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Hyperspectral Proximal Sensing of the Botanical Composition and Nutrient Content of New Zealand Pastures

**A thesis presented in partial fulfilment of the
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Abstract

The potential of hyperspectral proximal sensing to quantify sward characteristics important in making critical decisions on the management of sheep and dairy pastures in New Zealand has been investigated.

Hyperspectral data were acquired using an ASD FieldSpec[®] Pro FR spectroradiometer attached to the Canopy Pasture Probe (CAPP). The CAPP was developed to enable the collection of *in situ* reflectance data from New Zealand pasture canopies independent of ambient light conditions. A matt white ceramic tile was selected as a reflectance standard to be used with the CAPP, after testing a variety of materials. Pasture reflectance factor spectra between 350-2500 nm (with spectral resolutions of 3 nm between 350-1000 nm and 10 nm between 1000-2500 nm) and pasture samples were collected from six hill country and lowland areas, across all seasons (August 2006 to September 2007) in a number of regions in the North Island of New Zealand.

After pre-processing (e.g. spectral averaging, de-stepping, elimination of noisy wavelengths, smoothing) the spectral data collected from sites were correlated against pasture botanical composition (expressed as proportions of grass, legume and weed) and pasture nutrients (nitrogen, phosphorus, potassium, calcium, magnesium, sodium and sulphur) expressed in percentage of dry matter (%) and amount (kg ha⁻¹) using partial least squares regressions (PLSR). The accuracy and precision of the calibrations were tested using either the full cross-validation leave-one-out method or testing datasets. Regressions were carried out using the reflectance factor data per se and after mathematical transformation, including first derivative, absorbance and continuum-removed spectra. Overall best results were obtained using the first derivative data. The quality of predictions varied greatly with the pasture attribute, site and season.

Some reasonable results were achieved for the prediction of pasture grass and legume proportions when analysing samples collected during autumn (grass: $R^2 > 0.81$ and $SD/RMSEP \geq 2.3$ and legume: $R^2 > 0.80$ and $SD/RMSEP \geq 2.2$), but predicting pasture weed content was poor for all sites and seasons ($R^2 \leq 0.44$ and $SD/RMSEP \leq 1.2$). The inaccurate predictions might be explained by the fact that the diversity found in the field

and observed in the pasture spectral data was not taken into account in the pasture botanical separation.

The potential for using proximal sensing techniques to predict pasture nutrients *in situ* was confirmed, with the sensing of pasture N, P and K increased by the procedure of separating the data according to the season of the year. The full potential of the technology will only be realised if a substantial dataset representing all the variability found in the field is gathered. The importance of obtaining representative datasets that embrace all the biophysical factors (e.g. pasture type, canopy structure) likely to affect the relationship, when building prediction calibrations, was highlighted in this research by the variance in the predictions for the same nutrient using different datasets, and by the inconsistency in the number of common wavelengths when examining the wavelengths contributing to the relationship. The ability to use a single model to predict multiple nutrients, or indeed individual nutrients, will only come through a good understanding of the factors likely to influence any calibration function. It has been demonstrated in this research that reasonably accurate and precise pasture nutrient predictions ($R^2 > 0.74$ and $SD/RMSEP \geq 2.0$) can be made from fresh *in situ* canopy measurements. This still falls short of the quality of the predictions reported for near infrared reflectance spectroscopy (NIRS) for dried, ground samples analysed under controlled laboratory conditions.

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List of Abbreviations

A	autumn
Alf.	Alfredton
ASD	Analytical Spectral Devices – ASD Inc.
Ati.	Atiamuri
Bal.	Ballantrae
CAPP	canopy pasture probe
c.f.	compare or consult
Col.	Colyton
Conc.	Concentration (%)
CV	coefficient of variation
DM	dry matter
FDR	first derivative reflectance
FIA	flow injection analysis
FR	full range
ICP-OES	inductively coupled plasma-optical emission spectroscopy
IR	infrared
LV	latent variable
Max.	maximum
Man.	Manawahe
Min.	minimum
MIR	mid infrared
NIR	near infrared
NIRS	near infrared reflectance spectroscopy
PCA	principal component analysis
PLSR	partial least squares regression
PTFE	polytetrafluoroethylene
RMSE	root mean square error
RMSECV	root mean square error of cross-validation
RMSEP	root mean square error of prediction

RPD	ratio prediction to deviation
Rua.	Ruakura
SD	standard deviation
Sp	spring
Su	summer
SWIR	short-wave infrared
Tok.	Tokoroa
Vis	visible
W	winter