SENSORS FOR ASSESSING PASTURE QUALITY

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Abstract

There are a number of sensing technologies which are being researched to assess pasture quality. Recent efforts have concentrated on non-destructive methodologies that give farmers access to near real-time information to assist in informing pasture management decision making. Previously, only time consuming and destructive sampling has been employed with assessment of quality being completed through wet chemistry or laboratory based VIS/NIR techniques. This paper summarises the work where a variety of optical sensors were used to sense pasture quality parameters such as: crude protein (CP), acid detergent fibre (ADF), neutral detergent fibre (NDF), ash, dietary cation-anion difference (DCAD), lignin, lipid, metabolisable energy (ME) and organic matter digestibility (OMD) was evaluated. *In situ* canopy spectral reflectance was obtained from mixed pastures, under commercial farm conditions in New Zealand.

The approach was to use a hyper-spectral (ASD Field Spec® Pro) sensor and a 16-channel multi-spectral sensor (MSR 16R, Cropscan, Inc.) for predicting the pasture quality parameters. A three channel sensor (Crop Circle™; Model- ACS470, Holland Scientific) was also used to assess dry matter (DM) and crude protein availability (CPA).

The statistical methods were employed to establish a relationship between reflectance measurements and wet chemistry. In all cases these sensors showed that a number of the pasture quality parameters could be assessed with reasonable levels of explanation. For the multispectral sensor acceptable levels of explanation could be obtained and could be improved through season-specific models.

Introduction

In New Zealand dairy farming, grazed pastures are the main source of animal feed. Therefore, accurate assessment of pasture quantity and quality are essential for efficient and productive dairy farm management. Measurement of pasture quantity is more frequently used in pasture management, however, in recent years, concern about the pasture quality has been growing. Many scientists have proved that providing high quality pasture to animals substantially improves the animal performance and milk production (Holmes et al., 2007). Stocking rates can also be manipulated if the availability of the quality is predetermined. Furthermore, early detection of pasture quality helps the farm manager to improve the quality of pasture by decision making such as proactive fertiliser application and adjusting grazing intervals. In addition, good quality pasture also can reduce the enteric methane emissions (FAO, 2010). Generally, pasture quality represented by a combination of parameters such as crude protein, acid detergent fibre, neutral detergent fibre, ash lignin, lipid, metabolisable energy and organic matter digestibility (Holmes et al., 2007).

Traditionally, in order to measure the pasture quality parameters, laboratory based wet chemistry has been used, this is costly, laborious and time consuming, and required hazardous chemicals. Conversely, near infrared spectroscopy (NIRS) has become available for determining pasture quality parameters in a rapid and low cost way. Since the NIRS proved as a potential tool for estimating forage quality (Marten et al., 1985), it has been used widely in various commercial laboratories. Although NIRS is widely used, it involves destructive sampling, drying and grinding. Alternatively, remote sensing tools have been developed for in-field sensing of pasture parameters. In remote sensing, based on the position of the sensors, three types of sensors are available: space borne, air borne and proximal. Proximal sensors are promising in commercial agriculture because of instant results from the sensors and flexible to operate. These results provide the opportunity to make decisions immediately. Numerous researchers have conducted experiments to establish relationships between reflectance and pasture quality parameters (Pullanagari et al., 2011; Sanches, 2009). The aim of this publication is to provide the research updates of proximal sensing tools for estimating pasture quality.

Relevance of spectral reflectance for estimating pasture quality

Fundamentally, there is an explicit relationship between vegetation reflectance and biochemistry of corresponding vegetation (Curran, 1989). This led to development of many techniques to predict the biochemistry of vegetation using reflectance. Consequently, NASA launched a programme called “Accelerated Canopy Chemistry Programme” to examine the scope of imaging spectroscopy to predict forest foliar chemistry (NASA, 1994). They found interesting results that the reflectance values strongly correlated with foliar chemical parameters (Martin & Aber, 1997). After that, many scientists have attempted to examine the potential of sensing devices. In a review by Curran (1989) 42 absorption features in visible near infrared region of the electromagnetic spectrum have been listed that are related to various foliar chemicals. Peterson et al. (1988) showed that the absorption features in the region of 1500-1700 nm were attributable to lignin and starch. The visible and near infrared regions also have great potential for estimating chlorophyll which is essential parameter for plant growth and development. The absorption peaks around 695-990 nm and 1950-2400 nm were related to crude protein (Pullanagari et al., 2011). The red-edge region (670-780 nm) also has shown great potential for estimating chlorophyll and carotenoid pigments, and nitrogen concentration (Cho & Skidmore, 2006).

Sensor types

Based on the spectral resolution, the optical sensors classified into multispectral and hyperpsectral sensors. Multispectral sensors acquire spectral reflectance in a small number of broad wavelengths of the electromagnetic spectrum. For example, Cropscan™ sensor has 16 wavelengths, six in visible, three in near infrared and two in shortwave infrared region of the electromagnetic spectrum. Crop Circle has three wavebands (two in visible region and one in near infrared region of the electromagnetic spectrum). These sensors are widely available in the market and commercially have been used in cropping systems. Conversely, hyperspectral sensors being operated with contiguous narrow wavebands from visible (350 nm) to shortwave infrared region (2500 nm) of the electromagnetic spectrum. Generally, hyperspectral data require expensive computation as compared to multispectral data, and has more potential to describe vegetation features with high accuracy.

Table 1 The results of different experiments for estimating pasture quality parameters

Parameter	Coefficient of determination (r^2)	Type of sensor	Statistical method	Reference
Crude Protein	0.78	Hyperspectral	PLSR	(Pullanagari et al., 2011)
	0.85-0.93	Hyperspectral	PLSR	(Biewer et al., 2009)
	0.62	Hyperspectral	SMLR	(Kawamura et al., 2008)
	0.67	Hyperspectral	Vegetation indice	(Starks et al., 2006b)
	0.72	Multipsectral	SMLR	(Pullanagari et al., 2012)
	0.73	Hyperspectral	SMLR	(Starks et al., 2006a)
	0.68	Hyperspectral	ANN	(Starks & Brown, 2010)
	0.74	Multispectral	Vegetation indice	(Pullanagari et al., 2012)
	0.74	Hyperspectral	SMLR	(Zhao et al., 2007)
Acid detergent fibre	0.82	Hyperspectral	PLSR	(Pullanagari et al., 2011)
	0.23	Hyperspectral	Vegetation indice	(Starks et al., 2006b)
	0.48	Hyperspectral	SMLR	(Starks et al., 2006a)
	0.31	Hyperspectral	ANN	(Starks & Brown, 2010)
	0.52	Multispectral	SMLR	(Pullanagari et al., 2012)
	0.60	Multispectral	Vegetation indice	(Pullanagari et al., 2012)
	0.84	Hyperspectral	PLSR	(Biewer et al., 2009)
	0.16	Hyperspectral	SMLR	(Zhao et al., 2007)
	0.90	Hyperspectral	Vegetation indice	(Albayrak, 2008)
	0.79	Hyperspectral	PLSR	(Schut et al., 2006)
Neutral detergent fibre	0.75	Hyperspectral	PLSR	(Pullanagari et al., 2011)
	0.20	Hyperspectral	Vegetation indice	(Starks et al., 2006b)
	0.30	Hyperspectral	SMLR	(Starks et al., 2006a)
	0.28	Hyperspectral	ANN	(Starks & Brown, 2010)
	0.42	Multispectral	SMLR	(Pullanagari et al., 2012)
	0.58	Hyperspectral	SMLR	(Zhao et al., 2007)
	0.85	Hyperspectral	Vegetation indice	(Albayrak, 2008)
Ash	0.65	Hyperspectral	PLSR	(Pullanagari et al., 2011)
	0.87	Hyperspectral	PLSR	(Biewer et al., 2009)
	0.57	Hyperspectral	PLSR	(Schut et al., 2006)
Metabolisable energy	0.83	Hyperspectral	PLSR	(Pullanagari et al., 2011)
	0.80	Hyperspectral	PLSR	(Biewer et al., 2009)
Organic matter digestability	0.83	Hyperspectral	PLSR	(Pullanagari et al., 2011)

Statistical methods for explaining the foliar chemical information

A range of statistical methods have been devised to extract the useful information from the spectral reflectance of the vegetation. This process is made difficult because reflectance at each wavelength is influenced by a number of confounding characteristics of the vegetation. An approach of calculating vegetation indices and regressing against the desired vegetation parameter has been widely used in the experimental studies because of their simplicity in interpretation. Typically, a vegetation index mathematically calculated using reflectance values of the spectra at different wavelengths. For example, normalised difference vegetative index (NDVI), is a combination of visible and near infrared wavebands and is a prominent index for characterising the vegetation features. In reality, the sensitivity of the vegetation indices are influenced by many confounding factors such as soil background, moisture, leaf thickness, leaf angle distribution, sensor view angle and dead vegetation etc. Subsequently, to minimise the effect of external perturbing factors, a variety of vegetation indices were proposed which are reviewed by Yule & Pullanagari (2009). Based on the spectral resolution, the vegetation indices are divided into broadband and narrow band indices. Such narrow band indices derived from hyperspectral sensor data. Many studies (Donald et al., 2010; Flynn et al., 2008; Pullanagari et al., 2012) were attempted to correlate the vegetation indices to the desired property of green vegetation. However, due the availability of limited spectral information from vegetation indices, stepwise multiple regression (SMLR) was used in analysis for improving the prediction accuracy. It obtains the spectral information from many selected wavebands. SMLR is often used in lab-NIRS for analysing quality parameters of dry forage samples (Marten et al., 1985). However, SMLR has some limitations such as under-fitting and over-fitting of the models and it cannot deal the multicollinearity problems which is commonly exists in spectral data. To overcome these problems, partial least squares regression (PLSR) was introduced where it can effectively deal with multicollinearity and extracts useful information numerous variables particularly hyperspectral data (Pullanagari et al., 2011). The findings from several experiments had revealed that PLSR is a robust method for explaining the vegetation features with high accuracy (Biewer et al., 2009; Pullanagari et al., 2011). Furthermore, there are also some sophisticated methods such as artificial neural networks (ANN) made available for analysing the data. However, it is more complicated and hard to understand. Table 1 lists the success of various studies to predict pasture quality parameters using different sensors and statistical methods.

Conclusion:

Optical sensors have potential to explain the quality of pasture rapidly and non-destructively. This in-field sensing enables the farmer's decision making regarding stock management, feed budgeting and precision application of inputs which results in higher profit and lower environmental footprint.

Considerable research has been completed to develop techniques for explaining the pasture quality parameters using reflectance values derived from different sensors. The advances in sensing has progressed a long way towards improving the predictive ability of the models and to minimise the impact of other perturbing factors.

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