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# Hyperspectral imaging to measure pasture nutrient concentration and other quality parameters

**Yule I.J[1], Pullanagari R.R[1], Kereszturi G[1], Irwin M[1], McVeagh P[1], Cushnahan T.A[1], Cushnahan M.Z[1], White, M[2]**

(1) New Zealand Centre for Precision Agriculture, Institute of Agriculture and Environment, Massey University, Private Bag 11 222, Palmerston North, New Zealand (2) Ravensdown Fertiliser Co-operative Limited, 292 Main S Rd, Hornby, Christchurch, New Zealand

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***Abstract.*** *Managing pasture nutrient requirements on large hill country sheep and beef properties based on information from soil sampling is expensive because of the time and labor involved. High levels of error are also expected as these properties are often greatly variable and it is therefore extremely difficult to sample intensively enough to capture this variation. Extensive sampling was also not considered viable as there was no effective means of spreading fertilizer with a variable rate capability over this terrain. A large project was commissioned which looked to replace soil sampling in areas of mixed pasture with remotely sensed information from a hyperspectral imaging system to inform fertilizer application. One of the major objectives of the project was to establish whether hyperspectral imaging could map pasture nutrient concentration levels from aerial surveys. Canopy reflectance data was measured using a high resolution airborne visible-to-shortwave infrared (Vis-SWIR) imaging spectrometer measuring in the wavelength region 380 to 2500 nm to predict nutrient concentrations. The main nutrients of interest were nitrogen (N) phosphorus (P), potassium (K), sulfur (S).*

*Nutrient prediction models were developed using a number of regression, such as Support Vector Regression, methods which utilized calibrating ground based surveys. The level of explanation for the various nutrients is stated. High levels of explanation were achieved and the best training models were used to extrapolate the models to the whole farm. The methodology has been used over 8 geographical areas of New Zealand and in different seasons to maximize the levels of variation observed and avoid model over fitting. The project is working closely with Ravensdown Fertiliser Co-operative Limited who has funded the project in partnership with the New Zealand Ministry for Primary Industry. The project will allow the company to develop a much more precise and efficient* *nutrient planning and application service. The nutrient application will be completed through a fleet of topdressing aircraft and vehicles capable of variable rate application. The spatial maps demonstrate large variations in pasture nutrient content and other pasture quality parameters which are not normally measured and therefore not taken into account by farmers in their pasture management. Information from the project presents a significant opportunity to improve pasture management and resulting animal production.*

***Keywords.*** *Hyperspectral imaging, Pasture Management, Pasture Quality Management, Support Vector Regression, Remote Sensing, Precision Agriculture.*

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## Introduction

The transition from conventional farming to precision farming where high profitability can be targeted with minimal impact on the environment is a key driver for technological development. Nutrient content of pasture is a critical factor in improving grazing animal performance as it is closely related to the factors associated with health and weight gain. Measuring the nutrient content of pasture has historically relied on laboratory techniques or visual assessment. However, laboratory techniques involve expensive and time-consuming procedures, such as collection of physical plant and soil samples, and thus only limited numbers of samples can be analyzed. This type of sparse sampling procedure cannot provide spatially adequate information to capture the high level of spatial heterogeneity in pasture. A number of systems allow the farmer to estimate the yield from pasture based on various commercially available proximal sensors but none are available that can measure nutrient status. These systems are also limited by the time needed to survey large areas and in their lack of any geospatial reference which precludes targeted management. The steep nature of hill farms additionally precludes the use of many of these devices over much of their area. Therefore, intensive aerial sampling with spatial information is essential for precise pasture and farm management. This can be achieved by aerial remote sensing techniques which sample intensively, non-destructively, have geospatial references as well as high spatial resolutions and cover large areas in a short time.

Remote sensing technology based on measuring light reflectance has been successfully used on vegetation since the 1970s (e.g. Rouse Jr et al., 1974) and spawned a revolution in sensor development. The early sensors used discrete bands at a number of key locations in the electromagnetic spectrum and were later referred to as Multispectral sensors. Although still useful for many tasks, hyperspectral remote sensing is increasingly being used for mapping and monitoring crops (e.g. Dutta et al., 2015; Mahajan et al., 2014). The increasing use of hyperspectral technologies is largely due to the fact that these sensors measure many contiguous and narrow spectral channels (Goetz et al., 1985; Green et al., 1998). This continuous spectral information provides far greater detail on the target to develop a greater understanding of surface materials and to quantify the various physical and biochemical attributes of vegetation (Brandmeier et al., 2013; Chabrillat et al., 2002; Delegido et al., 2015; Manzo et al., 2015; Piiroinen et al., 2015; Zhang and Li, 2014). In addition to spectral information, hyperspectral imaging provides high-resolution spatial information of the scanned objects.

A large number of vegetation indices have been proposed to link the spectral information to an array of vegetation attributes using fitting functions (Fu and Burgher, 2015; Galvão et al., 2013; Kross et al., 2011; Rouse et al., 1974; Wang et al., 2003). However, vegetation indices carry limited information because they are based on mathematical combinations of two or three discrete bands. Rather than a few bands, the information from the full spectrum provides detailed information about the scanned objects; hence making accurate quantification possible. For instance, hyperspectral remote sensing has been shown to be a potential tool for accurately quantifying pasture quality attributes (Pullanagari et al., 2016). The relationships between spectral data and ground values were developed using multivariate statistics including Partial Least Squares Regression (PLSR) methods (Martin et al., 2008; Pellissier et al., 2015; Ramoelo et al., 2012), random forest (Ramoelo et al., 2015), artificial neural networks (Knox et al., 2011; Mutanga and Skidmore, 2004).

Hyperspectral sensors are now increasingly available and a cost-effective tool for agricultural research. The present investigation aims to illustrate the potential of hyperspectral imaging for quantifying nutrient concentrations of pasture on hill country farms in New Zealand.

## Materials and Methods

An AisaFENIX hyperspectral sensor manufactured by Specim (Finland) was used to obtain imagery for 8 farms in New Zealand. This AisaFENIX sensor was mounted in a Cessna 206 aircraft and was used along with a single antenna RT Oxford Survey+ Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU) system. The AisaFENIX sensor is capable of acquiring signals of electromagnetic radiation from 380 nm (VIS) to 2500 nm (SWIR) regions. It has a spectral sampling interval of 3.5–5.5 nm from the VIS and SWIR regions. The AisaFENIX sensor has a Field Of View (FOV) of 32.2°, as well as an Instantaneous Field of View (IFOV) of 0.084°.

The aerial survey was performed at a height of 700–800 m above ground level, at a ground speed of 110 knots at a swath width of 400-500 m. The surveys acquired data with a ground sampling distance of 1 m, and 448 spectral wavebands. The captured raw Digital Number (DN) data was converted to radiance values using CaliGeoPRO. The georectification was carried out using an 8 m resolution Digital Elevation Model. For atmospheric corrections, a physically based model of atmosphere based on MODTRAN5 was used to process the radiance images in ATCOR 4 (Richter and Schläpfer, 2002). This procedure reduced unwanted solar illumination and atmospheric effects, such as aerosol scattering and water vapor absorption from the imagery, ensuring the data could be directly compared with other atmospherically corrected spectra.

Within hours of the aerial survey, a ground survey was carried out at 80 sites within each farm selected using stratified sampling based on slope, aspect and soil. . Each of these 80 sampling locations had five selected sub-sites within which field spectrometry, plant tissue and soil samples were taken. The freshly cut plant samples were processed and examined for the major element concentrations, Nitrogen (N), Phosphorus (P), Potassium (K), Sulfur (S), using an Inductively Coupled Plasma Mass Spectrometer (ICP-MS) at the Analytical Research Laboratories Limited (ARL) of Ravensdown. Nutrient prediction models were developed by establishing the relationships between laboratory-generated values and spectral data using a Support Vector Regression (SVR) method. The SVR is a non-linear non-parametric method that is used to effectively extract relevant, subtle information from the full spectra (Verrelst et al., 2015).

## Results and discussion

The results of the method applied in this paper will be illustrated on a hill country farm, Patitapu Station (Figure 1). Patitapu Station (Farm-2) is situated in the North Island, New Zealand. The results include nutrient maps, calculated using SVR. In this study, all of the pasture nutrients were predicted with reasonable accuracy using the SVR method (see Table 1). Among all nutrients, nitrogen was predicted with highest accuracy (R2CV=0.75, RMSECV=0.40). These results support the findings of (Knox et al., 2012; Mutanga et al., 2005; Sanches et al., 2013).

**Table 1: Prediction Results for Pasture Nutrient Prediction Accuracy at Patitapu Station in 2015**

| Pasture nutrient | $R^2_{CV}$ | $RMSE_{CV}$ |
|---|---|---|
| Nitrogen | 0.75 | 0.40 |
| Phosphorus | 0.65 | 0.020 |
| Potassium | 0.71 | 0.43 |
| Sulfur | 0.70 | 0.06 |

The obtained nitrogen levels from Patitapu Station range from 1.6 to 4.5 % w/w. Nitrogen concentrations of 4.0-4.5 and 4.5-5.5 % w/w are considered critical ranges for maximum yield for

Ryegrass and white clover respectively (McNaught, 1970). The nitrogen level detected using hyperspectral imagery is very consistent with laboratory-based data from all the eight farms from New Zealand (Figure 2), highlighting that the method is capable to provide consistent results at reduced cost.

In order to communicate the results to end-users, these models were then used to generate high resolution (1 m) nutrient maps over eight farms. Before creating high resolution maps of nutrients an image classification was applied to isolate the pasture areas (e.g. Figure 1), in which the SVR method is calibrated using the unsupervised K-means classification in ENVI 5.2. Fine-scale nutrients maps help in characterizing the heterogeneity and spatial variability of pasture. The degree of spatial variability of nutrients is important for precise site specific management because the pasture growth and nutrient status is somewhat influenced by intrinsic and extrinsic factors, such as soil properties (texture, fertility, organic matter, pH), topography, slope and grazing management (Aarons et al., 2015). Grazers can use this information to manage feed supply and stocking rates. Managing fertilizer application site-specifically through the variable rate applications would optimize pasture productivity with the premise that either excessive fertilizer can be avoided or fertilizer deficiency can be corrected (Murray and Yule, 2007).

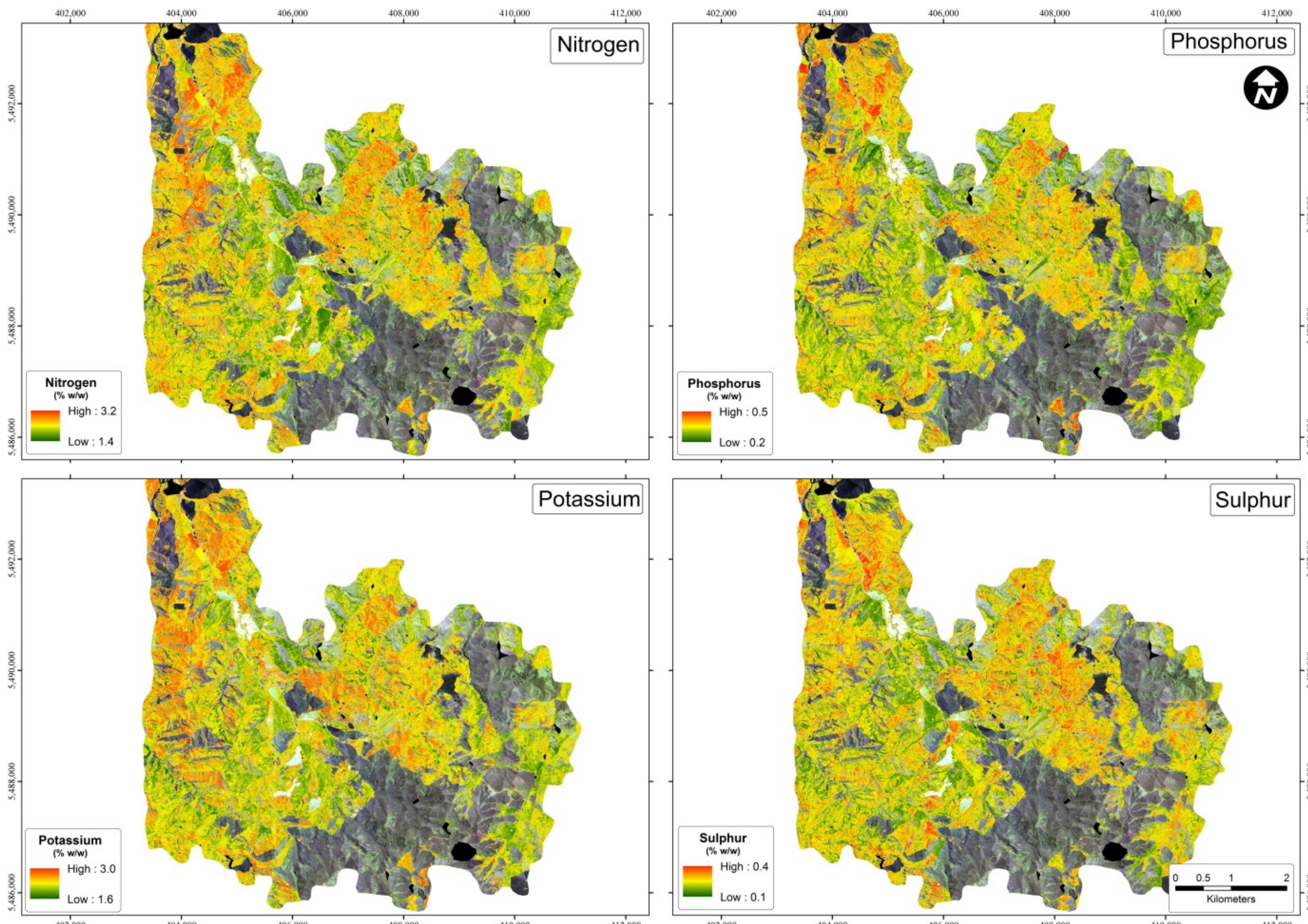


**Figure 1: Nutrient concentrations maps indicating Nitrogen, Phosphorus, Potassium and Sulfur concentrations on Patitapu Station (December 2015 survey).**

The descriptive statistics (mean and standard deviation) of the various pasture nutrients from each farm are presented in Figure 2. Farm-1 had the highest mean and standard deviation (variability) values for N, P and K. In contrast, Farm-4 had lowest mean and standard deviation values for N, P, K. There are significant differences in the mean values between the farms caused by variable soil properties, climatic conditions and pasture management practices.

The results from this study have shown that the information from AisaFENIX offers valuable opportunities for creating high resolution pasture nutrient content maps which could be used for implementing precision management practices such as stock manipulation and variable rate fertilizer application. Unlike laboratory techniques, hyperspectral imaging is a rapid and cost-effective technology that provides information to estimate multiple nutrient concentrations simultaneously.

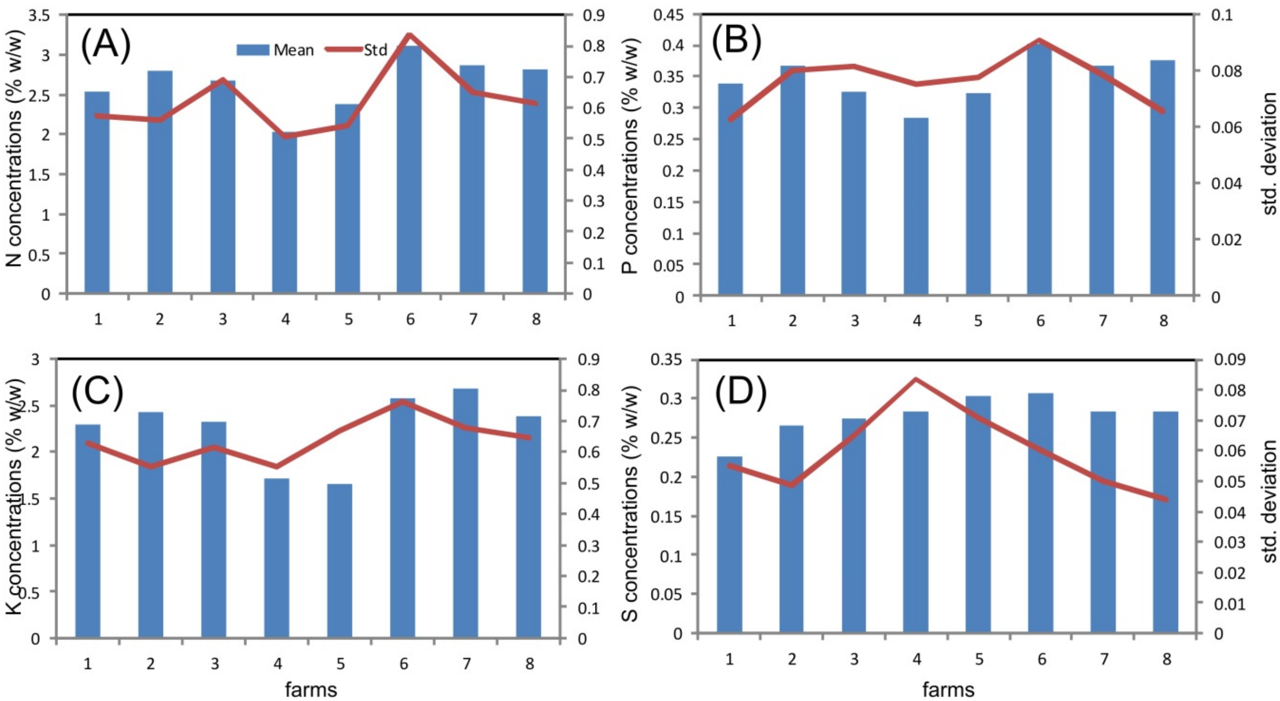


**Figure 1: Average and standard deviation of pasture nutrients (A – Nitrogen, B – Phosphorous, C – Potassium, D – Sulfur) at eight hill country farms**

## Conclusions

(1) Hyperspectral remote sensing is a useful tool to predict fine details of nutrient concentrations in plant tissue. Hyperspectral data and the applied methodology presented in this paper is suitable for developing better land-management practices.

(2) This technology enables rapid, cost effective sampling at paddock or farm scale with associated geospatial references. The imagery enables identification of the spatial pattern of nutrient concentrations at an unprecedented spatial resolution. The benefit to the end-user will require integration with variable rate fertilizer application technology to be able to effectively incorporate the information into farm management practices.

(3) This technology is easy to apply and fine-tune so it could be applied on other agricultural and vegetated areas worldwide, providing a new and exciting management tool.

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