In-field pasture quality measurement using near infrared spectroscopy

M. Challies,[a] K. Taukiri[a] and R. Dynes[b]
[a]AgReseach MIRINZ, PB 3123 Hamilton 3240, New Zealand.
Phone: +64 7 8385392, E-mail: michelle.challies@agresearch.co.nz
[b]AgResearch Lincoln, PB 4749, Christchurch 8140, New Zealand

Introduction

The objective of this study was to determine whether a near infrared (NIR) device could be used to assess New Zealand pasture quality attributes in the field using a mobile platform. This involved the development of a prototype device to enable collection of spectra from pastures in a trial, spanning multiple years and seasons. Data analysis techniques were then developed that allowed the consideration of all samples as a single dataset. Results for pasture quality attributes Acid Detergent Fibre (ADF), Dry Matter% (DM%) and Crude Protein (CP) are reported here, and reasons for poor calibration efficiency are discussed.

Improved pasture utilisation and feed quality would increase forage conversion efficiency and hence productivity and farm profitability. It could also enable the benchmarking of farms and the comparison of different management strategies and technologies. Pasture quality measurement would enable better management of this resource and using NIR as a means to do this has shown promise in the Netherlands[1] and Australia.[2]

Challenges of taking NIR spectra from fresh pasture include the presence of varying quantities of moisture on the grass as a result of rain or dew which is highly absorptive, and the waxy coating of the grass itself where more light can be reflected and potentially mask the spectral signatures of interest. A large data set was collected to overcome some of these issues.

Materials and methods

The dataset comprises 571 separate measurement sites (0.25 m^2 quadrats) taken from more than 50 paddocks from ten farms in the North Island of New Zealand. These included dairy, sheep and beef grazed pastures. Scans taken at differing heights and speeds gave over 3000 individual spectra. Following scanning, the 0.25 m^2 quadrats[3] were cut to ground level, sorted, dried, weighed and then sent to laboratories for a varied set of reference testing that included both NIRS and wet chemistry measurements.

A diode array spectrophotometer constructed by KES Analysis,[4] with a spectral range of 400–1700 nm, selected wavelength interval of 5 nm and 0.1 m diameter sensing zone, was adapted

Figure 1. TOBI measurement system.

for field use. With its own light source, spectra can be acquired in varying cloud coverage. This involved the mounting of the unit into a sealed container and onto the front of an All Terrain Vehicle (ATV) called TOBI (shown in Figure 1) such that the scan height relative to grazing height could be adjusted to low, medium and high settings, and to travel at speeds of 0, 5, 10, 15 and 20 km h^{-1}.

Within the main trial, the effect of scan height and speed were investigated for their effect on predictive performance.

Quadrat sites per paddock were chosen to capture the quality range for that paddock and marked out using pegged down sheets of polythene. For stationary trials, two sites within each quadrat were scanned in triple replicate representing 6.3% of the sample area, while for moving trials sub spectra were collected continuously as the TOBI drove across at the desired speed. The polythene markers allowed spectra to be differentiated between quadrats and strips of un-sampled pasture. Between 1 and 19 sub spectra were acquired per quadrat depending on sample rate and speed. Calibration tile (CT) spectra were acquired before and after scanning each paddock.

Data analysis was performed using Matlab R2006b[5] and the PLS_Toolbox.[6] As spectra were loaded, the bias of each trial (time point) was removed by correcting the CT spectra with the ratio between the maximum response of the source to the CT prior to calculation of reflectance. For moving trials sub spectra for each quadrat and speed were averaged prior to processing. Finally combining the spectra from all trials involved auto-scaling each spectrum according to the overall dataset mean and standard deviation. Figure 2 shows the difference between the corrected and uncorrected spectra by 2-component PCA highlighted by trial.

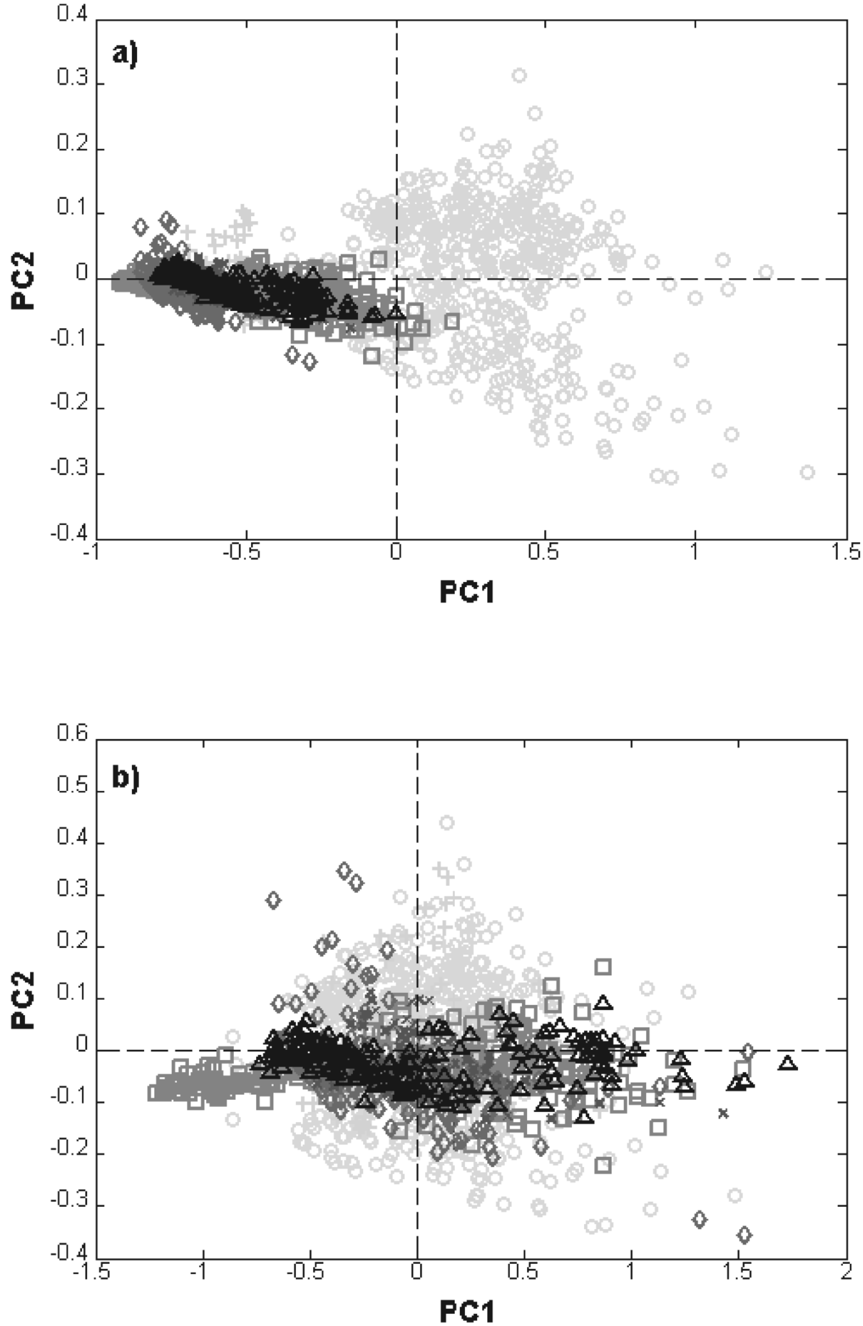

Figure 2. Two-component PCA of spectra uncorrected a), and corrected b) for the effect of trials. Trials 1 through to 6 are shown by circle, plus, square, diamond, cross and triangle symbols, respectively.

Spectra from unique quadrats were randomly divided into three groups, calibration, validation and test sets in the ratio 2:1:1. A variety of preprocessing methods were tested on the calibration dataset to establish the best case model for each attribute, applied to both Reflectance (REFL) and Absorbance (ABS) spectra with and without Enhanced Multiplicative Scatter Correction[7] (EMSC), to remove the effect of water and water temperature. Optimal PLS models were determined for each scenario by cross validation on the calibration set. The most successful treatments were selected by least *RMSEC* and were either General Least Squares weighting (GLS) or Standard Normal Variate scaling (SNV) coupled with GLS.

Results and discussion

The development and use of a mobile in-field NIR data collection device was essential to the progress of this study. Coupled with the finding that the effect of scan height and speed was not significant, spectra for entire paddocks can now easily and reliably be acquired, approaching the ultimate goal of spatial mapping of pasture quality in-field.

Validation results for three calibrations are shown in Table 1 where the Ratio of Prediction to Deviation (*RPD*) ranges between 0.96 and 1.20 meaning these parameters cannot be predicted accurately using these calibrations.[8] The scatter plot for DM% is shown in Figure 3 and illustrates several predictions against each reference measure and hence each quadrat, due to differing scan conditions such as height or speed.

These predictions cluster together suggesting that scans taken at approximately the same location generate comparable results and perform consistently. The average standard deviation of

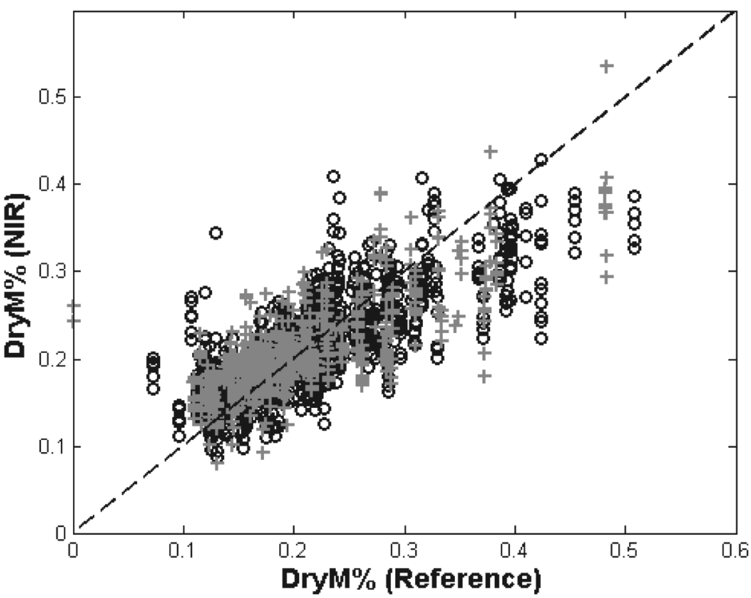

Figure 3. Best case PLS prediction for Dry Matter %. EMSC corrected REFL Spectra pre-processed by GLS+SNV, three factors. Calibration samples (black circles) and validation samples (grey plus symbols).

Table 1. Pasture quality attributes and validation metrics.

		Attribute		
		ADF	DM%	CP
	Total Samples	2160	2113	2154
	Pre-processing	ABS, GLS	EMSC(REFL), GLS+SNV	ABS, GLS
	PLS Factors	2	3	3
Calibration	Quadrats	276	274	275
	R^2_{CAL}	0.64	0.60	0.55
	$RMSEP_{CAL}$	2.69	0.04	2.74
	RPD_{CAL}	1.33	1.23	1.10
Validation	Quadrats	139	138	139
	R^2_{VAL}	0.55	0.56	0.43
	$RMSEP_{VAL}$	2.94	0.05	3.14
	RPD_{VAL}	1.20	1.11	0.96

predictions for DM% where more than one was generated per quadrat was 0.019, less than half the overall $RMSEP_{VAL}$ of 0.05.

Every quadrat was scanned from the stationary TOBI with a scan view of only 6.3% of the total quadrat area from which reference measurements were made. Therefore, although quadrats were selected by technicians for their visual homogeneity, it is probable the pasture quality varies within this region and will contribute to some degree to the error in the calibrations.

Conclusions

Calibrations have been made for a dataset spanning a wide range of pasture quality, however, to be of practical use these will need to be more accurate. Some benefit may yet be gained through classification of high versus low quality parameters. The trial spanned several years and contained a large number of confounding factors including weather, season, time of day and pasture types to capture the desired range of reference data. Improvements may be possible from targeted calibrations of subsets of this dataset where practical. Further analysis of later trials has suggested improved trial techniques, such as greater scan coverage of the quadrat area could vastly improve model performance.

Acknowledgements

This work was supported by funding from the Pastoral 21 partnership. The authors wish to thank G.R. Burling-Claridge and A. Litherland for their significant contributions to this project.

References

1. A.G.T. Schut and J.M.H. Ketelaars, *Grass and Forage Science* **58,** 385 (2003).
2. A. Edirisinghe, D.A. Henry, G.E. Donald and E. Hulm, *Animal Production in Australia* **25,** 35 (2004).
3. G.P. Cosgrove, K. Betteridge, V.J. Thomas and D.C. Corson, *Proceedings NZ Society of Animal Production* **58,** 25 (1998).
4. KES Analysis Inc., New York, USA.
5. Eigenvector Research Inc., Wenatachee, WA, USA.
6. The MathWorks Inc., Natick, MA, USA.
7. H. Martens and E. Stark, *J. Pharmaceut. Biomed.* **9,** 625 (1991).
8. P.C. Williams and D.C. Sobering, *J. Near Infrared Spectrosc.* **1,** 1 (1993).