Hyperspectral canopy reflectance as a potential tool to estimate and map pasture mass and quality

K. KAWAMURA[1], K. BETTERIDGE[2], D. COSTALL[2], I.D. SANCHES[3], M.P. TUOHY[3] and Y. INOUE[1]
[1]*National Institute for Agro-Environmental Sciences, Tsukuba, Ibaraki 305-8604, Japan*
[2]*AgResearch, Grasslands Research Centre, Palmerston North*
[3]*New Zealand Centre for Precision Agriculture, Massey University, Palmerston North*
kamuken@hiroshima-u.ac.jp

Abstract

Precision farming requires data on resource status at a very fine, within-paddock scale which is impractical to collect by traditional sampling methods. This paper demonstrates the potential of a modified field hyperspectral radiometer (spectro-CAPP) to predict and map spatial distribution patterns of herbage biomass and standing mass of nitrogen (N), phosphorous (P), potassium (K), and sulphur (S) in a 2.8 ha paddock on a Taupo hill country farm in November 2006. A partial least squares (PLS) regression model using a continuum-removed data transformation procedure gave an excellent prediction of the standing masses of N, P, and S (R^2>0.893); a good prediction of standing biomass (R^2 = 0.857); and moderate prediction of standing K (R^2=0.809). In each model the transformed data gave better predictions than the raw reflected spectral data. Using geostatistical analyses, pasture parameters were moderately or strongly spatially dependent with the average size of dry matter and nutrient biomass 'patches' ranging from 10 to 59 m. These results suggest that a 5 m interval grid sampling strategy would be suitable to develop a site-specific fertiliser application map in this hill environment, at a similar time of year.
Keywords: geostatistical analysis, pasture quality, semivariogram, spatial distribution

Introduction

For efficient pasture management, quantitative information on pasture biomass and quality and the spatial variation of these within and between fields is important. Intake of dry matter (biomass, BM), nitrogen (N), phosphorous (P), potassium (K) and sulphur (S) can each affect animal performance while low levels of these minerals in pasture can indicate low soil availability of these nutrients for plant growth. To refine management practices, farmers require information on spatial patterns of soil fertility so that plant nutrient requirements can be managed at the paddock or within-paddock scale using variable rate fertiliser application technologies (K. Betteridge *et al.* unpublished). Small scale sampling of biomass and nutrient mass might also improve feed planning and grazing strategy decisions, but this requires techniques that can measure pasture status quickly, cost effectively, and continuously across the paddock.

Hyperspectral radiometers can be used to measure the reflected light spectra of the pasture canopy to estimate pasture BM and quality (Kawamura *et al.* 2008; Mutanga *et al.* 2004; Schut *et al.* 2005; Starks *et al.* 2006). Typically these studies have focused on N, acid detergent fibre (ADF) and neutral detergent fibre (NDF) concentrations in fresh herbage. Nitrogen (Johnson 2001), ADF and NDF (Kawamura *et al.* 2008; Schut *et al.* 2006) can be predicted with >60% accuracy in the field, but to date the prediction of P, K and S, using canopy reflectance, has received little attention (Ferwerda & Skidmore 2007; Mutanga *et al.* 2004).

Spectral signatures of pasture need to be taken in cloud-free conditions to ensure a uniform quality of incident light, but this is a major limitation in New Zealand. The canopy pasture probe (spectro-CAPP), based on a hyperspectral radiometer (an ASD FieldSpec Pro FR Analytical Spectral Devices Inc. (ASD), Boulder, CO, USA) with a built in light source and a dark enclosure that is placed over the target pasture (Sanches *et al.* in press), circumvents this problem and was used in this study. The aims of this study were to estimate standing BM (kg DM/ha) and herbage mass of the nutrients N, P, K, and S (kg DM/ha) with the spectro-CAPP, and to map patterns of spatial distribution of these parameters within a target paddock.

Materials and Methods

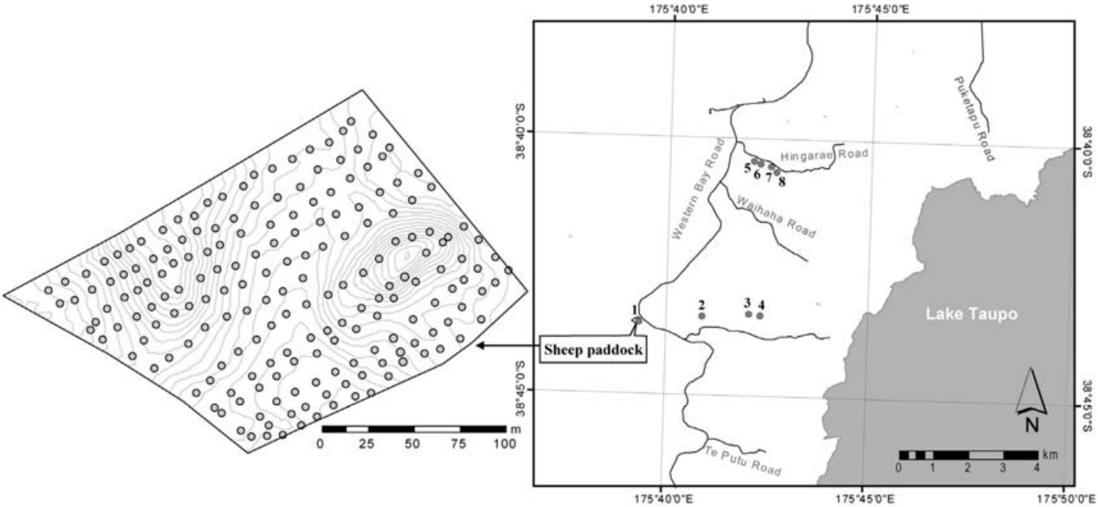
Study sites

This trial was conducted on the Motere Landcorp Ltd farm on the western side of Lake Taupo (Fig. 1). Eight paddocks of differing fertility status were selected to maximize the ranges in plant mass, chemical and physiological states. One 2.83 ha (target) paddock of these eight paddocks, was also used to develop the spatial distribution maps of standing BM and standing mass of nutrients (Fig. 1). The elevation ranged from 572 to 590 m above sea level.

Field reflectance measurements

Hyperspectral reflectance spectra were collected from 100 quadrats (0.09 m^2) spread across the eight paddocks, during 29-31 November 2006. The ASD spectro-radiometer has a spectral sampling interval of 1.4 nm in

Figure 1 Locations of eight paddocks on the western side of Lake Taupo, and the sampling map showing the 201 spectral reading sites superimposed on the digital elevation model (DEM) of the target, sheep paddock.



the 350–1000 nm range, and 2 nm in the 1000–2500 nm range. The spectral resolution (full-width-half-maximum; FWHM) is 3 nm in the 350–1000 nm range, and 10 nm in the 1000–2500 nm range, which were calculated to 1 nm resolution wavelengths (derived wavebands) for the output data, using software (RS2 for Windows®; ASD, Boulder, CO, USA).

In addition, separate spectral readings from 201 sites within the target paddock were gathered for the purpose of mapping the pasture parameters (see Fig. 1). The location of spectral measurements was determined using a very high resolution differential GPS (GeoExplorer 3, Trimble Navigation, Ltd., Sunnyvale, CA, USA).

The spectro-CAPP took 30 spectral readings of the pasture canopy at each sample site and was calibrated with a 295 mm × 295 mm matt white ceramic tile (San Lorenzo Blanco Niveo) (Sanches *et al*. in press).

Plant sampling and chemical analysis

Except for the 201 sites in the target paddock, all vegetation in the 0.09 m^2 (30 cm × 30 cm) 'reference' quadrats was clipped to ground level after measuring reflectance. Forage was dried at 60°C for 48 hours to determine BM and chemical analyses of dried forage were carried out at Hills Laboratory, Hamilton. The N concentration (mg/g) was measured following Kjeldahl digestion (Basson 1976). Estimates of K, P, and S concentration (mg/g) were made using an auto-analyser (TJA 1997). Herbage mass of N, P, K and S was the product of mineral content (%DM) and BM (kg DM/ha).

Spectral data processing

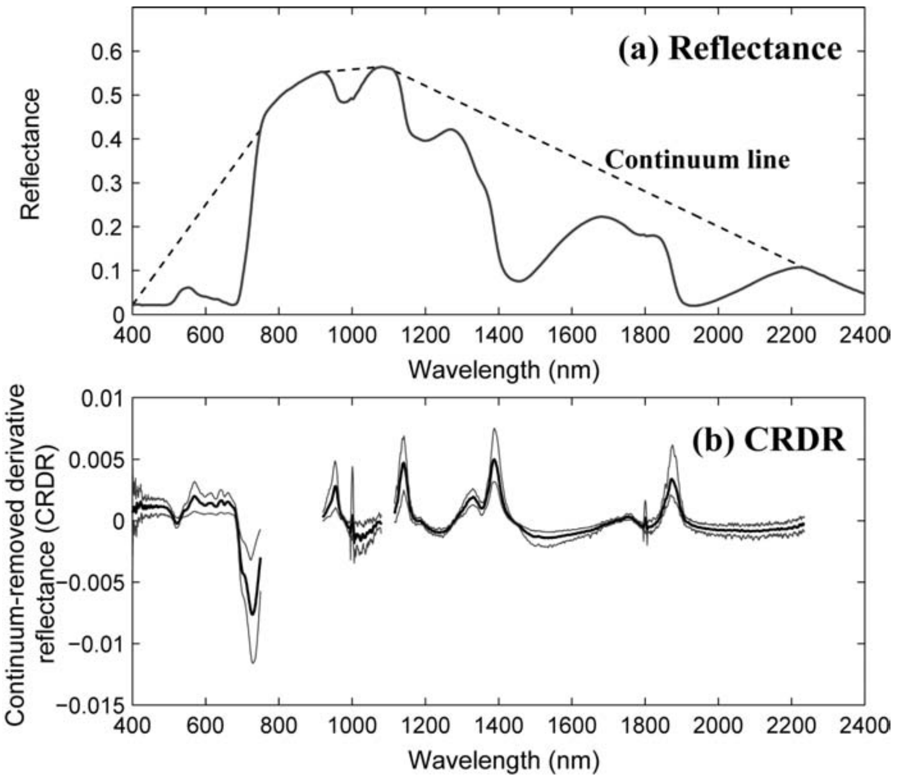
Spectral data of 2001 derived wavebands between 400 nm and 2400 nm were used in the analyses. Four of the 100 reference (training + test) samples were eliminated as outliers based on a principal component analysis (PCA) (Macho *et al.* 2001).

Canopy reflectance and the continuum-removed derivative reflectance (CRDR) (Mutanga *et al.* 2004) datasets were compared. The continuum is removed by dividing the reflectance value for each 1 nm derived waveband in the absorption feature by the reflectance level of the continuum line (convex hull) at the corresponding wavelength (Fig. 2a). Three regions (400-750, 920-1080, and 1115-2235 nm) were carefully selected to calculate continuum-removed features. The CRDR transformed data were calculated by applying a Savitzky-Golay smoothing filter (Savitzky & Golay 1964) (Fig. 2b). A third-order, seven-band moving polynomial was fitted through the original reflectance signatures. The parameters of this polynomial were subsequently used to calculate the derivative at the centre waveband of the moving spline window.

Statistical data analysis

The reference dataset was split into two equal-sized subsets; the training data (n=48) was used for making PLS calibration models; and test data (n=48) for testing purposes. In this case, the test dataset was created by taking every second sample from the sorted pasture parameters of interest (e.g. 2, 4, … , 94, 96 as the test data) such that the distribution patterns of the two datasets were similar. PLS regression analyses were performed using reflectance and CRDR datasets to predict BM and mass of nutrients (N, P, K, and S) using PLS Toolbox ver. 7.2 (Eigenvector Research, Inc., Manson, WA) in

Figure 2 Mean canopy reflectance spectrum (solid line) and its continuum line (dashed line) (a), used to derive the continuum-removed derivative reflectance (CRDR) (b).



Matlab software ver. 7.4 (Mathworks Inc., Sherborn, MA).

The accuracy of the calibration models was evaluated by the coefficient of determination (R^2), root mean squares error of prediction (RMSEP) and the ratio of prediction to deviation (RPD) (Williams 2001). The RPD value was the ratio of standard deviation (SD) in the test data to the standard error of prediction (SEP) or standard error of cross-validation (SECV), which was used to evaluate how well the calibration model could predict quantitative data. Based on RPD values, five levels of prediction accuracy were considered: (1) <1.5, the calibration is useful; (2) 1.5-2.0, there is a low possibility of distinguishing between high and low predicted values; (3) 2.0-2.5, approximate quantitative values of prediction can be made; (4) 2.5-3.0, quantitative prediction values are good, because the prediction error is reduced to less than half of the error made when using the mean composition; (5) >3.0, prediction values are excellent and are acceptable for analytical purposes in most near infrared spectroscopy (NIRS) agricultural applications.

Mapping

Spatial distribution maps of BM and mass of nutrients (N, P, K, and S) were generated from the separately measured 201-site spectro-CAPP and GPS datasets of the whole paddock by applying the calibration models. A geostatistical approach was used to model the optimal map grid size in the paddock using 'gstat' package ver. 0.9-40 (Pebesma 2004) on R statistical software ver. 2.5.1 (R Development Core Team 2007). Semivariances were first calculated to determine the spatial dependence within pasture parameters, then kriging was used to map the spatial distribution of pasture parameters within the target paddock. The nugget (c_o) value of a semivariogram indicates the random error in the dataset whereas the lag (h) indicates the variances explained by the spatial model. A low ratio of c_o: h (k) indicates the data have a very strong spatial structure whereas a high k value suggests the spatial structure is weak because of the large amount of random variation in the data. The semivariogram 'range' shows the average distance (or patch size) over which there is no significant change in value of the parameter. A small range requires intensive sampling to adequately represent the heterogeneous distribution of a parameter, and vice versa.

Results and Discussion

Table 1 shows results of the descriptive analysis for herbage mass and concentration of mineral components

Table 1 Descriptive analysis for herbage mass of biomass (BM), nitrogen (N), phosphorus (P), potassium (K) and sulphur (S), and concentrations of N, P, K and S in the training and test subsets.

Pasture parameters	Training data (n = 48)				Test data (n = 48)			
	Mean	Range	SD	CV	Mean	Range	SD	CV
Herbage mass of								
BM (kg DM/ha)	4064.5	791 - 9233	2359.1	59.7	3967.0	753 - 9086	2419.2	59.9
N (kg DM/ha)	96.3	20.3 - 212.2	52.2	55.0	94.2	13.3 - 192.1	51.2	55.2
P (kg DM/ha)	16.1	2.3 - 39.2	10.3	64.5	15.8	1.6 - 36.9	10.1	64.9
K (kg DM/ha)	86.5	11.0 - 233.7	59.7	69.0	89.8	1.3 - 294.2	64.4	72.2
S (kg DM/ha)	8.7	1.7 - 19.9	5.2	61.3	8.5	1.1 - 19.1	5.1	62.0
Concentration of								
N (mg/g)	25.2	16.7 - 41.5	5.7	22.6	24.9	16.3 - 38.7	5.4	21.7
P (mg/g)	3.9	2.4 - 5.2	0.7	19.3	3.8	2.0 - 5.1	0.7	19.9
K (mg/g)	21.1	0.3 - 34.3	5.5	29.9	20.8	0.2 - 32.9	5.6	30.3
S (mg/g)	2.2	1.4 - 3.2	0.4	19.0	2.1	1.3 - 3.2	0.4	19.1

SD: Standard deviation; CV: Coefficient of variance [= standard deviation / mean × 100 (%)]

Table 2 Number of PLS factors (Comps), coefficients of determination (R^2), root mean square errors of calibration (RMSEC) and prediction (RMSEP) in the training and test data, respectively, and the ratio of prediction to deviation (RPD) for Reflectance and CRDR spectral datasets used to predict herbage biomass (BM), and masses of N, P, K, and S (kg DM/ha).

Pasture parameter	Spectral data type	Training data			Test data		
		Comps	R^2	RMSEC	R^2	RMSEP	RPD
BM	Reflectance	6	0.902	750.78	0.812	1,029.19	2.30
	CRDR	5	0.974	374.50	0.857	930.94	2.57
N	Reflectance	8	0.951	11.48	0.893	18.87	2.85
	CRDR	5	0.970	8.90	0.895	17.14	3.04
P	Reflectance	7	0.944	2.41	0.913	3.16	3.23
	CRDR	5	0.976	1.59	0.943	2.43	4.20
K	Reflectance	4	0.748	29.61	0.770	30.83	2.07
	CRDR	3	0.865	21.71	0.809	28.43	2.24
S	Reflectance	7	0.944	2.41	0.913	3.16	3.23
	CRDR	5	0.976	1.59	0.943	2.43	4.20

Table 3 Parameters of the spherical semivariogram models used.

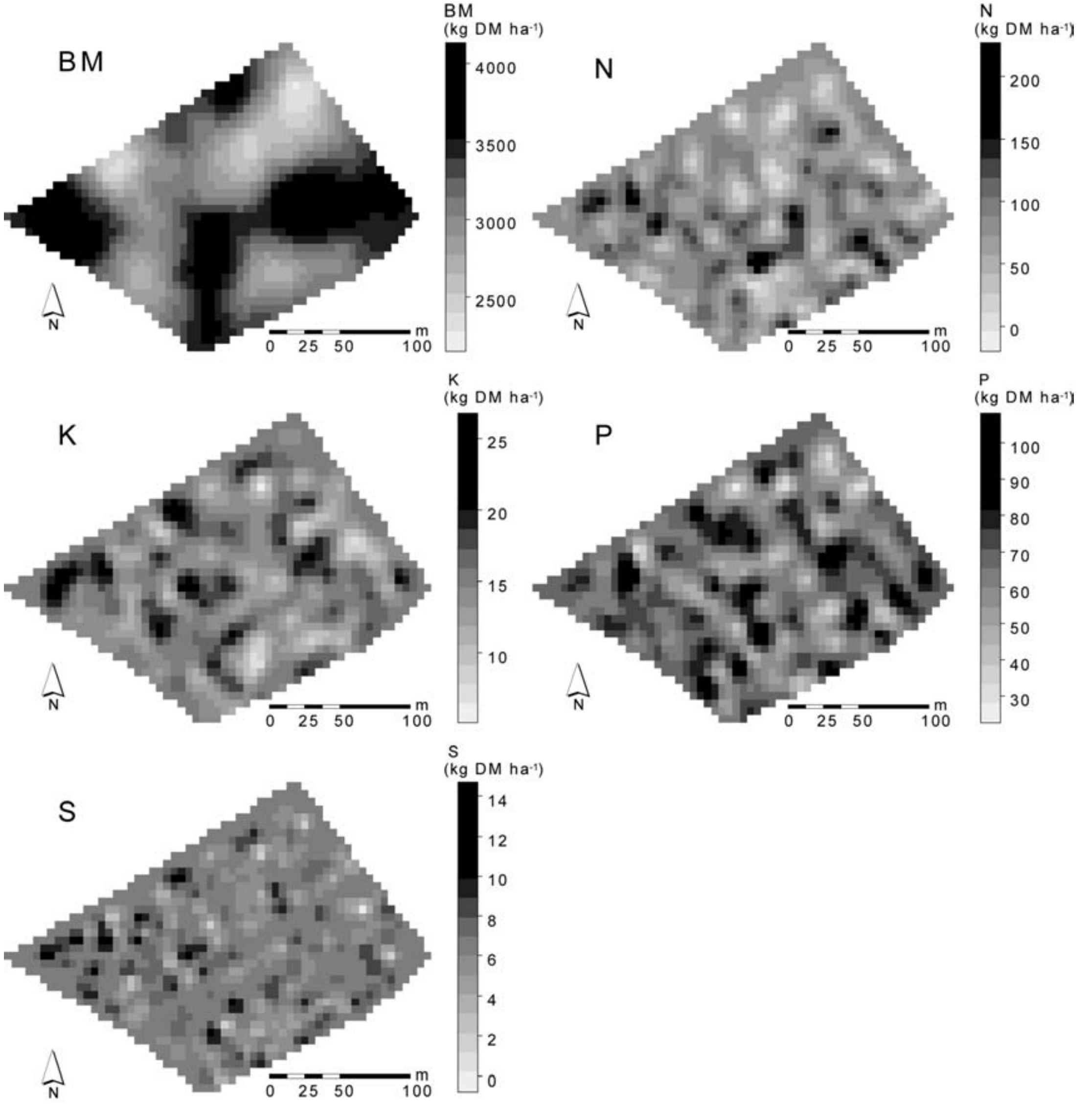
Pasture parameter	Semivariogram model type	Range (a)	Ratio k ($c_0/(c_0+c)$)
BM	Spherical	58.7	0.732
N	Spherical	17.4	0.082
P	Spherical	17.0	0.541
K	Spherical	16.6	0.577
S	Spherical	10.6	0.390

in the training ($n = 48$) and test ($n = 48$) datasets. Biomass at the start of this trial was unusually high, reflecting excellent spring growth at this time. The quality of the pasture was assessed visually as being high. Mean concentrations of P and K were in the optimal range for milking dairy cattle, but N and S would be classed as deficient (Roberts & Morton 1999). The lowest values in the range for each mineral were very deficient based on the milking cow standard, thereby providing a very good spread of data from which to derive calibration curves.

PLS calibration results between spectro-CAPP spectra and herbage BM, and masses of nutrients are shown in Table 2. In the training dataset, R^2 values for standing BM, and masses of N, P, K, and S were 0.902 to 0.974, 0.951 to 0.970, 0.944 to 0.976, 0.748 to 0.865, and 0.944 to 0.976, respectively. The optimum number of PLS factors selected for the model to predict pasture parameters ranged between 3 and 8, based on the leave-one-out cross validation process. As expected, lower R^2 values and larger prediction errors (RMSEP) were obtained for all parameters in the test dataset, compared to the training dataset. Higher R^2 values for standing masses of BM (0.857), and masses of N (0.895), P (0.943), K (0.809), and S (0.943) were derived when using CRDR data for estimating all pasture parameters compared to R^2 values based on reflectance data.

Statistical quality and future applicability of a calibration can be judged from the RPD value (Williams 2001). An RPD value greater than 3.0 is considered acceptable for analytical purposes in most of NIRS applications for agricultural products. However, some reports state that for field analysis an acceptable RPD value would be 2 or higher (Cohen *et al.* 2005). In the present study, CRDR data used in the PLS model gave an excellent prediction

Figure 3 Spatial distribution maps (5 m grid cells) of herbage biomass, and standing masses of N, P, K, and S in the target paddock.



of the standing masses of N, P, and S (RPD > 3.0), but gave only a moderately good prediction of standing biomass (RPD = 2.57). Although relatively lower prediction accuracy was achieved for standing K, it is still possible to make quantitative predictions using CRDR (RPD = 2.24).

Two parameters estimated in semivariograms are shown in Table 3. These were obtained by applying the PLS models to separately acquired spectro-CAPP data (CRDR datasets) in the target paddock. The *k* parameter for herbage BM, and masses of N, P, K, and S was 0.73, 0.08, 0.54, 0.58 and 0.39, respectively. The very low *k* value of N indicates a large lag *h* (variance explained by the spatial model) and the sampling density closely matched the spatial variation. However, the large *k* value for standing BM suggests that there is considerable random variation and/or recording error in these data.

The parameter range ((*a*), Table 3) of the semivariogram for BM was much wider (58.7 m) than for the other parameters (10.6-17.4 m). The small ranges indicate *spatially dependent* data which are highly heterogeneous within a paddock and require more intensive sampling than for BM with its large range value. Data with a large range are less *spatially dependent* because the rate of change across the paddock is more gradual; and sampling intensity can also be less.

K. Kawamura *et al.* (unpublished) have demonstrated that soil P fertility status can be predicted from knowledge of pasture P status. Thus, by producing a spatial distribution map of pasture P status, as we have in this study, we can also infer the soil Olsen P status at fine, within-paddock resolution. This lack of soil fertility resolution has been a major limitation to developing precision fertiliser requirement maps to optimise pasture response to fertiliser, financial returns and environmental outcomes (Betteridge *et al.* unpublished).

Kerry & Oliver (2003, 2004) pointed out that the sampling interval should be less than half the range of spatial variation in order to ensure that spatial dependence can be accommodated in future sampling. If the variation shows strong continuity, as with standing BM in our target paddock, the range parameter might be so large in relation to the size of the field, that sampling density based on the range would be too small to make a reliable spatial distribution map of BM. In the target paddock the minimum value of range was 10.6 m for standing S mass. Thus a sampling interval of about 5 m would be suitable to make a useful spatial distribution map. Therefore, 5 m grid cell maps of herbage BM and the masses of N, P, K, and S were generated in the target paddock using the ordinary kriging method (Fig. 3). These results not only give practical information to farm consultants when considering variable rate fertiliser strategies, but also provide useful insights relating to sampling strategies when collecting information for any similar agricultural situation requiring site specific data collection. Furthermore, such maps created using a grid cell sampling method allows the information to be used in further analyses within a geographic information system (GIS) with regard to environmental factors, such as soil fertility status, grazing intensity, elevation, slope, etc., (Kawamura *et al.* 2005) and excreta distribution patterns. Future study will examine environmental effects on spatial distribution patterns of pasture BM and mineral components using GIS technologies.

Conclusions

This study demonstrates the potential of hyperspectral imaging using the spectro-CAPP and PLS regression for estimating and mapping herbage biomass and the standing mass of four major nutrients, without confounding due to cloud cover. We also compared the predictive ability for these parameters between two spectral datasets; reflectance and CRDR, used in PLS regression analyses. Pasture parameters were estimated with lower RMSEP and higher RPD values with CRDR data transformations, providing more reliable estimates than from raw reflectance data. Based on geostatistical analysis and the need to sample at half the semivariance 'range', extracting data from aerial or satellite hyperspectral images at 5 m spacings across the target paddock will enable the creation of site-specific fertiliser application maps in hill country and lowland pastures. These spatial maps of pasture parameters can also be used to help interpret behaviour characteristics of animals fitted with GPS tracking devices.

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