Unveiling the potential of proximal hyperspectral sensing for measuring herbage nutritive value in a pasture-based dairy farm system

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Abstract

The aim of this thesis was to unveil the potential of proximal hyperspectral sensing for measuring herbage nutritive value in a pasture based-dairy farm system. Hyperspectral canopy reflectance and herbage cuts as well as data on herbage and supplement allocation, and milk production were collected regularly from Dairy 1 farm at Massey University during the 2016-17 and 2017-18 production seasons. Milk, fat and protein yields and body condition score of cows were measured at monthly herd tests while live weights were recorded daily. Calibration equations determining herbage the nutritive value traits digestible organic matter in dry matter, metabolisable energy (ME), crude protein, neutral detergent fibre and acid detergent fibre from hyperspectral canopy reflectance data were developed and validated using partial least squares regression. Canopy reflectance calibration models were able to determine the various herbage nutritive value traits with R^2 values ranging from 0.57 to 0.78. Variation of herbage nutritive value traits were mostly explained by month within production season (42.7% of variance among traits) followed by random error (33.4%), production season (13.1%) and paddock (10.7%). The relative importance of herbage nutritive value and other herbage quantity and climate-related variables in driving performance per cow in the herd was determined using multiple linear regression. Herbage metabolizable energy explained 20% to 30% of milk, fat and protein production per cow while herbage quantity and climate- related factors were relatively less important (below 15%). Random regression models were used to model lactation curves of milk, fat, protein and live weight to estimate daily ME requirements of individual cows. The daily ME estimated requirements was nearly a fifth above or below the daily mean ME supplied. The deviation of the daily ME estimated requirements of a cow from the actual ME supplied per cow in the herd was mostly explained by the observations made within a cow rather than between cows or breeds. Variation in herbage nutritive value in addition to the within and between cow variation of ME estimated requirements were high enough to justify the use of proximal hyperspectral sensing as measurement tool to assist with feed allocation decision-making. However, the potential of this technology could be further enhanced using more precise technologies to allocate herbage to individual cows or groups of cows. The potential benefits of more precise feed allocation will result in more efficient grazing management and thus improved utilisation of herbage and hence milk production.

Key words: proximal hyperspectral sensing, pasture-based dairy farm system, herbage nutritive value, variation

Dedicated to Xinyuan Li.

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List of Abbreviations

ADF= acid detergent fibre

AH= area of herbage offered

BCS= body condition score

CP= crude protein

CSI= cold stress index

DM= dry matter

DOMD= Digestible organic matter in dry matter

FP= fat percentage

FY= fat yield

HA= herbage allowance

HM= herbage mass

LW= live weight

LWC= live weight change

ME= metabolisable energy

MS= milksolids percentage

MSY= milksolids yield

MU= milk urea

MY= milk yield

NDF= neutral detergent fibre

NIR= near-infrared

NIRS= near-infrared spectroscopy

NV= nutritive value

PD= proportion of herbage in diet

PFR= protein to fat ratio

PI1= performance indicator 1

PI2= performance indicator 2

POP= period of production

PP= protein percentage

PY= milk protein yield

SWIR= short-wavelength infrared

T= daily mean temperature

THI= temperature humidity index

VisNIR= visible near-infrared

CHAPTER 1

Introduction

Dairy farming is an important pillar of the New Zealand economy. In 2017-18, the dairy industry processed around 20.7 billion litres of milk (3% of the milk produced globally) produced on 1.76 million hectares (DairyNZ 2019). Export revenue earned by the industry was $15.1 billion NZD (28% of total exports) generating jobs for 46,000 people. This success has been driven partly by the intensification of pasture-based dairy farm systems that over recent decades have held production costs low (Ma et al. 2018; Clay et al. 2019). However, intensification has also bought about environmental issues placing concerns about the increased use of resources as a means of controlling costs in a highly competitive industry. Thus, a focus towards improving efficiency of use of resources has been proposed as an alternative to intensification.

Precision agriculture technologies have the potential to improve the technical efficiency of dairy farm systems while keeping costs low. Some authors (French et al. 2014; Shalloo et al. 2018) have suggested that developments in the field of rapid herbage nutritive value (NV) measurement present an important opportunity to improve pasture utilisation in pasture-based dairy systems. Rapid herbage NV measurements can help management make more precise daily herbage and supplement allocation decisions by shifting from a dry-matter to a nutritional-based decision making. However, to date, research aimed at the development of rapid herbage NV measurement tools for their specific use in pasture-based dairy farm systems has been neglected.

Research involving proximal hyperspectral sensing (Kawamura et al. 2009; Pullanagari et al. 2012; Adjorlolo et al. 2015) has been successful in predicting the NV of herbage from canopy reflectance, offering a potential tool for rapid herbage NV measurement in the field. However, the research undertaken to date has provided limited evidence of the potential of proximal hyperspectral sensing for assisting with herbage and supplement allocation decision-making in pasture-based dairy farm systems. Primarily because previous research has not considered that NV decreases with canopy height and that only a limited portion is available to the grazing cow. In addition, reflectance from the lower canopy strata can influence the spectral signature obtained from the surface of canopy swards (Asner 1998) affecting the accuracy of proximal hyperspectral sensing for predicting NV from a limited portion of herbage. For proximal hyperspectral sensing to be potentially useful to support herbage and supplement allocation decision-making, then its ability to provide measurements that are representative of the herbage NV available to the grazing cows needs to be determined.

Moreover, it is unclear if rapid herbage NV measurement has potential for managing daily herbage and supplement allocation. Although herbage NV is a significant driver of the performance of grazing cows (Kolver 2003, Walker et al. 2004), herbage quantity (Dillon 2007, Baudracco et al. 2010, Pérez-Prieto and Delagarde 2013) and climate related (Bryant et al. 2007) factors can also influence cow performance, limiting the potential of herbage NV measurement in field-like conditions. For proximal hyperspectral sensing to be a useful tool for assisting with feed allocation, then the extent by which herbage NV varies and its importance on influencing cow performance in a pasture-based dairy farm system needs to be determined. Precise allocation of herbage and supplements to the herd on the basis of the nutrients supplied daily would also require estimates of the daily nutritional requirements of cows in the herd, which has proven challenging (Hills et al. 2015). Addressing all these issues would unveil the potential of proximal hyperspectral sensing for measuring the nutritive value of herbage in a pasture-based dairy farm system.

The hypothesis of this thesis is that proximal hyperspectral sensing has potential for measuring the nutritive value of herbage in a pasture-based dairy farm system.

The aim of this thesis was to investigate the potential of proximal hyperspectral sensing for measuring the nutritive value of herbage in a pasture-based dairy farm system. In order to achieve this aim, four specific objectives were determined:

1. To develop and validate calibration models for hyperspectral canopy reflectance data that are useful to determine herbage NV traits metabolisable energy (ME), crude protein (CP), neutral detergent fibre (NDF), acid detergent fibre (ADF) and organic matter digestibility in dry matter (DOMD) of the vertical portion of mixed ryegrass-white clover swards made available to the grazing cow in accordance with good grazing management practice.
2. To assess variation of herbage NV offered to lactating cows in time and space in a pasture-based dairy farm system using proximal hyperspectral sensing.
3. To determine the influence of herbage NV and other herbage quantity and climate related factors on the physical performance of a pasture-based dairy farm system on a per cow basis.

4. To determine the extent to which the deviation of the energy required by a cow from the energy supplied per cow to the herd throughout the production season in a pasture-based dairy farm varies.

1.1 Thesis outline

This thesis consists of seven chapters. The first two chapters are the introduction and the literature review. Chapter 3 studies the development and validation of calibration models for hyperspectral canopy reflectance data that are useful to determine herbage NV traits metabolisable energy (ME), crude protein (CP), neutral detergent fibre (NDF), acid detergent fibre (ADF) and digestible organic matter in dry matter (DOMD) of the vertical portion of mixed ryegrass-white clover swards that should be made available to the grazing cow in accordance with good grazing management practice. Chapter 4 determines the variation in time and space of the NV of mixed herbage offered daily to milking cows in a pasture-based dairy farm system measured using proximal hyperspectral sensing. It also addresses the relevance of rapid herbage NV measurement by discussing the implications of herbage NV variation to dairy cow performance and grazing management. Chapter 5 investigates the relative importance of daily variation of herbage NV and other herbage quantity and climate related factors on driving the physical performance in a pasture-based dairy farm system on a per cow basis. The results from this chapter determine the extent by which herbage NV measurement in field-like conditions can be relevant for informing decision making around the daily allocation of feed to cows. Chapter 6 determines the extent by which estimated requirements for ME of individual cows vary throughout the production seasons in a pasture-based dairy farm system and quantifies how such variation differs from the dietary ME supplied per cow in the herd. Finally, Chapter 7 discusses the overall findings of the thesis in terms of their implication to different aspects of grazing management and feed allocation decision-making, and identifies research opportunities to further study the topic before reaching the overall conclusion.

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CHAPTER 2

Literature review

2.1 New Zealand pasture-based dairy farm systems

New Zealand milk production is based on outdoor grazing of fresh mixed ryegrass (*Lolium perenne* L.) and white clover (*Trifolium repens* L.) herbage (Holmes 2007; Wales and Kolver 2017). Such reliance on fresh herbage has resulted in pasture-based dairy farm systems that produce milk seasonally as opposed to European or North American indoor feeding systems where milk production is sustained throughout the year (Hofstetter et al. 2014). The main philosophy driving milk production in New Zealand is to keep production costs low by transforming as much herbage into milk as possible (Holmes 2007). To do this, pasture-based dairy farm systems are designed to calve cows in spring so that the seasonal herbage growth pattern is matched with herd feed requirements.

Although most pasture-based dairy farm systems in New Zealand use spring calving, some production systems have been adapted to produce milk during winter by implementing either autumn calving, split calving (spring and autumn), or a year-round calving (Holmes 2007). Changing the calving pattern allows these production systems to obtain premium prices for the milk produced during winter which contributes to the higher costs associated with the use of higher levels of supplements during winter. Besides seasonality, other pasture-based dairy farm systems in New Zealand include organic milk production (Raedts et al. 2017; Le Heron 2018), A2 milk (i.e. milk with a low ratio of A1:A2 β-casein proteins) or the adoption of once a day milking throughout the production season (Edwards 2019).

DairyNZ (2017) suggests that New Zealand dairy farms can be characterised by five coexisting production systems defined on 1) the level of imported feed and 2) dry cows grazing off farm as: System 1: no imported feed is used, and supplements fed to the herd harvested from the effective milking area. Dry cows also graze within the effective milking area; System 2: between 1 to10% of imported feed is used as either supplement or dry cows grazing during winter; System 3: between 11 to 20% of imported feed is used to extend lactation (typically autumn feed) and for wintering dry cows; System 4: between 21 to 30% of imported feed is used at both ends of lactation and for wintering dry cows; System 5: more than 31% of imported feed is used throughout lactation.

2.2 Grazing management decisions in seasonal pasture-based dairy farm systems

To be able to consistently produce as much milk as possible from herbage, seasonal pasture-based dairy farm systems require a series of strategic, tactical, and operational grazing management decisions. Strategic, tactical, and operational refer to three management levels that resemble a hierarchical structure as conceptualised in Figure 2.1. In this hierarchy, long-term goals set by higher level strategic planning (> 1 year planning horizon) drive plans and goals of shorter-term lower level tactical (within a year planning horizon) and operational planning (1 to 30 days planning horizon) (Parker et al. 1997; Shadbolt and Bywater 2005; Cowan et al. 2013).

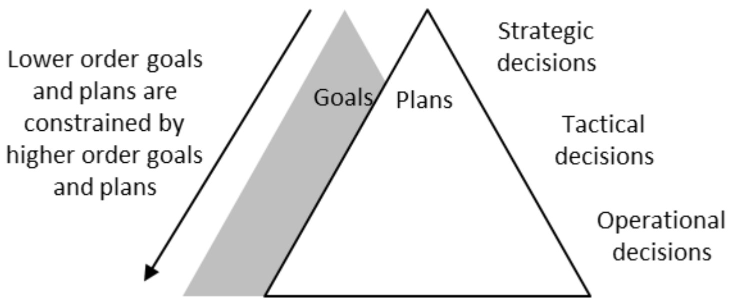

Figure 2.1 Conceptualisation of a hierarchy of plans and goals derived from management levels. Source: adapted from Cowan et al. (2013).

2.2.1 Strategic grazing management decisions

The overarching goal of strategic grazing management in a seasonal pasture-based dairy farm system is to closely match the seasonal herbage growth pattern with herd feed requirements. Key strategic grazing management decisions include definitions on the stocking rate (i.e. the number of cows per unit area), the conservation/supplementation policy, and calving and dry-off dates (Parker et al. 1997). Figure 2.2 illustrates the synchronisation of a conceptual pasture-based dairy farm system throughout a year.

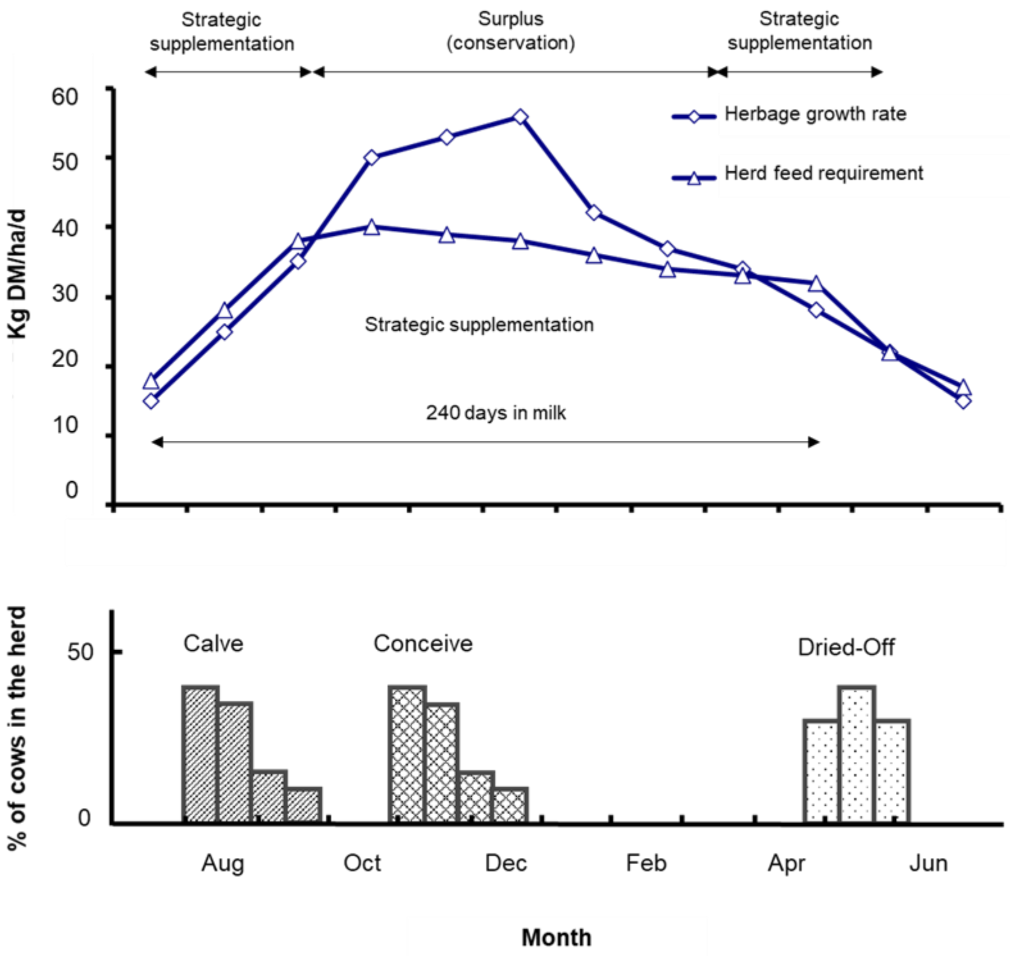

Figure 2.2 Synchronisation between herbage growth and herd feed requirements throughout a year in a conceptual spring calving pasture-based dairy farm system. Source: adapted from Holmes (2007).

Calving and dry-off dates determine the pattern of feed requirements of the herd throughout the year and thus the length of the milk production season. Calving date is based on the mating date of the previous year while dry-off date is determined by the body condition of cows and the availability of feed. Ideally, all cows in the herd must be mated within a short period of time so that cows calve in spring in a tight pattern. A tight calving pattern for cows has 88% of the herd calved by week 6 while a tight calving pattern for first calvers has 75% of heifers calved by week 3, and 92% calved by week 6 (DairyNZ 2019). After calving, a cow will be on average 240 days in milk before dry-off. As feed requirements increase after calving until the peak of milk production, calving of all cows should be synchronised so that the feed requirements of the herd coincide with the increasing rate of herbage growth. At times when the availability of herbage exceeds herd requirements, the feeding policy of a farm can use conservation of herbage in the form of silage or hay to be used to feed cows at times of deficit. In addition, other supplements can be strategically grown or brought into the farm depending on the overall feed demand of the herd, which is dictated by the stocking rate and if heifers are reared on or off farm. Some authors (Moller et al. 1996; Burke et al. 2002; Litherland and Lambert 2007) also highlight that, in addition to the seasonal herbage growth pattern, strategic grazing management of pasture-based dairy farm systems should also consider the seasonal variation of herbage nutritive value. For instance, Burke et al. (2002) suggest that excess protein in ryegrass-based diets during spring can be balanced if the production system incorporates planting of forages in adjacent strips, grazing separate paddocks or cutting and carrying herbage based on protein content to balance the diet.

2.2.2 Tactical grazing management decisions

Tactical grazing management refers to planning, implementing and controlling decisions when deviations from the strategic goals occur. Chapman et al. (2013) suggest that a major challenge for feed management in seasonal pasture-based dairy farm systems is to account for the inter-annual variability of herbage availability. Differences between expected and actual herbage growth rates within a year might signify that the plans for a year may change. Tactical grazing management deals with any shortcoming or over-supply of herbage availability (Cowan et al. 2013). Decisions about drying off date, selling cattle, and application of fertilisers are examples of tactical management decisions that can be used to cope with inter-annual variability in herbage growth rates as well as variation in expected input or output prices (Parker et al. 1997; Holmes 2007; Cowan et al. 2013; Field and Ball 1978; Macdonald et al. 2010). One of the most important decisions to undertake in a rotational grazing system is the adjustment of the grazing rotation length (i.e. grazing frequency) (Holmes 2007). Rotation length is used to control inter-annual variation of herbage availability by manipulating the amount of herbage consumed each day and this decision is considered an interface between tactical and operational planning (McCarthy et al. 2014).

2.2.3 Grazing rotation length

Regular monitoring the average herbage mass available at a farm (AHM) is an important metric for deciding grazing rotation length. Achieving AHM targets at selected times of the year will ensure there will be enough herbage in quantity and quality terms to meet production targets. Based on extensive research and farmer experience, Macdonald et al. (2010) describe a series of decision rules that have proven effective in managing grazing rotation across seasons. For instance, in early spring achieving an AHM target of 1800 kg DM/ha at balance date (i.e. the date when the expected herbage growth rate equals to herd feed demand) is important to ensure enough high-quality herbage at peak milk production months. If AHM is below target, cows will be underfed relative to requirements. Conversely, if AHM is above target, herbage quality and growth will decline, and milk production will be reduced. In most pasture-based dairy farm systems, rotation length varies from 1/20th of the area grazed each day in spring when herbage growth rate is high to 1/100th in winter when growth rates are low (Macdonald et al. 2010; Macdonald and Penno 1998). Reducing the length of the spring grazing rotation could be combined with making silage from excess herbage to maintain quality and transfer excess herbage to the summer (Macdonald and Penno 1998; Macdonald et al. 2010). In contrast, increasing grazing rotation length during autumn will help accumulate herbage mass to feed the herd after the next calving while ensuring cows reach a good body condition at calving. However, achieving AHM and body condition targets by managing grazing rotation during autumn might restrict herbage intake of cows and hence the use of supplementary feeds might also be required to achieve body condition score targets (Bryant 1990).

2.2.4 Operational grazing management decisions

Operational grazing management is responsible for daily allocation of herbage and supplements to the herd (McCarthy et al. 2014). Daily feed allocation has significant short-term consequences on animal performance and grazing efficiency, with the latter having longer-term consequences on herbage quality, regrowth and persistency (Fulkerson and Bryant 1993; Fulkerson and Donaghy 2001; Fulkerson et al. 2005). In pasture-based dairy farm systems where herbage is a significant component of the diet of cows, differences in herbage dry matter availability between paddocks is a major challenge to operational decision making. A paddock can be defined as a sub-division of a grazing management unit that is enclosed and separated from other areas by a fence or a barrier (Allen et al. 2011). The availability of herbage in a paddock can vary depending on a range of factors including farm infrastructure, topography or climate (McCarthy et al. 2014). Macdonald et al. (2010) describe that efficient grazing involves three key management decisions that managers must perform regularly: 1) when to graze herbage, which determines grazing frequency; 2) how hard to graze herbage, which determines grazing severity; and 3) how long to graze herbage, which determines grazing duration. These decisions are heavily dependent on having accurate estimates of herbage mass. However, herbage allocation can also involve monitoring other indicators such as day rotations, sward height, or grass leaf-stage (Sheath and Clark 1996; Mayne et al 2000; Fulkerson and Donaghy 2001; McCarthy et al. 2014).

2.3 The relationship between information and grazing management

The support of strategic, tactical and operational grazing management decisions requires information in accordance to the level of management (Chapman et al. 2013). For example, to support of strategic decisions, management would require the mean monthly estimate of the overall feed profile (i.e. feed supply and demand) in a farm throughout a year. This would either require having historical data or simulation tools that would allow the forecast of future scenarios. In contrast, deciding how much herbage to allocate to cows at any day requires information on the herbage available in the paddock to graze that day and an estimate of the feed demand of the herd.

In a simulation study by Beukes et al. (2015), the potential benefit of allocating feeds in a pasture-based dairy farm system based on accurate information on herbage mass availability was quantified. Beukes et al. (2015) found that precisely allocating herbage to cows daily can potentially improve farm profits by up to $525/ha by improving grazing efficiency and herbage production and by reducing costs associated with supplements use. The authors recognise that their study does not account for the impact of grazing on herbage quality nor variation of herbage quality in the model. Moller et al. (1996) suggested that the existing variation of herbage quality across New Zealand dairy farms could be further exploited to improve feed management decision making. However, there is no clarity whether variation of herbage quality consumed daily across the paddocks is enough to justify measurement nor if such variation would be an important driver of farm performance in a non-experimental setting. Most importantly, to date there is no commercially available tool that would provide rapid measurements of herbage quality on farms. More recently, some authors (French et al. 2014; Shalloo et al. 2018) suggested that developments in the field of rapid herbage nutritive value measurement presents an important opportunity to improve daily feed allocation decision-making in pasture-based dairy farm systems. In addition to rapid herbage nutritive value measurement, the adoption of individualised feeding and virtual fencing technologies has been proposed to improve efficiency of grazing of heterogeneous resources (French et al. 2014; Hills et al. 2016). However, Hills et al. (2015) suggest that addressing the variation of daily nutritional requirements of individual cows in the herd is a major limitation to the adoption of technologies aimed at feeding cows individually.

2.4 Defining herbage quantity and quality

The literature on pasture production and grazing management is inundated with definitions in relation to herbage quantity and quality that might lead to confusion and need clarification.

2.4.1 Herbage quantity

Herbage quantity is usually described in terms of herbage mass (HM). Herbage mass refers to the amount of green and dead plant material present in a delimited area cut at a given height (usually ground level height) and is most often expressed in kilograms of dry matter per hectare (kg DM/ha) (Allen et al. 2011; Kallenbach 2015). The term pasture cover is frequently used as a synonym for HM and is the herbage quantity term most widely adopted in the non-scientific community (Allen et al. 2011). Herbage mass is determined by height, density and water content. However, because herbage water content is highly variable, expressing herbage mass in dry matter (DM) over wet content is preferred. Lastly, herbage allowance (HA), defined as the herbage mass allocated to livestock (kg DM/cow/d), is another common term used to characterise herbage quantity.

2.4.2 Herbage quality

Herbage quality can refer either to the nutrient composition of herbage, the interaction between herbage nutrient composition and animal intake or to herbage morphological attributes associated with the selective grazing behaviour of the grazing animal that are associated with herbage quality.

Nutritive value (NV) refers to the concentration of energy and nutrients (e.g. water, proteins, fats, vitamins, minerals, and carbohydrates) available to the grazing animal that is contained in herbage tissue (Lambert and Litherland 2000). In practice, digestibility and metabolisable energy (ME) are the two NV traits most commonly used to assess quality in New Zealand pastures (Lambert and Litherland 2000). However, other NV traits such as crude protein (CP) and neutral detergent fibre (NDF) and acid detergent fibre (ADF) are also used to a lesser extent (Lambert and Litherland 2000).

The interaction between herbage NV and herbage intake is defined as feeding value (FV) and is a direct response measure of animal performance to herbage (Ulyatt 1970; Ball et al. 2001; Waghorn and Clark 2004). Herbage FV is determined by chemical analyses and animal feeding trials and is thus considered an indirect indicator of herbage quality. Expressing herbage quality as FV is a more complete metric of herbage quality compared to NV because it incorporates the effect of grazing selectivity on animal performance which is not accounted by NV.

Another way of defining herbage quality is in terms of the species and morphological composition of herbage (Lambert and Litherland 2000; Waghorn and Clark 2004). These two factors are associated with the selective grazing behaviour of animals and can also be used as a field indicator of herbage quality (Lambert and Litherland 2000). In general terms, animals tend to prefer leaf over stems, legumes over grasses, new green material on the top of the canopy over the less accessible dead material placed at the bottom of the canopy.

2.4.3 Herbage available

The term ‘available’ is often used to denote assumptions on herbage structural characteristics or harvesting procedures (Allen et al. 2011). In this thesis, herbage available is used to describe the quantity or quality of herbage above a grazing height threshold of 4 cm in height, which is defined as the top portion of the canopy that should be made available to the grazing cows according to good grazing management practice (Macdonald et al. 2010).

2.5 Herbage measurement tools

There are various tools or methods available for measuring quantity or quality of herbage. Common herbage quantity measures include mass, height and density of plants or tillers while herbage quality is most commonly assessed by herbage chemical composition, plant morphological composition, and species composition (Kallenbach 2015). However, given the large variation in herbage quantity and the importance of having this information for managing grazing in pasture-based dairy farm systems, more effort has been placed on the development of tools for measuring herbage quantity than quality (Dalley et al. 2009; Shaloo et al. 2018).

2.5.1 Herbage quantity measurement

On-farm herbage quantity can be measured by visual assessment, rising plate meters, sward sticks or electronic probes (Stockdale and Kelly 1984; Sanderson et al. 2001; Kallenbach 2015; Dalley et al. 2009). All these tools have proven reliable but time consuming or require experienced users for improved accuracy (Dalley et al. 2009). For instance, early work by Campbell and Arnold (1973) tested the accuracy of HM visual assessment of trained and untrained independent observers against actual measurements of HM. In their study, Campbell and Arnold (1973) found that untrained observers over-estimated the effects of height and under-estimated the effects of density in HM. However, in most cases (89%), visual assessment was able to predict HM with high accuracy ($R^2 > 0.70$). O'Donovan et al. (2002) quantified the effect of the level of HM on the accuracy of its assessment using the visual method and found that the ratio of actual to estimated HM decreased from 0.20 to 0.12 with HM increasing from 1000 kg DM/ha to 3000 kg DM/ha.

The C-Dax pasture meter (Lawrence et al. 2007) has recently been introduced to the market as a new tool to speed up the process of herbage mass assessment. C-Dax is a towed-behind attachment that can be used in any all-terrain vehicle. It comprises a series of light beams that create an accurate profile of herbage height as the sward breaks the light path as the vehicle moves (Lawrence et al. 2007). C-Dax can take a large number of measurements per time unit, incrementing the reliability of the instrument. Moreover, later versions of C-Dax have a Global Positioning System (GPS) that has been proven useful to map the spatial variation of herbage mass (Dennis et al. 2015). Alternative herbage mass mapping options to C-Dax include the addition of a GPS to a rising plate meter in combination to a smartphone (French et al. 2014). King et al. (2010) compared the accuracy C-Dax pasture meter with rising plate meter concluded that both tools have similar accuracies and that both benefit from the use of different seasonal calibration equations, specific to the region in which they are used.

More recently, the ability of predicting herbage mass of mixed swards from data collected using ultrasonic (Fricke et al. 2011) and a combination of ultrasonic and optical sensors (Fricke and Wachendorf 2013; Moeckel et al. 2017) was determined. Fricke et al. (2011) found that ultrasonic sensors can predict herbage mass with a R^2 of 0.78 and that predictions can be further improved if legume-specific mixtures (R^2= 0.79) and pure swards (R^2= 0.81) calibrations are developed. Fricke and Wachendorf (2013) found that combining ultrasonic and optical sensor data improves predictions of herbage mass (R^2 values of 0.83 for mixed swards and R^2 values of 0.88 to 0.90 for species-specific calibrations). However, using a similar approach to Fricke and Wachendorf (2013) but with data collected in field-like conditions, Moeckel et al. (2017) found that the accuracy of herbage mass from mixed swards could be predicted with R^2 values ranging from 0.42 to 0.52. Such lower accuracies when compared to studies performed under controlled conditions (e.g. Fricke et al. 2011; Fricke and Wachendorf 2013) suggest that further improvements of the technology must be made before it can be adopted for use in farm practice.

2.5.2 Herbage quality measurement

Field herbage quality assessment mostly consists on the evaluation of sward morphological characteristics such as leaf to stem ration, species composition and colour (Kallenbach 2015). However, the need for actual measurements of herbage NV is still reliant on collecting, preparing and analysing samples in a laboratory. This whole process is expensive and time consuming. Consequently, much effort has been placed on assessing the ability of optical sensors to determine herbage NV in the field (e.g.

Kawamura et al. 2008; Pullanagari et al. 2012a; Pullanagari et al. 2012b; Pullanagari et al. 2013; Adjorlolo et al. 2015).

Progress in sensor development has resulted in increased spectral and spatial resolutions and the possibility of studying herbage NV with greater accuracy and at different spatial and temporal scales (Ortenberg 2016; Godinho et al. 2018). For the purpose of field herbage NV measurement, a number of researchers have studied the relationships between canopy spectral features and herbage NV using proximal- optical (Roberts et al. 2015), multispectral (Pullanagari et al. 2012a; Pullanagari et al. 2013) and hyperspectral (Kawamura et al. 2008; Kawamura et al. 2009; Pullanagari et al. 2012b; Adjorlolo et al. 2015) sensors with varying success.

Overall, predictions of herbage NV from hi-resolution hyperspectral sensor data were found to be more accurate (Kawamura et al. 2008; Pullanagari et al. 2012b) than those using multispectral sensing (Pullanagari et al. 2012a; Pullanagari et al. 2013), and accuracies improve if an active lighting system is used (Pullanagari et al. 2012b). Proximal hyperspectral sensing has the potential for measuring herbage NV for use in farming. However, research to date has failed to address the relevance of proximal hyperspectral sensing for assessing herbage NV for their use in grazing management.

2.6 Relationship between herbage quality and canopy depth

There is a relationship between canopy depth and herbage quality, which determines the nutrient content in herbage that could potentially be consumed by the grazing cow. As canopy depth increases, the quality of herbage decreases as the leaf:stem ratio decreases and there is higher content of dead material (Delagarde et al. 2000; Nave et al. 2014). In a study involving ryegrass-dominant swards, Delagarde et al. (2000) quantified the variation of herbage NV with canopy height. In their study, Delagarde et al. (2000) measured the NV content from herbage samples cut at four heights (0 to 5, 5 to 10, 10 to 15 and >15 cm) collected for three months during three seasons (spring, summer and autumn) and for three regrowth ages (21, 28 and 35 days). The results showed that NDF concentration increased from 42 to 67.4% and CP decreased from 23.9 to 13.2% with decreasing heights. The vertical distribution of herbage NV was, on average, more affected by regrowth age than by season. However, the decrease of CP with regrowth age was more marked in the upper than the bottom stratum of the canopy. In contrast, the vertical gradient of NDF was unaltered by season or regrowth age.

The decrease in herbage NV was also described for ryegrass-white clover herbage by Cosgrove et al. (1998). In their study Cosgrove et al. (1998) noted at a single regrowth age and during autumn that content of ME decreased from 13.4 to 11.4 MJ/kg DM, CP from 31.2 to 20.4% and NDF increased from 37.8 to 50.9% from top quarter to the bottom quarter of the canopy. However, the author acknowledges that the influence of season on the vertical variation of herbage NV should be considered when designing a sampling strategy aimed at characterising herbage NV.

2.7 Fundamentals of vegetation spectral sensing

Spectral sensing refers to the measurement of reflected or emitted radiation of a targeted body (Lillesand et al. 2015; Campbell and Wynne 2011; Govender et al. 2007). Bodies reflect or absorb radiation in different ways depending on the material they are made of, their physical and chemical composition, the roughness their surface as well as geometry. Like any object, vegetation has its own characteristics which are reflected into spectral signatures. The property that is usually used to quantify these spectral signatures is known as spectral reflectance, which is defined as the ratio of the reflected energy to incident energy as a function of wavelength (Govender et al. 2007).

2.7.1 Canopy reflectance

In green vegetation, chlorophyll and other plant chemical and morphological structures determine reflectance in the visible portion of the electromagnetic spectrum (Figure 2.3). Chlorophyll is strongly related to absorption of energy in the blue and red regions (450 and 670 nm, respectively) but not in the green where reflectance is high (Gitelson and Merzlyak 1997). Chlorophyll levels are an indicator of health and nutritional status of plants due to its influence on plant growth (Gitelson and Merzlyak 1997). Reflectance values in the near infrared (NIR) portion of the spectra are related with structural properties of cells. Beyond the 1300 nm waveband, there are three major water absorption bands at 1400, 1900 and 2500 nm and there are also some minor absorption features associated with chemical bonds that are found in many organic compounds such as nitrogen, lignin, lipid and fibre at different wavelengths.

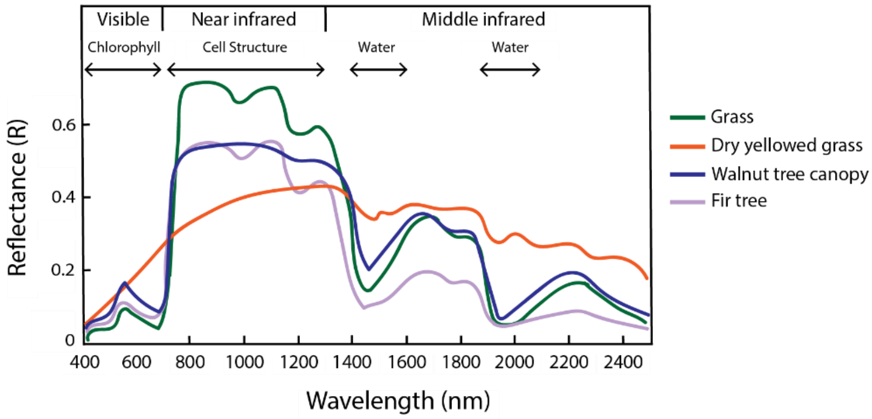

Figure 2.3 Spectral signatures for green grass, dry yellow grass, a walnut tree canopy and a fir tree. Source: adapted from Govender et al. (2007)

Canopy structural variables such as leaf area and leaf angle have a large influence on canopy reflectance (Asner 1998). Several studies (Asner 1998; Asner and Heidebrecht 2002; Numata et al. 2008) have demonstrated that non-photosynthetic plant tissue at the bottom of grass swards and soil background exposure can also influence canopy reflectance. This is of relevance when attempting to use canopy reflectance to study herbage characteristics of a limited portion of the vertical strata of the sward. Asner (1998) described that even at a high leaf area index (LAI) (LAI > 5), the lower strata of grass swards can influence canopy reflectance in the NIR region. Since the LAI of ryegrass-dominant swards of properly managed herbage is expected to reach between 4 and 6 at pre-grazing (Korte et al. 1984), the findings described by Asner (1998) suggest that predictions of herbage characteristics from a limited top portion of might be affected. Pullanagari et al. (2012b) also suggest that soil background and dead material can induce error in the prediction of herbage NV of mixed herbage from canopy reflectance.

2.7.2 Spectral data analysis

Many of the techniques used in the analysis of spectral data have been extensively reviewed by Pullanagari (2011). The analysis of spectral data is highly dependent on the type of data that is acquired by the sensor. For instance, hyperspectral sensors provide continuous reflectance data across wavelengths in the spectrum while multispectral sensors offer data on a reduced number of wavelength ranges (Govender et al. 2007). As a consequence, multivariate or machine learning techniques are most common in the analysis of hyperspectral data. Conversely, given a reduced number of wavelength ranges is available, relationships between spectral data and biophysical and biochemical characteristics of vegetation can be successfully established by using univariate regression methods that involve the development of indices such as the normalized difference vegetation index (Yule and Pullanagari 2009).

2.8 Principles driving grazing management

In rotational grazing, grazing management is driven by the idea that herbage defoliation must be beneficial for both plants and animals. In this sense, defoliation must promote herbage regrowth without altering persistency of the desirable species. In addition, harvested material must provide the grazing animal with an adequate source of feed in quantity and quality to satisfy their requirements to achieve production targets.

2.8.1 Optimising herbage production and quality: managing the plant

Understanding how herbage grows after defoliation is important to define grazing frequency since regrowth has significant consequences on herbage production and quality (Fulkerson and Donaghy 2001). After defoliation, grass-dominant swards accumulate mass following a sigmoidal pattern (Figure 2.4a). Regrowth is initiated by a slow growth rate phase (phase 1: the lag phase) in which photosynthetic activity is low due to reduced leaf area and regrowth is sustained by the mobilisation of non-structural carbohydrate reserves in the stubble (Figure 2.4b). As leaf area increases, increased photosynthetic activity results in the replenishment of carbohydrate reserves, with more energy being partitioned to growth of leaf, roots and the origination of new tillers. The consequence is an increment in the rate at which herbage grows (phase 2: the linear phase). However, as herbage grows in height, canopy closure prevents light penetration to the lower areas of the plant that result in less photosynthetic activity, with a consequent reduction in net growth due to respiration of shaded tissue (phase 3: ceiling yield). In addition to the reduction in herbage net growth, the accumulation of senescent tissue and plant decay that occurs after phase 3 results in a decrease of herbage quality and reduced number of tillers potentially affecting the persistence of ryegrass (Ong et al. 1978; Carton et al. 1989).

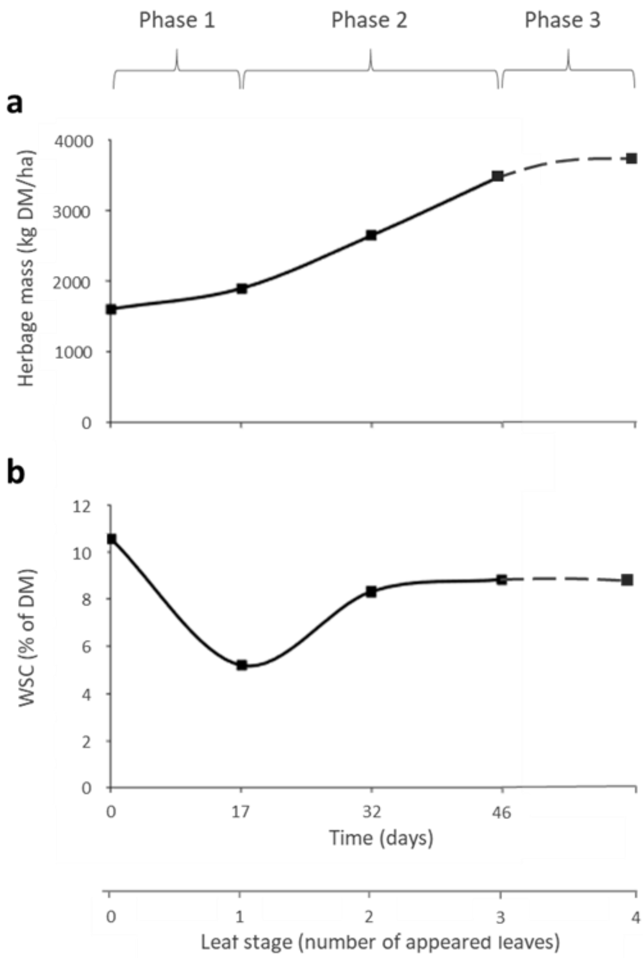

Figure 2.4 Regrowth cycle of ryegrass-dominant herbage plots defoliated by leaf stage or their day equivalent in the Waikato region of New Zealand from July to September. Herbage mass (a) and stubble water-soluble carbohydrate (WSC) reserves (b). Source: adapted using data from Lee et al. (2010) (——) and DairyNZ (2017) (- - -).

Grazing frequency

To maximise production of high quality herbage over the year, herbage must spend a greater proportion of time at the end of the linear phase of the regrowth curve and be grazed before losing quality. In ryegrass-dominant swards, if defoliation frequency is too high, there will not be enough leaf area to sustain high growth rates and ryegrass persistence will be negatively affected due to depletion of energy reserves. In contrast, if grazing frequency is too low, accumulation of dead material will result in less efficient photosynthetic activity and reduced herbage quality.

Grazing frequency can be determined by monitoring herbage mass, day rotations, sward height, or grass leaf regrowth stage. According to Fulkerson and Donaghy (2001) the grass leaf regrowth stage method is the most precise indicator of grazing frequency. This is because the grass leaf stage method is grounded on a sound understanding of the physiological processes involved in grass regrowth. In contrast, the other three methods depend on establishing empirical relationships with herbage growth rate that are subject to variation from climate (Lowe et al. 2008), soil moisture (Langworthy et al. 2019), soil fertility, species composition (Cullen et al. 2008; Lowe et al. 2008) and genetic variation within species (Fulkerson et al. 1994; Tozer et al. 2017) that lead to a less precise assessment of grazing frequency.

The relationship between herbage growth rate and herbage mass can be mathematically described by a quadratic function (Woodward et al. 1993; Woodward 2018) that is the derivative of the logistic function of accumulated herbage mass depicted in Figure 2.4a. In this quadratic function, herbage growth rate increases with herbage mass until reaching a growth peak indicating the herbage mass that would maximise growth rate. Thereafter, increasing herbage mass would result in reduced growth rates. Empirical research has shown that the optimum herbage growth rate in New Zealand pastures can be achieved with herbage mass ranging from 1087 to 3901 kg DM/ha (Brougham 1956; Bluett et al. 1998). Bluett et al. 1998 suggested that the optimum growth rate that maximises net herbage production in winter and early spring in New Zealand is 32.3 kg DM/ha/d and that this rate can be obtained with an herbage mass of 2500 kg DM/ha.

In ryegrass-dominant swards, the leaf-stage method is supported by the idea that ryegrass can only sustain three live leaves per tiller at a time, once a fourth leave emerges the first one dies (Davies 1960; Fulkerson and Donaghy 2001). Leaf stage is thus considered a genetically driven indicator of tissue turnover that can be used to indicate when grass is ready to be grazed (Fulkerson and Donaghy 2001). The interval for each ryegrass leaf to appear and expand mostly depends on temperature (Silsbury 1970) and to a lesser extent soil moisture availability (Van Loo 1992). In general, ryegrass grows at a rate of 10 to 20 kg DM/ha/d when defoliated at 1-leaf stage, 30 to 60 kg DM/ha/d at 2-leaf stage, and 90 to 110 kg DM/ha/d at 3-leaf stage. Fulkerson (1994) found that over the length of a year, defoliating ryegrass at 1 fully emerged leave produced less herbage (7673 kg DM/ha) compared to defoliating at 3 fully emerged leaves (10905 kg DM/ha).

Studies relating ryegrass leaf-stage defoliation and herbage NV (Fulkerson et al. 1998; Donaghy et al. 2008) show that changing defoliation frequency from leaf-stage 1 to 3 decreased ME from 11 to 8 MJ/kg DM and CP from 25% to 15%. Moreover, Lee et al. (2010) describes that consistently defoliating before the 2-leaf stage will reduce tiller initiation and thus ryegrass persistence.

Grazing severity and duration

The height or mass to which herbage is defoliated (i.e. post-grazing residual height or mass) is a function of the severity and duration of grazing. Grazing severity and duration influence regrowth, persistence and quality of herbage. According to Parsons et al. (1988), maximum production per hectare is achieved in a sward maintained at a relatively low sward height. This is because although at low height photosynthesis and gross tissue production may be reduced, there is an optimum balance between gross tissue production, herbage intake and leaf death and tiller initiation. Research shows that to optimise regrowth, persistence and quality of ryegrass-dominant swards while allowing adequate intake of herbage by dairy cows, herbage should be grazed to a height of 4 to 5 cm (Lee et al. 2008) or a mass of 1500 to 1600 kg DM/ha (Holmes and Roche 2007).

Korte et al. (1984) compared the effect of two grazing severity regimes (lax or hard grazing) on the production and quality of a ryegrass dominant swards over the length of 38 weeks. Grazing severity regimens were defined in terms of residual leaf area index (LAI), with more severe grazings leaving low residual leaf (LAI= 0 to 0.7) and less severe grazings leaving high residual leaf (LAI= 0.8 to 2.2). The experiment found no significant differences in herbage production between treatments ($p > 0.05$), which averaged 12.7 t DM/ha. However, swards subject to the more severe grazing regime had a higher proportion of leaf, a lower proportion of stem and accumulated more dead material than swards subject to the less severe grazing treatment, resulting in overall higher herbage quality. These results contrast a more recent study by Lee et al. (2008), who found that increasing defoliation severity by decreasing defoliation height from 100 to 20 mm did not alter the composition of leaf, stem and dead matter of ryegrass. Despite finding no differences in the morphological composition of ryegrass swards subject to different defoliation severities, Lee et al. (2008) found that increasing defoliation severity increased herbage CP concentration from 19.2 to 21.2%, linearly decreased NDF from 47.4 to 45.8% and ADF from 21.1 to 19.2% ($p < 0.01$). Moreover, the relationship between defoliation height and ME was nonlinear with the peak of 12.3 MJ/ kg DM being reached at a defoliation height between 60 to 70 mm ($p < 0.05$). This study also found that ryegrass tiller density was maximised when herbage was defoliated to a height ranging between 40 to 80 mm and found little influence of defoliation height on herbage production.

Fulkerson and Donaghy (2001) describe that the effect of grazing duration on herbage regrowth and persistence is like that of an extremely high grazing frequency. Using a controlled experiment involving mini swards of perennial ryegrass, Fulkerson et al. (1994) simulated the effect of three high defoliation frequencies (3, 6 and 3 + 6 days) on stubble (i.e. the basal portion of stems and leaves of plants left standing after harvest) water-soluble carbohydrates (WSC), ryegrass growth following regrowth to 3-leaf stage/tiller, and plant death. This study reported that redefoliating ryegrass at 3 days compared to 6 days resulted in lower WSC (60 vs. 106 mg/plant) lower regrowth (1.5 to 3.7 g DM/plant) and plant death (8 vs. 11%). However, results also showed that combining defoliation frequencies of 3 plus 6 had the most negative effects (15 mg/plant, 0.5 g DM/plant and 22% plant death). As described in section 2.8.1.1, the negative effects of increasing defoliation frequencies can be explained by the depletion of energy reserves that are used to grow new leaf area and the reduced net photosynthetic activity of this new leaf due to frequent defoliation, which ultimately leads to plant death.

2.8.2 Satisfying herd feed requirements: managing the cow

The main principle to maximise milk production for the whole production season in a pasture-based dairy farm system is to feed cows enough feed to satisfy their daily requirements (Macdonald et al. 2010). Offering cows too much or too little feed can be detrimental to the performance of the pasture-based dairy farm system as loss of efficiency and productivity are derived from below optimum post-grazing residual targets and increased wastage (Beukes et al 2015; Wilkinson et al. 2020).

Herbage allocation

Research has shown that when cows are given unrestricted access to herbage in quantity and quality, ME intake is the most limiting factor to milk production from herbage (Kolver and Muller 1998). Intake of ME is dependent on the ME content of herbage and on the amount of herbage (i.e. dry matter intake, DMI) grazing cows can consume. According to Hodgson and Brookes (1999), there are three factors influencing the potential DMI of a cow: 1) the nutrient requirements of the cow; 2) the physical limitations imposed by the distension of the organs in the digestive tract; and 3) the combination of herbage and animal factors affecting grazing behaviour. In an extensive review of literature on the topic, Bargo et al. (2003) concluded that the potential DMI of dairy cows fed only herbage sits at a range between 3.25 to 3.5% of their body live weight (LW). However, to achieve their potential herbage DMI cows must be given high herbage allowances.

The relationship between HA and herbage DMI is curvilinear and so is the relationship between milk yield and HA (Poppi et al. 1987; Moate et al. 2000; Baudracco et al. 2010; Pérez-Prieto et al. 2011). In a meta-analysis summarising data from various grazing experiments, Pérez-Prieto et al. (2011) describes that grazing cows herbage DMI response to HA increases from 0 to 12 kg DM/cow/d with HA increasing from 0 to 20 kg DM/cow/d. However, when HA increases beyond the 20 kg DM/cow/d threshold, the marginal response of DMI is relatively lower, with DMI increasing from 12 to 16 kg DM/cow/d with HA increasing from 20 to 60 kg DM/cow/d. These results indicate that while increasing HA can be used to maximise MY (Baudracco et al. 2010; Pérez-Prieto and Delagarde 2013), in practice, achieving the levels of herbage DMI required to maximise MY of cows would imply decreasing marginal responses to HA, and thus, decreasing grazing efficiencies because more herbage would be left uneaten. To maximise grazing efficiency and keep post-grazing residuals at target, cows must be allocated herbage below their potential DMI intake (Baudracco et al. 2010). Although such an approach would result in MY being lower than the potential, it is the basis of profitability in pasture-based dairy farm systems as it aims at optimising herbage utilisation and milk production per hectare rather per cow (Bargo et al. 2003; Baudracco et al. 2010).

Herbage DMI is a function of the time an animal spends grazing, the rate at which it takes a bite, and the size of the bite (Gordon and Lascano 1993). Herbage DMI is most sensitive to bite size, which depends on herbage height (Gordon and Lascano 1993). A short herbage signifies low herbage DMI because the animal cannot compensate a lower amount of herbage gathered in a single bite by increasing its bite rate and/or by grazing for a longer time. This situation usually happens at low HA or when herbage mass is too low (Gordon and Lascano 1993; Holmes 2007). Holmes (2007) suggests that daily intakes of dairy cows cannot be maintained with herbage heights below 8 to 10 cm. In such situations, animal performance is greatly limited by intake. However, when availability of herbage is not limiting, animal performance may be limited by herbage NV. Herbage of high NV have a rapid speed of passage through the digestive tract resulting in greater potential DMI (Lambert and Litherland 2000). In contrast, the speed of passage of low NV herbage is slow, constituting a physical limitation to intake (Poppi et al. 1987).

Supplement allocation

The main objective of supplementing grazing dairy cows is to increase total DMI and energy intake relative to that achieved with herbage-only diets (Stockdale 2000; Peyraud and Delagarde 2013;). However, when supplements are fed to grazing cows, substitution of supplements for herbage is likely to exist (Dillon 2007). The rate at which herbage is substituted (i.e. substitution rate) depends on type and level of supplement utilised and on herbage characteristics. There is a positive relationship between herbage quality and substitution rate (Bargo et al. 2003). Moreover, substitution rate is one of the main factors explaining MY response to supplementation, as high MY responses to supplementation can be achieved when herbage DMI is restricted and substitution rate is low (Bargo et al. 2003).

A literature review by Baudracco et al. (2010) suggests that the limits to MY response to supplements is likely to be set between 4 and 5 kg DM/cow/d, with higher levels of supplements resulting in declining marginal responses in MY. Marginal MY response to supplements also depends on animal factors such as genetic merit, genetics (New Zealand vs overseas) and physiological stage (Kolver et al. 2000; Dillon 2007; Bargo et al. 2003). Cows of high genetic merit for producing milk or cows with North American genetics that experience nutritional deficits when fed pasture-based diets experience greater responses to supplementary feeds compared to cows of low genetic merit or New Zealand genetics cows (Kolver et al. 2000; Berry et al. 2003). Moreover, cows in late lactation are also described to partition less nutrients to milk and more to weight gain, resulting in low MY responses to supplements (Kellaway and Harrington 2004). However, Penno (2002) argues that the effect of stage of lactation on MY response to supplements may be masked on New Zealand farms due to the lower herbage quality experienced in late lactation.

2.9 Gaps in research knowledge

The literature review has revealed that although herbage quality is a relevant factor influencing the performance of grazing cows, there are currently no available rapid herbage quality measurement tools that could be used to inform daily grazing management decisions in pasture-based dairy farm systems. The review also identified that daily herbage NV measurement could potentially improve grazing management by allowing a better match between pasture supply and herd feed demand. However, to ensure this happens, several gaps in research knowledge need to be bridged.

Proximal hyperspectral sensing can potentially be useful for measuring herbage NV in the field. There is plenty of research addressing the relationships between field canopy reflectance and herbage NV (e.g. Kawamura et al. 2008; Pullanagari et al. 2012b; Adjorlolo et al. 2015). However, no study to date has focused on the specific needs of grazing management. A conflict between reflectance from the lower canopy strata and the need to determine NV from the top portion of the canopy that is available to the grazing cow, signifies a potential limitation to the use of proximal hyperspectral sensing for measuring herbage NV. Research is required to investigate the ability of proximal hyperspectral sensing for predicting herbage NV from the top portion of the canopy that is available to the grazing cow.

In addition, the potential of proximal hyperspectral sensing for measuring herbage NV is also dependent on the daily variation of NV in the herbage supplied in a pasture-based dairy farm system. Research undertaken to study the variation of herbage NV in pasture-based dairy farm systems has mostly focused on collecting data to aid grazing management at the strategic level (Moller et al. 1996; Litherland and Lambert 2007). However, rapid assessment of herbage NV is likely to be of most value for aiding daily feed allocation decisions. Furthermore, while the relationships between herbage NV and the performance of grazing cows are well known (Kolver and Muller 1998; Bargo et al. 2003), no study has attempted to quantify the relative importance of these relationships with data collected under field-like conditions.

Having accurate estimates of herd feed requirements in addition to feed supply is important to precisely match daily feed supply and demand. The accuracy of the estimates of feed requirements at the herd level is dependent on individual cow variation in the herd. Moreover, researching the variation in feed requirements of individual cows has been identified as an opportunity in the quest of determining the potential of individualised feeding in pasture-based dairy farm systems (Hills et al. 2015). However, no study to date has attempted to estimate the extent to which feed supply of ME and a range of nutrients for a herd at pasture vary daily, nor the extent to which this supply differs from the actual requirements of both individual cows in a herd, and the herd as an aggregate.

Addressing the gaps in research knowledge identified in this literature review would lead to unveil the potential of proximal hyperspectral sensing for measuring herbage nutritive value and managing its allocation to best effect in a pasture-based dairy farm system.

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CHAPTER 3

Predicting herbage nutritive value using proximal hyperspectral sensing

3.1 Abstract

Proximal hyperspectral sensing of dairy herbage canopies has been shown to be suitable for estimating the nutritive value of herbage in the field. However, despite the suitability of this technology, the work done to date is of limited use to grazing management. This is because all the work to date has focused on determining the nutritive value of tissue in the whole sward vertical profile, without considering that only a limited portion of the vertical profile of the sward should be made available to the grazing cow. This study focuses on calibrating and validating models for hyperspectral canopy reflectance data that are useful to determine the nutritive value of ryegrass-white clover mixed herbage available to the grazing cow. Hyperspectral measurements and herbage cuts were collected from 269 sampling plots from a dairy farm from July 2017 to May 2018. Hyperspectral data were pre-treated by applying a Savitzky-Golay filter followed by a Gap–segment derivative algorithm. Herbage samples were analysed for determination of herbage nutritive value traits DOMD, ME, CP, NDF and ADF. Partial least squares regression was performed to calibrate the spectra against the five nutritive value traits. Results indicate that proximal hyperspectral measurements of dairy herbage canopies are useful to determine the nutritive value of the vertical portion of the sward that should be made available to the grazing cow. However, the accuracy of the models developed varied depending on the nutritive value trait. Relationships between the spectra and CP were stronger (R^2=0.78) than the relationships obtained between the spectra and DOMD, ME, NDF and ADF (0.57< R^2 <0.61). This study highlights that the characterisation of herbage nutritive value of a limited portion of the vertical strata of the canopy may come at the expense of a potential loss in accuracy of the calibration models. The possibility of being able to use proximal sensing for the estimation of herbage nutritive value in the field could contribute to more efficient grazing management with potential economic benefits for the farming business.

Key words: proximal hyperspectral sensing, nutritive value measurement, dairy herbage, grazing management

3.2 Introduction

With increasing environmental concerns and the need to remain low-cost in a competitive industry, improving the efficiency with which herbage is converted into milk remains the best strategy to maintain New Zealand's competitive advantage in dairying. Research suggests that improved knowledge of herbage mass availability of the farm can increase dairy farm profits by increasing the precision of daily herbage allocation (Beukes et al. 2015). Nevertheless, allocating herbage with a sole focus on herbage mass measurement may not always result in the most optimal allocation decisions. This is because, given a desired level of performance, demand for herbage depends on the energy and nutrient content available in the herbage allocated to the animals (i.e. its nutritive value, NV) (Waghorn and Clark 2004). The decision on the amount of herbage to allocate to cows may therefore differ if herbage resources vary in their NV (Poppi 1996). Thus, if differences in herbage NV among the many herbage resources to graze on a farm are not considered in the allocation process, then differences between actual and expected herbage intakes should be expected. At any grazing event, different than expected, actual dry-matter intakes can result in daily animal performance, animal response to supplements and post-grazing residual targets not being met (Dillon 2007; Ganche et al. 2013). In the long term, consistently defoliating herbages at suboptimal post-grazing residual heights will result in increased feed wastage, reduced herbage production, herbage persistence, herbage utilisation, NV and milk production at the farm level, ultimately reducing the potential profitability of the farm system (Lee et al. 2007; Macdonald et al. 2010; Beukes et al. 2015).

Recently, Shalloo et al. (2018) and French et al. (2014) suggested that rapid, objective herbage NV measurement presents an important opportunity to improve grazing management on pasture-based dairy farm systems. Nevertheless, these authors argue that the lack of measurement tools available for their use on farms has limited the possibility of taking advantage of such opportunity. Objective measurement of herbage NV has traditionally involved grab sampling representative samples of herbage at the height grazed by the cows and sending these to a laboratory for analysis (Cosgrove et al. 1998). Analysis of samples for dairy cow nutrition usually involves determination of digestible organic matter in dry matter (DOMD), metabolisable energy (ME), crude protein (CP), neutral detergent fibre (NDF) and acid detergent fibre (ADF) (Waghorn and Clark 2004). Wet chemistry or near-infrared spectroscopy (NIRS) are the most common laboratory techniques used for the determination of herbage NV (Marten et al. 1989; Corson et al. 1999). The whole process of collecting, preparing and analysing samples is expensive and time-consuming, making it impractical for their use in rapid decision-making.

Alternatively, field assessment of herbage quality indicators such as leaf stage of grass species (Fulkerson and Donaghy 2001), leaf to stem ratio, stage of growth, species composition and proportion of legume in the sward, can be used as surrogate measures of herbage NV (Bell 2006; Chapman et al. 2014). Although useful, these indicators fail to provide the actual objective measures required for precise diet formulations, because other factors such as soil moisture and fertility also affect herbage NV (Ball et al. 2001; Waghorn and Clark 2004; Muller 2011).

Recently, increasing attention is being placed on sensing technology as a suitable tool for delivering rapid and objective measures of herbage NV (Shalloo et al. 2018). Spectral signatures of herbage canopies have unique features that are useful to characterise biochemical properties associated with their NV (Govender et al. 2007; Thenkabail and Lyon 2016). For instance, it is well established that canopy reflectance in the visible region of the electromagnetic spectrum is strongly determined by chlorophyll pigments (Thenkabail and Lyon 2016). Since most nitrogen in plant tissue is contained in chlorophyll-protein complexes, strong relationships between canopy reflectance in the visible wavelengths and CP content have been established (Mutanga et al. 2004; Pullanagari et al. 2012b).

Progress in sensor development has resulted in increased spectral and spatial resolutions and the possibility of studying herbage NV with greater accuracy and at different spatial and temporal scales (Thenkabail and Lyon 2016; Godinho et al. 2018). Sensors mounted on satellites or unmanned aerial vehicles (UAVs) have been valuable for studying the spatial variation of NV of sown pastures and natural grasslands with detail and at large scales (Govender et al. 2007; Yule et al. 2015; Ali et al. 2016; Kawamura et al. 2017). Although useful for studying the spatial variation of vegetation, the challenges imposed by the weather (Von Bueren et al. 2015), cloud distortive effects (Ali et al. 2016) and the unavailability of satellite images on a regular basis (Ali et al. 2016) pose a limit to the temporal scale at which remote tools can be used. Alternatively, proximal sensors offer a flexible alternative to the study of phenomena requiring regular and frequent spectral measurements.

Proximal sensors can be carried by hand or mounted on vehicles for speed capability (Gebbers and Adamchuk 2010) and used in conjunction with active lighting systems to allow independence of ambient light (Sanches et al. 2009). A number of researchers have studied the relationships between canopy spectral features and herbage NV using proximal- optical (Roberts et al. 2015), multispectral (Pullanagari et al. 2012a; Pullanagari et al. 2013) and hyperspectral (Kawamura et al. 2008; Kawamura et al. 2009; Pullanagari et al. 2012b; Adjorlolo et al. 2015) sensors with varying success. Overall, empirical models based on hi-resolution hyperspectral sensor data are more accurate than those using multispectral sensing, and accuracies improve if an active lighting system is used. Although much of the research on the topic has focused on establishing empirical relationships in relatively well-controlled conditions, recent research (Pullanagari et al. 2012b; Adjorlolo et al. 2015) demonstrate that hyperspectral sensing is also suitable for measuring herbage NV in the field. These advances show the potential of sensing technology for their use in commercial farm management, but despite success, the work done so far is of limited use for their use in grazing management.

To date, all of the work on the topic has focused on finding relationships between the spectra of canopies and the NV of tissue in the whole herbage profile, without considering that NV decreases with canopy depth (Cosgrove et al. 1998; Delagarde et al. 2000; Nave et al. 2014) and that only a limited portion of the vertical profile of herbage should be made available to the grazing cow (Macdonald et al. 2010). Consequently, if hyperspectral sensing is to provide a useful tool to support grazing management, canopy spectra should be able to predict the NV of the portion of the herbage that should be grazed instead of the complete vertical profile. On the other hand, although proximal hyperspectral sensors measure the first surface they sense (Sanches 2009), there is evidence that, even at full closure, canopy spectral signatures of grass herbage can also be influenced by the lower strata not grazed by cows (Asner 1998). This could potentially affect the use of proximal hyperspectral sensing for predicting of herbage NV for grazing management, as sensed but ungrazeable material at the bottom of the canopy might affect the calibration of the instrument. Research is required to determine the capability of proximal hyperspectral sensing to measure herbage NV of the portion of herbage that should be made available to the grazing cow. If found useful, proximal hyperspectral sensors can provide a rapid NV measurement tool that could be useful to allocate herbage and supplements to cows with greater precision, with positive consequences to the overall efficiency of the farm system.

This chapter focuses on calibrating and validating models for hyperspectral canopy reflectance data that are useful to determine herbage NV traits DOMD, ME, CP, NDF and ADF from the vertical portion of the sward that should be made available to lactating dairy cows in accordance to good grazing management practice.

3.3 Materials and method

3.3.1 Study site

This study was conducted at Dairy 1 (D1), a dairy farm owned by Massey University and located in Palmerston North, New Zealand. The annual mean rainfall at the location is 980mm, the mean annual temperature is 13.1°C and the mean low and mean high temperatures are 8.5 and 17.8°C, respectively (NIWA 2018). Herbage resources on the farm are mostly composed of perennial ryegrass (*Lolium perenne* L.) and white clover (*Trifolium repens* L.) mix, with some herbages also including red clover (*Trifolium pratense*) as part of the mix. Weeds such as buttercup (*Ranunculus* spp.) and annual poa (*Poa annua*) and herbs as chicory (*Cichorium intybus* L.) and plantain (*Plantago lanceolata*) are also likely to be found but in small abundance. Farm soils comprise a complex assemblage of free-draining alluvial soils including Rangitikei Loamy Sand, Manawatu Fine Sandy Loam, Manawatu Sand Loam/Gravelly phase, Manawatu Mottled Silt Loam and Karapoti Brown Sandy Loam, with these soils being well drained and naturally fertile. Irrigation is available on nearly 25% of the farm area and is used during summer when soil water deficits are likely to occur.

3.3.2 Canopy spectral measurements

Canopy spectral measurements were collected every two to three weeks from 31 July 2017 to 10 May 2018 from paddocks at pre-grazing stage (herbage mass of 2600 kg DM/ha or more) using an ASD FieldSpec 4 High Resolution spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA). The spectroradiometer acquires spectra in a wavelength range from 350 to 2500 nm and has a spectral resolution of 3 nm in the VisNIR (350 – 1000 nm) and of 8 nm in the NIR-SWIR (1001–2500 nm) region of the spectrum. The spectral sampling interval of the instrument is factory set at 1.4 nm and 1.1 nm for the VisNIR and NIR-SWIR wavelengths, respectively. This feature defines the interval, in wavelength units, between data points in the measured spectrum and is independent of the spectral resolution (Hatchell 1999). In order to simplify further data analysis, wavelength units along the spectrum were standardised to 1 nm with the user interface software ASD RS[3].

Noise caused by changes in daylight and wind conditions was minimised by using the instrument in combination with a Canopy Pasture Probe (CAPP) system as developed by Sanches (2009). The CAPP consists of an inverted handled black plastic bin with a 50 watt tungsten-quartz-halogen lamp (ASD Inc., Boulder, CO, USA) attached on top. The CAPP lamp was powered by a 12v, 8000 mA lithium polymer battery, which ensured a stable source of light at maximum intensity for a day of fieldwork. Factory-calibrated radiance units were converted to reflectance units by calibrating the instrument against a clean ceramic white tile that was used as a reflectance standard of 100% light reflectance (i.e. R=1) (Sanches et al. 2009). The field-of-view of the spectroradiometer is 25°, which resulted in a measured circled surface area of 316 cm^2.

Hyperspectral canopy reflectance measurements were collected from 286 plots that were situated in the field so as the maximum range of herbage quality conditions was covered. A sampling plot consisted of the area delimited by a 50 x 50 cm wooden quadrat within which canopy reflectance measurements were acquired. In order to maximise spectral characterisation of the herbage canopy within the area delimited in each sampling plot, two measurements were acquired from three adjacent points each (i.e. measurement points) (Figure 3.1), six spectral measurements per sampling plot in total. The six spectral measurements were later averaged in order to obtain a single canopy signature per sampling plot. After spectra from each plot were acquired, photos of the canopies were taken to be used as ancillary data.

Figure 3.1 Canopy spectral measurement of a sampling plot.

3.3.3 Herbage cuts

After canopy spectral measurements in each sampling plot were acquired, herbage was cut to 4 cm in height using hand electric grass clippers and with the aid of a sward stick for height determination. The decision on the cutting height was made upon agreed principles of efficient, profitable grazing management for pasture-based dairy systems as summarised by Macdonald et al. (2010). After cutting, herbage samples were stored in labelled clean plastic bags in a polystyrene box with freeze pads in order to avoid heat deterioration of samples. Once the day of fieldwork was completed, samples were weighed, oven dried at 70°C for 48hs following the standard recommendation by the USDA (Marten et al. 1989). Thereafter, dried herbage samples were ground to pass a 1 mm sieve and stored in individual sealed plastic bags in a dark dry place for further determination of NV.

3.3.4 Determination of the nutritive value of herbage samples

Bench-top near-infrared spectroscopy (NIRS) was used to determine ME (MJME/kg DM) and percentages of DOMD, CP, NDF and ADF in DM of dried and ground herbage spectral samples. Details on the accuracy of the calibration models used for the determination of herbage NV of herbage samples are provided in Appendix A.

3.3.5 Spectral data pre-treatment

Processes of transformation and signal processing were used to reduce abnormalities in the spectral measurements before relationships between canopy spectra and their nutritional characteristics could be established. Abnormalities across spectra might occur at random or systemically due to instrument internal factors such as differences in calibration among detectors (ASD Inc., Boulder, CO, USA) or external factors such as light leakage, background noise or excess of humidity during data collection in the case of field sampling (Sanches 2009). Pre-treatment of hyperspectral data is important to enhance absorbance features of the measured object by reducing the incidence of these abnormalities. In this study, the main objective was to determine the energy and nutrient content of herbage available for the grazing cow from absorbance features of herbage canopies, for which the development of empirical models were required. Benefits of pre-treatment include increasing the repeatability of the modelling method, model robustness and accuracy (Stevens et al. 2013).

The first step of pre-treatment was to reduce the signal gaps between the domains of the detector arrays by applying a splice correction gap of five using VisuaSpectPro software version 6.2. Increased noise at both ends of the spectrum due to increased noise caused by ambient light leaking into the CAPP during data collection, resulted in spectra in wavelengths ranging from 350 to 500 nm and from 2400 to 2500 nm being removed. The first approach to noise removal was to average the spectral measurements corresponding to each sample. Stevens et al. (2013) describe that by performing n repetitions of the measurements and averaging individual spectra, noise can decrease by a factor of $\sqrt{n}$. Further transformation involved converting the spectra from reflectance units (R) to absorbance units (log (1/R)). Converting spectra to absorbance units is useful to reduce non-linearity and therefore improve the accuracy of spectral regression models based on numerous wavelengths (Burns and Ciurczak 2007).

Residual noise caused by additive and multiplicative scattering effects unrelated to the chemical nature of the samples (Burger and Geladi 2007) were treated by applying the 'gapDer' function available in the package Prospectr for R software (Stevens et al. 2013) to the converted spectra. This function applies the Savitzky-Golay filtering followed by a Gap–segment derivative algorithm to the data. The window size of the smoothing filter was set at 45 and the gap-derivative function calculated for a first order derivative of segment size 20. Further abnormalities such as the effects of variation in baseline shift and curvilinearity were corrected by de-trending the spectrum by fitting a 2nd–order polynomial to the signal and then subtracting it (Barnes et al. 1989). The final transformation step was to standardise the spectra by centring each wavelength to a zero mean and scaling it to a variance of one. Standardisation of spectra is useful to reduce multicollinearity among wavelengths and to increase accuracy of prediction models (Stevens et al. 2013). From now on, the spectral data that resulted from the spectra pre-treatment described above will be referred to as the first derivative of absorbance (FDA).

A principal component analysis (PCA) was performed on the canopy reflectance data in order to explore the presence of outliers in the dataset. PCA converts a large number of possibly correlated variables (i.e. wavelengths) to a limited number of principal components that explain the most variance in a dataset (Jobson 2012). Outlier identification was based on sample principal components scores and supported by ancillary photography data and their interpretation in light of the literature on the topic. Samples identified as outliers were excluded from further analyses.

3.3.6 Calibration model development

Hyperspectral calibration models were developed for predicting the selected NV traits from canopy spectral data using the partial least-squares (PLS) regression modelling technique implemented with the PLS package for R software (Mevik and Wehrens 2007). The general regression equation to describe the calibration models can be conceptualised using the following notation:

$$y=b_1x_1+b_2x_2+\ldots+b_nx_n+e$$

where: y is the NV trait response variable of interest, x are independent latent variables obtained from reduced wavelengths, b are the partial regression coefficients, and e is the residual error that is not explained by the model.

PLS is a multivariate regression technique that is useful in developing prediction models using data sets that contain many predictor variables (e.g. wavelengths) that are possibly correlated, and the number of samples is relatively few (Jobson 2012). This technique reduces the high number of wavelengths in hyperspectral data to few uncorrelated latent variables (LVs) and then regresses the scores of the LVs that account for the most variance to the response variable of interest.

In this study, the optimal number of LVs to retain in the models was selected as that yielding the minimum root mean square error of leave-one-out cross-validation (RMSE-CV) during the modelling procedure. In the leave-one-out technique, calibration models are trained using all of the samples but one that is left out for internal accuracy assessment. The process of training and validating the model is performed iteratively until all samples in the dataset have been used for validation. Thereafter, the algorithm calculates the root mean square error (RMSE) using model predictions and the actual values set aside across all iterations.

The contribution of each wavelength to the predictive capability of the models was interpreted by calculating the variable importance in projection (VIP) (Wold et al. 1993) and PLS regression coefficients (RC) (Haaland and Thomas 1988) using the VIP and RC functions available in the package 'plsVarSel' for R software (Mehmood et al. 2012). The VIP measures the importance of each predictor variable (wavelength) based on a model with a defined number of factors (LVs) (Wold et al. 1993) whilst the PLS regression coefficients are a single measure of association between each wavelength and the response variable (Mehmood et al. 2012).

3.3.7 Model accuracy assessment

Model accuracy, defined as the overall distance between predicted and observed values (Zar 1999), was assessed by randomly splitting the spectral dataset into two independent sets: training and validation sets. The training set comprised 80% of all data and was used to calibrate the models as explained in Section 3.3.6. The validation set comprised the remaining 20% of all data and was used to test the capability of calibrated models of predicting a set of unknown samples. Data partitioning ratio was based on recommendation of Pullanagari (comm. Pers.).

Metrics used for assessing goodness of fit measures of the calibration equations in the training and validation data sets are presented in Table 3.1.

Table 3.1 Goodness of fit measures of the calibration equations applied to the training and validation data sets.

Metric	Equation	
Coefficient of determination	$R^2= \frac{\sum_{i=1}^{n} (\hat{y}-\bar{y})^2}{\sum_{i=1}^{n} (y-\bar{y})^2}$	(a)
Root mean square error	$RMSE=\sqrt{\frac{\sum_{i=1}^{n} (\hat{y}-y)^2}{n}}$	(b)
Relative prediction error	$RPE = \frac{RMSE}{\bar{y}} \times 100$	(c)
Bias	$Bias=\frac{1}{n} \sum_{i=1}^{n} (\hat{y}-y)$	(d)
Ratio of prediction to deviation	$RPD=\frac{SD(y)}{RMSE}$	(e)

$\hat{y}$ = predicted value, y = measured value, $\bar{y}$ = mean of measured values, n = number of observations, SD = standard deviation of measured values.

The coefficient of determination and the RMSE are the most common metrics used for model fit assessment. The R^2 (a) indicates the proportion of the variance in the reference data that is accounted for by the regression model. RMSE (b) is the standard deviation of the residuals (prediction errors) and represents an absolute measure of model accuracy. The RPE is the RMSE expressed as a percentage of the mean of the measured values (c), resulting in a standardised measure that is useful to compare models predicting responses of different magnitudes and/or units. Bias (d), is the mean difference between the predicted and measured values and is useful to identify systemic errors in the models. Negative bias values indicate a generalised sub-estimation by the models, while positive values indicate over-estimation. Finally, RPD (e) (William 1987) is the factor by which prediction accuracy increases compared with using the mean of measured values. A RPD value greater than 2 indicates that the calibration equation has good prediction and a RPD value lower than 2 indicates that predicted values are of poor quality and the equation cannot be used in practice.

3.4 Results

3.4.1 Descriptive statistics of reference nutritive values and spectral data

Descriptive statistics of herbage NV reference data used in the development and external validation of canopy spectral calibration models are summarised in Figure 3.2.

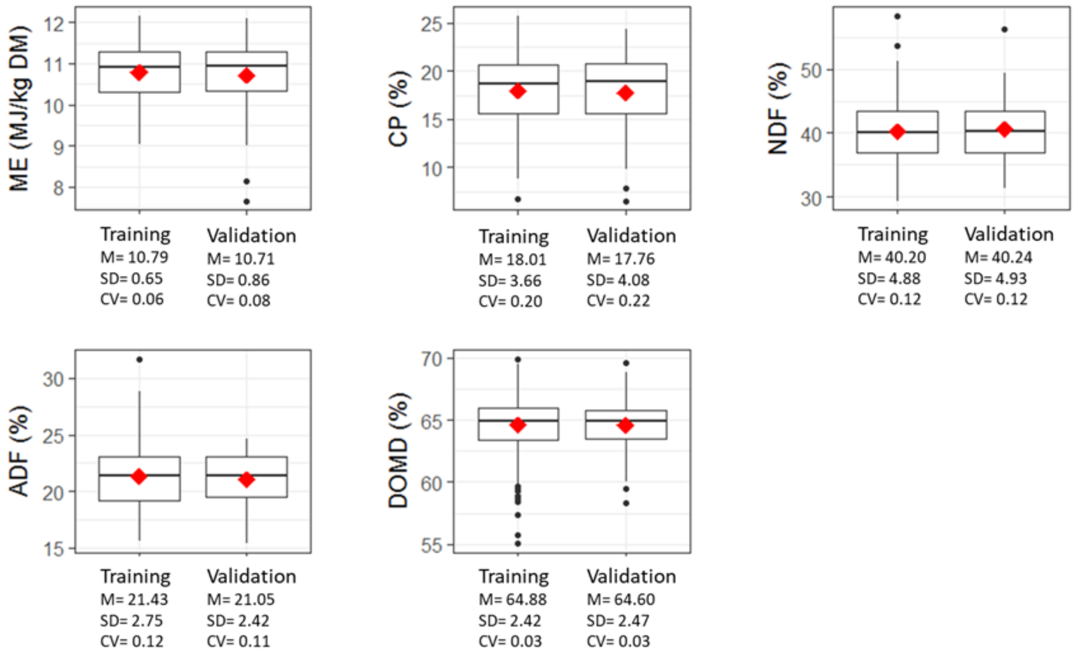

Figure 3.2 Boxplots, means (M), standard deviations (SD), and coefficients of variation (CV) of measured herbage NV traits for the training (n=217) and testing (n=52) datasets (Diamond shaped points indicate mean values). ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

Crude protein was the most variable NV trait in both datasets (CV= 20% and 22% for the training and testing datasets, respectively) and DOMD was the least variable (CV= 3% for both datasets). Dispersion of NV was sufficient to establish significant interrelationships between the traits measured (Table 3.2).

Table 3.2 Correlation matrix of herbage nutritive value (NV) traits of training and validation herbage samples.

	Training					Validation				
Trait	ME	CP	NDF	ADF	DOMD	ME	CP	NDF	ADF	DOMD
ME	1.00					1.00				
CP	0.17^{**}	1.00				0.21^{*}	1.00			
NDF	-0.77^{***}	-0.17^{*}	1.00			-0.86^{***}	-0.25^{*}	1.00		
ADF	-0.78^{***}	-0.16^{*}	0.89^{***}	1.00		-0.87^{***}	-0.20^{*}	0.95^{***}	1.00	
DOMD	0.73^{***}	0.13^{*}	-0.89^{***}	-0.75^{***}	1.00	0.82^{***}	-0.16^{*}	-0.90^{***}	-0.82^{***}	1.00

* Significant at $p < 0.05$, ** Significant at $p < 0.01$, *** Significant at $p < 0.001$.
ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

Significant and positive relationships ($p < 0.05$) were observed between fibre traits and among DOMD, CP and ME and, with traits in these two groups being negatively associated to each other (Table 3.2). The strength of the relationships varied among traits with stronger correlations being observed among DOMD, ME and NDF and weaker correlations between CP and NDF, ADF, ME and DOMD.

3.4.2 Canopy spectra outliers

A score plot summarising the results of the principal component analysis performed on the canopy reflectance data is shown in Figures 3.3. Spectral samples with score values close to the mean appear close to the origin of the score plot, while samples that are distant to the origin are far distant to the mean and can be considered outliers.

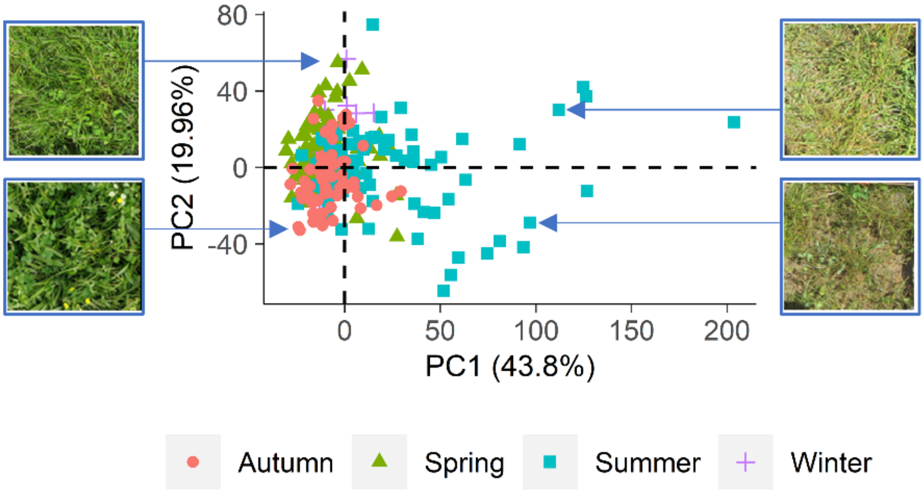

Figure 3.3 Score plot of herbage canopy reflectance data. PC1= principal component 1, PC2= principal component 2.

Results of the PCA indicated that the first two principal components explained 63.76% of the variance in the dataset, with PC1 and PC2 being accounted for 43.8% and 19.9% of the total variance, respectively. Score values in Figure 3.3 show that the optical features of canopy spectral samples collected in summer had a high influence on explaining variation of PC1, as scores of these samples tend to vary along the horizontal, rather than the vertical axis of the plot. Conversely, samples collected in spring, autumn, and winter had the highest influence on determining PC2. A visual assessment of canopy photographs led to suggest that abundance of senescent leaves might explain variance associated with PC1 and that canopy structural features (i.e. leaf area index, LAI and leaf angle distribution, LAD) could be driving spectral variance associated with PC2 (example photos in Figure 3.3). Visual assessment of canopies associated with extremely high scores for PC1 indicated that seventeen of these samples with relatively high abundance of senescent leaves, standing litter and soil background exposure could be considered outliers and excluded from further analyses. The correlations between reflectance of each wavelength and the two main principal components (Figure 3.4) show that a higher number of VIS and far-SWIR wavelengths were correlated with PC1 while relatively more wavelengths in the NIR region of the spectrum were related to PC2.

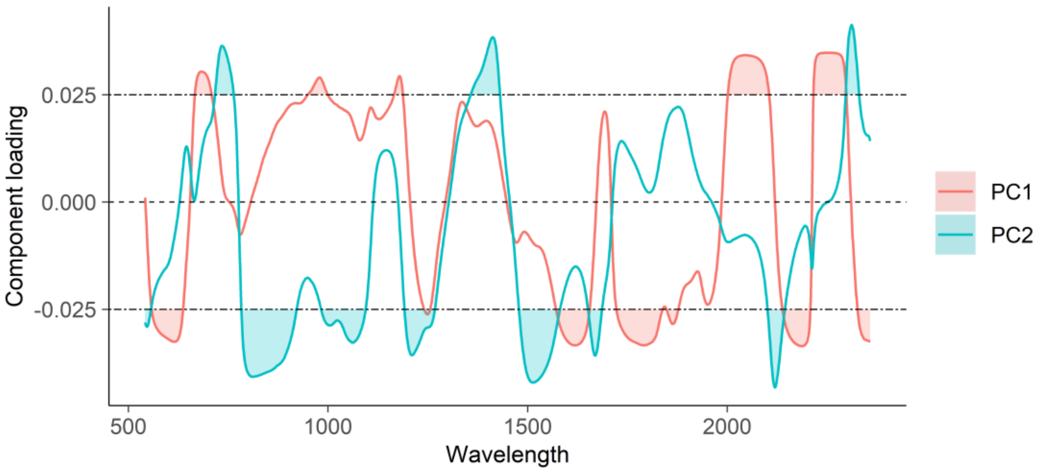

Figure 3.4 Component loadings of herbage canopy reflectance. The shaded area highlights wavelengths with loadings higher than 0.025 or lower than -0.025. PC1= principal component 1, PC2= principal component 2.

3.4.3 Canopy spectra

Descriptive statistics of herbage canopy spectral data are summarised in Figure 3.5.

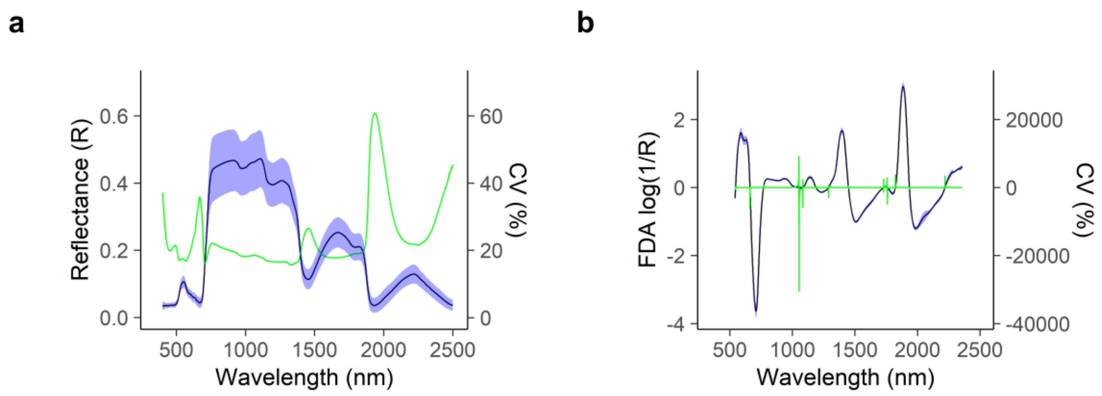

Figure 3.5 Reflectance (a) and first derivative of absorbance (FDA) (b) of herbage canopies. The black solid line is the wavelength mean value and the blue shaded area represents the data within one standard deviation above and below the mean. The green solid line is the coefficient of variation expressed as a percentage (CV%) (n=269).

As shown in Figure 3.5, canopy reflectance (a) exhibited the typical pattern associated with vegetation spectral signatures (Thenkabail and Lyon 2016). Canopy reflectance variation was higher in wavelengths ranging from 1200 to 1400 nm and from 1500 to 1800 nm. After pre-treatment (b), spectra variation was higher in the waveband centred at 660 nm of the visible region, the waveband centred at 1200 nm, with higher variation being also observed in SWIR wavelengths ranging from 1600 to 1800 nm.

3.4.4 Partial least squares

Model accuracy

The overall accuracy of PLS regression models was satisfactory (Table 3.3). Accuracy values for the trained and the validation data were consistent. Low RMSE, RPE and bias values and high R^2 and RPD values indicated that the spectra of canopies were useful to predict the NV of the portion of the herbage that should be made available to the grazing cow. However, model accuracy varied depending on the NV trait modelled.

Table 3.3 Accuracy of partial least-squares regression calibration models built for determining the nutritive value (NV) traits of herbage available for grazing from canopy spectral measurements using the training and validation datasets.

Dataset	NV trait	R^2	RMSE	RPE	Bias	RPD
Training	ME	0.57	0.43	4.01	-6.71e-16	1.53
	CP	0.78	1.72	9.57	-2.75e-15	2.53
	NDF	0.59	3.13	7.79	-1.90e-15	1.58
	ADF	0.59	1.77	8.28	2.84e-15	1.56
	DOMD	0.61	1.52	2.35	4.19e-16	2.07
Validation	ME	0.58	0.55	5.15	-7.27e-02	1.27
	CP	0.79	1.87	10.51	-8.44e-03	2.12
	NDF	0.60	3.08	7.59	-4.00e-01	1.21
	ADF	0.53	1.64	7.81	7.24e-02	1.34
	DOMD	0.66	1.44	2.22	-3.19e-01	1.79

ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

The results show that crude protein was predicted with the highest accuracy among all NV traits (R^2= 0.78 and RPD = 2.53), with the accuracies of the remaining models being relatively lower (0.61 > R^2 > 0.57 and 2.07 > RPD > 1.53).

Wavelength contribution to the predictive capability of the calibration models

The VIP scores and regression coefficients in Figure 3.6 illustrate the contribution of each wavelength to the predictive ability of the calibration models. As suggested by Chong and Jun (2005) a VIP threshold value of 1 was used to indicate the predictor variables that are of high importance for predicting the response variable of interest. Similarly, regression coefficients above or below zero indicate positive or negative relationships between wavelengths and the predicted variable of interest, respectively.

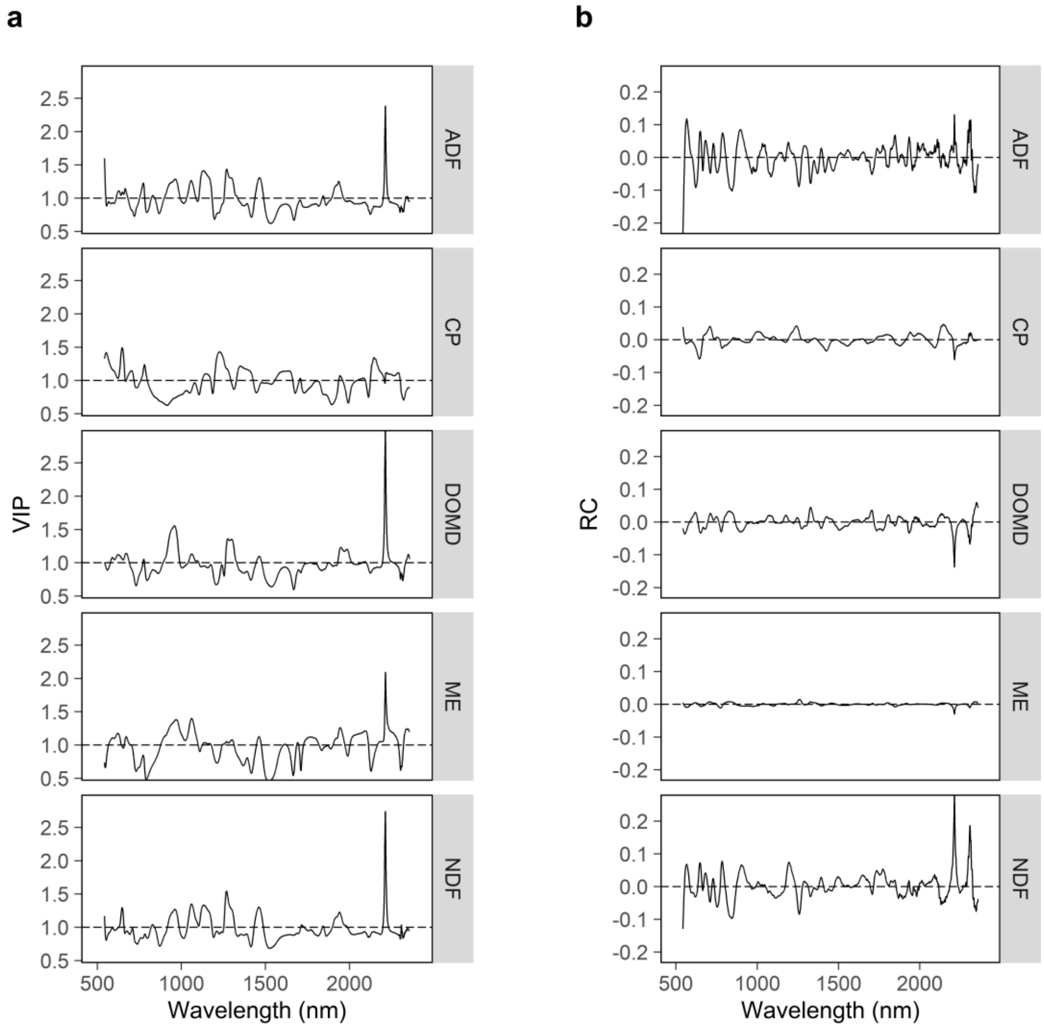

Figure 3.6 Variable of importance in projection (VIP) scores and regression coefficients (RC) of canopy spectral calibration models developed for the determination of herbage nutritive value traits. ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

There were a number of wavelengths in the VIS (540–700 nm), NIR (750–800 nm, 900–1000 nm and 1100–1400 nm) and SWIR (1820–1880 nm and 2125–2300 nm) regions of the spectrum (Figure 3.6) that were important and common predictors across models.

Greater similarities in the VIP patterns were observed between the fibre calibration models, and between the fibre and DOMD and ME models. Wavelengths in the 2200 to 2240 nm range were particularly important for the calibration of ADF, NDF, DOMD and ME, with absorbance in these wavelengths being positively related with fibres but negatively related with DOMD and ME. Other relevant wavelengths associated with these calibrations were located in the 580 to 635, 660 to 690 nm, 910 to 990 nm, 1270 to 1330 nm, 1900 to 1980 nm, 2210 to 2280 nm and 2320 to 2350 nm ranges, with the 1820 to 1860 nm range being of particular relevance for ADF and NDF but not for DOMD or ME.

The FDA in wavelengths ranging from 540–570 nm and from 730–780 nm was of high importance in the determination of CP. Likewise, absorbance in SWIR wavelengths ranging from 2140 to 2300 nm region was also an important determinant of CP.

3.5 Discussion

3.5.1 Usefulness of the calibrations for grazing management

The mean herbage nutritive values of the samples used in the development and validation of canopy spectral calibration models for the determination of herbage NV were similar to benchmark values commonly used in the dairy industry (DairyNZ 2017). DairyNZ (2017) reports reference values for ryegrass-based herbages of ME=10.7 MJ/kg DM, CP= 16.8% and NDF= 47.3% for their use as a feed for dairy cows throughout the production season. Similar values for ME, CP, DOMD, NDF and ADF are found in Holmes (2007) and Moller (1997). These similarities indicate that the samples collected were an adequate standard with reference to the NV of the herbage available for grazing management, and therefore, suitable for the purpose of this study. Although the correlations between CP and any of the other NV trait measured were not very strong, correlations found here were consistent with previous research (Moller 1997) and are explained by the relative contribution of the chemical constituents of plant cells present on herbage samples and their relationship with the different measured herbage NV traits.

3.5.2 Identification of spectral outliers

Although this research did not set out to study the influence of soil background cover, litter or canopy structural attributes on canopy spectral signatures, the results of the PCA performed on canopy spectra sustained by the visual assessment of canopy samples led to suggest that these factors could be influencing acquired spectral data. Previous studies (Asner 1998; Asner and Heidebrecht 2002; Numata et al. 2008) demonstrated that non-photosynthetic plant tissue and soil background exposure have a strong influence on determining canopy reflectance of grass swards in the VIS and far-SWIR regions of the spectrum. Moreover, Asner (1998) describes that canopy structural variables such as LAI and LAD of green vegetation have a greater influence on canopy reflectance in NIR wavelengths. The fact that VIS and far-SWIR specific wavelengths that were relevant contributors to PC1 and were also related to non-grazeable attributes of canopy spectra (e.g. soil background exposure or abundance senescent plant tissue) by previous research was a useful guide to assess the cause of the differences among spectral samples and the identification of potential outliers. The exclusion of potential outliers from the development of spectral calibration models was useful to obtain calibrations that were more representative of the diet of the grazing cow, and therefore more suitable for the purpose of this study.

3.5.3 Predictive capability of calibration models

Model accuracy results are the summary of a combination of field, pre-treatment and analytical processes. Mathematical transformation of the spectra was useful to enhance the optical properties of biochemicals in the canopy and reduce the incidence of noise, allowing the replicability of results and robustness of the modelling method. Hyperspectral sensors provide with opportunities to develop a range of measurements given the richness of the data acquired by these systems (Numata 2012). In this study, the complete spectrum was used by applying a PLS regression statistical approach for the development of calibrations, but other approaches can be used. For instance, previous studies have built vegetation indices from hyperspectral data to study chemical composition of grasslands (Serrano et al. 2002; Fava et al. 2009) or used a continuum removal of normalised absorption features to identify and select specific wavebands associated with a response variable of interest (Serrano et al. 2002; Mutanga et al. 2004; Mutanga et al. 2005). The PLS approach used in this study allowed yielding predictive capability to wavelengths that would be most likely overlooked if only limited wavebands in the spectra were used. This is of particular relevance with data collected in field-like conditions, since the interaction between abiotic and biotic factors can influence optical features of canopies (Hill 2004), affecting the determination of biochemical attributes of plants from pre-established spectral features. Although using a full spectrum PLS regression approach is beneficial when dealing with spectra collected in variable conditions, Biewer et al. (2009) describe that this approach can be further improved if the statistical method is coupled with a wavelength selection criteria.

Consistency of accuracy for calibration and validation datasets across models indicated that the models were robust and therefore useful for predicting new samples (Biancolillo and Marini 2018). This finding was of relevance to this study since it signified that proximal hyperspectral sensing could potentially be used in an array of field conditions with confidence, with this attribute being a desirable characteristic of herbage measuring tools for farmers (Eastwood and Dela Rue 2017). However, as expected, the accuracies of the calibrations developed from field spectral measurements were much lower than the threshold values used in bench-top NIRS spectroscopy (Malley et al. 2004). In NIRS-determined laboratory analyses for agricultural products, predictions are deemed ‘Inadequate’ with $R^2 < 0.70$ and RPD < 1.75. According to these threshold values, only CP was determined with some degree of usefulness. Nevertheless, Biewer et al. (2009) suggest that field measurements reduce prediction accuracy of NIRS models and so therefore, accuracies lower than laboratory reference standards could also indicate ‘good results’.

There were inconsistencies among the various field studies linking herbage NV and the spectra of herbage canopies (Kawamura et al. 2008; Pullanagari et al. 2012b; Adjorlolo et al. 2015). Our models were able to predict CP, ME, NDF and ADF with lower R^2 values than Pullanagari et al. (2012b) (R^2= 0.82, R^2= 0.83, R^2= 0.75, R^2= 0.82 for CP, ME, NDF and ADF, respectively). The R^2 value obtained for CP in this research was higher than Adjorlolo et al. (2015) (R^2= 0.51) and Kawamura et al. (2008) (R^2= 0.46). Results for the fibre models were similar to the models reported by Adjorlolo et al. (2015) (R^2= 0.60 for NDF and ADF) but higher than the NDF model by Kawamura et al. (2008) (R^2= 0.37) and lower than the ADF model (R^2= 0.65). Despite the difference in the sampling method and differences in the pre-treatment of spectral data, all the models were developed using PLS on the first derivative of canopy reflectance. A major factor influencing model accuracy among studies (and between the models in this study), seemed to be associated with the variability of the reference NV data used in the calibrations, with better performing models being associated with higher coefficients of variation for any of the NV traits considered.

The effect of the variability of the dataset used on model accuracy can be illustrated by the following observation: Pullanagari et al. (2012b) were able to predict ME with a RMSE of 0.46 and a RPD of 2.46 using training data of mixed herbage with a SD of 1.16, while this study reports a similar RMSE (0.43) but a lower RPD (1.53) using a less variable dataset (SD=0.7). Because RPD is calculated as the ratio between RMSE and SD (Equation e in Table 3.1) and there were similar predictive errors between the models, the higher RPD found by Pullanagari et al. (2012b) compared to this study is likely to be associated with the higher variability of their dataset rather than in the methods used. Similar observations about the influence of the variability of the dataset on model performance were made by other authors (Biewer et al. 2009; Sanches 2009). The little variability of the data collected was most likely associated with the sampling strategy chosen, and thus the objective of this study. Because modelling of spectra aimed at characterising herbage NV of herbage to allocate to grazing cows (i.e. herbage at pre-grazing stage), the variability of NV was expected to be low since it is the purpose of management to control the quality and quantity of herbage offered to the animals (Macdonald et al. 2010). In addition, because data were collected from a single farm, little variation of herbage NV influential factors including soil type, soil fertility, fertilisation and grazing policy have most likely contributed to the reduced variability of herbage NV samples.

The fact that CP was predicted with higher accuracy than DOMD, ME, NDF and ADF (Table 3.3) may partially reflect the incidence of the herbage sampling method used. Asner (1998) describes that even when the leaf area index is high (LAI>5), the lower strata of a sward can influence the spectral signature of grass canopies. If nutrient content in the lower strata, consisting of tissue of low protein and high fibre content (thus, low digestibility and ME), had an influence on the spectral measurements, but was not considered in the calibrations, then such mismatch may partially explain the lower performance of the fibre, DOMD and ME models over the CP model. In this study, it was assumed that because herbage samples were collected at pre-grazing stage, the incidence of the lower strata on canopy reflectance would be minimal. However, it is not possible to assert if the lower strata had a significant influence on canopy spectra from the data collected in this research.

The technique used to acquire spectra in the field might also have contributed to predictive error. This is because the characterisation of the optical properties of the herbage confined to the area set by the wooden quadrat (Figure 3.1) may have not been adequate given the limited number and distribution of spectral measurements acquired within the sampling plot. The error associated with the determination of herbage NV of reference samples is also likely to have influenced the accuracy of the models. For instance, a lower error associated with the determination reference values for CP compared to NDF (Table A.1 in Appendix A), may partially explain the better predictions of CP over NDF by their respective canopy spectral models. The success of the NIRS calibration technique is dependent on good quality reference data (Corson et al. 1999). Thus, better predictions can be expected if models are built exclusively with wet chemistry determined reference data, as this is the standard procedure to determine the true value of nutrient content in animal feed samples (Marten et al. 1989). An example of the NV of fifty reference samples determined using wet chemistry, NIRS and proximal hyperspectral sensing of herbage canopies is available in Appendix B.

3.5.4 Wavelength contribution for predicting herbage nutritive value

The commonalities in the VIP patterns shown across calibration models in Figure 3.6 can be explained by the overlapping absorption features associated with different plant materials. In this sense, reflectance of vegetation is primarily influenced by the optical properties of plant materials including proteins, lignin, cellulose, sugar and starch, which are mostly composed of C–O, O–H, C–H and N–H bonds (Clark and Lamb 1991). The vibrations of these bonds, image the absorptions of different plant materials. However, because different materials can have similar and overlapping absorption features, a single waveband cannot be directly related to the chemical abundance of one plant constituent. It is thus the relative response to the many wavelengths of the spectrum that is the feature that defines the determination of a plant material from their spectra. Materials that are similar in composition would exhibit similar reflectance patterns than those with completely different bonding structures. Such characteristic can be easily observed when comparing the VIP patterns for ADF and NDF (Figure 3.6). NDF and ADF are compounds of celluloses and lignin, with the absence of hemicelluloses in ADF (NRC 2001) being the main biochemical difference between these fibres, so not surprisingly these models were influenced by almost the same wavelengths.

The relationships between FDA in the far-SWIR region and the four herbage NV traits can be associated with the absorption of C–H bends common in organic compounds. Clark and Lamb (1991) describes that digestibility of the fibrous portion of plants in highly related with absorbance in the 2300 nm. Moreover, Curran (1994) identifies that absorptions around 910 to 990 nm relate to oil and starch content, while absorptions at 1200 nm and between 1900 to 1980 nm relate to starch, cellulose and lignin and at 1820 nm with cellulose. The concentration of chlorophyll-protein complexes in plant tissue and their optical features can explain the relationship between VIS and red-edge wavelengths and CP. In this sense, chlorophyll pigments are good absorbers of electromagnetic energy in the visible region (Curran 1994) and the photosynthetic activity of chlorophylls is highly responsible of reflectance in the red-edge wavelengths (Curran 1994; Kokaly and Clark 1999; Pettai et al. 2005). Because chlorophylls are the major source of protein in vegetation, the relationships between VIS and red-edge wavelengths can explain content of CP in herbage tissue. At the far end of the spectrum, the relationships between canopy FDA and CP can be attributed to the ability of the sensor of detecting chemical bond activity linked to N. Curran (1994) identifies that the wavebands centred at 2130, 2180 and 2300 nm are linked to the absorption mechanism of vibration of N–H and C–H stretch bonds in proteins.

Many of the wavelengths that were relevant predictors of the calibrations developed here were also useful in previous studies linking the spectra of fresh canopies and their NV (Mutanga et al. 2004; Kawamura et al. 2008; Pullanagari et al. 2012b; Adjorlolo et al. 2015). For instance, visible wavelengths and wavelengths ranging from 2140 to 2300 nm were consistently important in the determination of CP (Adjorlolo et al. 2015; Kawamura et al. 2008; Mutanga et al. 2004; Pullanagari et al. 2012b) while spectra around 2220 to 2250 nm was consistently related to ADF (Kawamura et al. 2008; Pullanagari et al. 2012b). Interestingly, in this study a relatively large proportion of wavelengths in the NIR-plateau (800–1400 nm) were related to any of the NV traits compared to other studies. The NIR plateau is highly determinant of canopy health and structural features such as LAI and biomass (Thenkabail and Lyon 2016) and has a limited to null relationship with the concentration of biochemicals in plant tissue (Curran 1994). It is possible that reflectance in wavelengths in this region is acting as a covariate of herbage NV in our models, resulting these wavelengths in an indirect measure of the NV trait. For instance, it would be expected that at pre-grazing stage a vigorous canopy of high LAI could be associated with a higher CP content than an unenergetic canopy of low LAI. Darvishzadeh et al. (2008) identified that LAI of grass canopies is strongly determined by reflectance at 1114 nm, because this wavelength has been related with CP in our modelling, then it is likely that the explanation suggested above be true. It is also possible that water absorption is acting as a confounding factor in the models, resulting in a relatively higher importance being attributed to NIR- over SWIR wavelengths. Kumar et al. (2002) describes that water absorption can overshadow biochemical features at wavelengths beyond 1400 nm and that this is the main reason of improved predictions from dried over fresh foliage in laboratory studies. The continuum removal method developed by Kokaly and Clark (1999) can reduce the influence of the water absorption bands on the determination of any attribute of interest up to 10% by selecting only the bands with absorption features that are relevant to these attributes.

3.6 Conclusion

This study shows that proximal hyperspectral measurements of dairy herbage canopies are useful to determine the nutritive value of the vertical portion of herbage that is available to the grazing cow. The PLS regression approach used in this research indicate that the relationships between the spectra and CP were stronger (R^2= 0.78) than the relationships obtained between the spectra and DOMD, ME, NDF and ADF ($0.57 < R^2 < 0.61$). This study highlights that, although useful from a cow nutrition standpoint, the characterisation of the NV of a limited portion of the vertical strata of herbage may come at the expense of a potential loss in accuracy in the calibration of canopy spectra. This is because the lower strata of herbage may influence the optical features of canopies even at high biomass levels (pre-grazing stage). Being able to utilise proximal sensing for measuring the NV of the herbage available to the grazing cow in the field could lead to more efficient grazing management. Improved precision of herbage allocation at any single grazing event can lead to potential short- and long-term efficiency and productivity gains at the farm level. Despite potential benefits of rapid herbage NV measurement, further research is required to analyse the variation of herbage NV on a day-to-day basis and to discuss the potential relevance that such variation could have on the nutrition of the dairy cow.

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CHAPTER 4

Variation of herbage nutritive value offered to dairy cows assessed by proximal hyperspectral sensing

4.1 Abstract

A large volume of research has been undertaken to study variation of herbage nutritive value from dairy pastures but work to date has failed to provide the adequate level of detail required for its use in daily grazing management. This study describes temporal and spatial variation of herbage nutritive value offered daily to cows on a pasture-based dairy farm system using proximal hyperspectral sensing. It also determines the extent to which variation of nutritive value justifies daily nutritive value measurement. Hyperspectral data was collected from 12 sampling plots from four to six paddocks at pre-grazing every two to three weeks during production seasons 2016-17 and 2017-18 at Massey University's Dairy 1 farm, Palmerston North, New Zealand. Nutritive value traits: metabolisable energy, crude protein, neutral detergent fibre, acid detergent fibre and digestible organic matter in dry matter were determined from hyperspectral samples using calibrations developed in chapter 3. Variation of herbage nutritive value offered daily to cows was analysed using descriptive statistics. Mixed linear models which used production seasons and months within production seasons as fixed effects and paddocks as random effects were used to compute multiple comparisons of least-squares means of herbage nutritive value. An ANOVA was performed with random linear models using production seasons, months within production seasons and paddocks as random effects in order to determine the extent to which herbage nutritive value measurement was justifiable in face of these sources of variance. Least-squares means comparisons results show that the nutritive value of herbage dropped during summer compared to spring or autumn months ($p < 0.05$), but also that the nutritive value of herbage offered from march onwards varied between production seasons ($p < 0.05$). Relative contribution of month within production season to nutritive value variance was higher than (42.7%) production season (13.1%) or paddock (10.7%). Random error accounted for an average of 33.4% of total variance across nutritive value traits, suggesting that there is potential use for nutritive value measurement. Day-to-day variation of herbage suggests that content of metabolisable energy can be a limitation to cow performance from grazed herbage, while crude protein is often found in excess to requirements. The implications of herbage nutritive value variation in time and space for grazing management are also discussed.

Key words: spatial and temporal variation, herbage nutritive value measurement, proximal hyperspectral sensing, pasture-based dairy farm system

4.2 Introduction

Rapid measurement of herbage nutritive value (NV) has been proposed as a potentially suitable means of improving efficiency in pasture-based dairy farm systems (French et al. 2014; Shalloo et al. 2018). This is because having information on the NV of herbage readily available for grazing could help farmers make more efficient daily feed allocation decisions (Shalloo et al. 2018). However, the high cost and time involved in sampling and the lack of commercially available rapid measurement tools have made such approach to management unfeasible in practice. More importantly, it is still not clear if having rapid measurements of herbage NV would be beneficial to improving the daily efficiency of grazing in pasture-based dairy farm systems.

Research has been undertaken to study the temporal and spatial variation of NV of herbage on dairy pastures (Wilson et al. 1995; Moller et al. 1996; Cosgrove et al. 1998; Litherland and Lambert 2007; Bell et al. 2018), with temporal variation being understood as that arises when space is held constant and spatial variation as the one when time is constant (Chesson 1985). Few reports are found in the literature that provide the adequate level of detail required to understand the potential benefits of herbage NV variation for daily grazing management. Most research has focused on the study of variation of herbage NV over time (Moller et al. 1996; Bell et al. 2018) and space (Cosgrove et al. 1998; Bell et al. 2018) of a reduced number of paddocks, or variation obtained from data from multiple farms in order to draw generalisations of the seasonality of herbage NV (Wilson et al. 1995; Litherland and Lambert 2007). However, conditions of soil moisture, soil fertility, climate and grazing management factors can influence herbage NV (Ball et al. 2001; Waghorn and Clark 2004). This creates the necessity of having a more detailed description of the variation of the NV of herbage offered at each farm in order to inform more precise grazing management.

Recent advances in precision agriculture have made possible the use of spectral-based tools for herbage NV measurement in the field (Kawamura et al. 2009; Pullanagari et al. 2012; Adjorlolo et al. 2015). On chapter 3 it was shown that proximal hyperspectral sensing can be specifically used for herbage NV measurement for dairy grazing management. Seems as this technological advancement has opened the possibility of studying variation of herbage NV at the level of detail that has not been studied before and that could be suitable to support operational grazing management. Information on the

NV of herbage offered daily to cows throughout the production season could also help clarify the extent to which herbage NV variation would justify the use of such a measurement tool by farmers. Moreover, a precise description of the variation of the NV of herbage offered to cows would also help to discuss the opportunities and challenges that such variation would bring to improving cow performance and grazing management. The objective of this chapter was to describe the spatial and temporal variation of the nutritive value of herbage offered to lactating dairy cows in a pasture-based dairy farm system using proximal hyperspectral sensing. A second objective was to determine the extent to which herbage NV variation justifies its measurement and to discuss the implications of such variation to dairy cow performance and grazing management.

4.3 Materials and method

4.3.1 Study site and herbage resources

The farm selected for this study was Dairy 1 (D1), which is owned by Massey University and located in Palmerston North, New Zealand. The farm is operated as a commercial dairy farm, but also serves as a platform for teaching, research and extension. The farm is managed as a profitable, low input, sustainable pasture-based dairy farm with a once-a-day (OAD) milking, spring calving system.

Climate in the location is temperate, with an annual rainfall of 980 mm, annual temperature of 13.1°C and low and mean high temperatures of 8.5 and 17.8°C, respectively (NIWA 2018). Farm soils comprise a complex assemblage of free-draining alluvial soils including Rangitikei Loamy Sand, Manawatu Fine Sandy Loam, Manawatu Sand Loam/Gravelly phase, Manawatu Mottled Silt Loam and Karapoti Brown Sandy Loam, with these soils being well drained and naturally fertile. Irrigation is available on nearly 25% of the farm area and is used during summer when soil water deficits are likely to occur.

Herbage resources available on the farm are composed of perennial ryegrass (*Lolium perenne* L.) and white clover (*Trifolium repens* L.) mix, with some herbage resources also including red clover (*Trifolium pratense*) as part of the mix. Weeds such as buttercup (*Ranunculus* spp.) and annual poa (*Poa annua*) and herbs as chicory (*Cichorium intybus* L.) and plantain (*Plantago lanceolata*) are also likely to be found but in small abundance. Other herbage resources in the farm include mixed herb crops comprising chicory (*Cichorium intybus*), red clover (*Trifolium pratense*) and plantain (*Plantago lanceolata*), and monocultures of turnip (*Brassica campestris ssp. rapifera*), rape (*Brassica napus*) and lucerne (*Medicago sativa*) that are grazed strategically to fill seasonal dry matter supply deficits but these were not part of this study.

4.3.2 Data collection

Nutritive value of herbage from selected paddocks at pre-grazing was measured every two to three weeks from 10 August 2016 to 21 May 2017 and from 31 July 2017 to 19 May 2018. In each farm visit, between four to six paddocks in the farm manager's weekly grazing plan were measured. Nutritive value traits ME (MJ/kg DM), percentages of CP, DOMD, ADF and NDF in DM of herbage were determined from canopy hyperspectral measurements using the calibrations developed in chapter 3. In each paddock, hyperspectral data were acquired from twelve sampling plots distributed following a "W" shaped pattern across the length of the paddock. Special care was taken while measuring in order to avoid dung and urine patches. The number of plots per paddock was defined following recommendation of Cosgrove et al. (1998) who suggested that twelve samples are required to determine the mean herbage NV of a paddock with accuracies of ± 0.5 MJ/kg DM for ME, and of ± 5% for CP, NDF and ADF. The spectrometer was calibrated against a clean ceramic white tile that was used as a reflectance standard of 100% light reflectance after measuring every three sampling plots. The description of the instrument used to acquire spectra, the definition of 'sampling plot' and the calibrations used to determine the different herbage NV traits are detailed in chapter 3 of this thesis. At the end of this study, samples corresponding to grazing events over 186 days were collected.

4.3.3 Data analysis

Descriptive statistics were used to describe the spatial and temporal variation of the nutritive value of herbage offered to cows. Daily data correspond to descriptive statistics on the number of samples collected from paddocks that were grazed on that day. Mean values were used to characterise the NV of herbage offered at each grazing day while spatial variation is presented as boxplots and coefficients of variation (CV%).

Analysis of variance for the different NV variables were performed using the 'lmer' function available in the 'lme4' package for R software (Bates et al. 2007) with the following mixed linear model,

$$NV_{ijk} = \mu + Y_i + M_{j:i} + P_k + e \qquad \text{(equation 4.1)}$$

where:

NV_{ijk} is the herbage NV variable (ME, CP, ADF, NDF or DOMD) measured in the i-th year, in the j-th month and in the k-th paddock; μ is the mean value of NV; Y_j is the fixed of the i-th year (production season 2016-17 or 2017-18); $M_{j:i}$ is the fixed effect of the j-th month (July, August, September, October, November, December, January, February, March, April or May) nested within the i-th year; P_k is the random effect of the k-th paddock (identification code of 52 paddocks); e is the random residual error. Least squares means were obtained and used for multiple mean comparisons using the least significance difference test as implemented in the 'emmeans' package (Lenth et al. 2018). P-values were adjusted using the Bonferroni method.

The mixed model of equation 4.1 was converted into a random model considering all factors as random effects to obtain estimates of variance components for year (σ^2_y), month nested within year ($\sigma^2_{m:y}$), paddock (σ^2_p) and residual error (σ^2_e). The total variation was calculated as the sum of all variance components ($\sigma^2_T = \sigma^2_y + \sigma^2_{m:y} + \sigma^2_p + \sigma^2_e$. The relative contribution of year, month, paddock and residual error for each of the herbage NV traits was expressed as the percentage of the total variation.

4.4 Results

Descriptive statistics of pooled samples of herbage NV are presented in Table 4.1 and descriptive statistics depicting the temporal and spatial variation of herbage NV are presented in Figures 4.1 to 4.5.

Table 4.1 Descriptive statistics of herbage NV measured using proximal hyperspectral sensing at Dairy 1, Massey University, Palmerston North.

Trait	N	mean	SD	CV (%)	min	max
ME, MJ/kg DM	2760	10.9	0.58	5.3	7.5	13.4
CP, %DM	2760	18.3	2.95	16.2	5.9	30.4
NDF, %DM	2760	39.2	3.73	9.5	16.7	59.1
ADF, %DM	2760	20.6	2.55	12.4	9.4	33.1
DOMD, %DM	2760	65.5	2.75	4.2	52.7	84.1

ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter content in the herbage.

Descriptive statistics of pooled data used to define the daily offer of herbage NV indicate that concentration of CP was the most variable NV trait, while concentration of DOMD the least variable (Table 4.1).

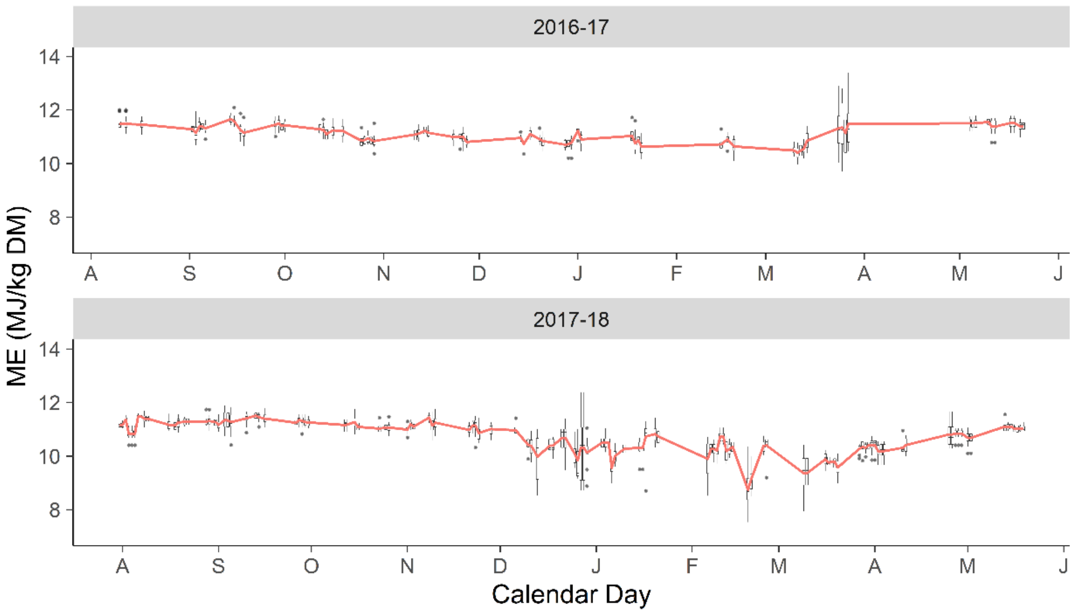

Figure 4.1 Temporal (linear extrapolation of means indicated by the solid line) and spatial (boxplots) variation in metabolisable energy (ME) of herbage offered daily to dairy cows during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University, Palmerston North.

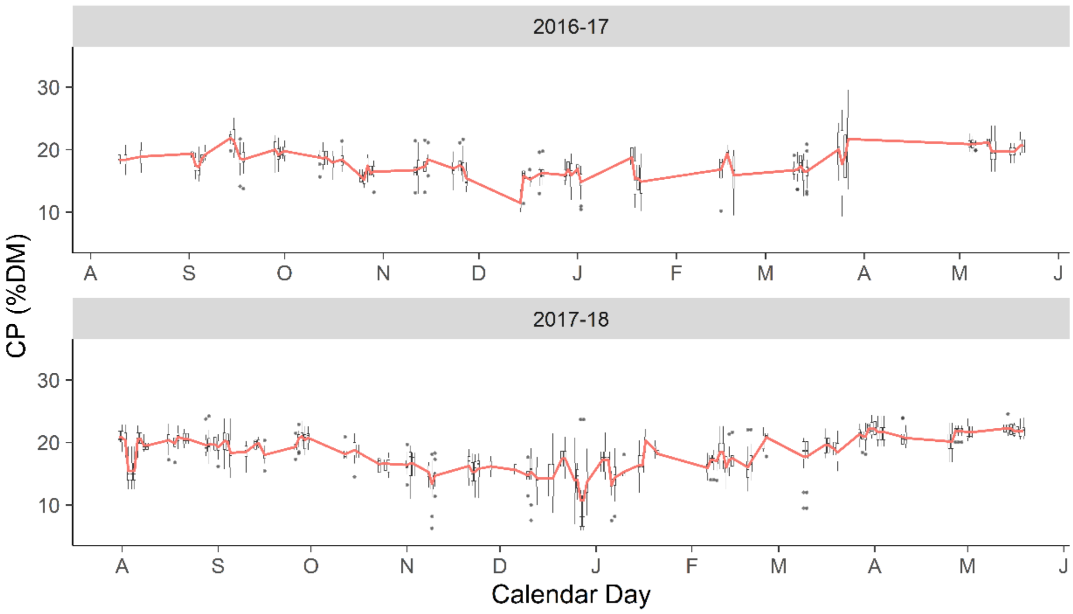

Figure 4.2 Temporal (linear extrapolation of means indicated by the solid line) and spatial (boxplots) variation in crude protein (CP) of herbage offered daily to dairy cows during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University, Palmerston North.

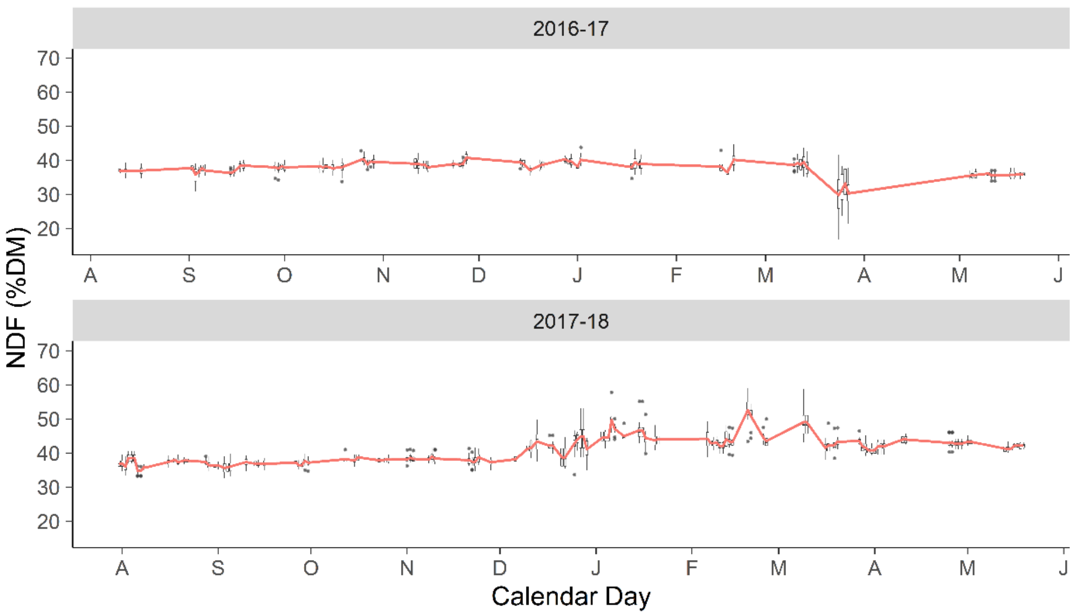

Figure 4.3 Temporal (linear extrapolation of means indicated by the solid line) and spatial (boxplots) variation in neutral detergent fibre (NDF) of herbage offered daily to dairy cows during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University, Palmerston North.

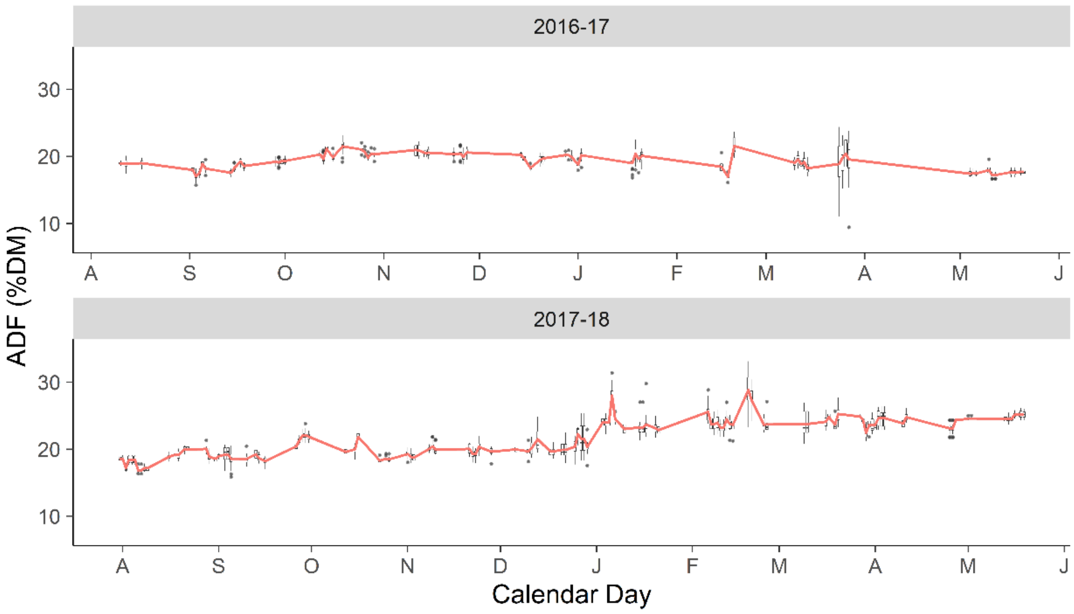

Figure 4.4 Temporal (linear extrapolation of means indicated by the solid line) and spatial (boxplots) variation in acid detergent fibre (ADF) of herbage offered daily to dairy cows during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University, Palmerston North.

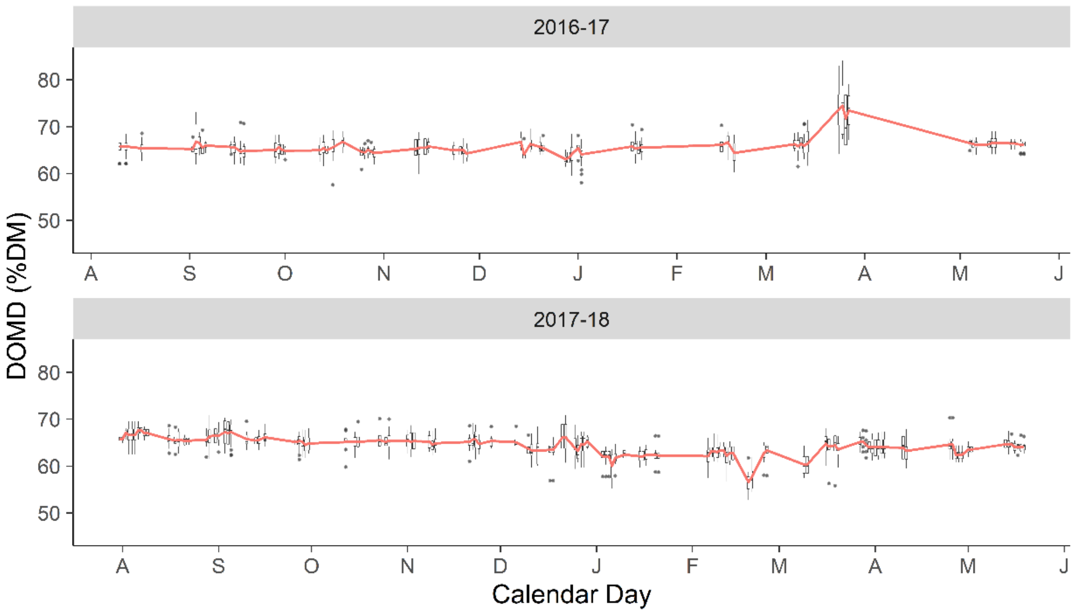

Figure 4.5 Temporal (linear extrapolation of means indicated by the solid line) and spatial (boxplots) variation in digestible organic matter in dry matter (DOMD) of herbage offered daily to dairy cows during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University, Palmerston North.

Trends depicted by means and the extrapolation of means between calendar days in Figures 4.1 to 4.5 show that the NV of herbage offered was relatively higher during spring and autumn days and lower in summer days (i.e. relatively higher ME, CP and DOMD and lower NDF and ADF in spring and autumn days vs. lower ME, CP and DOMD and higher NDF and ADF in summer days). Boxplots show that the spatial variation of any of the herbage NV traits was relatively higher for resources offered in summer days than those offered in spring or autumn days. Moreover, spatial dispersion of herbage NV was relatively higher for resources offered during 2017-18 production season ($0.91\% > CV > 35.45\%$) than resources offered during 2016-17 production season ($0.52\% > CV > 62.73\%$). In general, spatial dispersion of CP was greater ($2.49\% > CV > 62.73\%$) than the spatial dispersion of ME, NDF, ADF and DOMD ($0.52\% > CV > 23.20\%$).

Comparisons of least-squares means of herbage NV available among months and years in which data were collected statistically confirm the seasonal trends described above (Figure 4.6). Differences of herbage NV during late winter and spring months (July to November) were not significant for any of the NV trait but for CP, which were non-significant from July to October (Figure 4.6). During summer months (December to February), the NV of herbage offered significantly dropped, as ME, CP and DOMD decreased and fibres increased. The NV of herbage offered to cows increased from March onwards but there were significant differences between production seasons. In autumn, contents of ME, CP, NDF and ADF in herbage offered during 2016-17 production season were like those offered on spring but reported a higher NV than the herbage offered during autumn months of 2017-18 production season. Finally, LS mean differences between production seasons indicated that herbage offered during 2016-17 production season had 0.34 MJ/kg DM more ME ($t(2689)= 16.2$, $p <0.0001$), 0.79% less CP ($t(2689)= -6.25$, $p <0.0001$) 3% less NDF ($t(2689)= -22.71$, $p <0.0001$), 2.1% less ADF ($t(2689)= -30.32$, $p <0.0001$) and 1.5% more DOMD ($t(2689)= 11.34$, $p <0.0001$) than 2017-18 production season.

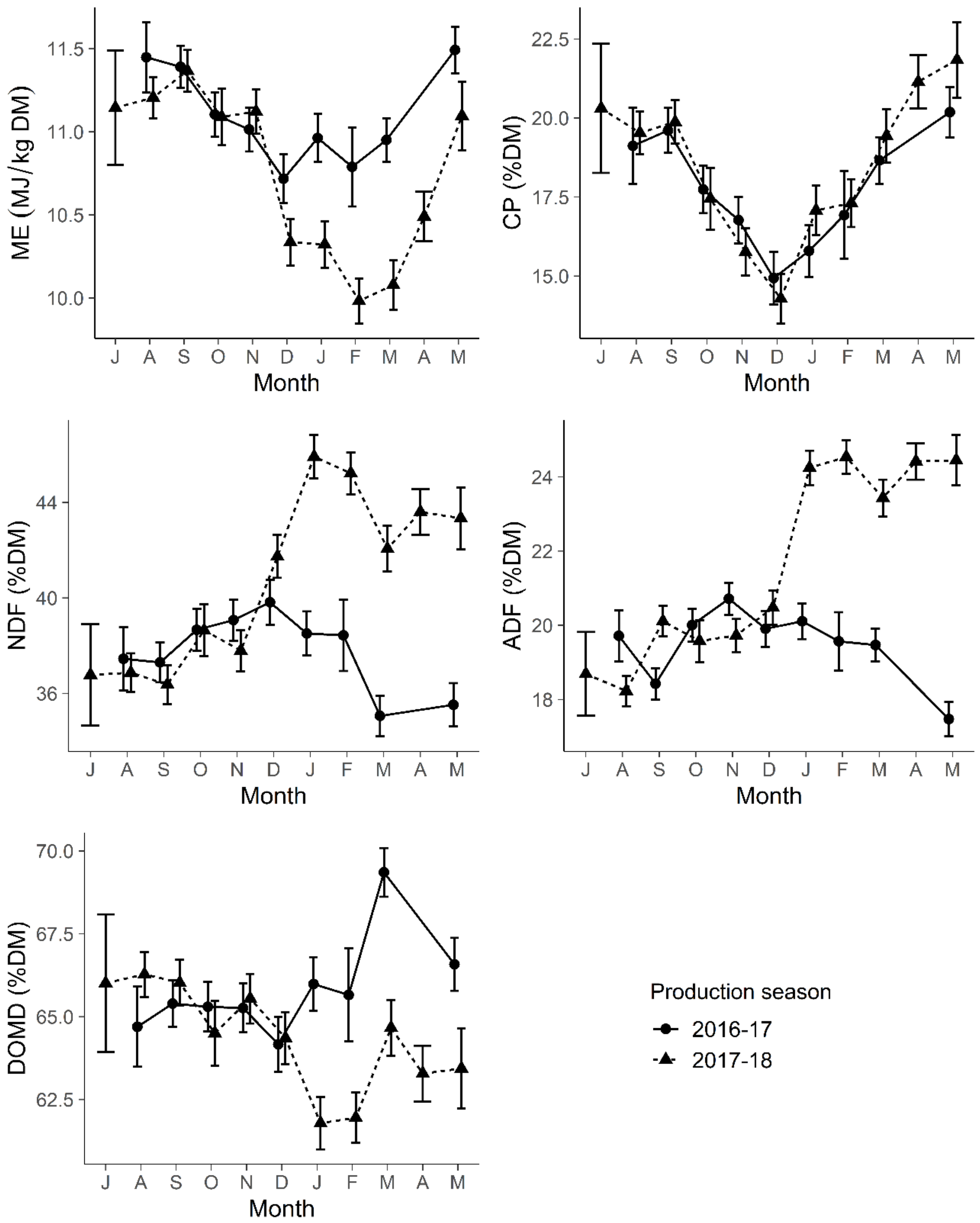

Figure 4.6 Least-squares means of herbage nutritive value for two production seasons (2016-17 and 2017-18) across months (from July to May) measures using proximal hyperspectral sensing at Dairy 1, Massey University, Palmerston North. ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter. Error bars indicate a 95% confidence interval for the LS mean.

Results from the random effects models in Table 4.2 show that DOMD was the herbage NV trait with the highest percentage of variance left unexplained (e^2= 51.3%) while ADF was the trait which was better explained (e^2= 16.6%). Month within the production season had the greatest influence on the determination of any of the herbage NV traits ($m{:}y^2$= 42.7% on average across NV traits) while paddock the least (p^2= 10.7% on average across NV components). Production season had greater influence on fibre traits but had no influence on CP.

Table 4.2 Variance decomposition of herbage nutritive value traits assessed using proximal hyperspectral sensing at Massey University's Dairy 1 farm during two production seasons (2016-17 and 2017-18) across months (from July to May).

Trait	σ^2_y	$\sigma^2_{m:y}$	σ^2_p	σ^2_e	σ^2_T	y^2	$m{:}y^2$	p^2	e^2
ME	0.04	0.18	0.04	0.12	0.38	11.2	46.2	11.7	30.9
CP	0.00	4.29	1.18	4.29	9.78	0	43.9	12.1	43.9
NDF	3.74	8.13	2.08	4.45	18.34	20.3	44.2	11.3	24.2
ADF	1.88	4.05	0.49	1.28	7.71	24.4	52.5	6.4	16.6
DOMD	0.87	2.33	1.06	4.48	8.74	9.9	26.7	12.1	51.3

σ^2_y= variance explained by random effect of year, $\sigma^2_{m:y}$= variance explained by random effect of month nested within year, σ^2_p= variance explained by random effect of paddock, σ^2_e= variance explained by random error, σ^2_T= total variance. y^2= variance explained by random effect of year expressed as a percentage of total variance, $m{:}y^2$= variance explained by random effect of month nested within year expressed as a percentage of total variance, p^2= variance explained by random effect of paddock expressed as a percentage of total variance, and e^2= variance explained by random error expressed as a percentage of total variance.
ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

4.5 Discussion

The aim of this study was to describe the variation of the nutritive value of herbage offered to lactating dairy cows in a pasture-based dairy farm system using proximal-hyperspectral sensing technology. In addition, it also sought to determine if the extent variation in herbage NV traits would justify their measurement and to discuss the implications of herbage NV variation for dairy cow performance and grazing management.

4.5.1 Variation of herbage nutritive value

Daily variation of mean values of ME, CP, NDF, ADF and DOMD of the herbage offered to cows throughout the two production seasons were within guideline ranges commonly used in the dairy industry (Holmes 2007; DairyNZ 2019), compiled from feed laboratory data (Litherland and Lambert 2007) or data obtained from research on specific dairy farms (Moller et al. 1996) (Table 4.3).

Table 4.3 Ranges of mean herbage nutritive values obtained throughout a production season (from July to May) in four reference studies.

	Reference							
	Holmes (2007)		DairyNZ (2017)		Litherland and Lambert (2007) [1]		Moller et al. (1996)	
Trait	min	max	min	max	min	max	min	max
ME, MJ/kg DM	9	12	8	12.5	9	13	-	-
CP, %DM	14	30	9	35	11	33	13	32
NDF, %DM	35	60	35	65	25	63	25	60
ADF, %DM	-	-	-	-	16	35	22	36
DOMD, %DM	-	-	-	-	62	92	65	80

[1]Data from 6300 herbage samples collected from dairy farms across New Zealand from 2002 to 2005.
ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

Results also suggest that management was able to maintain a relatively stable herbage NV on offer to cows throughout both production seasons, as seasonality of data was much reduced compared to that reported in other studies (Moller et al. 1996; Holmes 2007; Litherland and Lambert 2007).

The range of coefficients of variation of herbage NV described in this study indicated that there were paddocks with either higher or lower herbage NV spatial variation than sampled paddocks in other studies (Cosgrove et al. 1998; Bell et al. 2018). Although data in previous studies were comparable to the data presented here, it is important to highlight that the studies by Cosgrove et al. (1998) and Bell et al. (2018) involved a reduced number of paddocks (1 and 2, respectively) and a limited timeframe for data collection, which may help explain the relatively higher range of herbage NV spatial variation observed in this study. Results also showed that the spatial variation of

CP across herbage resources was higher than the spatial variation of any other NV trait. Such finding was consistent with Cosgrove et al. (1998) who reported that the spatial variation of CP (CV= 13.6%) was higher than the spatial variation of ME, NDF or DOMD (CV ranging from 4.4 to 9.1%) and Bell et al. (2018) who also reported higher spatial variation for herbage CP (CV ranging from 18 to 23%) compared to ME, NDF and ADF (CV ranging from 2 to 13%).

Variation of herbage NV across months within a production season and between production seasons is most likely the reflection of monthly (m:y^2) and inter-seasonal (y^2) effects associated with seasonality of temperature and rainfall. Temperature is a major contributor to herbage NV through its effect on plant phenology (Buxton and Fales 1994; Chapman et al. 2014). Rising temperature increases the rate of plant development, reduces leaf/stem ratio and hence NV of herbage decreases as plants enter maturity (Buxton and Fales 1994; Lambert and Litherland 2000; Litherland and Lambert 2007). Lower but increasing temperature from July onwards coincides with a higher NV of herbage observed from July to October whilst the peak of temperature in January-February coincides with lower NV of herbage offered during summer months (Figure 4.7). From summer onwards, herbage NV was dependent on the production season, which seemed to be associated with the effect of the interaction of temperature and rainfall on herbage NV as 2017-18 production season was warmer and dryer (mean temperature of 14.3°C and accumulated yearly rainfall of 1112.2 mm) compared to 2016-17 production season (mean temperature of 13.3°C and accumulated yearly rainfall of 933 mm) (NIWA 2018). These environmental differences could also help explain overall differences in herbage NV between production seasons.

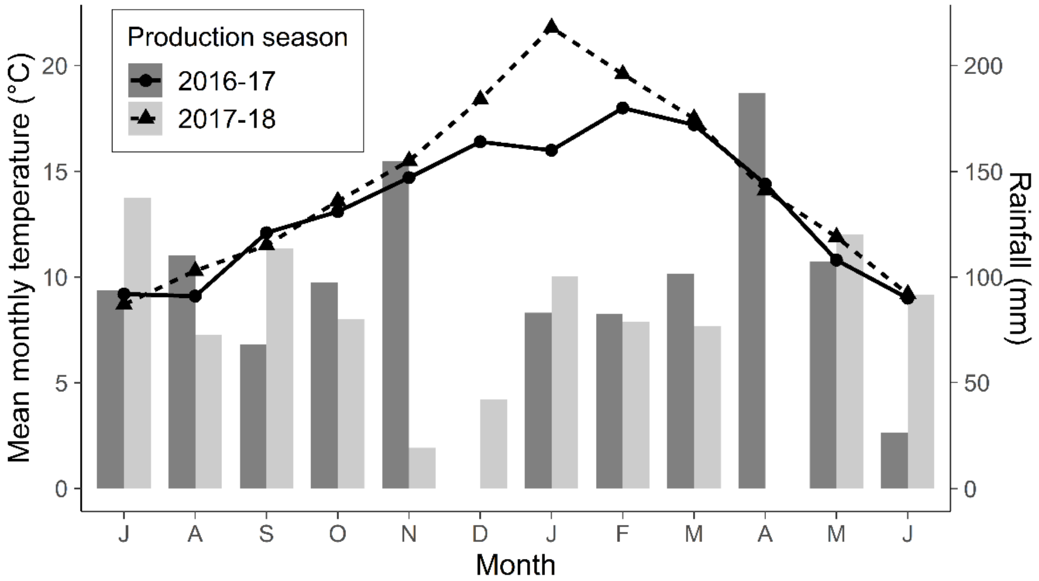

Figure 4.7 Mean monthly temperature (lines) and accumulated monthly rainfall (columns) during the 2016-17 and 2017-18 production seasons. Source: based on data from NIWA (2018).

Variation in soil nutrient content and soil moisture among the paddocks of the farm can also explain variation of herbage NV to the extent indicated by the random paddock effect. Although the effects of these factors on the NV of mixed herbage are described as being smaller than the effects of temperature (Buxton and Fales 1994; Buxton 1996), strong deficits of water or soil nutrients can significantly influence herbage NV at the plant or sward level (Buxton 1996; Kuchenmeister et al. 2013). For instance, experimental research by Kuchenmeister et al. (2013) found that the content of CP of white clover plants in a ryegrass-white clover mixture subject to severe water stress decreased by 18.9% compared to herbage subject to moderate or no water stress deficit while concentrations of NDF and ADF increased by 5.8 and 1.6%, respectively. In ryegrass, water deficit can trigger senescence of leaves and the mobilisation of nutrients and carbohydrates, resulting in herbage of low NV (Chapman et al. 2014). Water stress deficit can also affect the persistence of species in the sward, hence affecting the relative abundance of species and therefore the NV (Buxton 1996). Moreover, variation of soil nutrients, particularly N, can also influence concentration of CP in plant tissue, although in normal conditions this effect is relatively small (Buxton and Fales 1994; Shepherd and Lucci 2013).

Decisions affecting the severity, duration and frequency of grazing can have consequences on the temporal and spatial variation of the NV of herbage on offer and can help to explain such variation. Grazing intensity, determined by decisions affecting severity and duration of grazing, can influence the NV of herbage at successive grazing events due to the accumulation of dead material (Lee et al. 2008). Recent research has proved that consistently grazing herbage to an even residual mass of 1800 to 2000 kg DM/ha (high residual) compared to grazing to 1500 to 1600 kg DM/ha (target residual) can reduce CP in 3.5% and ME in 0.8 MJ/ kg DM (Burggraaf et al. 2018). Differences in the decision-making affecting the intensity of grazing among paddocks may be a reason for the greater daily variation of herbage NV during summer. Moreover, the stocking rate used in the pasture-based dairy farm system under study was low (2.1 cows/ha) compared to regional (2.7 cows/ha) and national (2.8 cows/ha) averages (DairyNZ 2019), which may indicate high herbage allowances and therefore relatively lax grazing events. In these situations, selectivity by cows is likely, and therefore uneven post-grazing residuals can result in increased spatial variation of herbage NV at successive grazing events.

The literature on grazing management recommends that the frequency of grazing ryegrass-based herbage should be based on the assessment of the leaf stage of ryegrass tillers, since this would optimise regrowth and NV without affecting the persistency of the plant (Lee et al. 2008; Macdonald et al. 2010; McCarthy et al. 2014). However, anecdotical evidence (Hirst et al. 2014) suggest that farmers tend to overlook leaf stage for herbage mass monitoring or set a fixed date based on the time since last grazing to inform their decision-making. If this is the case in the study farm, then differences in the leaf stage at grazing can contribute to explaining the observed daily variation of herbage NV on offer (e^2). Research shows that the NV of ryegrass tillers decreases as the number of emerged leaves increases, as younger leaves are of higher NV than the older ones (Turner et al. 2006; Chapman et al. 2012). For instance, Chapman et al. (2012) found that content of DOMD and CP in laminae from leaves in tillers appearing successively from first-leaf- to third-leaf stages decreased at a rate of about 10% while content of NDF and ADF increased at a similar rate. Similar findings were reported by Turner et al. (2006) who also describes that the overall drop in NV of laminae from third- to fourth-stage leaves is even higher (16%) and Fulkerson et al. (1998) who describes similar trends for NV measured at the whole-sward level. Although grazing at early leaf stages will maximise NV, grazing before the emergence of the second leaf will penalise regrowth rates and threaten plant survival. Consequently, optimal timing for grazing ryegrass is recommended to be set between the second and third leaf stages. If paddocks in our study were grazed within a wider range leaf stages, that could partially explain short-term variation of herbage NV.

4.5.2 Implications of herbage nutritive value variation to dairy cow performance

Concentration of CP of herbage offered throughout spring, summer and autumn were mostly in excess of recommended values suggested by DairyNZ (2017) of 18%, 16% and 14% for early, mid and late lactation, respectively to be required to sustain high levels of milk production on dairy farms. However, there was a period during December 2017-18 when offer of CP was lower than requirements. Mean values for NDF throughout both production seasons were also above the minimum requirement range of 27 to 35%, while ADF fell within the recommended range of 19 to 21% across all periods of production except for the late 2017-18 production season when ADF was significantly high. These observations suggest that if sufficient herbage quantity is available, cow performance from the herbage offered on the farm would be most likely be limited by ME, which is consistent with much of the literature describing the nutritional limitations of herbage on New Zealand pasture-based dairy farm systems (Moller et al. 1996; Holmes 2007; Litherland and Lambert 2007). Although variation of herbage CP across months was appropriate to sustain high levels of milk production, it is important to highlight that on 7% of the monitored days the minimum requirement of CP was not met.

Deficits in CP observed for herbage offered during summer days might require supplementation (Moller et al. 1996). Excess CP in spring or autumn days can have negative consequences on cow performance. On the one hand, the process of synthesis and excretion of excess N in the form of urea requires energy that would otherwise be used for production processes. Tyrrell (1970) estimated the costs of excretion in 3.05 MJ of ME per 100g of N synthesised. On the other hand, excess CP was also associated with poor reproductive performance (McCormick et al. 1999; Ipharraguerre and Clark 2005). There were no days when NDF values were below minimum threshold values required to sustain ruminal and cow health. Concentration of NDF varied in a range from 29.8% to 52.6%, values which were associated with normal values of ruminal ph on cows fed 100% herbage diets (Kolver and De Veth 2002). However, high values of NDF might pose limitation to cow performance by limiting herbage intake due to rumen fill, particularly in summer, when herbage ME is low. For instance, using an example by Nicol and Brookes (2007) in which a dairy cow of 450 kg of live weight producing 15 litres of milk and gaining 0.5 kg of live weight would require 180 MJ of ME/day or 16.4 kg DM/day of herbage at 11 MJ/kg DM to satisfy their ME requirements, the same cow would need to eat 20.7 kg DM/day if fed the paddock of the lowest NV in our study (ME= 8.7 MJ/kg DM and NDF= 52.6%). However, such estimation is unrealistic if the effect of NDF on herbage intake is accounted for in the estimation of intake. In this sense, using the equation of Mertens (1987), which considers the effect of NDF on rumen fill, the maximum intake achievable by the example cow grazing the low NV paddock would be 14.1 kg DM/day.

Spatial variation of the NV of herbage within a paddock can influence the nutrition of cows by altering energy costs associated with grazing activity. Research has shown that cows tend to prefer green leafy herbage associated with high NV over brown dead material of low NV (Chapman et al. 2007). Increased time spent on the processes of walking, searching and handling preferred feeds when exposed to heterogeneous resources might signify higher energy costs and less energy therefore destined to production processes (NRC 2001). Nevertheless, the energy costs associated with high spatial variation are most likely to be low. For instance, following Nicol and Brookes (2007) recommendation for energy requirements of dairy cattle, a 450 kg Jersey x Friesian cow producing 2 kg MS/day would require 1.2 MJ of ME per extra km walked horizontally during grazing or 1.8 MJ of ME/km in an easy hilly terrain. Considering that the average distance walked by a cow while grazing is about 0.5 km (Oudshoorn et al. 2008), then the energy required by the cow in the example above walking twice the average distance would still be relatively low compared to their total energy required for maintenance and production in a day (193 MJ/day).

4.5.3 Implications of herbage nutritive value variation to grazing management

In this study, variation of herbage NV traits were assessed through the effects of production season, months within a production season and day, which denote differences at temporal scales and thus implications at different management levels. Although the hyperspectral tool used in this research was not intended to forecast NV for their use in strategic or tactical planning, data presented here can be used retrospectively to draw some discussion on the implication of herbage variation on grazing management. In this sense, the high variation of herbage NV during the production season indicates that such seasonality can influence strategic decision-making. Having a detailed profiling of the feed available on a farm on an energy and nutrient content basis can help management better adjust supply and demand of feed throughout the production season by influencing key strategic decisions like stocking rate, calving date, conservation/supplementation policy and drying off date. Differences of herbage NV between production seasons from summer onwards, for all NV traits except CP, indicate that tactical adjustments to farm strategy based on herbage NV content might have been required. Lower levels of ME and high fibre content of herbage offered in the summer of the 2017-18 production season would have required extra supplementary feeds to meet demand, assuming the pasture-based dairy farm system had such feed at hand.

Results suggest that having accurate measurements of the NV of herbage offered daily to cows can potentially help management consistently achieve cow performance and post-grazing residual targets through more efficient pasture allocation planning of each grazing event. This is because rapid NV measurement can be used to exploit up to 31% of variance of ME that were not attributed to differences between paddocks, months or seasons and which is most likely limiting cow performance from herbage. As mentioned, suboptimal post-grazing residuals would result in a loss of NV of herbage at subsequent grazings, lower herbage utilisation and productivity in the long term. Following up on the example in section 4.5.2, the cow would have to increase her intake of herbage by 6.6 kg DM/cow if fed herbage of lower ME (8.7 MJ/kg DM) compared to herbage of higher ME (11 MJ/kg DM) in order to sustain the required performance level. Thus, assuming a homogenous mob on a 100% herbage diet grazing two paddocks at the same allowance and mass but either low or high ME content, differences in intake resulting from differences in ME and rumen fill constraints imposed by NDF, would signify different grazing intensities between paddocks. Consequently, residual herbage masses after grazing will most likely differ from preestablished targets if NV differences are not accounted for while budgeting daily herbage allocation. Alternatively, farmers can plan daily allocation of herbage by balancing diets considering alternate paddocks with herbage of different NV. Nevertheless, although this example emphasises the implication of herbage NV measurement on efficient daily herbage allocation planning, it is important to highlight that, in practice, farmers can also adjust their herbage allocation plans according to milk yield (Macintosh and McNae 2001) or the residuals after allocation (Hirst et al. 2014).

Given tactical constraints, perhaps the most relevant implication of daily herbage NV measurement to operational grazing management relates to the use of supplements when nutritional deficits or excess from herbage are identified. As discussed in section 4.5.2 in this chapter, ME content is likely to be a major constrain to animal nutrition from herbage, particularly during summer where greater variation exists. In this situation better adjustment of grazing due to more efficient feed allocation might help increase harvesting efficiency of herbage and reduce substitution of herbage for supplements, improving utilisation of herbage in the long term. Similarly, excess herbage CP levels can be balanced with other feeds to perhaps minimise the impact of N leaching on the environment.

If the level of nutrition available from paddocks of high spatial variation can sustain adequate levels of cow nutrition, then higher spatial variation of herbage NV might signify that management will have to reduce the incidence of selectivity by cows. When faced with spatial heterogeneity cows will tend to graze preferred species of high NV in detriment of low NV species (Chapman et al. 2007). This effect would lead to uneven post-grazing residuals and deterioration of pasture, particularly during summer when heterogeneity is higher. In order to control this, mowing before or after grazing (i.e. topping) was found to increase herbage NV and milk yield (Kolver et al. 1999). Alternatively, the use of herbage mapping combined with virtual fencing technologies has been proposed to improve efficiency of grazing of heterogeneous resources (French et al. 2015). Although work in this line was proposed with focus on herbage mass mapping, the concept could be further expanded to include herbage NV. Finally, the sampling strategy used in this study signifies that paddocks of high herbage NV spatial variation (e.g. summer herbage) might require a higher number of samples to obtain mean estimates with the same level of confidence that estimations for paddocks of low variation (e.g. spring herbage). This sampling issue can be solved with the use of aerial spectral imaging, which can be used to estimate herbage NV of relatively large areas at high spatial resolution (Yule et al. 2015; Shorten et al. 2019). However, weather conditions can pose significant challenges to the use of this technology for regular monitoring of herbage in the field (Von Bueren et al. 2015), posing limitations for their use for operational grazing management.

4.6 Conclusion

Proximal hyperspectral sensing technology was useful to characterise daily and spatial variation of the NV of herbage offered to lactating cows in a pasture-based dairy farm system. The study farm exhibited normal values for ME, CP, NDF, ADF and DOMD consistent with seasonal pasture-based dairy farm systems. The proportion of variance that was not accounted for by differences between paddocks, months and production seasons which ranged from 16.6 to 51.3% across NV traits partially justifies the use of their measurement from a NV variation standpoint. From the herbage offered, CP was in excess of the requirements of lactating dairy cattle while ME seemed to be the most limiting factor to animal performance. High spatial variation of paddocks fed during summer signify that a larger number of samples would be required in order to obtain a precise estimation of the mean values of herbage NV. Using real-time accurate measurements of herbage NV can help farmers plan their operational grazing management in order to accurately allocate herbage and feed to achieve more precise grazing and animal performance targets. Further research is required to quantify the extent to which this daily variation of herbage NV can influence the performance of the herd in a pasture-based dairy farm system.

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CHAPTER 5

Influence of herbage and climate factors on daily performance per cow in a pasture-based dairy farm system

5.1 Abstract

Including a measure of nutritive value to support daily allocation of herbage to cows has been proposed as an opportunity to improve efficiency of grazing in pasture-based dairy farm systems. However, it is not clear the extent to which knowing the variation in nutritive value of the herbage on offer would be beneficial to control the performance per cow in the herd since animal performance can be affected by other herbage quantity and climate related factors that are not easier to control. The objective of this chapter was to determine the relative importance of the nutritive value of herbage, and other herbage and climate related factors on the performance per cow in a pasture-based dairy farm system. Data on milk production, live weight, body condition score, weather, herbage nutritive value and herbage quantity were collected every two to three weeks from August 2016 to May 2017 and from July 2017 to May 2018 from Dairy 1, Massey University, Palmerston North. Data were analysed using multiple linear regression, principal components regression and partial least squares regression. Results indicated that herbage metabolizable energy explained from 20% to 30% of the production of milk, fat and protein per cow. Herbage quantity and climate factors were relatively less important than herbage nutritive value in defining performance per cow in the herd. Developing feeding strategies aimed at improving the efficiency of feeding of cows by exploiting daily variation of herbage nutritive value to better match daily supply of nutrients animal nutritional requirements may be useful to improve the overall performance per cow of pasture-based dairy farm systems.

Key words: herbage nutritive value measurement, herbage quantity, climate, herd performance per cow, pasture-based dairy farm system

5.2 Introduction

Daily allocation of herbage to cows in pasture-based dairy farm systems has traditionally focused on monitoring the quantity of herbage available over the nutritive value (NV). The dairy industry encourages the use of herbage quantity measurement tools and monitoring of the leaf stage of ryegrass to promote good grazing management practices that would optimise NV and regrowth of herbage, while satisfying demand by animals (DairyNZ 2017). This suggest that by implementing good grazing management practices there would be relatively little need for herbage nutritive value measurement, as such an approach would anyways result in optimal NV. However, there is evidence that farmers are not always able to make the optimal grazing management decisions to achieve the potential productivity of their farms (McCarthy et al. 2014). There are also other factors than grazing management, including species composition, soil moisture, soil fertility and climate, that also affect the NV of herbage (Ball et al. 2001; Waghorn and Clark 2004; Muller 2011).

Regardless of the cause, and as shown in chapter 4, variation of the NV of herbage offered to dairy cows is likely to exist. Daily variation of herbage NV could result in times at which the supply and demand of nutrients required by cattle are not matched and that therefore, the actual performance per cow is different from that expected by farmers, resulting in inefficient grazing management. It is well known that herbage intake, which is controlled by the allowance of herbage offered, is a major factor determining marginal performance of grazing dairy cows (Bargo et al. 2003; Dillon 2007; Baudracco et al. 2010; Pérez-Prieto and Delagarde 2013). However, other climate factors such as temperature (West 2003; Bryant et al. 2007) and herbage related factors such as the NV of herbage also plays a significant role in influencing performance per cow (Kolver 2003; Walker et al. 2004). Herbage of high NV has more energy and nutrients available per unit of dry matter available for production and maintenance functions (Waghorn and Clark 2004). In addition, nutritious herbage passes more rapidly through the animal's digestive tract allowing greater intakes, and therefore higher performances (Poppi et al. 1987; Lambert and Litherland 2000).

Including a measure of NV to support daily allocation of herbage has been proposed as an opportunity to improve efficiency of grazing in pasture-based dairy farm systems (Shalloo et al. 2018). Such inclusion would allow a more precise match between demand and supply of herbage by extending the focus from adequate quantity to adequate nutrition. The lack of commercial tools that would allow farmers to rapidly measure herbage NV in a timely fashion has most likely contributed to the lack of the adoption of such practice. However, increasing advances have been made in the development of tools to measure the NV of herbage in the field for pasture management (French et al. 2014; Shalloo et al. 2018), with chapter 3 being specifically intended to address this issue for the context of dairy grazing management.

The possibility of being able to quantify herbage NV in the field could be beneficial to improve the efficiency of grazing management and enhance the performance of pasture-based dairy fam systems. However, it is not clear the extent to which knowing the daily variation of the nutritive value of herbage could be used to control the performance per cow in pasture-based dairy farm systems. Although the influence of herbage NV on animal performance is well known (Kolver and Muller 1998), much of the research on this topic was performed in experimental-like conditions where animals have controlled access to pastoral resources. For rapid measurement of herbage NV to be useful for farmers, field data is required to determine the extent to which daily variation of herbage NV could influence performance per cow in a pasture-based dairy farm system. By determining the extent to which herbage NV can drive performance of grazing milking cows in field-like conditions, this study can contribute to the discussion of the importance that should be given to monitoring herbage NV and to the design of feeding strategies that account for the variation of herbage NV. The objective of this chapter was to determine the influence of herbage NV, and other herbage and climate related factors on the daily performance of a pasture-based dairy farm system on a per cow basis.

5.3 Materials and method

5.3.1 Description of the pasture-based dairy farm system

This study was conducted at Dairy 1 (D1) at Massey University, Palmerston North, New Zealand during the 2016-17 and 2017-18 production seasons. Dairy 1 is a low-input pasture-based dairy farm system with spring calving and where all the cows in the herd are milked once a day (OAD) for the full production season.

During the 2016-17 and 2017-18 production seasons, the dairy herd consisted of 260 and 255 cows, respectively, which were allocated to an effective area of 119.7 ha, resulting in a stocking rate of about 2.1 cows/ha. The herd consisted of 25.4% Holstein-Friesian, 22.4% Jersey and 52.4% Holstein-Friesian x Jersey crossbreed. All the 65 paddocks in the milking platform have race access and irrigation is available to 35.4 ha and replacement heifers are grazed off-farm.

The diet offered to cows is mostly composed of home-grown feed. Forage resources grown at D1 are: 1) grass/legume herbage mix (ryegrass/white and red clover) (76% of farm effective area), 2) herb/legume herbage mix (plantain, chicory, white clover, red clover) (12%) and 3) crops (lucerne and maize) (12%). Excess herbage growth during spring and crops are made into silage or hay and fed to cows at times when feed is in deficit.

Further description of the herbage resources available on the farm as well as an overall description of the climate and soils of the farm can be found in section 4.3.1.

5.3.2 Data collection

Herbage

Herbage mass (HM) and NV of herbage from paddocks at pre-grazing were measured every two to three weeks from August 2016 to May 2017 and from July 2017 to May 2018. At each measurement period, between four to six paddocks in the farm manager's weekly grazing plan were measured.

Herbage mass was estimated using a C-Dax pasture meter with auto lift (C-Dax 2019) towed behind an All-Terrain Vehicle. The pasture meter determines average herbage height as the sward breaks the light path of a light emitting and sensing photodiode array at 20 mm spacing. The instrument can take up to 200 measurements per second or 18,500 readings over single 500 m run. In order to have a good characterisation of herbage within a paddock, runs were made following a "W" shaped pattern across the length of the paddock. Data collected within each paddock were averaged and converted to herbage mass using the following equation developed by D1 technical staff:

$$\text{HM (kg DM/ha)} = 752 + 16.3 \times \text{Height (mm)} \qquad \text{(equation 5.1)}$$

Nutritive value traits DM, ME, CP, ADF and NDF of each paddock were determined from canopy hyperspectral measurements acquired from twelve sampling plots distributed along the runs performed with the pasture meter. The number of plots was defined following recommendation of Cosgrove et al. (1998) who suggest that twelve samples are required to determine the mean herbage NV of a paddock with accuracies of ± 0.5 MJ/kg DM for ME, and of ± 5 % for CP, NDF and ADF. The description of the instrument used to acquire spectra, the definition of sampling plot and the calibrations used to determine the different herbage NV traits are detailed in chapter 3.

At each grazing event, the paddock identification number, date and area allocated to the animals were recorded. When there was more than one paddock being grazed in a day, the mean HM and NV of the herbage on offer for the day was determined by weighting the area of the paddocks allocated to the herd. The amount of herbage on offer on a day-to-day basis was calculated by multiplying HM by the daily area allocated to the cows. Herbage allowance (HA) was calculated by dividing the amount of herbage on offer for the day by the number of grazing cows.

Climate

Weather data (mean, max and min air temperatures, relative humidity, wind speed and rainfall) for the days in which the grazing events took place were obtained from the national climate database (NIWA 2018) (Station: Palmerston North Ews, latitude= -40° 22' 55.02", longitude= 175° 36' 32.94"). Weather data was used to calculate a temperature humidity index (Davis et al. 2003) and a cold stress index (Donnelly 1984) as follows:

$$THI = 0.8\ Tmax + [RH\ (Tmax - 14.4)] + 46.4 \qquad \text{(equation 5.2)}$$

where THI is temperature humidity index, Tmax is daily maximum temperature (°C) and RH is mean daily percent relative humidity divided by100.

$$CSI = [11.7 + (3.1\ WS^{0.5})]\ (40 - T) + 481 + 418\ (1\text{-}e^{-0.04\ R}) \qquad \text{(equation 5.3)}$$

where CSI is cold stress index (kJ/m^2/h), WS is mean daily wind speed (m/s), T is mean daily temperature (°C), e is Euler's number (mathematical constant) and R is total daily rainfall (mm).

Pasture-based dairy farm system performance per cow

Milk production at the farm was monitored using the dairy company actual milk return records. Records for daily milk, milksolids, fat, protein and milk urea obtained at the vat were divided by the number of cows milked that day. Daily live weights (LW) of cows identified with a radio frequency electronic identification system (Allflex New Zealand Ltd., Palmerston North, New Zealand) were automatically measured every morning after milking using an automatic race walkover scale situated in the exit of the milking shed (WoW xR-3000, Tru-Test Ltd., Auckland, New Zealand). The body condition score (BCS) of all cows in the herd was assessed once every month using a 10-point scale by a research technician. In order to account for missing data and to allow the daily characterisation of LW and BCS, these parameters were modelled for each of the cows as a function of their days in milk using Legendre polynomials of 3rd order over the two production seasons. These models were used to generate LW and BCS data for each day in which the cows were present in the milking shed. For each calendar day, LW and BCS generated data were averaged in order to obtain single daily values representative of the herd. The average change in live weight (LWC) of the herd was calculated as the difference in LW between successive days. Calculated performance per cow in the herd data were paired with herbage and weather data from the day after the grazing event took place.

Total number of observations

At the end of the study 178 daily observations containing complete information on herbage, weather and animal performance data were obtained. Subsequently, data gathered after day 250 of the beginning of milking in both production seasons were discarded from further analyses. It was considered that the quantity of herbage offered to animals in this latter period was limited and that the performance of cows would most likely be driven by the physiological stage of the animals rather than as a response to herbage NV.

5.3.3 Development of overall performance indicators

A principal component analysis (PCA) was performed on the performance per cow data to develop two overall performance per cow indicators. Prior analysis, data were scaled to a zero mean and a standard deviation of one. The PCA was performed using the 'prcomp' function available in R software (R Development Core Team 2011). This function uses the single value decomposition factorisation method to transform a set of correlated variables into a set of uncorrelated principal components (PC) that better expose the various relationships among the original variables. Loadings of the first (PC1) and second (PC2) principal component were interpreted in light of the original variables and PC1 and PC2 were thereafter termed Performance Indicator 1 (PI1) and Performance Indicator 2 (PI2), respectively. Scores of each observation were used as overall indicators of daily performance per cow. The sign of the scores were rescaled based on the interpretation of the principal components to a minimum of zero and a maximum of one hundred.

5.3.4 Statistical analysis

In order to determine the influence of grazing management decisions on the quantity of herbage offered to cows, herbage NV and the climate on the variation in daily performance per cow, three statistical modelling approaches were used: multiple linear regression (MLR), principal components regression (PCR) and partial least squares regression (PLS). The variables used in the modelling are summarised in Table 5.1.

Table 5.1 Variables used in the models

Variable ID	Description	Units
X-Explanatory variables		
HM	herbage mass	kg DM/ha
HA	herbage allowance	kg DM/cow/d
AH	area of herbage offered	ha/d
PD	proportion of herbage in diet	% of dietary DM
ME	herbage metabolisable energy	MJ/kg DM
CP	herbage crude protein	% DM
NDF	herbage neutral detergent fibre	% DM
ADF	herbage acid detergent fibre	% DM
Fibre	NDF + ADF	% DM
DM	herbage dry matter	% FM
T	daily mean temperature	◦C
THI	temperature humidity index	index
CSI	cold stress index	kJ/m2/h
Rain	rainfall	mm/d
POP	period of production: Early= between day 1 and day 90 from the beginning of milk production; Mid= 91 to 180 days; Late= 181 to 250 days.	Coded as dummy variable
Y	production season: 2016= 2016-17 production season; 2017= 2017-18 production season.	Coded as dummy variable
Y-Dependent variables		
MYpc	milk yield per cow in the herd	L/cow
MSYpc	milksolids yield per cow in the herd	kg MS/cow
MSPpc	milksolids percentage per cow in the herd	% MY
FPpc	milk fat percentage per cow in the herd	% MY
PPpc	milk protein percentage per cow in the herd	% MY
FYpc	milk fat yield per cow in the herd	kg F/cow
PYpc	milk protein yield per cow in the herd	kg P/cow
PFRpc	milk protein to fat ratio per cow in the herd	Ratio
MUpc	milk urea per cow in the herd	kg MU/cow
LWpc	live weight per cow in the herd	kg LW/cow
LWCpc	live weight change per cow in the herd	kg LW/cow
BCSpc	body condition score per cow in the herd	index (1–10 scale)
PI1*	performance indicator 1	index (0–100 scale)
PI2*	performance indicator 2	index (0–100 scale)

* PI1 and PI2 correspond to Principal Component 1 and Principal Component 2, respectively.
FM= herbage fresh matter (kg)

Multiple linear regression

Multiple linear regression was used to determine the relationship between a dependent variable and several independent explanatory variables as described by the following equation:

$$\mathbf{y} = \mathbf{X}\,\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad \text{(equation 5.4)}$$

where **y** is a vector of responses for *n* observations, **X** is a matrix of explanatory variables for *n* observations, **β** is a matrix of regression parameters and **ε** is a vector of random errors.

The objective of MLR is to find the estimate of **β** so that the sum of the squares of the differences between the observed dependent variable those predicted by the multiple linear function is minimised. Such objective is achieved by calculating the ordinary least squares estimator of **β** as:

$$\hat{\boldsymbol{\beta}} = \left(\mathbf{X}'\,\mathbf{X}\right)^{-1}\mathbf{X}'\,\mathbf{y} \qquad \text{(equation 5.5)}$$

MLR modelling was implemented with the package 'caret' available for R software (Kuhn 2015). A key assumption in MLR modelling is that all the explanatory variables to include in a model are independent of each other. This is important to reduce the incidence of multicollinearity, which can lead to increased variance of the coefficient estimates and make these estimates very sensitive to minor changes in the model. In order to avoid the problems associated with multicollinearity, highly correlated variables were excluded from the models by setting a cut-off value for pair-wise correlations of 0.9. The MLR algorithm used a step-wise variable selection criteria based on the computation of the Akaike information criterion (AIC). The AIC deals with the trade-off between the goodness of fit of the model and the simplicity of the model. In step-wise regression, variables are included and excluded iteratively from the set of explanatory variables with the AIC being calculated with each iteration. Once all the possible combinations of variables are considered, the model with the lowest AIC value is selected.

Principal components regression

Principal components regression can be described as a two-step process in which the explanatory variables are decomposed into principal components and then the dependent variable is regressed on the resultant principal component scores. The general

PCR model can be conceptualised using a similar notation than equation 5.4, but replacing the matrix of explanatory variables for a matrix of scores that result from the matrix decomposition described by the following equation:

$$\mathbf{X} = \mathbf{T}\,\mathbf{P}' + \mathbf{E} \qquad \text{(equation 5.6)}$$

where **X** is a matrix of *n* observations described by *p* explanatory variables, **T** is a score matrix for the *n* observations, **P** is a matrix of component loadings that correspond to a combination of linear relationships of the original variables and **E** is a matrix of random errors.

The principal component model is defined by the matrix product $\mathbf{T}\,\mathbf{P}'$, with the first principal component $\mathbf{t}\,\mathbf{p}'$ being obtained by singular value decomposition, where **t** is a vector of scores and **p'** is a transposed vector of component loadings. Similar to MLR, the PCR algorithm uses the least squares to regress **y** onto the vector corresponding to the first component $\mathbf{t}_1$ to estimate $\hat{\boldsymbol{\beta}}_1$. Thereafter, the following components are defined with respect to their orthogonality to the previous one, and estimations of their corresponding $\hat{\boldsymbol{\beta}}$ coefficients are obtained. Because principal components are orthogonal to one another, PCR easily overcomes the problem of multicollinearity.

Data were also analysed using the principal components regression (PCR) algorithm available in the package ‘caret’ for R software (Kuhn 2015). Prior to data analysis, explanatory variables were standardised to a mean equal to zero and a variance of one.

The PCR algorithm was combined with a leave-one-out cross-validation procedure, which was used to identify and determine the optimal number of components to retain in the model. The criterion on the number of components to retain was based on the ‘onesigma’ criterion for variable selection (Hastie et al. 2005). According to this criterion, starting from a model including all the components ordered from PC1 to the PC exhibiting the least variation, the optimal model is the first model where the RMSE-CV is within one standard error of the absolute minimum.

Partial least squares regression

Alternatively to MLR and PCR, a PLS regression modelling approach was performed also using the package ‘caret’ for R software (Kuhn 2015).

Similar to PCR, PLS aims at explaining a dependent variable from the scores of the few components resulting from the decomposition of a matrix of explanatory variables. The main difference between PLS and PCR is that PLS uses the variation of the dependent variable to guide the decomposition of the matrix of explanatory variables. Consequently, at a given level of accuracy, PLS models usually require fewer components to explain a response compared to PCR models.

In PLS terminology, the principal components that result from the decomposition of matrices are termed latent variables and follow a similar notation to that introduced in equation 6. Because PLS decomposes **X** onto **TP** structures guided by **y**, loading weights **w** define the direction in the space spanned by $\mathbf{X}_{a-1}$ of maximum covariance with **y**. The underlying PLS model for a single dependent variable is therefore defined as:

$$\mathbf{y} = \mathbf{T}\,\mathbf{q}' + \mathbf{e} \qquad \text{(equation 5.7)}$$

where **y** is a vector of responses for the *n* observations, **T** is a score matrix for the *n* observations, **q** is a vector of latent variable loadings and **e** is a vector of random errors.

Considering equations 6 and 7, the system of equations can be rearranged as:

$$\mathbf{y} = \mathbf{X}\,\mathbf{P}\,\mathbf{q}' + \mathbf{e} \qquad \text{(equation 5.8)}$$

and the matrix of $\hat{\boldsymbol{\beta}}$ coefficients that result from fitting a linear regression model as the one described in equation 5.4 are defined in the PLS method by establishing the relationship between **P** and **q** as conceptualised in the following equation:

$$\hat{\boldsymbol{\beta}} = \frac{\mathbf{y}}{\mathbf{X}} = \mathbf{P}\,\mathbf{q}' \qquad \text{(equation 5.9)}$$

where **q** is found by least squares regression of **y** on **T.**

The ‘caret’ package uses the modified kernel algorithm 1 published by Dayal and MacGregor (1997) to compute PLS scores and loading vectors. Like the method described for PCR, data were standardised prior to the analysis. Likewise, the optimal number of components to retain in the PLS model was chosen following the onesigma criterion based on the calculation of the RMSE-CV that resulted from applying a leave-one-out cross-validation procedure.

Model assessment and determination of the importance of explanatory variables

The performance of the developed models was assessed by calculating the coefficient of determination (R^2) and the root mean square error (RMSE). Based on these metrics, the MLR modelling approach, which resulted in overall higher R^2 values and lower RMSE values compared to PCR and PLS models was used to further investigate the relationships and importance of explanatory variables on cow performance.

MLR coefficients were used to investigate the relationships between explanatory and response variables. Furthermore, the relative importance of the explanatory variables on defining the final MLR models was expressed in terms of their relative contribution to the overall R^2. The relative importance metric was calculated using the method described by Lindeman (1980) and implemented with the function 'calc.relimp' available in the package 'relatimpo' for R software (Groemping and Matthias 2013).

5.4 Results

5.4.1 Overall per cow performance indicators

Two principal components: PC1 and PC2, were accountable for 50% and 20% of the variance of the data, respectively. The PCA was used to summarise the structure of the response dataset. In further analyses, the scores corresponding to PC1 and PC2 are termed Production Index 1 and Production Index 2, respectively and their interpretation is based on the component loadings in Table 5.2. As indicated by their loadings, the component that captured the most variability (PC1) was closely associated with yields of milk, milksolids, milk fat and milk protein. Conversely, the relatively less variable PC2 was associated with body condition score, live weight, change in live weight, milk urea and the percentages of milk fat and milk protein.

Table 5.2 Principal component loadings for the principal components 1 and 2 (PC1 and PC2, respectively).

Variable	PC1 (50%)[1]	PC2 (20%)[1]
MYpc	-0.40	0.04
MSYpc	-0.37	0.17
MSPpc	0.32	0.34
PFRpc	0.05	0.02
FPpc	0.28	0.31
PPpc	0.30	0.31
FYpc	-0.37	0.16
PYpc	-0.36	0.18
MUpc	-0.04	0.31
LWpc	0.25	0.32
LWCpc	0.11	-0.43
BCSpc	-0.23	0.44

[1]Variance explained for by the components within brackets.
MYpc= milk yield per cow in the herd, MSYpc= milksolids yield per cow in the herd, MSPpc= milksolids percentage per cow in the herd, FPpc= milk fat percentage per cow in the herd, PPpc= milk protein percentage per cow in the herd, FYpc= milk fat yield per cow in the herd, PYpc= milk protein yield per cow in the herd, PFRpc= milk protein to fat ratio per cow in the herd, MUpc= milk urea per cow in the herd, LWpc= live weight per cow in the herd, LWCpc= live weight change per cow in the herd, BCSpc= body condition score per cow in the herd

5.4.2 Descriptive statistics

Descriptive statistics of the variables used in the models are summarised in Table 5.3. Production indices 1 and 2, milk urea, and yields for milk, milksolids, protein and fat were the response variables that varied the most (68.2% > CV > 11.1%), while the most variation of explanatory variables was observed for the area of herbage allocated daily to the cows, herbage allowance, proportion of herbage in the diet and temperature (34.7% > CV > 25.7%). Relatively little variation was found for any of the measured NV traits. However, the variation of DM and CP was relatively higher (19.8% and 12.3%, for DM and CP, respectively) than the variation of herbage ME and fibre (8.5% and 4.7%, respectively).

Table 5.3 Descriptive statistics of modelling variables.

Variable	N	Mean	SD	CV%	Min	Max
X-Explanatory variables						
HM, kg DM/ha	140	2908	204	7.0	2514	3487
HA, kg DM/cow/d	140	29.50	8.54	28.9	10.89	46.28
PD, % DM	140	77.32	27.4	27.3	23.0	100.0
AH, ha/d	140	2.29	0.79	34.7	0.50	4.04
ME	140	10.86	0.52	4.7	9.36	11.66
CP, % DM	140	17.49	2.15	12.3	10.77	21.89
Fibre, % DM	140	60.12	5.15	8.57	51.56	77.70
DM, % FM	140	21.80	4.32	19.8	15.38	35.78
T, ◦C	140	15.02	3.86	25.7	6.39	23.32
THI	140	66.18	7.02	10.6	51.69	81.04
CSI, kJ m^{-2}/h	140	1199	78.4	6.5	1085	1495
Rain, mm/d	140	2.76	4.82	-	0.00	25.40
Y-Response variables						
MYpc, L/cow/d	140	16.08	2.13	13.25	9.53	19.77
MSYpc, kg MS/cow/d	140	1.47	0.16	11.1	0.90	1.76
MSPpc, % MY	140	9.06	0.38	4.2	8.57	10.47
FPpc, % MY	140	5.20	0.23	4.5	4.77	6.00
PPpc, % MY	140	3.96	0.19	4.91	3.63	5.51
FYpc, kg F/cow	140	0.83	0.09	11.41	0.52	1.00
PYpc, kg P/cow	140	0.63	0.07	11.18	0.38	0.78
PFRpc, ratio	140	0.76	0.03	4.2	0.65	0.84
MUpc, kg MU/cow	140	0.06	0.02	32.7	0.03	0.13
LWpc, kg LW/cow	140	479.1	4.03	0.84	474.0	492
LWCpc, kg LW/cow	140	0.03	0.41	-	-1.57	1.33
BCSpc, (1–10 scale)	140	4.61	0.18	3.8	4.42	5.02
PI1, (1–100 scale)	140	67.05	22.68	33.83	0	100
PI2, (1–100 scale)	140	28.13	19.18	68.17	0	100

HM= herbage mass, HA= herbage allowance, AH= area of herbage offered, PD= proportion of herbage in diet, ME= herbage metabolisable energy, CP= herbage crude protein, DM= herbage dry matter, FM= herbage fresh matter, T= daily mean temperature, THI= temperature humidity index, CSI= cold stress index, Rain= rainfall, MYpc= milk yield per cow in the herd, MSYpc= milksolids yield per cow in the herd, MSPpc= milksolids percentage per cow in the herd, FPpc= milk fat percentage per cow in the herd, PPpc= milk protein percentage per cow in the herd, FYpc= milk fat yield per cow in the herd, PYpc= milk protein yield per cow in the herd, PFRpc= milk protein to fat ratio per cow in the herd, MUpc= milk urea per cow in the herd, LWpc= live weight per cow in the herd, LWCpc= live weight change per cow in the herd, BCSpc= body condition score per cow in the herd, PI1= performance indicator 1, PI2= performance indicator 2.

The variability observed in the data yielded the correlations presented in Table 5.4. There were significant relationships among most performance per cow variables ($-0.5 \geq r \geq 0.5$ and $p < .05$). Yields for milk, milksolids, fat and protein were positively related to each other but negatively related to the percentages of fat and protein in milk and live weight.

As expected, negative relationships were observed between contents of ME and of DM and fibre in herbage ($-0.78 \geq r \geq -0.85$). There were also significant relationships between CP and any other herbage NV trait, but the strength of these relationships was relatively weak ($0.62 \geq r \geq -0.33$).

Herbage allowance was positively related to HM, the proportion of herbage in diet, as well as with the area of herbage allocated to the animals and the ME content of herbage ($0.88 \geq r \geq 0.51$). Although there were significant relationships between the determinants of herbage quantity and the various performance per cow variables, the strength of these relationships was not strong ($r \leq 0.46$). Herbage ME was positively related to yields for milk, milksolids, fat and protein, BCS and the production index 1 ($0.72 \geq r \geq 0.66$). Moreover, content of CP in herbage was positively related to BCS.

Temperature and the temperature-humidity index were negatively related with yields for milksolids, milk fat, milk protein, BCS and production index 2 ($0.83 \geq r \geq 0.51$). The relationships between the period of production and all the cow performance indicators were significant. The amount of milk, milksolids, milk fat and milk protein produced on a day to day basis, as well as the average condition score of the cows in the herd decreased as production progressed from early to late stages.

Table 5.4 Pearson correlation coefficient (r) matrix for herbage, climate and per cow performance variables (n= 140).

Variable	HM	HA	AH	PD	ME	CP	Fiber	DM	T	THI	CSI	Rain	MYpc	MSYpc	MSPpc	PFRpc	FPpc	PPpc	FYpc	PYpc	MUpc	LWpc	LWCpc	BCSpc	PI1	PI2	POP	Y
HM	1																											
HA	**0.51*****	1																										
AH	0.28***	**0.86*****	1																									
PD	0.49***	**0.88*****	**0.73*****	1																								
ME	0.31***	**0.54*****	0.35***	0.47***	1																							
CP	0.15	0.25**	0.05	0.2*	0.45***	1																						
Fiber	-0.16	-0.48***	-0.28***	-0.44***	**-0.85*****	-0.33***	1																					
DM	-0.41***	**-0.54*****	-0.39***	-0.47***	**-0.78*****	**-0.62*****	**0.53*****	1																				
T	-0.28***	-0.4***	-0.06	-0.36***	**-0.58*****	-0.32***	**0.62*****	0.4***	1																			
THI	-0.24**	-0.44***	-0.12	-0.39***	**-0.56*****	-0.35***	**0.59*****	0.4***	**0.9*****	1																		
CSI	-0.08	0.04	0.12	0	-0.12	-0.08	0.11	0.07	0.09	0.08	1																	
Rain	-0.1	0.04	0.06	0.01	-0.04	0.01	0.04	0.01	0.02	0.08	**0.8*****	1																
MYpc	0.31***	0.39***	0.23**	0.37***	**0.66*****	0.14	-0.49***	**-0.51*****	-0.47***	-0.42***	-0.2*	-0.13	1															
MSYpc	0.31***	0.41***	0.19*	0.39***	**0.69*****	0.17*	**-0.57*****	**-0.51*****	**-0.57*****	**-0.51*****	-0.16	-0.08	**0.97*****	1														
MSPpc	-0.22*	-0.16	-0.21*	-0.19*	-0.34***	0.02	0.07	0.31***	-0.01	0.01	0.28***	0.26**	**-0.73*****	**-0.55*****	1													
PFRpc	-0.24**	-0.41***	-0.45***	-0.33***	-0.34***	-0.07	0.21*	0.29***	0.18*	0.2*	-0.18*	-0.14	-0.09	-0.1	0.03	1												
FPpc	-0.1	0.02	-0.01	-0.04	-0.17*	0.05	-0.02	0.17*	-0.07	-0.06	0.33***	0.3***	**-0.64*****	-0.47***	**0.91*****	-0.38***	1											
PPpc	-0.3***	-0.34***	-0.4***	-0.32***	-0.45***	-0.01	0.16	0.4***	0.07	0.09	0.14	0.14	**-0.66*****	**-0.52*****	**0.87*****	**0.52*****	**0.58*****	1										
FYpc	0.34***	0.46***	0.26**	0.43***	**0.72*****	0.18*	**-0.59*****	**-0.54*****	**-0.58*****	**-0.53*****	-0.11	-0.05	**0.96*****	**0.99*****	**-0.54*****	-0.25**	-0.4***	**-0.58*****	1									
PYpc	0.25**	0.32***	0.09	0.31***	**0.62*****	0.15	**-0.52*****	-0.44***	**-0.53*****	-0.46***	-0.2*	-0.12	**0.95*****	**0.97*****	**-0.55*****	0.13	**-0.56*****	-0.4***	**0.93*****	1								
MUpc	0.01	0.21*	0.01	0.15	0.29***	0.48***	-0.21*	-0.29***	-0.38***	-0.43***	0.02	0.05	0.08	0.11	0.05	-0.03	0.05	0.04	0.11	0.11	1							
LWpc	-0.18*	-0.05	-0.11	-0.09	-0.19*	-0.06	-0.13	0.24**	0.03	0.05	0.18*	0.2*	**-0.52*****	-0.4***	**0.74*****	0.2*	**0.6*****	**0.72*****	-0.42***	-0.36***	0.07	1						
LWCpc	-0.03	0.02	0.33***	-0.02	-0.28***	-0.12	0.32***	0.09	0.45***	0.39***	0.13	0.04	-0.26**	-0.35***	-0.06	-0.04	-0.04	-0.08	-0.33***	-0.36***	-0.21*	-0.06	1					
BCSpc	0.26**	0.39***	-0.03	0.37***	**0.69*****	**0.53*****	**-0.69*****	**-0.51*****	**-0.83*****	**-0.78*****	-0.14	-0.03	**0.58*****	**0.67*****	-0.12	-0.13	-0.06	-0.15	**0.67*****	**0.64*****	0.46***	-0.11	**-0.56*****	1				
PI1	0.32***	0.36***	0.2	0.36***	**0.65*****	0.17	-0.44***	**-0.51*****	-0.45***	-0.41***	-0.23**	-0.17*	**0.98*****	**0.93*****	**-0.8*****	-0.13	**-0.69*****	**-0.74*****	**0.92*****	**0.9*****	0.11	**-0.64*****	-0.28**	**0.58*****	1			
PI2	0.02	0.18*	-0.19	0.14	0.34***	0.35***	**-0.52*****	-0.17*	**-0.64*****	**-0.59*****	0.06	0.15	0.07	0.27**	**0.53*****	0.04	0.47***	0.48***	0.25**	0.27**	0.48***	**0.51*****	**-0.67*****	**0.69*****	0	1		
POP	-0.26**	-0.4***	-0.1	-0.37***	**-0.7*****	-0.34***	**0.63*****	0.5***	**0.71*****	**0.66*****	0.15	0.04	**-0.8*****	**-0.82*****	0.44***	0.17*	0.34***	0.45***	**-0.82*****	**-0.78*****	-0.34***	0.38***	0.42***	**-0.85*****	**-0.81*****	-0.39***	1	
Y	-0.19*	-0.32***	-0.39***	-0.29***	-0.3***	-0.04	0.34***	0.23**	0.12	0.12	-0.13	-0.14	0.05	0.01	-0.17*	0.14	-0.21*	-0.08	-0.02	0.04	0.06	-0.04	0	-0.07	0.06	-0.1	0.01	1

Bold numbers indicate $-0.5 \geq r \geq 0.5$.

* Significant at $p < 0.05$, ** Significant at $p < 0.01$, *** Significant at $p < 0.001$.

HM= herbage mass, HA= herbage allowance, AH= area of herbage offered, PD= proportion of herbage in diet, ME= herbage metabolisable energy, CP= herbage crude protein, DM= herbage dry matter, T= daily mean temperature, THI= temperature humidity index, CSI= cold stress index, Rain= rainfall, MYpc= milk yield per cow in the herd, MSYpc= milksolids yield per cow in the herd, MSPpc= milksolids percentage per cow in the herd, FPpc= milk fat percentage per cow in the herd, PPpc= milk protein percentage per cow in the herd, FYpc= milk fat yield per cow in the herd, PYpc= milk protein yield per cow in the herd, PFRpc= milk protein to fat ratio per cow in the herd, MUpc= milk urea per cow in the herd, LWpc= live weight per cow in the herd, LWCpc= live weight change per cow in the herd, BCSpc= body condition score per cow in the herd, PI1= performance indicator 1, PI2= performance indicator 2, POP= period of production, Y= production season.

5.4.3 Model results

Model fit metrics indicate that for any response variable, the three modelling approaches resulted in similar R^2 and RMSE values (Table 5.5). Most response variables were explained with high R^2 values ($0.93 \geq R^2 \geq 0.68$) and only milk fat percentage, milk urea, milk protein to fat ratio and live weight change were explained with relatively lower R^2 values ($0.34 \geq R^2 \geq 0.54$).

Table 5.5 Metrics of fit for multiple linear regression (MLR), principal components regression (PCR) and partial least squares regression (PLS) models.

	MLR			PCR			PLS		
Response variable	R^2	RMSE	No. vars	R^2	RMSE	No. Cmps	R^2	RMSE	No. LVs
MYpc	0.80	0.95	9	0.83	0.98	9	0.83	1.00	3
MSYpc	0.76	0.08	4	0.77	0.09	6	0.74	0.08	2
MSPpc	0.73	0.20	10	0.61	0.23	14	0.69	0.22	6
PFRpc	0.34	0.03	9	0.32	0.03	1	0.33	0.03	1
FPpc	0.54	0.16	7	0.58	0.16	9	0.55	0.17	3
PPpc	0.76	0.09	10	0.75	0.10	15	0.70	0.11	7
FYpc	0.79	0.04	7	0.82	0.05	8	0.79	0.05	2
PYpc	0.68	0.04	5	0.69	0.04	7	0.70	0.04	2
MUpc	0.38	0.02	7	0.44	0.02	2	0.44	0.02	1
LWpc	0.70	2.20	10	0.63	2.47	14	0.60	2.50	7
LWCpc	0.47	0.28	6	0.43	0.31	12	0.44	0.31	4
BCSpc	0.96	0.04	10	0.97	0.04	15	0.96	0.04	9
PI1	0.84	9.05	9	0.82	9.85	9	0.83	10.23	4
PI2	0.78	8.95	10	0.73	9.56	15	0.68	9.75	9

MYpc= milk yield per cow in the herd, MSYpc= milksolids yield per cow in the herd, MSPpc= milksolids percentage per cow in the herd, FPpc= milk fat percentage per cow in the herd, PPpc= milk protein percentage per cow in the herd, FYpc= milk fat yield per cow in the herd, PYpc= milk protein yield per cow in the herd, PFRpc= milk protein to fat ratio per cow in the herd, MUpc= milk urea per cow in the herd, LWpc= live weight per cow in the herd, LWCpc= live weight change per cow in the herd, BCSpc= body condition score per cow in the herd, PI1= performance Indicator 1, PI2= performance Indicator 2.

The number of explanatory variables retained by the MLR models ranged from 4 to 10, whereas the optimal number of principal components retained by the PCR models ranged from 1 to 15 and those retained by the PLS regression models from 1 to 9. Regression coefficients for the different MLR models are shown in Table 5.6 and regression coefficients for PCR and PLS models are shown in Tables C.1 and C.2 of Appendix C, respectively. The relative importance of the linear regressors that were estimated for the different response variables is shown in Table 5.7.

Table 5.6 Estimated multiple linear regression coefficients.

Response variable	Explanatory variable: Intercept	HM	HA	AH	PD	ME	CP	DM	Fibre	T	THI	CSI	Rain	POP: Early	POP: Mid	Y: 2016
MYpc	-8.59	0.00089†	-0.077*	0.82*		1.67***			0.07*			-0.0021†		3.98***	3.04***	-0.64**
MSYpc	0.28					0.09***								0.27***	0.21***	-0.03**
MSPpc	15.84	-0.00029*	0.032***	-0.34***		-0.39***			-0.03***	-0.03***		0.0010***		-0.74***	-0.58***	0.15**
PFRpc	1.44	-0.00003*	0.002*	-0.03***		-0.04**		-0.001†	0.001†	0.001†		-0.0001*				0.01†
FPpc	7.69		0.004†			-0.16**			-0.02***	-0.02***		0.0008***		-0.43***	-0.37***	
PPpc	9.22	-0.00025***	0.021***	-0.26***		-0.30***		-0.006†	-0.02***	-0.01†		0.0002†		-0.30***	-0.22***	0.11***
FYpc	-0.25			0.01†		0.09***	-0.005†		0.002†					0.16***	0.11***	-0.02*
PYpc	0.36					0.03*						-0.0001†		0.12***	0.09***	-0.01†
MUpc	-0.04	-0.00003**	0.001**	-0.01*		0.01†	0.003***		0.001*		-0.001**					
LWpc	604.49		0.416***	-3.29***	-0.03†	-5.46***	-0.471**	-0.159†	-0.85***				0.15***	-8.56***	-6.56***	-1.18*
LWCpc	-0.15	0.00060***	-0.057***	0.74***		-0.14*									-0.16**	-0.16**
BCSpc	5.10	-0.00008***	0.014***	-0.16***			0.005†	-0.003†	0.003***	-0.01**	-0.002†			0.19***	0.06***	0.02**
PI1	-273.23	0.00830†	-0.879**	8.81**		22.05***			1.53***			-0.0305**		45.59***	33.53***	-5.72**
PI2	227.24	-0.02630***	2.877***	-31.05***		-5.97†			-1.40***	-1.35***		0.0333**		-11.80**	-11.61***	5.02**

†Significant at $p < 0.1$, * Significant at $p < 0.05$, ** Significant at $p < 0.01$, *** Significant at $p < 0.001$

MYpc= milk yield per cow in the herd, MSYpc= milksolids yield per cow in the herd, MSPpc= milksolids percentage per cow in the herd, FPpc= milk fat percentage per cow in the herd, PPpc= milk protein percentage per cow in the herd, FYpc= milk fat yield per cow in the herd, PYpc= milk protein yield per cow in the herd, PFRpc= milk protein to fat ratio per cow in the herd, MUpc= milk urea per cow in the herd, LWpc= live weight per cow in the herd, LWCpc= live weight change per cow in the herd, BCSpc= body condition score per cow in the herd, PI1= performance indicator 1, PI2= performance indicator 2

HM = herbage mass, HA= herbage allowance, AH= area of herbage offered, PD= proportion of herbage in diet, ME= herbage metabolisable energy, CP= herbage crude protein, DM= herbage dry matter, T= daily mean temperature, THI= temperature humidity index, CSI= cold stress index, Rain= rainfall, POP:Early= period of production defined between day 1 and day 90 from the beginning of milk production, POP:Mid= period of production defined between day 91 and day 180 from the beginning of milk production,Y:2016= 2016-17 production season.

Table 5.7 Relative importance of multiple linear regressors.

Response variable	Explanatory variable															
	HM	HA	AH	PD	ME	CP	Fibre	DM	T	THI	CSI	Rain	POP: Early	POP: Mid	Y: 2016	R^2
MYpc	0.03	0.04	0.02		0.20		0.08				0.02		0.21	0.18	0.03	0.80
MSYpc					0.30								0.30	0.15	0.01	0.76
MSPpc	0.02	0.03	0.04		0.12		0.05		0.03		0.06		0.11	0.22	0.05	0.73
PFRpc	0.02	0.06	0.11		0.05		0.02	0.02	0.01		0.03				0.01	0.34
FPpc		0.01			0.05		0.04		0.04		0.09		0.10	0.21		0.54
PPpc	0.04	0.06	0.10		0.15		0.06	0.05	0.02		0.01		0.07	0.16	0.04	0.76
FYpc			0.03		0.24	0.03	0.12						0.24	0.11	0.02	0.79
PYpc					0.22						0.02		0.28	0.14	0.01	0.68
MUpc	0.02	0.04	0.03		0.03	0.14	0.02			0.10						0.38
LWpc		0.03	0.03	0.01	0.08	0.02	0.18	0.04				0.04	0.13	0.15	0.01	0.70
LWCpc	0.02	0.11	0.24		0.08									0.02	0.01	0.47
BCSpc	0.02	0.07	0.06			0.05	0.11	0.05	0.17	0.14			0.25	0.04	0.00	0.96
PI1	0.03	0.04	0.02		0.21		0.08				0.03		0.23	0.18	0.03	0.84
PI2	0.02	0.09	0.13		0.04		0.12		0.17		0.02		0.09	0.10	0.01	0.78

MYpc= milk yield per cow in the herd, MSYpc= milksolids yield per cow in the herd, MSPpc= milksolids percentage per cow in the herd, FPpc= milk fat percentage per cow in the herd, PPpc= milk protein percentage per cow in the herd, FYpc= milk fat yield per cow in the herd, PYpc= milk protein yield per cow in the herd, PFRpc= milk protein to fat ratio per cow in the herd, MUpc= milk urea per cow in the herd, LWpc= live weight per cow in the herd, LWCpc= live weight change per cow in the herd, BCSpc= body condition score per cow in the herd, PI1= performance indicator 1, PI2= performance indicator 2

HM= herbage mass, HA= herbage allowance, AH= area of herbage offered, PD= proportion of herbage in diet, ME= herbage metabolisable energy, CP= herbage crude protein, DM= herbage dry matter, T= daily mean temperature, THI= temperature humidity index, CSI= cold stress index, Rain= rainfall, POP:Early= period of production defined between day 1 and day 90 from the beginning of milk production, POP:Mid= period of production defined between day 91 and day 180 from the beginning of milk production,Y:2016= 2016-17 production season.

The relative importance of herbage related variables on explaining any of the responses was higher than the importance of the climatological variables (Table 5.7). Moreover, herbage quantity defining variables namely herbage area, herbage mass, herbage allowance and proportion of herbage in diet were relatively less important on explaining the various responses than the differences in herbage NV.

Most responses in performance per cow, except for milk urea and milk protein to fat ratio were significantly ($p < 0.001$) influenced by the period of production (Table 5.6). Herbage ME was significantly related with all performance per cow variables ($0.001 > p > 0.1$) except for BCS. Variation of herbage ME accounted for as much as 30% of the variation of milksolids and as little as 3% of the variation of the of milk urea. Moreover, regression coefficients in Table 5.6 indicate that herbage ME was positively related to milk, milksolids, fat, protein, milk urea, BCS and PI1 and negatively related to the percentages of milk constituents, live weight, live weight change and PI2.

Fibre influenced performance per cow in the same way herbage ME did. However, the influence of fibre on any performance per cow response variable was of a lower magnitude compared to ME, as indicated by the lower regression coefficients and the lower relative importance of fibre on explaining the various responses in terms of their R^2. Fibre was more important in explaining LW than ME (18% vs 8% of the variation of LW for fibre and ME, respectively), with higher levels of fibre resulting in lower LW.

Crude protein was of high relative importance in explaining variation of milk urea (14% of R^2) and of relatively less importance to explain BCS, milk fat yield and LW (5%, 3% and 2% of R^2, respectively). Higher levels of crude protein in herbage were associated with higher levels of urea in milk and BCS but lower milk fat yield and LW. DM was a significant factor explaining milk protein to fat ratio, milk protein yield, LW and BCS, but the relative importance of DM was relatively low (< 5% of R^2).

Herbage quantity variables were significant predictors of most of the performance per cow response variables measured ($p < 0.05$). However, as mentioned above, the relative importance of herbage quantity associated variables on performance per cow was, in general, relatively small ($1 < \%$ of $R^2 < 24$) compared to the importance of herbage of NV ($3 < \%$ of $R^2 < 24$). Changes in the area of herbage allocated to cows were responsible for explaining 24% of the variation of live weight change, 13% of production index 2, 11% of milk protein to fat ratio and 10% of milk protein percentage, with higher areas being related with higher changes in live weight, but lower milk fat to protein ratio, milk protein percentage and PI2. Interestingly, the influence of herbage allowance on performance per cow responses was opposite to that observed for herbage mass and area, as indicated by the opposite sign of their regression coefficients (Table 5.6). Although HM significantly explained many of the performance per cow variables, its importance was relatively small (from 2 to 4% of R^2).

Temperature and cold-stress index were significantly related to the highest number of performance per cow variables. Temperature was particularly important for explaining BCS (17% of R^2) and PI2 (17% of R^2), with these two variables decreasing with higher temperatures. CSI was important in explaining the variation in the percentages of protein (9% of R^2) and milksolids (6% of R^2), with higher CSI being related to percentages of protein and solids in milk.

5.5 Discussion

This chapter was set out to determine the influence of the nutritive value of herbage and other herbage and climate related factors on the performance of a pasture-based dairy farm system on a per cow basis. The following sections discuss the findings of this study in light of the existing literature on the topic.

5.5.1 Pasture-based dairy farm system performance per cow

An interesting feature in this research was the development of performance indices based on a multivariate analysis of the data. Such analysis allowed the synthesis of the assessment of the various performance per cow metrics used in this study into two indexes: PI1 and PI2. PI1 was associated with yields of milk, milksolids, fat and protein in milk produced per cow in the herd, which are important determinants of net profit in pasture-based systems (Hanrahan et al. 2018). On the other hand, PI2 was more closely related with milk urea, live weight, live weight change and BCS per cow. Urea in milk is a useful indicator of appropriateness of the ratio of crude protein to energy in the diet of dairy cows (Moller et al. 1993). Excess crude protein in the diet of grazing dairy cows was associated with reduced milk production (Moller et al. 1993) and reduced reproductive performance (McCormick et al. 1999). Moreover, live weight, live weight change and BCS are also relevant for defining feeding targets for maintenance, production and reproductive functions of dairy cows (AFRC 1993). Changes in a cow's body condition score and live weight provide information about the cow's current nutrient intake relative to their requirements (Roche et al. 2009).

It is important to highlight that there was no relationship between PI1 and PI2 since the principal components resulting from the PCA are orthogonal. However, this does not mean that relevant variables defining the components are not related since principal components are the result of a combination of linear relationships of the original variables (Abdi and Williams 2010) and loadings in Table 5.2 indicate that all the original performance variables yielded, to some extent, to the two most relevant principal components. Consequently, relationships between PI1- and PI2-related variables exist as supported by the correlations in Table 5.4. In this sense, although energy stored as BCS (Roche et al. 2007) and live weight (Berry et al. 2006) have a close relationship with milk production, a comprehensive literature review by Roche et al. (2009) describes that there are inconsistencies in the associations between BCS and milk production, with published data indicating both positive and negative relationships.

5.5.2 Seasonality of the farm system influence on performance per cow

The fact that any performance per cow metric was highly dependent on the period of production can be explained by the characteristic seasonality of low-cost pasture-based dairy farm systems. In these systems, milk production, and thus cow performance, are driven by availability of herbage, which is dependent on seasonal factors such as rainfall and temperature (Holmes 2007). In practice, the system is managed to ensure that cows calve in a tight pattern before spring and are dried-off in autumn so as the requirements of the herd are matched with the typical temperate herbage growth pattern (Parker et al. 1997). By doing this, the physiological stage of the cows in the herd is synchronised so as the earlier stages of the milk production process result in cows producing higher yields of milk, milksolids, fat and protein compared to the later stages in the production process.

The physiological stage of a cow is a relevant factor driving milk production and composition (Bargo et al. 2003; Kolver 2003; Walker et al. 2004). The increment in the percentages of fat and protein in milk in the later stages of the production process are a consequence of higher yields for fat and protein relative to milk volume. Similar to milk production, live weight and BCS are also affected by the physiological status of the cows, with both live weight and BCS profiles being similar to an inverted lactation curve.

Loss of live weight and BCS mobilisation in the early stage of lactation are most likely to be genetically driven (Roche et al. 2009). However, the literature is not conclusive on the reason for the increase of these parameters after nadir (between 40 to 100 days after calving); with studies (Berry et al. 2006; Roche et al. 2007) suggesting that nutrition plays the most significant role at these stages. Because herbage NV, herbage quantity and some climate factors were controlled for in the analysis of the data, there might be other factors other than herbage NV associated with the seasonality of the farm system that were not considered in this study that might be influencing animal performance (e.g. proportion of legumes in the herbage mix).

5.5.3 Herbage nutritive value and quantity influence on performance per cow

A relevant finding in this research is that the ME of the herbage available to the animals was able to explain a large proportion of the variability of the performance per cow of the pasture-based dairy farm system. Metabolisable energy is a well-known factor limiting milk production in pasture-based dairy farm systems (Kolver and Muller 1998; Kolver 2003; Wales and Kolver 2017). In these systems, herbage ME is a relevant driver of animal performance, particularly when the amount of herbage available to cows does not limit dry matter intake. Higher ME signifies more energy per unit of DM being available for processes of milk production and can also signify higher intakes of herbage, resulting in increased milk production (Waghorn and Clark 2004).

Dry matter intake is understood to be the single most important factor driving performance of grazing dairy cows and is mostly controlled by HA (Dillon 2007; Poppi et al. 1987). In this study, the importance and level of significance of HA on explaining animal performance were relatively lower than those of herbage ME, indicating that HA posed less limits to milk yield than herbage ME. This is an important finding because it means that measuring herbage NV in addition to herbage quantity may be beneficial to devise strategies to optimise milk production.

The relationship between HA and milk yield is curvilinear, with the marginal response of milk yield decreasing as HA increases, hence management is concerned with controlling HA in order to optimise grazing efficiency while ensuring a level of dry matter intake to sustain a desired level of milk yield. Bargo et al. (2003) describes that a practical guide to optimise herbage utilisation is to define a HA of 25 kg DM/cow/d when cows are also fed supplements. Moreover, a meta-analysis on the effect of HA on milk production on dairy cows, Pérez-Prieto and Delagarde (2013) identified that the response of milk yield to HA is low (0.003 lts kg/HA) when HA increased from 40 to 60 kg DM/cow/d. The mean HA in this study was 29.5 kg DM/cow/d. This value suggests that, in the light of the existing literature, the cows in the study were, on average, offered enough herbage to not limit DMI and thus animal performance. Hence, the higher relevance of herbage ME over HA for explaining any of the animal performance indicators.

Interestingly, herbage ME was negatively related with milk protein percentage. This is possibly caused by a shortfall in the supply of CP relative to ME, which may result in insufficient amino acids being available to satisfy the needs for milk protein synthesis. Walker et al. (2004) reported that CP in excess of requirements have variable (negative to positive response) effects on the percentage of protein in milk, but usually increase the yield of protein when the protein source is balanced for milk protein synthesis. Excess protein in herbage relative to the requirements of the cows may also be a reason for explaining the positive relationship between CP and milk urea (Sinclair et al. 2014).

The negative relationship between fibre content and live weight may be the consequence of reduced rumen fill, resulting from reduced dry matter intakes associated with higher fibre content. Fibre increases chewing time and reduces rate of passage of herbage through the digestive system of cows (Waghorn et al. 2007). Chewing is necessary to break fibre to increase rate of digestion of the cellulose and hemicellulose and to enable undigested residues to pass out of the rumen (Dado and Allen 1995; Allen 1996). Consequently, higher levels of fibre in herbage reduced DMI which may explain the negative relationship between fibre and live weight.

The area of herbage offered to the cows was the herbage quantity defining variable that was of most importance for explaining performance per cow, and it was of particular relevance for the case of live weight change and PI2. It is likely that controlling the area of herbage has provided the farm manager with more accurate allocation than controlling HA. This may be because measuring area is more accurate than measuring herbage mass, as seasonal changes in the structure and species composition of mixed swards might have required changes in the estimation of HM with the rapid pasture meter (King et al. 2010)

5.5.4 Climate influence on performance per cow

The THI, which combines the effects of temperature and humidity relative to a standard level of thermal stress had a significant negative influence on BCS. When cows are heat stressed, heat gained exceeds heat lost triggering physiological, anatomical or behavioural changes in the attempt to maintain heat balance (West 2003). Davis et al. (2003) proved that as THI increases dairy cows tend to reduce their intake of DM in order to control heat stress. In New Zealand, work by Bryant et al. (2007) describes that THI values above 68, 69 and 75 reduce milk production of Holstein, Jersey and Holstein x Jersey cows, respectively arguably due to the negative effect of heat stress on DMI. Although THI values calculated in this study were, on average, lower than threshold values described by Bryant et al. (2007) there were 56 days in which cows were exposed to conditions of heat stress of THI above 68. It is possible that due to heat stress, cows restrict intake of dry matter and that this is reflected in higher mobilisation of energy from body condition to milk production, explaining the negative relationship between THI and BCS.

In accordance to Gao et al. (2017), this study found a negative relationship between THI and milk urea. Interestingly, THI had no significant effect on milk production or milk composition traits. However, there were significant negative relationships between temperature and percentages of protein and fat in milk and their ratio. Negative relationships between temperature and milk fat and protein percentages were also identified by Yano et al. (2014). The fact that THI and temperature are related to different animal performance metrics may relate to differences in the accuracies of temperature and humidity data. The mechanisms regulating concentration of protein in milk during heat stress are largely unknown (Amamou et al. 2019). Possible regulation of milk protein may involve increased protein turnover and competition for amino acids for other functions (Bequtte and Backwell 1997) and limitations in the precursor supply caused by the reduction in mammary blood flow (Gao et al. 2017). Moreover, milk fat percentage may be explained by reductions in proportions of acetate in the rumen (Bandaranayaka and Holmes 1976).

The relative importance of cold temperature on performance per cow was low compared to high temperatures. Similar to this study, Bryant et al. (2007) found positive linear relationships between CSI and percentages of fat and protein in milk. Bryant et al.

(2007) argues that a CSI of 1300 kJ/m^2/h should be treated as a tentative upper threshold at which cow performance is reduced due to cold temperatures, a condition that is not usual in seasonal farm systems where cows are not milked during winter.

5.5.5 Chosen strategy for data analysis

Although three modelling approaches were used to analyse the data, the MLR approach was preferred over PCR or PLS. Both PCR and PLS have many advantages over MLR, including the ability to robustly handle a large number of non-orthogonal descriptor variables while providing good predictive accuracy and a much lower risk of chance correlation. However, major limitations of PCR and PLS include a higher risk of overlooking real correlations and sensitivity to the relative scaling of the descriptor variables, which limit the interpretation of results in the light of the objectives set by this research. In addition, because there were not large differences among the performance of the various models, the option of choosing MLR over the other two approaches was justified.

5.5.6 Opportunities to improve farm management

Results in this study suggest there were opportunities that could be considered by management to improve performance per cow in the pasture-based dairy farm system under scrutiny. Given that performance per cow was highly influenced by herbage ME, having rapidly available information of both performance per cow and herbage ME could potentially be useful to improve feed allocation by allowing a more precise match between supply and demand of energy, potentially resulting in more efficient grazing and feed use. Similarly, having rapidly available information on the CP content of herbage could be useful to define feeding strategies to reduce the negative effect excess N could have on cow performance and the environment. Excess dietary CP in Dairy 1, as inferred from the positive relationship between herbage CP and milk urea, can be controlled by feeding cows with a diet balanced for energy and CP content (Nousiainen et al. 2004; Maltz et al. 2013). This can be done, for example, by replacing herbage of high CP with maize or cereal silage of low CP content (Klein et al. 2002; Ledgard et al. 2006). By doing this, the risk of negatively affecting the reproductive performance of cows (McCormick et al. 1999) or excreting high levels of N-urine that could leak into waterways (De Klein et al. 2002) could be reduced. Furthermore, supported by the evidence in this study, a future scenario of climate change characterised by increasing temperature suggest that the diet offered to the herd could also be formulated to account for the negative effect of increasing temperature on BCS. Previous studies have identified that bentonite clay supplementation can improve ruminal fermentation or performance of lactating dairy cows during stressful conditions that can compromise ruminal function, such as heat stress (Zhu et al., 2016; Acharya et al., 2017; Jiang et al. 2018). The use of cattle heat stress monitors or weather stations could then complement the use of rapid NV measurement to define feeding strategies and improve pasture-based feeding to mitigate the negative effects of heat stress of cow performance.

5.6 Conclusion

This study shows that day-to-day variation of herbage nutritive value in a pasture-based dairy farm system is a relevant driver of performance on a per cow basis. Results indicated that the daily variation of herbage ME explained from 20% to 30% of the production of milk, milk fat and milk protein per cow. Herbage quantity and climatological factors were relatively less important than herbage NV in defining performance per cow. These results indicate that measuring herbage NV is potentially relevant for informing decision making around the daily allocation of feed to cows. Maintaining or improving the NV of the herbage offered to cows is thus a key challenge for the dairy farm management. Developing feeding strategies aimed at improving the efficiency of feeding of cows by exploiting the variation of herbage NV to better match daily supply of nutrients animal nutritional requirements may be useful to improve the overall performance of pasture-based dairy farming systems. In order to achieve this, further research is required to investigate the extent at which daily variation of herbage NV would influence requirements of individual grazing cows in the herd.

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CHAPTER 6

Variation of metabolisable energy estimated requirements of milking cows in a pasture-based dairy farm

6.1 Abstract

The objective of this study was to determine the extent to which the deviation of the daily metabolisable energy estimated requirements of a cow from the actual ME supplied per cow in the herd throughout the production season in a pasture-based dairy farm varies. Data from herd tests, milk production, herbage and feed allocation were collected during production seasons 2016-17 and 2017-18 at Dairy 1, Massey University, New Zealand. Orthogonal polynomials of third order were used to model lactation curves for yields of milk, fat, protein and live weights of each cow in the milking herd for every day during both production seasons. Linear extrapolation was used to impute missing data for herbage metabolisable energy, pre- and post-grazing herbage mass, area of herbage offered to cows and allocation of feeds other than herbage. Daily dietary metabolisable energy supplied to and required by cows for maintenance, lactation, changes in live weight and pregnancy were calculated using the AFRC (1993) energy system. A repeated measures ANOVA for the deviation of the daily metabolisable energy estimated requirements of a cow from the actual energy supplied per cow in the herd was performed using a linear model that included the random effects of breed and cow. Results show that daily estimated requirements for metabolisable energy of cows varied (CV= 18.8%) and that this variation was higher in earlier than in later stages of the production season. The estimated energy required daily by the milking herd was, on average, nearly a fifth above or below the daily mean energy supplied. Moreover, the mean deviation of the estimated energy requirements of a cow from the energy supplied per cow in the herd 14.39 MJ/cow/d (SD= 39.02 MJ/cow/d) and this deviation was mostly explained by observations made within a cow rather than between cows or breeds. The potential of managing the variation of energy requirements of individual cows in pasture-based dairy farm systems is also discussed.

Key words: daily metabolisable energy balance, pasture-based dairy farm, cow variation, modelling.

6.2 Introduction

Supply of metabolisable energy (ME) from herbage has been identified as a major factor limiting performance of cows in pasture-based dairy farms (Holmes 2007, Nicol and Brookes 2007). In most pasture-based dairy farms, allocation of herbage and other feeds is calculated on a dry-matter basis, where assumptions are made about the ME content of the diet and the total ME requirements of the herd in order to achieve performance targets while maintaining low costs (Waghorn 2007). This is the opposite to the approach used in intensive indoor dairy farms where a total mixed ration (TMR) feeding system is used to feed animals on an individual animal basis and costs are diluted by improving productivity of cows and enhancing feed conversion efficiency (Tozer et al. 2004; Bargo et al. 2002).

The use of recent technological advances in herbage mass (HM) and herbage nutritive value (NV) measurement has been proposed as a means of improving the efficiency of grazing and the use of feeds on extensive pasture-based dairy farm systems (Shalloo et al. 2018; French et al. 2014). It is believed that efficiency gains would arise from shifting from a dry-matter basis to a nutrition centred allocation basis. This shift in focus would suggest a change in the management approach towards the likes of the TMR system. However, for such an approach to be operational in practice, precise knowledge on the nutritional demand of cows in the milking herd is required.

Climate, diet and animal factors are responsible for changes in the feed demand of a milking herd (Bargo et al. 2003). Within a milking herd, daily demand for nutrition, and in particularly energy, of individual lactating cows depends on the level of milk produced, live weight, mobilisation of body tissue, and stage of gestation all of which are characterised by typical lactation curve patterns that are a function of the day since a cow started producing milk (Macciotta et al. 2011). Lactation curve models can be mechanistic or empirical. Mechanistic models are theoretical representations and underlying assumptions of the processes driving lactation while empirical models correspond to statistical representations of the reality being modelled (Macciotta et al. 2011). When herd test data is available, fitting Legendre orthogonal polynomials using random regression is a flexible option to obtain a good characterisation of individual lactation curves and allow variation of curves among cows.

In addition to lactation curve modelling, the choice of the energy feeding system is important to define the energy requirements of individual cows. Various energy feeding systems are currently adopted in Europe (INRA 1989; AFRC 1993) and North America (NRC 2001), being the AFRC (1993) also widely used to estimate energy requirements of grazing dairy cows in New Zealand. Yan et al. (2003) assessed the performance of the AFRC, NRC and INRA feeding systems using data from long-term feeding studies and found no major differences in the estimation of energy requirements among systems except for the energy required for live weight change; where the NRC outperformed the INRA and AFRC systems. More recently, a review by Tedeschi et al. (2014) has concluded that simpler feeding systems, such as the AFRC (1993), are more resilient to variation in conditions among studies and robust enough to characterise milk production around the world.

Although several researchers (Auldist et al. 2019; Heard et al. 2011; Doyle et al. 2006) have determined the relationships between the ME content of diets and their influence on the nutrition and performance of milking cows, these studies have been carried out under controlled conditions or involved few animals, making conclusions from such studies unscalable to the actual farm situation. Moreover, given the intrinsic dynamics of seasonal farming, it is unclear the extent to which individual requirements for ME of cows in a milking herd would vary given also the variation of the energy content supplied daily in the diet. Knowing the extent to which requirements for ME of individual cows in a pasture-based dairy farm vary will contribute to the discussion of how such variation could potentially be used to improve efficiency on pasture-based dairy farm systems.

The objective of this study was to determine the extent to which the deviation of the energy required by a cow from the energy supplied per cow to the herd throughout the production season in a pasture-based dairy farm varies. This study also sought out to discuss pathways of improving the efficiency of managing herbage and supplements given variation of requirements for ME of individual cows.

6.3 Materials and method

This study was conducted at Dairy 1 farm at Massey University, Palmerston North, New Zealand during 2016-17 (starting August 2016 to May 2017) and 2017-18 (from July 2017 to May 2018) production seasons. The farm is characterised for being a low input pasture-based system with spring calving in which all cows are milked once daily throughout the production season. The main source of feed available on the farm is freshly grazed ryegrass (*Lolium perenne L.*) and white clover (*Trifolium repens L.*) herbage mix. Mixed herb crops comprising chicory (*Cichorium intybus*), red clover (*Trifolium pratense*) and plantain (*Plantago lanceolata*), and monocultures of turnip (*Brassica* *campestris ssp. rapifera*), rape (*Brassica napus*) and lucerne (*Medicago sativa*) are also grazed strategically to fill deficits in seasonal dry matter supply. Periodically, maize and herbage silages and other supplements are also used. During 2016-17 and 2017-18 production seasons, the dairy herd consisted of 260 and 255 cows, respectively, which were allocated an effective area of 119.7 ha. The herd breed composition was 25% Holstein-Friesian (F), 14% Holstein-Friesian crossbred (FX), 26% Holstein-Friesian-Jersey crossbred (FJ), 12% Jersey crossbred (JX) and 22% Jersey (J) based on the breed grouping criteria proposed by Handcock et al. (2019).

6.3.1 Data collection

Daily yields of milk (MY), fat (FY) and protein (PY) from cows in the herd were obtained from herd tests for fat and protein percentages and somatic cell counts performed monthly during the two production seasons. Live weights (LW) of individual cows identified with a radio frequency electronic identification system (Allflex New Zealand Ltd., Palmerston North, New Zealand) were automatically measured every morning after milking using a race walkover scale (WoW xR-3000, Tru-Test Ltd., Auckland, New Zealand). Calving dates, dry-off dates and dates of withholding periods for milk due to medicinal treatment were also documented. Volume of milk and kilograms of milk solids, fat and protein produced daily by the herd were monitored using the dairy company actual milk vat return records.

Herbage mass (HM) and metabolisable energy content (ME) of herbage from paddocks pre-grazing were measured every two to three weeks. At each measurement period, between four to six paddocks in the farm manager’s weekly grazing plan were measured. Herbage mass was estimated using a C-Dax pasture meter with auto lift (C-Dax 2019) towed behind an All-Terrain Vehicle following a “W” shaped pattern across the length of the paddock. C-Dax herbage height data collected within each paddock were averaged and converted to herbage mass by calculating HM (kg DM/ha) = 752 + 16.3 Height (mm). Metabolisable energy was determined from canopy hyperspectral measurements acquired from twelve sampling plots distributed along the runs performed with the pasture meter. The number of plots was defined following recommendation of Cosgrove et al. (1998) who suggested that twelve samples are required to determine the mean herbage ME of a paddock with accuracies of ± 0.5 MJ/kgDM. A detailed description of the instrument and calibration used to determine herbage ME and the definition of sampling plot can be found in chapter 3. At each grazing event, the area of herbage allocated to the cows was recorded. Post-grazing HM was measured using the same method as the one used to quantify HM at pre-grazing.

Daily allocation of feeds other than herbage were obtained from records from the farm. The ME and gross energy (GE) content of the various feeds supplied to the cows was assumed and obtained from the studies presented in Table 6.1.

Table 6.1 Assumptions on metabolisable energy (ME) and gross energy (GE) of feeds other than fresh herbage offered to cows during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University.

Feed source	ME (MJ/kgDM)	GE[1] (MJ/kgDM)	Reference
Herbage silage	9.5	19	DairyNZ (2017)
Herbage baleage	10.2	19	DairyNZ (2017)
Chicory	12.5	18.4	DairyNZ (2017)
Rape	12.9	18.4	Westwood and Mulcock (2012)
Turnips	12.0	18.4	DairyNZ (2017)
Lucerne	11.0	18.4	DairyNZ (2017)
Maize silage	10.3	19	DairyNZ (2017)
Tapioca	12.8	18.8	DairyNZ (2017)
Dried distillers grains	12.5	18.8	DairyNZ (2017)

[1]all GE values were assumed following recommendations of AFRC (1993)

6.3.2 Data editing

In order to obtain a complete description of the feed offered daily at the farm during the two production seasons, days with missing data for HM, area of herbage offered to cows, post-grazing HM, herbage ME and allocation of feeds other than herbage were imputed using linear extrapolation.

The amount of herbage DM consumed by the herd at any paddock in any day was calculated as:

$$HC = (HM_{pre\text{-}grazing} - HM_{post\text{-}grazing})\ AH$$

where HC is the herbage consumed by the herd (kg DM), $HM_{pre\text{-}grazing}$ is the herbage mass at pre-grazing (kg DM/ha), $HM_{post\text{-}grazing}$ is the herbage mass at post-grazing (kg DM/ha) and AH is the area of herbage allocated to cows (ha).

6.3.3 Modelling of cow lactation curves and validation of milk production at farm level

Orthogonal polynomials of third order were used to model lactation curves for MY, FY, PY and LW for each individual cow in each production season. Regression models for each trait were defined as a polynomial function of a cow's days in milk after calving as:

$$Y_{t(c:y)}= (\beta_0P_0+ \beta_1P_1 + \beta_2P_2+ \beta_3P_3) + (\alpha_0P_0+ \alpha_1P_1 + \alpha_2P_2+ \alpha_3P_3) +e_{t(c:y)}$$

where $Y_{t(c:y)}$ is the trait measured at day t after calving of cow c within production season y, β_0 to β_3 are fixed regression coefficients for the polynomial functions P_0 to P_3 that denote the effect of the population mean on Y, α_0 to α_3 are random regression coefficients for the polynomial functions P_0 to P_3 that denote the effect of cow nested within each production season on Y, P_0 to P_3 are Legendre polynomial functions of orders 0 to 3 as defined below, and $e_{t(cy)}$ is the random residual error. Coefficients of the orthogonal polynomial were calculated as:

$$P_0(t)= 1;\ P_1(t)= x;\ P_2(t)= \frac{1}{2}\,(3x^2\text{-}1);\ \text{and}\ P_3(t)= \frac{1}{2}\,(5x^3\text{-}3x)$$

where x is the number of days after calving standardised to a maximum lactation length of 270 days and calculated as: x= -1 + 2 ((t - 1) / (270 - 1)).

Estimates of the fixed and random regression coefficients were obtained by solving the mixed model equations using the restricted maximum likelihood procedure as implemented in the R software package 'lme4' (Bates et al. 2007).

The models developed here were used to predict MY, FY, PY and LW for each cow in the herd for every calendar day of the 2016-18 and 2017-8 production seasons. At any given day, a cow was assumed to be in the milking herd if the day was one week after their calving date or before their drying-off date and there were no records of the cow being withhold from milking. Modelled yields of milk, fat and protein of individual cows were added by calendar day and daily totals were validated against actual milk production obtained in the milk vat. Modelled lactation curves were then used to estimate requirements for ME of each of the cows in the milking herd at every calendar day along production seasons as described in the following section.

6.3.4 Metabolisable energy requirements of cows and energy balance at the herd level

The metabolisable energy content in the diet supplied daily to the herd was calculated as the weighted average of the ME content of the feed source in relation to the quantity of feed supplied in dry matter (DM). Likewise, metabolicity of the diet (qm), calculated as the quotient ME/GE, was also based on the weighted average of the energy contents of feeds, where the value for GE of fresh herbage was assumed at 18.4 MJ/kg DM and values for ME and GE of the remaining feeds were also assumed and presented in Table 6.1.

Efficiency of ME use for the various animal functions were calculated following AFRC (1993) equations:

Efficiency for maintenance:	$k_m = 0.35\ qm + 0.503$
Efficiency for lactation:	$k_l = 0.35\ qm + 0.420$
Efficiency for live weight gain:	$k_g = 0.95\ k_l$
Efficiency for live weight loss:	$k_t = 0.84$
Efficiency for growth of conceptus:	$k_c = 0.133$

The amount of ME required for maintaining (ME_m) a cow at any given calendar day was calculated as the addition of the energetic requirements for their fasting metabolism (Fm) and an activity allowance (Ac) that assumed a constant walking distance of 3 km as: ME_m (MJ/d) = (Fm + Ac) / k_m, where Fm (MJ/d) = 1 (0.53 (LW_d / 1.08)$^{0.67}$, Ac (MJ/d) = 0.0016 LW_d, and LW_d is the modelled live weight of a cow at calendar day d.

Cow ME requirement for lactation (ME_l) was calculated as ME_l (MJ/d) = EV_l MY 1.03 / k_l where EV_l is the energy value of a kilogram of milk calculated as EV_l (MJ/kg) = 0.376 F + 0.209 P + 0.948, 1.03 is a factor assuming the density of milk at 1.03 kg/l and F and P are concentrations of milk fat and protein expressed as percentages of milk yield, respectively.

Metabolisable energy requirement for live weight change (ME_g) was calculated as ME_g (MJ/d) = EV_g LWC / k_g if a cow was gaining weight or as ME_g (MJ/d) = EV_g LWC k_t / k_l if a cow was losing weight, where EV_g is the energy value of a kilogram of live body tissue assumed constant at 19 MJ/kg (AFRC 1993) and LWC is the daily live weight change of a cow as determined by the first derivative of modelled daily live weights.

The level of ME required to sustain the growth of the conceptus (ME_c) was calculated as EV_c / k_c where EV_c is the energy retained by the fetus at any given day after conception and calculated as EV_c (MJ/d) = 1 / 40 W_c (E_t 0.0201 $e^{-0.0000576t}$), where E_t (MJ) was derived from log10 (E_t) = 151.665 – 151.64$e^{-0.0000576t}$ and is the total energy retained by the fetus at day t after conception and W_c is the calf weight at birth calculated as W_c (kg) = ($LW_m^{0.73}$ – 28.89) / 2.064, where LW_m is a cow's averaged live weight between days 100 and 200 after calving. Conception date of each cow was calculated by subtracting 283 days to the date of calving at the subsequent production season. It was assumed that cows not present in the herd in the subsequent production season were empty with an EV_c equal to zero.

The total cow requirements for ME (ME_t) were adjusted for feeding level as:

$$ME_t \text{ (MJ/d)} = [\ 1 + 0.018\ (FL - 1)\ ]\ (ME_m + ME_l + ME_g + ME_c)$$

where FL is the feeding level calculated as a multiple of ME_m.

Estimated requirements for ME_t of individual cows were added by calendar day to determine the daily ME estimated requirements of the herd. Then, herd energy requirements were contrasted with daily ME supplied at the farm. The difference between the amount of ME estimated requirements of the herd and the amount of ME supplied daily was calculated considering a ±5% tolerance on the ME supply. This tolerance was based on the error associated with the herbage ME sampling method (±5 MJ/kg DM) in relation to the mean ME value of the diet.

Descriptive statistics were used to visualise variation of estimated requirements for ME_t of individual cows along with the actual ME supplied per cow in the herd (ME_s; MJ/cow/d). Variation of daily ME_t estimated requirements of cows within calendar days was represented by boxplots, while averaged daily ME_t estimated requirements grouped by breed were used to represent daily energy required by each of the five breeds in the herd.

The difference between a cow's daily ME_t estimated requirements and ME_s was calculated and defined as the deviation of the daily ME_t estimated requirements of a cow from the actual ME supplied per cow in the herd (DME; MJ/d).

6.3.5 Statistical analysis

A repeated measures analysis of variance for DME was performed using the 'lmer' function available in the 'lme4' package for R software (Bates et al. 2007) with the following linear model,

$$DME_{ij} = \mu + B_i + C_j + e$$

where:

DME_{ij} is the deviation of the daily total metabolisable energy estimated requirements of cow i of breed j from the metabolisable energy supplied per cow in the herd, μ is the mean value of DME, B_j is the random effect of the j-th breed (either F, FX, FJ, JX or J), C_i is the i-th cow in the herd (318 different identification classes) and e is the random residual error associated with each observation.

Estimates of variance components for breed (σ^2_b), cow (σ^2_c) and residual error (σ^2_e) were used to calculate total variance (σ^2_T) as $\sigma^2_T = \sigma^2_b + \sigma^2_c + \sigma^2_e$. The contribution of breed, cow and residual error were also expressed as the percentage of the total variance.

6.4 Results

Descriptive statistics on cow variables collected via herd tests, cow live weights, daily yields of milk, fat and protein per cow calculated from milk vat records as well as data collected on herbage and feeds supplied to the herd during 2016-17 and 2017-18 production seasons at Massey University's Dairy 1 are presented in table 6.2.

Table 6.2 Descriptive statistics of variables describing daily yields of milk, fat, protein and live weights of individual cows, daily yields of milk, fat and protein per cow calculated from milk vat records, herbage measurements and feed allowances measured at Dairy 1, Massey University, Palmerston North.

	Production season							
	2016-17				2016-17			
Variable	N	mean	SD	CV (%)	N	mean	SD	CV (%)
Daily yields of individual cows								
Milk, L	2296	15.6	6.05	38.8	1933	16.3	6.4	39.3
Fat, kg	2296	0.81	0.26	32.1	1932	0.84	0.3	35.7
Protein, kg	2296	0.63	0.19	30.2	1933	0.65	0.21	32.3
Live weight, kg	34646	493.9	69.5	14.1	33064	491.9	65.2	13.3
Daily yields per cow calculated from milk vat records								
Milk, L	300	14.4	3.21	22.3	302	14.7	3.42	23.2
Fat, kg	300	0.78	0.13	16.7	302	0.77	0.15	19.5
Protein, kg	300	0.59	0.10	16.9	302	0.60	0.10	16.7
Herbage								
Pre-grazing HM, kg DM/ha	66	2960.7	208.6	7.0	111	2920.1	211.2	7.2
Post-grazing HM, kg DM/ha	66	1798.8	147.8	8.2	111	1702.5	119.7	7.0
ME, MJ/kg DM	66	11.2	0.31	2.8	111	10.7	0.53	5.0
Area of herbage, ha/d	66	2.4	0.83	34.6	111	1.92	0.81	42.2
Feed allowances								
Herbage silage, kg DM/cow/d	66	1.13	1.63	-	111	1.31	2.41	-
Herbage bailage, kg DM/cow/d	66	0	0	-	111	0.12	0.33	-
Chicory, kg DM/cow/d	66	1.26	1.74	-	111	1.56	2.07	-
Rape, kg DM/cow/d	66	0	0	-	111	0.25	0.97	-
Turnips, kg DM/cow/d	66	0.15	0.87	-	111	0.54	1.37	-
Lucerne, kg DM/cow/d	66	0.55	1.32	-	111	0	0	-
Maize silage, kg DM/cow/d	66	0	0	-	111	0.1	0.56	-
Tapioca, kg DM/cow/d	66	0	0	-	111	0.32	0.66	-
DDG, kg DM/cow/d	66	0	0	-	111	0.53	1.04	-

HM= herbage mass, ME=metabolisable energy, DDG= dried distillers grains.

Validation of modelled milk, fat and protein produced daily by the milking herd against actual milk production obtained at the milk vat are presented in Figure 6.1. Modelling of individual cow milk traits upscaled to the herd level was able to explain variability of milk obtained at the milk vat with high R^2 and low RPE values ($R^2 > 0.95$ and RPE < 9%).

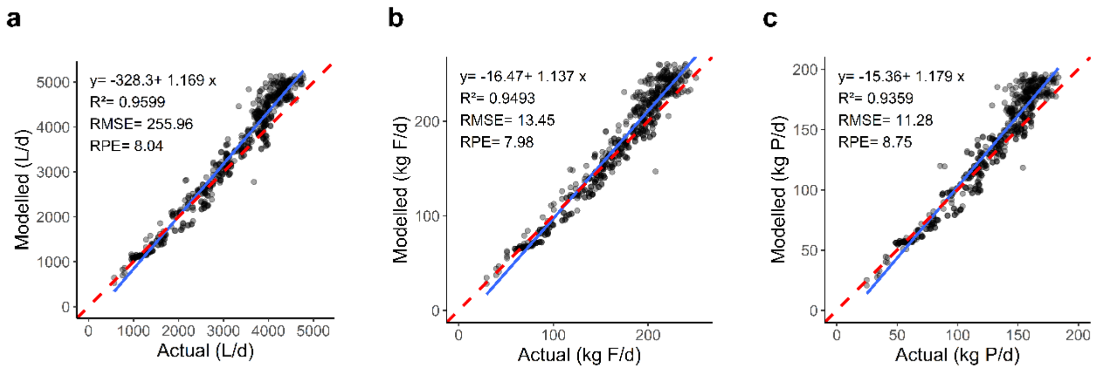

Figure 6.1 Validation of modelled milk (a), fat (b) and protein (c) produced daily by the milking herd against actual milk production measured in vat at Dairy 1, Massey University, Palmerston North. (——) linear regression line, (- - -) reference line with intercept of 0 and slope of 1. y= dependent variable of the linear regression equation denoting modelled daily milk production, x = independent variable of the linear regression equation denoting actual daily milk production measured in the milk vat, R^2= coefficient of determination, RMSE= root mean squared error, RPE: relative prediction error.

Composition of the ME of the diet consumed daily by the cows in the milking herd throughout the production seasons is shown in Figure 6.2.

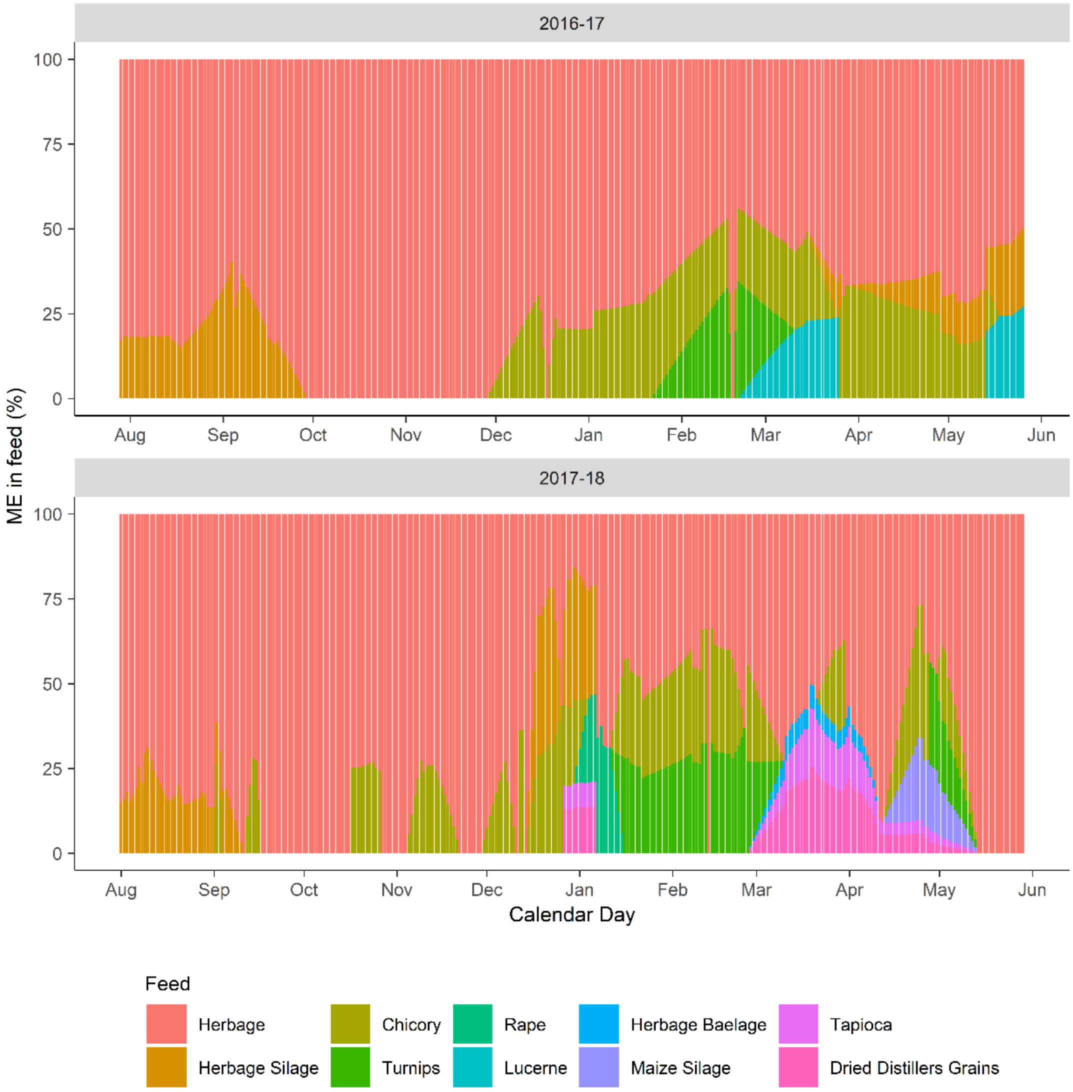

Figure 6.2 Metabolisable energy (ME) composition of feed allocated daily to the milking herd during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University, Palmerston North.

Herbage supplied an average of 73% of the ME consumed daily by the milking herd in the farm. However, as shown in Figure 6.2, the supply of ME from herbage in relation to the many feeds offered varied within and between production seasons. Early on in the seasons, the ME in the diet was composed of about 80% herbage and 20% herbage silage, reaching to 100% herbage on most spring days. As the production season unfolded, crops such as chicory, turnips and rape became available and supplied cows with a source of ME during summer and into the autumn. However, the use of these crops occurred earlier in 2017-18 than in 2016-17. From February onwards in 2017-18, lucerne and herbage silage were replaced with herbage baleage, maize silage, tapioca and DDG and there was a decrease in the use of herb crops as sources of ME compared to the 2016-17 production season.

There were significant relationships ($p < 0.001$) between the amount of ME supplied daily by management to the milking herd and the daily ME estimated requirements of the herd on both production seasons, with both production seasons exhibiting similar R^2, RMSE and RPE values (Figure 6.3).

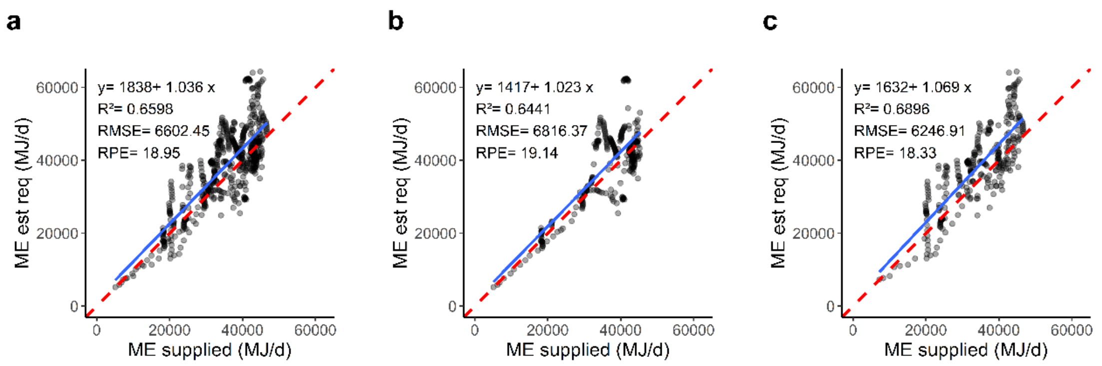

Figure 6.3 Relationship between daily metabolisable energy (ME) supplied and ME estimated requirements of the milking herd at Dairy 1, Massey University, during production seasons 2016-17 and 2017-18 (a), 2016-17 only (b) and 2017-18 only (c). (——) linear regression line, (- - -) reference line with intercept of 0 and slope of 1. y= dependent variable of the linear regression equation denoting estimated requirements for ME of the milking herd, x = independent variable of the linear regression equation denoting actual ME supplied to the milking herd, R^2= coefficient of determination, RMSE= root mean squared error, RPE: relative prediction error.

The amount of ME supplied daily to the milking herd throughout production seasons matched the estimated requirements of the milking herd on 25% of the days. Conversely, ME was under-supplied by about 30 MJ/cow/d on 64% of the days and over-supplied by 4.3 MJ/cow/d on 11% of the days. The depiction of daily supply and demand for ME in Figure 6.4 shows that most of the days in which intake of ME was below the estimated requirements for ME of the herd to sustain modelled performance levels were at the start of the production seasons. However, there were also various days during summer in which the energy balance was also negative (daily ME supplied below ME estimated requirements).

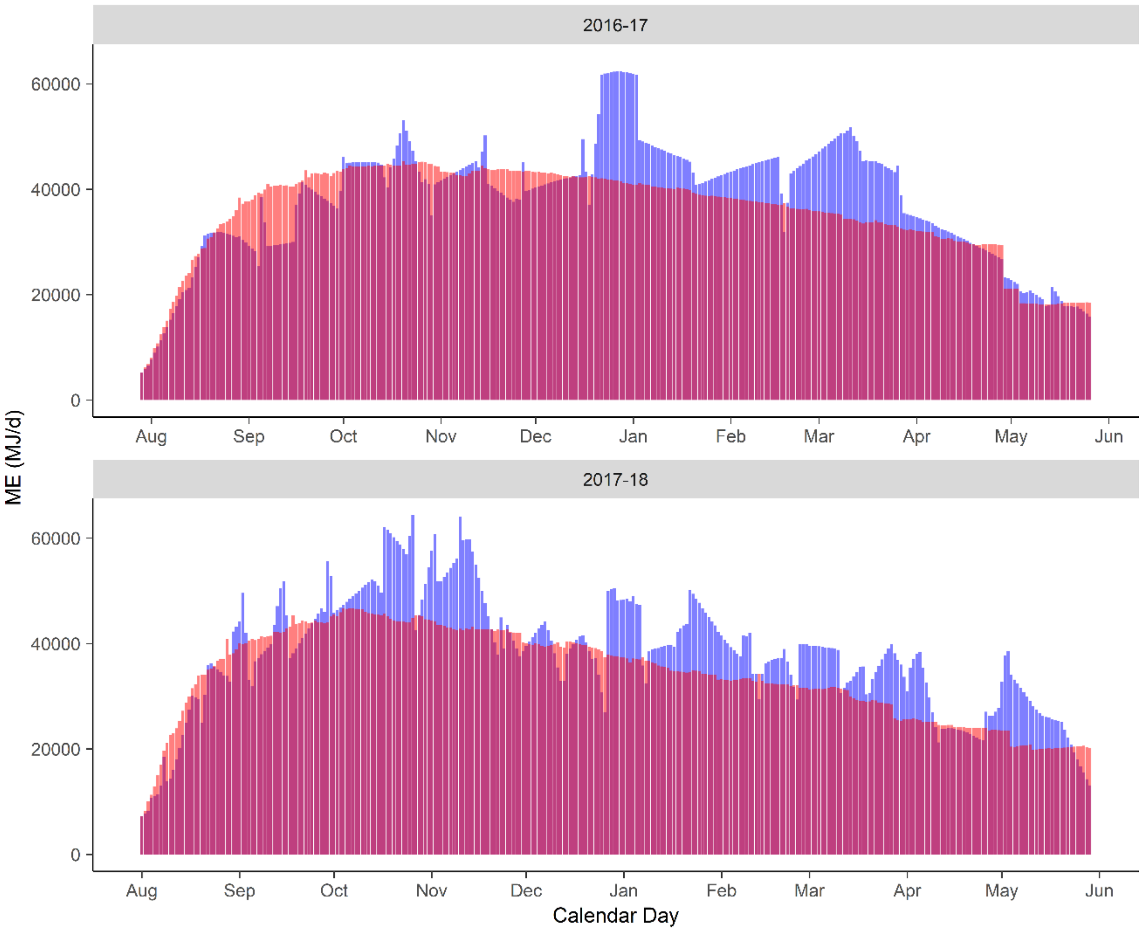

Figure 6.4 Daily metabolisable energy (ME) supplied to the milking herd and ME estimated requirements of the milking herd at Dairy 1, Massey University, during the 2016-17 and 2017-18 production seasons.

Variation of the estimated requirements for ME_t of individual milking cows throughout production seasons was high (CV= 18.8%). Results in Figure 6.5 show that the variation of daily ME_t estimated requirements of individual cows in the milking herd per calendar was greater at earlier than at mid to later stages of the production seasons, as denoted by the higher ranges and interquartile ranges of the boxplots from August to late December compared to those from January onwards. Holstein-Friesian was the breed whose estimated requirements for ME_t varied the most (CV= 18.7%) while Jersey the least (CV= 16.9%). Figure 6.5 also shows that the average level of ME supplied per cow in the herd was at most days below the level required by F or FX cows but higher than that required by J cows.

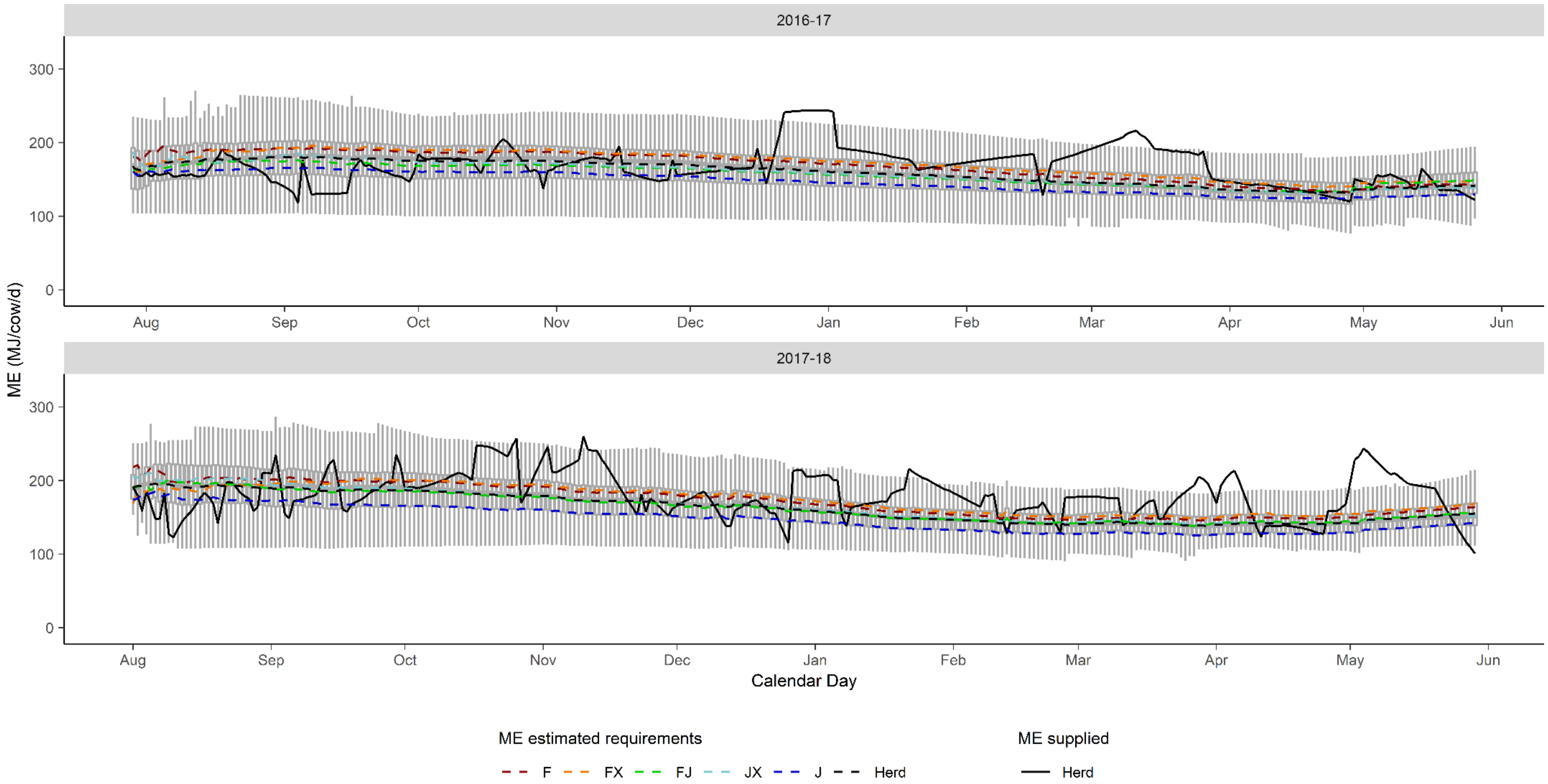

Figure 6.5 Daily variation of dietary metabolisable energy (ME) supplied per cow in the herd, mean ME estimated requirements per cow in the herd, mean ME estimated requirements per cow grouped by breed, and dispersion of ME estimated requirements of individual cows (boxplots) during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University, Palmerston North. F= Holstein-Friesian, FX= Holstein-Friesian crossbred, FJ= Holstein-Friesian-Jersey crossbred, JX= Jersey crossbred, J= Jersey.

The mean DME calculated throughout productions seasons was 14.39 MJ/cow/d and the standard deviation was 39.02 MJ/cow/d. Results of the analysis of variance performed on DME in Table 6.3 show that the relative contribution of breed and cow total variance was relatively low compared to the error associated with observations within cows indicated by the random error term (e^2). Moreover, differences in DME between cows were nearly four times greater than differences between breeds.

Table 6.3 Variance decomposition of the deviation of the daily total metabolisable energy estimated requirements of a cow from the actual metabolisable energy supplied per cow in the herd (DME) at Dairy 1, Massey University, during 2016-17 and 2017-18 production seasons.

	σ^2_c	σ^2_b	σ^2_e	σ^2_T	c^2	b^2	e^2
DME	471.5	120.2	1027.0	1618.7	29.1	7.4	63.4

σ^2_b= variance explained by the random effect of breed, σ^2_c= variance explained by the random effect of cow, σ^2_e= variance explained by the random error, σ^2_T= total variance, b^2= variance explained by the random effect of breed expressed as a percentage of total variance, c^2= variance explained by the random effect of cow expressed as a percentage of total variance, e^2= variance explained by random error expressed as a percentage of total variance.

6.5 Discussion

Mean values of daily yields per cow of milk, fat and protein obtained from herd tests were slightly higher than yields calculated from milk vat records. Moreover, mean yields reported here were, on average, about 46%, 50% and 51% higher than the yields of milk, fat and protein, respectively reported in other comparable studies (Clark et al. 2006; Tong et al. 2002; Holmes et al. 1992) using once a day milking and performed on similar conditions but using higher stocking rates (> 3 cows/ha). Despite the differences in yields, mean live weights used here were within the ranges of live weights reported in the studies mentioned before (375–511 kg LW). Mean and standard deviation values of herbage ME indicated that this variable was within the normal values commonly found in the literature (DairyNZ 2017; Holmes 2007; Litherland and Lambert 2007). Likewise, herbage mass measures at pre-grazing were within normal ranges observed for ryegrass dominant herbage swards (2200–3700 kg DM/ha) (Pérez-Prieto and Delagarde 2013; Holmes 2007) while herbage mass measures obtained at post-grazing were slightly higher than the most frequent measures observed by McCarthy et al. (2014), which ranged from 1480 to 1760 kg DM/ha. Higher than normal post-grazing residuals might help explain the higher yields measured in this study compared to those reported in other comparable studies (Clark et al. 2006; Tong et al. 2002; Holmes et al. 1992).

Modelling of lactation curves of individual cows throughout production seasons was able to capture the production of milk in the vat. However, the negative offsets and slopes greater than one in the linear regression equations in Figure 6.1 indicate that modelling tended to overestimate production as measured in the milk vat at days with high levels of production and to underestimate production at lower levels of production, but that although significant ($p<0.001$), the magnitude of these effects was minimal. It is important to highlight however that milk vat records might not be an accurate representation of the actual milk produced daily at the farm, since milk produced at the farm was used to rear calves and was not included in the milk vat records, also the milk from any cow on medication was not included in the vat. Because demand for milk by calves is high when milk production levels are high, the differences between herd tests and milk vat records can explain the differences between yields measured at herd tests and yields calculated from milk present in the vat (Table 6.2), and therefore, the slight overestimation by the modelling approach. The underestimation of milk produced at lower levels of production by modelling might be the consequence of underestimating the number of cows being milked at the beginning of the production seasons when production is low, as this number was set by a fixed milk withholding period of seven days, which might have been lower than the actual number of cows milked at that stage. Moreover, while orthogonal polynomial functions are appropriate to accurately model lactation curves, it is well established that this approach tends to introduce errors at both ends of the lactation curves (Silvestre et al. 2006; Brotherstone et al. 2000), and these errors can also help explain the differences between modelled and actual milk produced at the vat, particularly at both ends of the production seasons.

Accuracy and bias metrics describing the relationship between the daily ME supplied and estimated requirements of the herd (Figure 6.3) indicated that there were opportunities in the farm to further improve the balance between supply and demand of energy. An RPE value of 18.9% means that the daily ME estimated requirements of the herd were, on average, nearly a fifth above or below the daily mean ME supplied. Moreover, there was a slight systematic tendency to under supply ME as denoted by the slope greater than one in the equation regression in Figure 6.3. The profile of the ME supplied against that required daily by the herd shows that most of the undersupplied days were at early stages in the production seasons. This is consistent with theoretical representations of dry matter supply and demand in seasonal pasture-based dairy farm systems (Holmes 2007). The relative undersupply of dietary ME at early stages in the production seasons is well known and is explained by cows entering a stage of negative energy balance postpartum that is characterised by physical constrain of intake and weight loss to support metabolic functioning (Ingvartsen and Andersen 2000). In order to support this idea, daily live weight of cows grouped by breed can be found in Figure D.1 in Appendix D. Although feeding strategies can be developed to overcome the effects of the negative energy balance at early lactation, allowing for the physiological capability of cows to rapidly mobilise energy from fat tissue instead of incorporating sources of energy in the diet is perhaps the most profitable strategy for managing feed at this stage. Oversupply of energy during most days from October onwards signifies that supplements could have been saved if allocation of feeds was made based on rapid measurements of herbage ME. However, this would have not only required rapid ME measurement tools but also precise forecasting tools that were able to accurately assist with tactical planning and budgeting for the season.

Greater dispersion of individual cow daily ME_t estimated requirements at early stages of the production seasons can be explained by greater variation of peak yields than in persistency of lactations of individual cows in the herd. This can be supported by the high levels of ME supplied per cow that occurred after January in both production seasons (Figure 6.5) that are most likely to have contributed to sustain persistency of lactation after peak yields. If daily variation of estimated requirements for ME_t is grouped by breed and compared against the mean dietary ME supplied per cow in the herd, then results show that the energy required by F cows was below the mean energy supplied per cow on 49% of the days studied, while this metric was only 17% for J cows. Holstein-Friesian cows must have a different grazing behaviour (i.e. bite rate, bite mass and/or grazing time) compared to J cows in order to achieve greater intakes to satisfy their energy demands.

The contribution of within cow variation on explaining variance of DME can be partially explained by the fact that daily estimated requirements for ME_t of individual cows throughout lactations varied more than the variation of the supply of ME per cow at the herd level throughout the production seasons. Because of this, the differences of

DME within individual cows were greater than the differences of DME between cows or breeds. This finding stresses on the importance of performing regular monitoring of a cow's energy requirements to inform daily allocation of energy to cows. Most pasture-based dairy farm herds are managed as a single mob, where all cows have access to the same feed resources and thus a precise fit between energy demand and supply of each individual cow is unlikely to be easily implemented. However, having accurate estimates of the energy requirements of individual animals and the energy content of the diet on any given day can potentially help management to achieve a more precise balance between demand and supply of energy though improved decision-making without having to bring significant changes to the production system or management.

The potential of managing variation of energy requirements of individual cows in pasture-based dairy farm systems requires controlling cows on herbage. Hills et al. (2016) identified virtual fencing and individualised feeding as suitable technologies to implement precise feeding of grazing cows in pasture-based systems. The main idea behind these technologies is to provide cows with restricted access to resources based on their energy and nutritional needs, so that the farm system is more efficient. Cows with low requirements for energy can be grouped and given access to herbage of lower ME and supplements according to their individualised requirements levels, while cows requiring higher energy levels can be allocated to herbage of higher energy content and fed supplements accordingly. Similarly, controlled access of cows to herbage can be based on the genetic merit of cows so that cows of higher milk production genetic potential are fed to maximise milk responses to herbage and supplements while cows of lower genetic merit are fed to minimise costs.

6.6 Conclusion

This study found that the daily ME_t estimated requirements of individual milking cows grazing in a pasture-based dairy farm varied to a great extent (CV= 18.8%). This variation was higher in the earlier than later stages of the production season. The daily ME_t estimated requirements of the herd were, on average, nearly a fifth above or below the daily ME supplied at the farm. The deviation of the daily ME_t estimated requirements of a cow from the actual ME supplied per cow in the herd was mostly explained by the observations made within a cow rather than between cows or breeds as lactation has the greater influence on the total ME_t requirements of cows. Having accurate estimates of the daily ME_t requirements of individual cows can potentially improve the efficiency of the farm system by allowing a more precise fit between supply and demand for feed. However, for such information to be useful, changes to the farm system are most likely to be required. Experimental research is required to determine the actual benefit of having accurate estimates of ME_t requirements of individual cows for managing feed in pasture-based dairy farm systems.

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CHAPTER 7

Overall discussion and conclusion

This thesis identified the need to bridge the research gap that exists between the development and potential proximal hyperspectral sensing as a rapid herbage nutritive value (NV) measurement tool to inform grazing management and feed allocation decisions in a pasture-based dairy farm system. In order to fill this gap in research, this thesis achieved four outcomes:

1. This thesis developed and validated calibration models for hyperspectral canopy reflectance data that were useful to determine the herbage NV traits metabolisable energy (ME), crude protein (CP), neutral detergent fibre (NDF), acid detergent fibre (ADF) and digestible organic matter in dry matter (DOMD) of ryegrass-white clover mixed herbage available to the grazing cow .
2. Proximal hyperspectral sensing was used to assess the extent by which the NV of herbage offered daily to lactating cows in a pasture-based dairy farm varied in time and space during two production seasons. A measure of the proportion of variance that was not accounted for by differences between paddocks, months and production seasons was used to determine the relevance of herbage NV measurement.
3. The relative importance of daily variation of herbage NV traits and other herbage quantity and climate related factors on driving the physical performance on a per cow basis was determined, and findings were used to justify the extent by which variation of herbage NV can drive the performance per cow of the pasture-based dairy farm.
4. Finally, a modelling approach was used to determine the extent by which estimated requirements for ME of individual cows varied and how such variation differed from the dietary ME supplied per cow in the herd.

Findings related to the outcomes listed above were presented in chapters 3 to 6, respectively, where results were also discussed in terms of their implication to different aspects of grazing management and feed allocation decision-making. This chapter brings together major challenges and opportunities found throughout the thesis and discusses how findings could be valuable to aid daily grazing management and feed allocation decisions in a pasture-based dairy farm system. Further research opportunities are identified to advance study the topic.

7.1 Overall discussion

7.1.1 On the accuracy of proximal hyperspectral sensing and the determination of herbage nutritive value at the paddock level

To be valuable for rapid assessment of herbage NV in a pasture-based dairy farm system, firstly, proximal hyperspectral sensing of canopies needed to provide predictions that were a true representation of actual herbage NV available at the sampling units (i.e. sampling plot). Canopy reflectance calibration models built using data obtained from proximal hyperspectral sensing were able to determine various NV traits of herbage with R^2 values ranging from 0.78 to 0.57 (chapter 3). The accuracies of the canopy spectral calibration models developed in this study were lower than the accuracies reported by Pullanagari et al. (2012) ($0.83 > R^2 > 0.75$) but higher than the accuracies reported by Kawamura et al. (2008) ($0.65 > R^2 > 0.37$) and Adjorlolo et al. (2015) ($0.60 > R^2 > 0.51$). Despite differences in the spectral pre-treatment methods used among these studies, a major factor contributing to the differences in accuracies was the variability of the datasets used in the development of the calibration models, with the studies that used more variable datasets reporting the most accurate models. More importantly, different from any other study in the literature, this thesis only measured NV from the vertical portion of herbage that is available to the grazing cow (Macdonald et al. 2010; DairyNZ 2017) instead of the NV of the whole canopy vertical profile. Because NV decreases with canopy depth (Delagarde et al. 2000; Nave et al. 2014), but spectra from lower strata can influence reflectance measured at the surface of the canopy even at high herbage mass (i.e. canopy closure) (Asner 1998), having a more appropriate characterization of the NV of herbage available to cows might have been at the expense of a potential loss of accuracy of canopy spectral calibration models.

In addition to the accuracies with which field herbage NV measurements were determined, the characterisation of the NV of herbage available at the grazing management unit (i.e. the paddock) was also potentially affected by the sampling strategy. In this thesis, the mean value of herbage NV of a paddock was determined from hyperspectral measurements taken from about twelve sampling plots distributed following a ‘W’ pattern to systematically cover the area of the paddock. If the distribution of sampling plots within a paddock was scattered into well-defined patches that were not measured while sampling, then the sampling pattern used could potentially result in mean values of herbage NV that were not representative of the paddock. Furthermore, it is also important to highlight that animals grazing spatially heterogenous herbage mixtures tend to select for preferred species (Chapman et al. 2007), which might lead to differences between the NV of herbage offered in paddocks and that is actually consumed by cows if selectivity is not controlled by management. If paddocks were to be grazed laxly so that cows can select herbage patches in order to maximise performance, then the sampling strategy used to characterise the NV of herbage available to cows should consider such behaviour. On the other hand, given spatial variation of herbage NV within paddocks (chapter 4) and time constraints imposed by the operability of proximal hyperspectral sensing instruments in the field, the number of sampling plots measured per paddock in this study could have also influenced the characterisation of herbage NV at the paddock level.

The choice of the number of sampling plots was based on Cosgrove et al. (1998), who determined that twelve herbage samples collected from the top ¾ of the canopy height are required to determine the mean NV of a ryegrass-white clover mix during autumn at the paddock level with standard errors of ± 0.5 MJ/kg DM for ME, and of ± 5% for CP, NDF and ADF. However, the standard error with which the NV of a paddock is determined is highly dependent on the number of samples used, which also depends on how much herbage NV varies in space. Chapter 4 identified that the spatial variation of herbage NV within anyone paddock varied highly depending on the season, and therefore, different sample sizes would be required to characterise herbage NV of paddocks in different seasons with the same level of precision (i.e. standard error). For example, Figure 7.1 illustrates how the standard error of the mean of herbage ME decreases exponentially as sample size increases. Moreover, the figure also shows that, given a pre-determined standard error of the mean, more samples are required in summer or autumn compared to spring or winter.

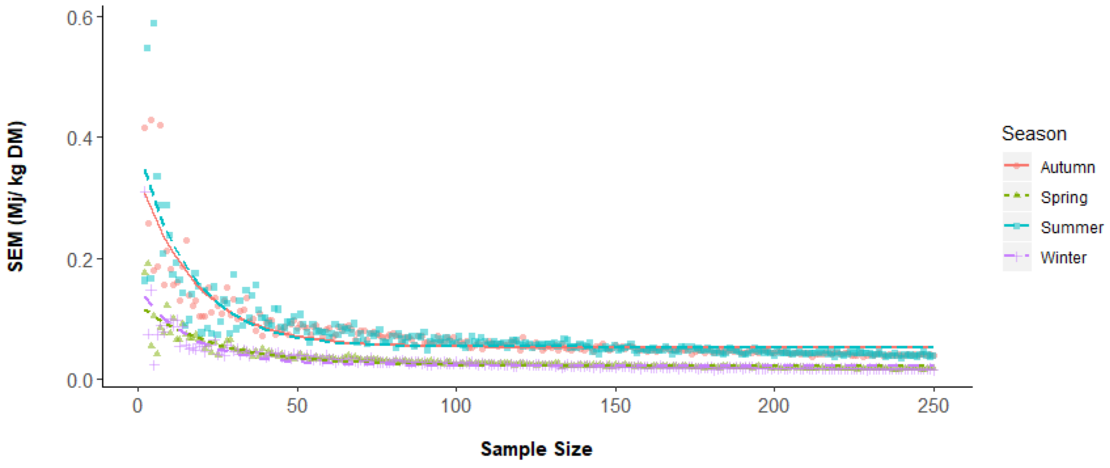

Figure 7.1 Standard error of the mean (SEM) of herbage metabolisable energy assessed by proximal hyperspectral sensing as a function of sample size by season. Source: built with data collected in this study.

The NV of the herbage offered to cows in this study varied significantly between production seasons and between months within production seasons (chapter 4). This variation was most likely associated with differences in temperature and rainfall through their influence on plant phenology and abundance of species, and therefore NV (Chapman et al. 2014; Buxton and Fales 1994). The extent to which herbage NV varies seasonally is well documented (Bell et al. 2018; Litherland and Lambert 2007; Moller et al. 1996), however, different from previous studies, this thesis provided with more detailed description on the extent to which herbage NV varied in a particular pasture-based dairy farm system. Because herbage NV data were collected from multiple paddocks over a lengthy period, this research was able to differentiate the effects of the paddock from the effects of production seasons and months within production season on the various herbage NV traits measured. This was useful to quantify the extent by which herbage NV could be determined from factors considering different temporal scales (i.e. production seasons and/or months) or paddock-specific attributes, and more importantly, it provided a basis to justify herbage NV measurement from a daily NV variation standpoint.

7.1.2 On the importance of herbage nutritive value on cow performance and the potential value of its measurement in a pasture-based dairy farm system

In addition to the capability of delivering rapid measurements, the potential value of using proximal hyperspectral sensing for measuring herbage NV is also dependent on the importance herbage NV has on driving performance per cow in the pasture-based dairy farm system, as this would partially justify the use of the tool for practical purposes. Chapter 5 showed that the relative importance of herbage ME content on determining yields of milk, fat and protein per cow in the herd (20–30% of R^2) was higher than any other NV trait, herbage or environmental related factor analysed in this study (0–24% of R^2). Supply of ME has been identified as the most limiting factor of milk production of cows grazing herbage of high NV compared to cows fed a full nutrient positive control ration (total mixed ration, TMR) (Kolver and Muller 1998; Kolver 2003). It has been described that under normal management conditions, milk production from herbage is driven by herbage intake which is mainly controlled by herbage allowance (HA) (Dillon 2007; Holmes 2007). However, this study found that ME content in herbage was more important than HA on driving performance per cow, for which it was argued that herbage fed to cows varied more in ME than in quantity, hence the higher importance of herbage ME. This is an important finding since no study to date has reported data obtained in field-like conditions where no control other rather than regular management is considered, moreover such finding suggests that ME measurement can be potentially valuable for controlling performance of cows through better managing supply of ME in relation to ME requirements.

Although it is well established that lactating cows require energy for maintenance, activity, pregnancy, milk production and gaining weight (INRA 1989; AFRC 1993; NRC 2001), no study to date has attempted to quantify the extent by which daily total requirements for ME of individual cows (ME_t) in a pasture-based dairy farm system varies throughout the production season. Likewise, there is no evidence in the literature of studies estimating how the difference between daily ME_t requirements of cows and the amount of ME supplied per cow in the herd varies. Based on the modelling of lactation curves of individual cows and herbage ME measurements, chapter 6 showed that daily ME_t estimated requirements of individual cows varied throughout the two production seasons under consideration (CV= 18.8%) and that these requirements were, on average, nearly a fifth above or below the daily average ME supplied per cow in the herd. It is important to notice however, that this imbalance was unlikely to be as high if the actual amount of ME consumed by individual cows was considered, as competition between cows has most likely resulted in high energy requirements cows having higher energy intakes and low energy requirements cows having lower intakes.

At the herd level, daily supply of ME matched the estimated requirements of the herd on 25% of the days, while an under-supply of ME of about 30 MJ/cow/d occurred on 64% of the days and an over-supply of 4.3 MJ/cow/d occurred on 11% of the days. Such finding signified that during days when energy supply was short, cows were unlikely to be able to fulfil their ME_t estimated requirements, potentially affecting cow performance. In contrast, when supply was in excess to requirements, cow performance would be higher than expected or post-grazing residuals would be higher than targets. This suggests that having information about the ME content of the diet in addition to information about the performance of cows can be valuable to improve allocation of herbage and supplements to cows as a result of a better matching between daily supply and demand of ME at the herd level. A better match between daily supply and demand for ME at the farm level could potentially lead to consistently achieving grazing targets and cow performance targets, which would then lead to improved growth, utilisation and NV of herbage while ensuring sustainable levels of milk production in the longer term (Macdonald et al. 2010; Beukes et al. 2015). Moreover, high ME_t estimated requirements variation within and between cows (chapter 6) suggested that practices aiming at exploiting individual cow variation potentially beneficial for the farm system.

The content of CP from herbage measured at Dairy 1 throughout 2016-17 and 2017-18 production seasons was at various times in excess of protein requirements as established by dairy industry guidelines (chapter 4). Excess CP has also been noticed in other studies on dairy pastures across New Zealand (Litherland and Lambert 2007; Moller et al. 1996). Despite anecdotal evidence suggesting that CP is supplied in excess in New Zealand, no study to date has been able to quantify the extent by which dietary CP exceeds protein requirements of dairy cows. Chapter 5 provided further evidence of such excess as results showed that herbage CP and the amount of milk urea produced per cow in the herd were significantly related ($p>0.001$). Cows fed CP in excess tend to increase production of ruminal ammonia, which is toxic to the cow and needs to be synthesised into urea and excreted via urine or milk (Moller et al. 1993; Kebreab et al.2002). Because there is a positive relationship between milk urea and urea in blood, monitoring milk urea has been proposed as a useful indicator of excess dietary CP (Moller et al. 1993; Nousiainen et al. 2004).

Excess dietary CP has negative consequences for the cow and the environment. Excess dietary CP been negatively related to cow fertility (Ferguson and Chalupa 1989; McCormick et al. 1999; Ipharraguerre and Clark 2005) due to the toxic effects of ammonia and its metabolites on gametes and early embryos, through deficiencies of amino acids, and by exacerbations of negative balances of energy (Ferguson and Chalupa 1989). The metabolic process of synthesis and excretion of N in the form of urea leaves less energy available for animal functioning (Tyrrell et al. 1970), with this cost being significant in terms of total energy requirements (Reed et al. 2017). On the other hand, nitrogen losses due to excess CP in pasture-based dairy farm systems has been shown to result in increased N leaching to surface and ground waters as well as N emissions to the atmosphere in the form of nitrous oxide (N_2O) (Chapman and Parsons 2017).

As mentioned above, the negative effects of excess dietary CP can be controlled by supplying cows with more balanced diets. This is an area where the determination of herbage CP using proximal hyperspectral sensing can be particularly valuable. Having actual measurements of herbage CP can be useful to allocate herbage and other feeds so as the negative impacts of excess CP on both cows and environment are minimised. For instance, levels of herbage CP up to 30% in autumn as measured at Dairy 1 (chapter 4) are well above the 14% recommended by DairyNZ (2017) and in such situations, herbage CP measurement provides an objective measure to lower the CP content of the diet by replacing herbage with alternative feeds of lower CP. Replacing herbage with maize or cereal silage could reduce N leaching losses and N_2O emissions per unit of milk by 20 to 30% (De Klein et al. 2002; Ledgard et al. 2006). Alternatively, the fact that about 44% of the variation in herbage CP offered at Dairy 1 was not related to either production season, month within the season, or paddock (chapter 4) suggests that measuring the content of CP of paddocks readily available for grazing could be potentially useful to formulate diets involving the mixture of herbage from different paddocks.

7.1.3 Using proximal hyperspectral sensing nutritive value measurement to allocate herbage and supplements

Rotational grazing is widely adopted to control herbage allocation in New Zealand pasture-based dairy farm systems (Holmes 2007). Under rotational grazing, herbage from a proportion of the grazeable farm area is allocated daily to the milking herd based on current estimations of the average dry matter requirements of cows and availability of herbage mass as well as future expectations of herbage growth, herbage utilisation and milk production. Based on plans for the whole season and current grazing and cow performance targets, the herbage area to allocate each day is controlled with fixed and mobile electric fences. When the amount of dry matter from herbage is insufficient to satisfy herd dry matter requirements, supplements can be used. Conversely, excess herbage can be stored for its use at times of deficit. As discussed in sections 7.1.1 and 7.1.2, because the NV of herbage offered to cows varied over time even in the short-term, and because nutritional requirements of cows in the herd also varied, it was argued that allocation decisions can potentially be improved if the NV of herbage, and ME in particular, in addition to quantity is considered. Such approach would allow a more precise match between supply and demand for feed at the farm level. However, for decisions based on herbage NV measurement to be more useful, changes to farm system might be required.

As suggested in section 7.1.2, high variation of ME_t estimated requirements between and within cows signifies that measurement of herbage ME can serve as the basis for individualised feeding. In pasture-based dairy farm systems, supplementation of cows is usually determined by the average nutritional requirements of the herd, rather than by those of individual cows (Little et al. 2016). Research conducted to compare flat-rate and individualised feeding strategies (Leaver, 1988; Gill and Kaushal, 2000) have shown no production advantage of individualized feeding over flat-rate feeding of concentrate supplements. However, these experiments were conducted with all cows having *ad libitum* access to herbage and do not represent actual practice on farms. A recent random survey involving 500 farmers in New Zealand shows that 29% of respondents had computer-controlled in-shed feeding systems, 24% had automatic drafting systems, 23% had electronic animal-identification readers, 8% had electronic milk meters and 7% had automatic animal weighing installed in their farms (Dela Rue et al. 2019). The adoption of all these technologies by New Zealand farmers show that that despite a lack of scientific evidence there might be benefits to be gained from individualised feeding in pasture-based dairy farm systems.

The assessment of herbage ME by proximal hyperspectral sensing can serve as the basis to define strategies aimed at optimising individualised feeding responses of cows grazing herbage (Hills et al. 2015). Under individualised feeding, cows with higher MEt estimated requirements could potentially be fed more ME than lower MEt estimated requirements cows, leading to a more efficient use of ME. Such approach could be further enhanced if data on the genetic merit for milk production of individual cows were used to inform individual feeding. Cows of high genetic merit partition more energy towards milk and less towards body tissue than low genetic merit cows (Agnew and Yan, 2000), and thus, their milk production response to supplements is relatively low (Kennedy et al. 2003). Savings of feed should be expected if the genetic merit of cows is considered for the decision of allocating feed individually, as less feed could be potentially allocated to high genetic merit cows without altering milk production. Moreover, recent research by Fischer et al. (2020) proved that restricting dry matter intake of cows that are less efficient compared to cows that are more efficient in converting feed and milk energy can significantly narrow the differences between cows, suggesting that overconsumption could be a driver of inefficiency and that controlling it could be a suitable strategy for reducing methane emissions without altering productivity of dairy farms.

Spatial variation of herbage NV can be exploited by controlling the movement of the grazing cow on the farm (Hills et al. 2016). Virtual fencing is a technology that can be used for this purpose. Virtual fencing controls the movement of the grazing cow by using a combination of GPS, movement sensors, and wireless technologies without the need for an actual fence. Using information on the spatial variation of herbage NV and quantity as well as the nutritional requirements of cows, can allow specific areas of herbage to be allocated to individual cows or groups of cows according to their energy and nutritional requirements. By doing this, more efficient grazing can be achieved as the effect of selectivity by cows is diminished. However, the use of proximal hyperspectral sensing as part of this set of technologies poses some challenges as it is limited by its operational capability as a mapping tool. Alternatively, aerial spectral imaging can be used to determine herbage NV of relatively large areas at high spatial resolution (Yule et al. 2015; Shorten et al. 2019). However, weather conditions create significant challenges to the use of this technology for regular monitoring of herbage in the field (Von Bueren et al. 2015), particularly for their use in daily grazing management. As discussed earlier in this section, virtual fencing can also be combined with individualised feeding systems to feed cows to yield or genetic potential for milk production. Although the most commonly used individualised feeding systems are located in the milking shed (Dela Rue 2019), alternative feeders currently in the market such as Zeedy (Zeedy 2020) allow bringing individualised feeding to the paddocks.

7.2 Limitations of the thesis and suggestions for further research

This thesis has provided evidence that justifies the use of proximal hyperspectral sensing as a rapid herbage NV measurement tool in a pasture-based dairy farm system. However, the results obtained suggest some limitations for using this technology and hence the need to consider further research to enhance this technology for use in NZ pasture based dairy farms.

- Limitations imposed by the choice of the pasture-based dairy farm system

The data used in this study was collected from Massey University's Dairy 1 farm, which is characterised as a low input pasture-based dairy farm system. Dairy 1 however, is by no means representative of the production systems present in New Zealand or internationally. This limits the results reported in the thesis as conclusions cannot be extrapolated to other situations where other types of productions systems are available. For instance, a production system 5 as described by DairyNZ (2017) is a New Zealand high input pasture-based dairy farm system that uses between 25 to 40% of imported feed in the yearly diet of cows. In high input production systems such as type 5, the herbage component of the diet of cows is lower than in Dairy 1 (production system 2), and thus, variation of herbage NV is likely to play a less significant role in driving performance. Consequently, measuring herbage NV in high input systems might be less relevant. Research is required to determine the extent to which proximal hyperspectral herbage NV measurement could be useful in more intensified pasture-based dairy farm systems.

- Limitations imposed by the choice of the feeding system

In this thesis, calculation of energy requirements of cows was based on the AFRC (1993) energy feeding system, but other energy systems could have been used (e.g. INRA 1989; SCA 1990; NRC 2001; Fox et al. 2004; CSIRO 2007). Experimental research has found that the AFRC system can underestimate requirements for MEt of cows grazing pasture- (Dijkstra et al. 2008) or silage-based diets (Yan el at. 2003), the AFRC system was preferred over other systems due its simplicity and because its equations have served as the basis to the development of various decision support tools used in New Zealand (Frater et al. 2015). Moreover, the use of alternative systems to AFRC would have required addressing the inputs used in the calculation of energy requirements and the determination of the energy content of feeds. For instance, the NRC (2001) system uses net energy units as the basis of the calculation of energy requirements and energy values of feeds and so, using the NRC (2001) system would have required specific calibration models of hyperspectral canopy reflectance.

As the use of different energy systems might have required specific hyperspectral canopy reflectance calibrations for different herbage NV traits. In this thesis, hyperspectral canopy reflectance calibrations for protein were developed for the CP system. However, the CP system does not work well for balancing diets for protein as it does not differentiate the requirements of ruminal microbes and the requirements of the host animal (AFRC 1993, NRC 2001). A major advancement to the CP system is the metabolisable protein (MP) system (Burroughs et al. 1974), which does account for effects of microbes in the rumen. However, the use of the MP system would require the determination of the energy available for microbial growth (fermentable metabolizable energy [FME]), which is calculated by discounting the energy content of lipids and fermentation end products of herbage. However, because lipid content of herbage has been poorly predicted from hyperspectral canopy reflectance data (Pullanagari et al. 2012), the adaptation of proximal hyperspectral sensing to the MP system is limited. Further research involving more advanced machine learning algorithms to determine FME and lipid content of herbage from hyperspectral canopy reflectance would be of great use for the implementation of the MP system based on the use of proximal hyperspectral sensing. Such research would be helpful to determine how balanced for protein pasture-based dairy farm systems diets are and to therefore explore the potential impact of excess dietary protein on system performance and the environment.

- Need for experimental research

This thesis assessed the potential value of using proximal hyperspectral sensing herbage NV measurement by quantifying variation of herbage NV and energy requirements of cows in a pasture-based dairy farm system, and discussing how this information could be used for daily grazing management and feed allocation. However, experimental research is required to quantify the actual value of using the tool in practice. An experiment can be undertaken to compare the effect of allocating herbage and feed to cows according to energy and protein balance with the aid of proximal hyperspectral sensing herbage NV measurement against current farm practice.

7.3 Overall conclusion

Canopy reflectance models built using proximal hyperspectral sensing data were shown to be accurate in predicting the NV of the vertical portion of ryegrass-white clover mixed herbage available to the grazing cow. Evidence from data collected from Massey University's Dairy 1 farm, showed that temporal and spatial variation of herbage NV in addition to the variation of ME_t estimated requirements that exists within and between cows in the milking herd and were large enough to justify the use of proximal hyperspectral sensing as a rapid herbage NV measurement tool to assist with feed allocation decision-making. However, the potential use of this technology could be further enhanced if coupled with other precision technologies aimed at controlling animal behavior at grazing and allocation of herbage to individual cows or groups of cows. The potential benefits of precise herbage and supplement allocation decisions relate to more efficient grazing management and thus improved utilization of herbage and milk production. Moreover, environmental benefits could also be expected as the result of more efficient use of herbage and supplements.

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Appendix A

Development and validation of bench-top near-infrared spectroscopy calibration models

Bench-top near-infrared spectroscopy (NIRS) calibration models were developed for determination of DOMD, ME, CP, NDF and ADF of the 286 dried-ground herbage samples collected in this study. The data used for the development of these calibrations were obtained from a subset of the samples collected in this study and a complementary dataset provided by the New Zealand Centre for Precision Agriculture (NZCPA) at Massey University, Palmerston North. The complementary dataset consisted of dried-ground herbage spectral data and their associated wet chemistry NVs.

Fifty of the 286 samples collected in this study were selected for wet-chemistry analysis. The selection was performed by applying the Kennard-Stone algorithm implemented in the 'Prospectr' package for R software (Stevens et al. 2013) to the spectra of dried and ground herbage samples. Kennard-Stone selects samples that are uniformly distributed over the predictor space defined by candidate samples (Kennard and Stone 1969). The algorithm calculates Mahalanobis distance to select samples based on the spread of the data in a multidimensional space. Thereafter, the fifty selected samples were sent to the Nutrition Laboratory of the Institute of Food Science and Technology at Massey University, Palmerston North for determination of ME (MJME/kg DM) and percentages of DOMD, CP, NDF and ADF in DM.

Dry mater was determined using the procedure described by the Association of Official Analytical Chemists (AOAC 2005; method 930.15). Determination of DOMD was performed following the procedure described by Roughan and Holland (1977). Metabolisable energy was calculated from the equation MJME/kg DM = DOMD x 0.16 (McDonald 2002). CP was calculated from the equation CP = N (%) x 6.25, where the average nitrogen (N) content of protein was assumed to be 16%, (Marten et al. 1989) and N was determined following the Dumas method (AOAC 2005; method 968.06).. Percentages of ADF and NDF were determined using Ankom nylon bags following AOAC (2005) methods 2002.04 and 973.18, respectively.

Wet chemistry NV data and spectra corresponding to dried and ground herbage sample material was merged with the complementary dataset. The reference dataset resulted in a maximum of 3808 samples. Spectra of the reference dataset was pre-treated following the procedure described in Section 3.3.5 and then used to develop and validate dried-ground herbage spectra calibration models for the selected NV traits following the procedure described in Section 3.3.6. Model accuracy indicators for the training and validation datasets are summarised in Table A.1.

Table A.1 Accuracy of PLS regression calibration models built for determining the nutritive value (NV) of dried and ground herbage spectral measurements using training and validation datasets.

Dataset	NV trait	n	R^2	RMSE	RPE	Bias	RPD
Training	ME	1892	0.91	0.45	4.26	-2.43E-16	3.58
	CP	1606	0.95	1.02	5.68	3.32E-15	5.29
	NDF	191	0.87	3.56	6.94	-1.00E-15	3.01
	ADF	191	0.79	2.29	8.37	-4.84E-16	2.46
	DOMD	176	0.91	2.52	4.37	3.59E-15	3.99
Validation	ME	471	0.92	0.43	4.04	2.60E-02	3.46
	CP	399	0.94	1.13	6.34	8.10E-02	4.27
	NDF	44	0.87	2.95	5.76	7.04E-01	2.86
	ADF	44	0.76	2.27	8.24	-3.00E-02	1.84
	DOMD	40	0.95	1.68	2.93	-2.49E-01	4.55

ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

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Appendix B

Comparison of nutritive value of samples determined with different methods

The relationship of the nutritive value of fifty samples determined using wet chemistry, near-infrared spectroscopy and proximal hyperspectral sensing of herbage canopy was assessed. Correlation coefficients of NV traits and NV data as determined by the three methods are shown in Table B.1 and Figure B.1, respectively.

Table B.1 Correlation coefficients of nutritive value (NV) traits of fifty samples as determined by wet chemistry (WET), near-infrared spectroscopy (NIRS) and proximal hyperspectral sensing of herbage canopy (PHS). (n=50, $p < 0.001$)

NV trait		WET	NIRS
ME	NIRS	0.89	
	PHS	0.65	0.74
CP	NIRS	0.97	
	PHS	0.80	0.86
NDF	NIRS	0.90	
	PHS	0.69	0.67
ADF	NIRS	0.83	
	PHS	0.66	0.60
DOMD	NIRS	0.92	
	PHS	0.65	0.74

ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

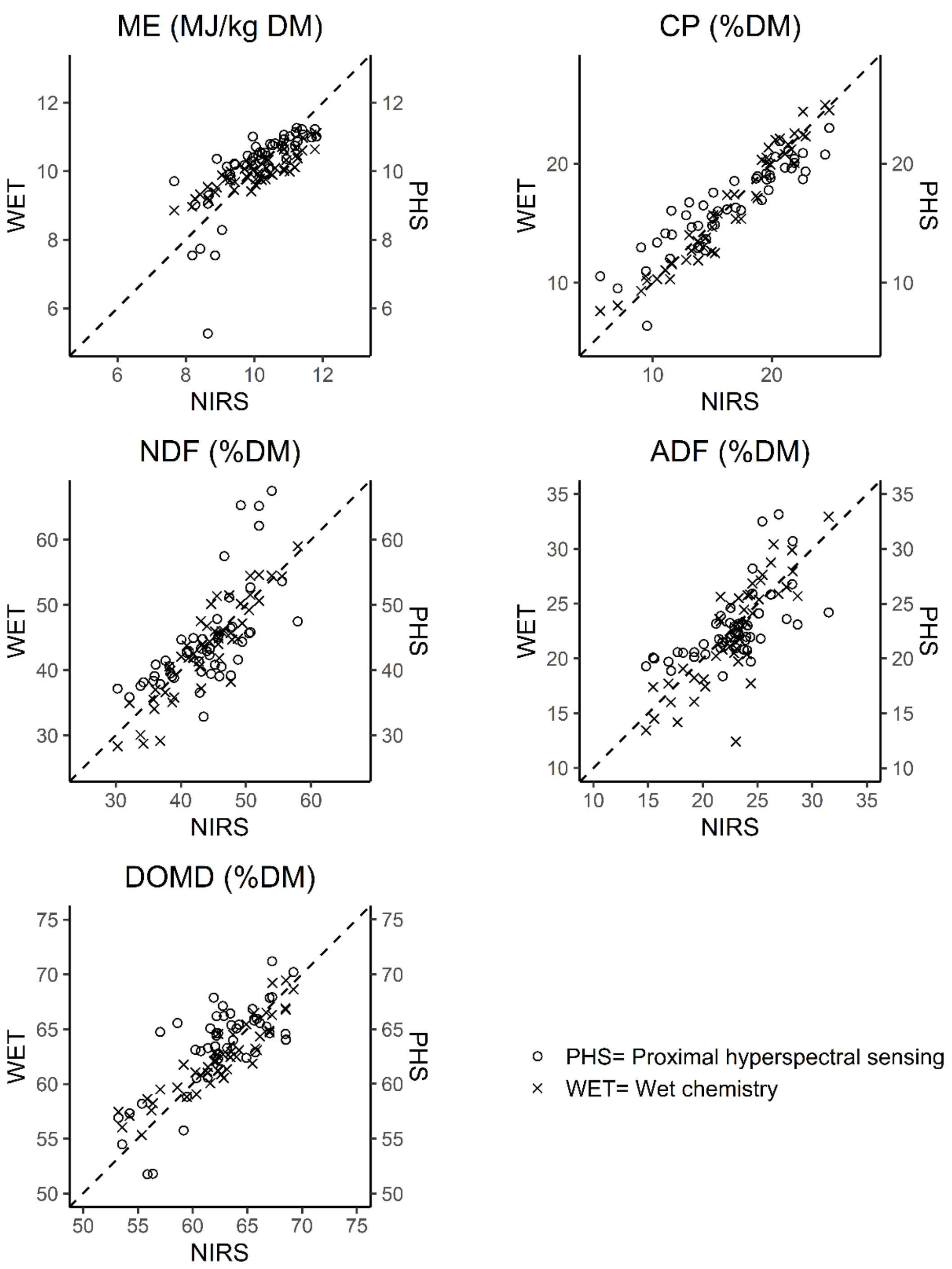

Figure B.1 Nutritive value of samples determined by wet chemistry analysis (WET), bench top near-infrared spectroscopy (NIRS) and proximal hyperspectral sensing of herbage canopies (PHS) (n= 50). (- - -) reference line with intercept of 0 and slope of 1. ME= metabolisable energy, CP= crude protein, NDF= neutral detergent fibre, ADF= acid detergent fibre, DOMD= digestible organic matter in dry matter.

Appendix C

Table C.1 Estimated principal components regression coefficients.

Response variable	Explanatory variable																
	Intercept	HM	HA	AH	PD	ME	CP	DM	Fibre	T	THI	CSI	Rain	POP: Early	POP: Mid	POP: Late	Y: 2016	Y: 2017
MYpc	16.08	0.034	0.028	-0.030	0.075	0.322	-0.024	-0.216	-0.010	0.092	0.232	-0.241	0.071	0.700	0.339	-1.142	-0.112	0.112
MSYpc	1.47	0.001	-0.001	-0.006	-0.001	0.033	-0.003	-0.023	-0.027	-0.018	-0.013	-0.002	0.001	0.015	0.028	-0.048	-0.014	0.014
MSPpc	9.16	0.000	0.042	-0.073	0.010	-0.274	-0.021	-0.032	-0.238	-0.119	-0.022	0.048	0.038	-0.096	-0.081	0.197	0.022	-0.022
PFRpc	0.76	-0.001	-0.001	-0.001	-0.001	-0.002	-0.001	0.001	0.002	0.001	0.001	0.000	0.000	-0.001	0.000	0.001	-0.001	0.001
FPpc	5.20	0.012	0.012	-0.001	0.008	-0.005	-0.016	0.036	-0.057	-0.044	-0.052	0.054	0.018	-0.066	-0.050	0.128	0.006	-0.006
PPpc	3.96	-0.052	0.201	-0.211	-0.018	-0.153	0.005	-0.022	-0.101	-0.033	0.011	0.017	-0.003	-0.056	-0.015	0.078	0.026	-0.026
FYpc	0.83	0.008	0.003	-0.004	0.005	0.021	-0.007	-0.005	-0.018	-0.003	0.005	-0.003	0.007	0.022	0.010	-0.035	-0.008	0.008
PYpc	0.63	0.001	-0.002	-0.005	-0.002	0.014	-0.002	-0.009	-0.011	-0.008	-0.006	-0.002	-0.001	0.006	0.012	-0.020	-0.006	0.006
MUpc	0.06	0.000	0.000	-0.001	0.000	0.001	0.002	-0.001	-0.001	-0.002	-0.002	-0.001	-0.001	0.002	-0.002	-0.001	-0.001	0.001
LWpc	479.13	0.280	1.021	-0.817	-0.101	-3.331	-1.106	-0.905	-4.740	-0.077	-0.271	-0.045	0.852	-1.205	-0.817	2.233	-0.388	0.388
LWCpc	-0.07	0.007	0.077	0.166	-0.118	-0.012	0.033	-0.012	0.043	0.061	0.030	0.040	-0.035	-0.055	0.010	0.048	-0.015	0.015
BCSpc	4.61	-0.018	0.118	-0.128	0.008	0.008	0.010	-0.008	-0.015	-0.026	-0.008	0.004	-0.005	0.049	-0.015	-0.036	0.006	-0.006
PI1	67.05	0.136	0.084	-0.311	0.535	2.621	0.766	-2.964	1.851	1.144	2.457	-3.130	0.448	8.260	3.828	-13.283	-0.875	0.875
PI2	28.13	-5.340	25.944	-24.887	-1.450	-4.062	-0.922	-1.196	-7.702	-5.121	0.036	2.186	0.452	-1.442	-1.842	3.660	1.171	-1.171

MYpc= milk yield per cow in the herd, MSYpc= milksolids yield per cow in the herd, MSPpc= milksolids percentage per cow in the herd, FPpc= milk fat percentage per cow in the herd, PPpc= milk protein percentage per cow in the herd, FYpc= milk fat yield per cow in the herd, PYpc= milk protein yield per cow in the herd, PFRpc= milk protein to fat ratio per cow in the herd, MUpc= milk urea per cow in the herd, LWpc= live weight per cow in the herd, LWCpc= live weight change per cow in the herd, BCSpc= body condition score per cow in the herd, PI1= performance indicator 1, PI2= performance indicator 2.
HM = herbage mass, HA= herbage allowance, AH= area of herbage offered, PD= proportion of herbage in diet, ME= herbage metabolisable energy, CP= herbage crude protein, DM= herbage dry matter, T= daily mean temperature, THI= temperature humidity index, CSI= cold stress index, Rain= rainfall, POP:Early= period of production defined between day 1 and day 90 from the beginning of milk production, POP:Mid= period of production defined between day 91 and day 180 from the beginning of milk production, POP:Late= period of production defined between day 181 and day 250 from the beginning of milk production Y:2016= 2016-17 production season, Y:2017= 2017-18 production season.

Table C.2 Estimated partial least squares regression coefficients.

Response variable	Explanatory variable																
	Intercept	HM	HA	AH	PD	ME	CP	DM	Fibre	T	THI	CSI	Rain	POP: Early	POP: Mid	POP: Late	Y: 2016	Y: 2017
MYpc	16.08	0.073	-0.024	0.050	-0.027	0.511	-0.157	-0.293	-0.083	0.009	0.133	-0.087	0.052	0.489	0.397	-0.981	-0.166	0.166
MSYpc	1.47	0.007	0.003	-0.005	0.004	0.028	-0.008	-0.014	-0.018	-0.019	-0.013	-0.009	-0.004	0.026	0.020	-0.051	-0.016	0.016
MSPpc	9.16	-0.012	0.080	-0.122	0.011	-0.138	0.005	0.031	-0.180	-0.118	-0.029	0.044	0.031	-0.138	-0.064	0.222	0.028	-0.028
PFRpc	0.76	-0.001	-0.003	-0.003	-0.002	-0.002	0.000	0.002	0.001	0.001	0.001	-0.001	-0.001	-0.001	0.000	0.001	-0.001	0.001
FPpc	5.20	0.002	0.027	0.000	0.009	-0.037	-0.011	0.043	-0.036	-0.056	-0.046	0.040	0.022	-0.043	-0.054	0.108	0.013	-0.013
PPpc	3.96	-0.035	0.095	-0.150	0.019	-0.161	0.017	-0.006	-0.115	-0.051	0.017	0.007	0.014	-0.048	-0.015	0.069	0.024	-0.024
FYpc	0.83	0.005	0.003	0.000	0.003	0.017	-0.005	-0.009	-0.010	-0.011	-0.007	-0.003	0.000	0.015	0.012	-0.030	-0.010	0.010
PYpc	0.63	0.002	0.000	-0.005	0.001	0.011	-0.003	-0.005	-0.007	-0.008	-0.005	-0.006	-0.003	0.012	0.008	-0.022	-0.007	0.007
MUpc	0.06	0.000	0.001	0.000	0.001	0.001	0.002	-0.001	-0.001	-0.002	-0.002	0.000	0.000	0.002	-0.002	0.000	0.000	0.000
LWpc	479.13	-0.050	2.735	-2.158	-0.267	-2.980	-0.741	-0.508	-4.391	-0.389	0.225	-0.161	0.988	-1.490	-0.533	2.216	-0.299	0.299
LWCpc	-0.07	-0.009	-0.022	0.237	-0.087	-0.030	0.022	-0.043	0.024	0.055	0.013	0.042	-0.036	-0.056	0.012	0.046	-0.027	0.027
BCSpc	4.61	-0.014	0.106	-0.123	0.011	-0.001	0.006	-0.017	-0.022	-0.027	-0.006	0.007	-0.007	0.052	-0.017	-0.036	0.005	-0.005
PI1	67.05	0.567	-1.403	0.374	-0.739	6.275	-0.441	-3.645	2.330	1.373	2.058	-1.728	-0.084	7.898	3.191	-12.16	-1.351	1.351
PI2	28.13	-4.744	23.40	-22.51	-1.503	-7.046	-1.916	-3.034	-9.656	-5.792	0.536	2.527	0.079	-0.625	-2.493	3.523	0.963	-0.963

MYpc= milk yield per cow in the herd, MSYpc= milksolids yield per cow in the herd, MSPpc= milksolids percentage per cow in the herd, FPpc= milk fat percentage per cow in the herd, PPpc= milk protein percentage per cow in the herd, FYpc= milk fat yield per cow in the herd, PYpc= milk protein yield per cow in the herd, PFRpc= milk protein to fat ratio per cow in the herd, MUpc= milk urea per cow in the herd, LWpc= live weight per cow in the herd, LWCpc= live weight change per cow in the herd, BCSpc= body condition score per cow in the herd, PI1= performance indicator 1, PI2= performance indicator 2
HM = herbage mass, HA= herbage allowance, AH= area of herbage offered, PD= proportion of herbage in diet, ME= herbage metabolisable energy, CP= herbage crude protein, DM= herbage dry matter, T= daily mean temperature, THI= temperature humidity index, CSI= cold stress index, Rain= rainfall, POP:Early= period of production defined between day 1 and day 90 from the beginning of milk production, POP:Mid= period of production defined between day 91 and day 180 from the beginning of milk production, POP:Late= period of production defined between day 181 and day 250 from the beginning of milk production Y:2016= 2016-17 production season, Y:2017= 2017-18 production season.

Appendix D

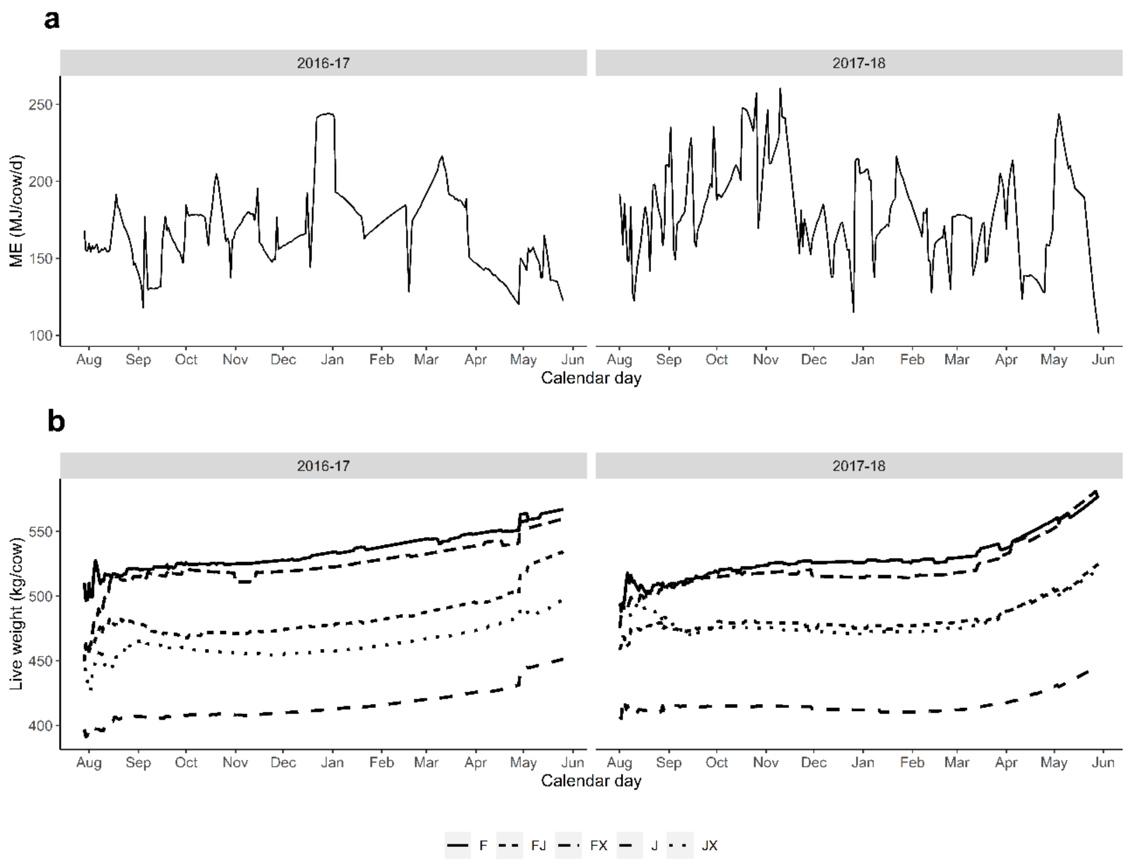

Figure D.1 Metabolisable energy (ME) estimated requirements per cow per day (a) and daily live weight of cows grouped by breed (b) during the 2016-17 and 2017-18 production seasons at Dairy 1, Massey University, Palmerston North. F= Holstein-Friesian, FX= Holstein-Friesian crossbred, FJ= Holstein-Friesian-Jersey crossbred, JX= Jersey crossbred, J= Jersey.