	10	2	2	1	1	1		1	7		5	12
Medic	*Medicago spp.*															
Red clover	*Trifolium pratense*						1			1						
Subterranean Clover	*Trifolium subterraneum*	1	3	1				1		2			2	1	8	6
Suckling clover	*Trifolium dubium*			1												
White clover	***Trifolium repens***	**11**	**77**	**85**	**11**	**79**	**92**	**6**	**78**	**86**	**8**	**70**	**81**	**7**	**117**	**77**
Herb																
Chicory	*Cichorium intybus*															
Plantain	***Plantago lanceolata***	**4**	**15**	**27**	**23**	**27**	**54**	**28**	**61**	**68**	**5**	**50**	**53**	**5**	**52**	**57**
Weed																
Black nightshade	*Solanum nigrum*															
Bracken	*Pteridium esculentum*															
Borage	*Borago officinalis*														1	
Buttercup	*Ranunculus spp.*									2			1			
Californian thistle	*Cirsium arvense*															
Catsear	***Hypochaeris radicata***	**1**		**7**	**1**	**3**	**11**		**8**	**10**	**4**	**39**	**29**	**7**	**11**	**12**
Chickweed	*Stellaria media*											3	5			
Daisy	*Bellis perennis*															
Dandelion	***Taraxacum officinale***			**1**	**1**		**3**		**6**	**18**		**2**	**4**	**3**	**10**	**7**
Dock	*Rumex spp.*			2				1		7		5	6		2	1
Foxglove	*Digitalis purpurea*								2		2					
Hawkbit	*Leontodon taraxacoides*	1				1	2									
Hawkweed	*Hieracium spp.*															
Hydrocotyle	*Hydrocotyle spp.*															
Mallow	*Malva spp.*														3	9
Moss																
Mouse ear chickweed	*Cerastium spp.*										2	11	10		5	12
Nodding thistle	*Carduus nutans*															
Pennyroyal	*Mentha pulegium*			6			4									1
Redroot	*Amaranthus powellii*															
Rush																
Sedge																
Selfheal	*Prunella vulgaris*															
Shepherds purse	*Capsella bursa-pastoris*															
Sorrel	*Rumex acetosella*							1								
Stinking mayweed	*Anthemis cotula*		1			1	1	2	1		1	4	6			
Storksbill	*Erodium moschatum* and *E. cicutarium*		1							1		1	1			1
Thistle	***Cirsium arvense and C. vulgare***			**1**	**4**	**4**	**10**	**1**	**5**	**3**		**2**	**1**		**3**	**9**
Vetch	*Vicia sativa*															
Willow weed	*Persicaria maculosa*															
Yarrow	*Achillea millefolium*			1			2		5	10		2	4			

		NAT Autumn 2014			NAT Spring 2014			NAT Autumn 2015			NER Spring 2014			NER Autumn 2015		
	Most abundant species	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Grasses	**Botanical name**															
Barley grass	*Critesion murinum*														1	2
Browntop	***Agrostis capillaris***	**118**	**98**	**58**	**127**	**91**	**46**	**105**	**105**	**46**	**131**	**63**	**38**	**182**	**71**	**46**
Chewings fescue	***Festuca rubra***	**2**	**5**	**1**				**9**	**4**	**5**	**14**	**14**	**20**	**12**	**15**	**6**
Cocksfoot	***Dactylis glomerata***	**2**	**3**	**23**	**4**	**4**	**12**	**2**	**11**	**11**	**9**	**14**	**17**	**11**	**41**	**30**
Couch	*Elytrigia repens*															
Creeping bent	*Agrostis stolonifera*	12	11	2												
Crested dogstail	***Cynosurus cristatus***	**21**	**29**	**27**	**1**	**5**	**19**	**2**	**14**	**28**	**1**	**1**	**1**	**2**	**16**	**24**
Danthonia	*Rytidosperma spp.*				7	6	6				2					
Indian doab	*Cynodon dactylon*															
Italian ryegrass	*Lolium multiflorum*				9	11										
Kikuyu	***Pennisetum clandestinum***															
Meadow fescue	*Festuca pratensis*															
Paspalum	*Paspalum dilatatum*															
Phalaris	*Phalaris aquatica*															
Poa	***Poa pratensis* or *P. trivialis***		**2**	**3**		**22**	**35**		**3**	**4**	**1**	**28**	**42**		**8**	**29**
Poa annua	*Poa annua*															
Ratstail	*Sporobolus africanus*															
Perennial ryegrass	***Lolium perenne***	**181**	**84**	**38**	**177**	**91**	**47**	**240**	**73**	**43**	**168**	**73**	**42**	**163**	**79**	**55**
Soft brome	***Bromus hordeaceus***					**1**	**6**		**1**			**2**	**7**		**1**	
Sweet vernal	***Anthoxanthum odoratum***	**10**	**15**	**7**	**35**	**43**	**34**		**13**	**17**	**28**	**51**	**47**		**5**	**2**
Tall fescue	*Schedonorus phoenix*															
Vulpia hair grass	*Vulpia spp.*															
Yorkshire fog	***Holcus lanatus***	**54**	**55**	**45**	**32**	**58**	**49**	**40**	**67**	**44**	**23**	**63**	**57**	**18**	**47**	**44**
Legume																
Alsike clover	*Trifolium hybridum*															
Lotus	*Lotus pedunculatus*		1	1												
Medic	*Medicago spp.*															
Red clover	*Trifolium pratense*						1									
Subterranean Clover	*Trifolium subterraneum*		1		1	4	6			2		4	1		1	1
Suckling clover	*Trifolium dubium*			1		1										
White clover	***Trifolium repens***		**56**	**68**		**39**	**67**	**1**	**43**	**69**	**12**	**75**	**99**	**6**	**101**	**118**
Herb																
Chicory	*Cichorium intybus*															
Plantain	***Plantago lanceolata***		**4**	**12**		**2**	**6**		**1**	**3**						
Weed																
Black nightshade	*Solanum nigrum*			1												
Bracken	*Pteridium esculentum*															
Borage	*Borago officinalis*															
Buttercup	*Ranunculus spp.*		1	17			3		11	24						
Californian thistle	*Cirsium arvense*															
Catsear	***Hypochaeris radicata***		**3**	**8**		**2**	**9**		**2**	**19**						**6**
Chickweed	*Stellaria media*			1						1						
Daisy	*Bellis perennis*															
Dandelion	***Taraxacum officinale***		**5**	**24**					**1**	**4**						**4**
Dock	*Rumex spp.*			1			2		1	1						
Foxglove	*Digitalis purpurea*															
Hawkbit	*Leontodon taraxacoides*															
Hawkweed	*Hieracium spp.*															
Hydrocotyle	*Hydrocotyle spp.*															
Mallow	*Malva spp.*															
Moss										3						
Mouse ear chickweed	*Cerastium spp.*					2	6			1			6			
Nodding thistle	*Carduus nutans*															
Pennyroyal	*Mentha pulegium*															
Redroot	*Amaranthus powellii*		1	8												
Rush							3									
Sedge												1				
Selfheal	*Prunella vulgaris*					5										
Shepherds purse	*Capsella bursa-pastoris*															
Sorrel	*Rumex acetosella*															
Stinking mayweed	*Anthemis cotula*															
Storksbill	*Erodium moschatum* and *E. cicutarium*															
Thistle	***Cirsium arvense and C. vulgare***		**8**	**13**		**3**	**7**		**3**	**8**	**1**	**1**	**7**			**2**
Vetch	*Vicia sativa*															
Willow weed	*Persicaria maculosa*						2									
Yarrow	*Achillea millefolium*		2	5					1	5			5	1	9	17

	Most abundant species	NTT Spring 2014			NTT Autumn 2015			NPT Spring 2015			NPT Autumn 2016		
		1	2	3	1	2	3	1	2	3	1	2	3
Grasses	**Botanical name**												
Barley grass	*Critesion murinum*												
Browntop	***Agrostis capillaris***	**124**	**70**	**39**	**159**	**47**	**35**	**204**	**81**	**40**	**156**	**75**	**46**
Chewings fescue	***Festuca rubra***	**14**	**6**		**2**	**4**	**4**	**9**	**9**	**9**	**16**	**24**	**13**
Cocksfoot	***Dactylis glomerata***	**5**	**32**	**61**	**8**	**73**	**46**	**3**	**9**	**22**	**4**	**29**	**29**
Couch	*Elytrigia repens*	1	2	1	1	1	2						
Creeping bent	*Agrostis stolonifera*												
Crested dogstail	***Cynosurus cristatus***	**4**	**10**	**11**	**21**	**60**	**49**		**2**	**9**	**13**	**32**	**48**
Danthonia	*Rytidosperma spp.*								1				1
Indian doab	*Cynodon dactylon*			1	3		1						
Italian ryegrass	*Lolium multiflorum*	10	3										
Kikuyu	***Pennisetum clandestinum***												
Meadow fescue	*Festuca pratensis*			1									
Paspalum	*Paspalum dilatatum*												
Phalaris	*Phalaris aquatica*												
Poa	***Poa pratensis* or *P. trivialis***		**11**	**17**		**8**	**9**		**16**	**7**		**4**	**9**
Poa annua	*Poa annua*			4									
Ratstail	*Sporobolus africanus*	3	1		2	4			1				
Perennial ryegrass	***Lolium perenne***	**163**	**70**	**44**	**162**	**71**	**26**	**111**	**64**	**72**	**105**	**69**	**42**
Soft brome	***Bromus hordeaceus***	**2**	**23**	**18**	**1**	**1**	**1**		**5**	**12**			**2**
Sweet vernal	***Anthoxanthum odoratum***	**7**	**17**	**13**	**1**	**3**	**1**	**7**	**26**	**32**	**4**	**14**	**20**
Tall fescue	*Schedonorus phoenix*			1									
Vulpia hair grass	*Vulpia spp.*								1				
Yorkshire fog	***Holcus lanatus***	**49**	**57**	**40**	**29**	**61**	**48**	**49**	**103**	**57**	**81**	**85**	**44**
Legume													
Alsike clover	*Trifolium hybridum*												
Lotus	*Lotus pedunculatus*			1				1	1	6			4
Medic	*Medicago spp.*			1									
Red clover	*Trifolium pratense*			1									
Subterranean Clover	*Trifolium subterraneum*	1		3		1	1		1	3			1
Suckling clover	*Trifolium dubium*	1	7	19				2	5	5			1
White clover	***Trifolium repens***	**16**	**87**	**87**	**7**	**31**	**71**	**6**	**54**	**88**	**8**	**40**	**98**
Herb													
Chicory	*Cichorium intybus*						1						
Plantain	***Plantago lanceolata***		**1**	**22**		**11**	**17**		**5**	**14**	**1**	**2**	**11**
Weed													
Black nightshade	*Solanum nigrum*												
Bracken	*Pteridium esculentum*												
Borage	*Borago officinalis*												
Buttercup	*Ranunculus spp.*		1							4			
Californian thistle	*Cirsium arvense*				1	1	1						
Catsear	***Hypochaeris radicata***					**3**	**13**		**3**	**8**		**6**	**12**
Chickweed	*Stellaria media*						2						
Daisy	*Bellis perennis*			1					1				
Dandelion	***Taraxacum officinale***			**1**			**3**						**1**
Dock	*Rumex spp.*											1	
Foxglove	*Digitalis purpurea*												
Hawkbit	*Leontodon taraxacoides*												
Hawkweed	*Hieracium spp.*							1					1
Hydrocotyle	*Hydrocotyle spp.*												
Mallow	*Malva spp.*						3						
Moss						1	3						
Mouse ear chickweed	*Cerastium spp.*								1	4			
Nodding thistle	*Carduus nutans*												
Pennyroyal	*Mentha pulegium*												
Redroot	*Amaranthus powellii*					1	1						
Rush													
Sedge				2		2	1					1	2
Selfheal	*Prunella vulgaris*												
Shepherds purse	*Capsella bursa-pastoris*												
Sorrel	*Rumex acetosella*												
Stinking mayweed	*Anthemis cotula*												
Storksbill	*Erodium moschatum* and *E. cicutarium*				3	1							
Thistle	***Cirsium arvense and C. vulgare***		**2**	**11**		**5**	**16**	**2**	**6**	**2**		**1**	**1**
Vetch	*Vicia sativa*												
Willow weed	*Persicaria maculosa*												
Yarrow	*Achillea millefolium*										1	4	1

		SCD Spring 2015			SCD Autumn 2016			SLA Spring 2015			SHA Spring 2015			SHA Autumn 2016		
	Most abundant species	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Grasses	**Botanical name**															
Barley grass	*Critesion murinum*															
Browntop	***Agrostis capillaris***	**59**	**34**	**24**	**72**	**34**	**26**	**98**	**102**	**50**	**18**	**23**	**41**	**91**	**80**	**50**
Chewings fescue	***Festuca rubra***										**12**	**11**	**13**	**11**	**9**	**7**
Cocksfoot	***Dactylis glomerata***	**5**	**18**	**13**	**12**	**39**	**25**	**11**	**31**	**34**		**5**	**2**		**2**	**6**
Couch	*Elytrigia repens*															
Creeping bent	*Agrostis stolonifera*															
Crested dogstail	***Cynosurus cristatus***				**1**	**17**	**19**				**1**	**7**	**13**	**1**	**5**	**18**
Danthonia	*Rytidosperma spp.*		4	2	3	7	1	28	33	13						
Indian doab	*Cynodon dactylon*															
Italian ryegrass	*Lolium multiflorum*															
Kikuyu	***Pennisetum clandestinum***															
Meadow fescue	*Festuca pratensis*															
Paspalum	*Paspalum dilatatum*											1			1	2
Phalaris	*Phalaris aquatica*		8	2					1							
Poa	***Poa pratensis* or *P. trivialis***		**22**	**9**				**1**	**3**	**8**		**6**	**6**			**1**
Poa annua	*Poa annua*															
Ratstail	*Sporobolus africanus*										2	4	6	12	12	8
Perennial ryegrass	***Lolium perenne***	**91**	**32**	**9**	**102**	**46**	**19**	**93**	**39**	**42**	**201**	**43**	**22**	**200**	**56**	**26**
Soft brome	***Bromus hordeaceus***	**11**	**16**	**11**								**1**				**1**
Sweet vernal	***Anthoxanthum odoratum***	**15**	**24**	**26**	**2**	**7**	**2**	**126**	**98**	**40**	**75**	**70**	**45**	**4**	**32**	**25**
Tall fescue	*Schedonorus phoenix*	33		1	5											
Vulpia hair grass	*Vulpia spp.*	34	26	8	3	3		8	7	6						
Yorkshire fog	***Holcus lanatus***	**9**	**36**	**16**	**2**	**7**	**8**	**18**	**30**	**31**	**11**	**35**	**32**	**19**	**36**	**27**
Legume																
Alsike clover	*Trifolium hybridum*			1												
Lotus	*Lotus pedunculatus*										1		1			
Medic	*Medicago spp.*		2													
Red clover	*Trifolium pratense*															
Subterranean Clover	*Trifolium subterraneum*	8	3	4									2			
Suckling clover	*Trifolium dubium*	4	6	9					7	11	5	5	7	1	2	1
White clover	***Trifolium repens***	**5**	**24**	**64**		**12**	**11**	**5**	**17**	**49**	**5**	**58**	**62**	**2**	**36**	**38**
Herb																
Chicory	*Cichorium intybus*															
Plantain	***Plantago lanceolata***		**3**	**3**		**4**	**1**				**2**	**23**	**41**	**2**	**27**	**52**
Weed																
Black nightshade	*Solanum nigrum*															
Bracken	*Pteridium esculentum*			1											1	1
Borage	*Borago officinalis*															
Buttercup	*Ranunculus spp.*															
Californian thistle	*Cirsium arvense*				4	3	1									
Catsear	***Hypochaeris radicata***	**1**		**2**					**1**	**2**	**15**	**40**	**41**	**4**	**35**	**59**
Chickweed	*Stellaria media*			11								1				
Daisy	*Bellis perennis*									1						
Dandelion	***Taraxacum officinale***		**1**	**1**			**3**	**2**	**15**	**56**						
Dock	*Rumex spp.*															
Foxglove	*Digitalis purpurea*															
Hawkbit	*Leontodon taraxacoides*															
Hawkweed	*Hieracium spp.*									1						
Hydrocotyle	*Hydrocotyle spp.*										1	9	8	1	10	14
Mallow	*Malva spp.*			1								2			1	3
Moss									2	3						
Mouse ear chickweed	*Cerastium spp.*									2			2			2
Nodding thistle	*Carduus nutans*					1										
Pennyroyal	*Mentha pulegium*												1		3	3
Redroot	*Amaranthus powellii*															
Rush																2
Sedge																
Selfheal	*Prunella vulgaris*															
Shepherds purse	*Capsella bursa-pastoris*		1													
Sorrel	*Rumex acetosella*					1										
Stinking mayweed	*Anthemis cotula*															
Storksbill	*Erodium moschatum* and *E. cicutarium*			2			2									1
Thistle	***Cirsium arvense and C. vulgare***	**2**	**3**	**3**						**9**		**2**	**4**	**1**	**1**	**2**
Vetch	*Vicia sativa*									2						
Willow weed	*Persicaria maculosa*															
Yarrow	*Achillea millefolium*	1	8	9	2	8	11									