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Mapping of macro and micro nutrients of mixed pastures using airborne AisaFENIX hyperspectral imagery

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ABSTRACT

On-farm assessment of mixed pasture nutrient concentrations is important for animal production and pasture management. Hyperspectral imaging is recognized as a potential tool to quantify the nutrient content of vegetation. However, it is a great challenge to estimate macro and micro nutrients in heterogeneous mixed pastures. In this study, canopy reflectance data was measured by using a high resolution airborne visible-to-shortwave infrared (Vis–SWIR) imaging spectrometer measuring in the wavelength region 380–2500 nm to predict nutrient concentrations, nitrogen (N) phosphorus (P), potassium (K), sulfur (S), zinc (Zn), sodium (Na), manganese (Mn) copper (Cu) and magnesium (Mg) in heterogeneous mixed pastures across a sheep and beef farm in hill country, within New Zealand. Prediction models were developed using four different methods which are included partial least squares regression (PLSR), kernel PLSR, support vector regression (SVR), random forest regression (RFR) algorithms and their performance compared using the test data. The results from the study revealed that RFR produced highest accuracy ($0.55 \leqslant R^2_{CV} \leqslant 0.78$; $6.68\% \leqslant nRMSE_{CV} \leqslant 26.47\%$) compared to all other algorithms for the majority of nutrients (N, P, K, Zn, Na, Cu and Mg) described, and the remaining nutrients (S and Mn) were predicted with high accuracy ($0.68 \leqslant R^2_{CV} \leqslant 0.86$; $13.00\% \leqslant nRMSE_{CV} \leqslant 14.64\%$) using SVR. The best training models were used to extrapolate over the whole farm with the purpose of predicting those pasture nutrients and expressed through pixel based spatial maps. These spatially registered nutrient maps demonstrate the range and geographical location of often large differences in pasture nutrient values which are normally not measured and therefore not included in decision making when considering more effective ways to utilized pasture.

1. Introduction

Pasture nutrient composition is a key determinant of animal productivity and farm profitability and is influenced by a large number of environmental factors such as soil type (chemical and physical properties), water availability, fertilizer inputs, altitude, slope angle, slope aspect, land use, climate, and farm management decisions (White and Hodgson, 2000). Nutrient maps provide data needed to understand how these factors interact and create opportunities to assess the impact of management changes. These data allow the establishment of benchmarks and support adoption of precision agriculture practices. Furthermore, nutrient maps can be used to monitor how animal interactions such as stocking density and grazing behavior might influence urine and dung, nutrient acquisition by plants (Pasari et al., 2014).

The assessment of pasture quality is typically carried out by analyzing the concentrations of various nutrients through a series of methodologies in the laboratory; however, they are labor-intensive, costly, time-consuming, and limited to point sampling. Laboratory and field spectrometers can be used for analyzing nutrient concentrations of vegetation, these methods allow a number of nutrients to be determined from a single sample; however, they are often limited to point to paddock scale (Phillips et al., 2006; Kawamura et al., 2009; Pullanagari et al., 2012). Airborne hyperspectral imaging (AHI) measures reflectance spectra as images enabling us to map vegetation biochemistry from pixel, to paddock, farm, catchment and regional scales (Beeri et al., 2007). These different data resolutions have the potential to be used for a wide variety of land uses.

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Vegetation canopy chemistry, such as pigments, cellulose, lignin, nitrogen (N), fiber, phosphorus (P), have been successfully quantified by AHI (Curran et al., 1997; Knox et al., 2011; Skidmore et al., 2010). This quantification is based on the vegetation absorption features corresponding to biochemistry present across the spectrum caused by elemental and molecular interactions (Curran, 1989; Kokaly et al., 2009). Since the development of the first airborne imaging spectrometer Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) designed by Jet Propulsion Laboratory (JPL), National Aeronautics and Space Administration (NASA) (Green et al., 1998), hyperspectral imaging or imaging spectroscopy has become widespread in many disciplines from mineral exploration to biochemical mapping of vegetation (Goetz et al., 1985). Consequently, with advancement of the technology substantial progress has been made towards the development of full spectral range high fidelity airborne imagining spectrometers by commercial and research institutes (Asner et al., 2012; Schaepman et al., 2015). AHI data is not constrained by spatial resolution and provides greater flexibility in monitoring the local or minor changes on the surface. Although intensive research has been conducted to determine nutrient concentrations and quality attributes of vegetation using field spectroradiometers (Mutanga and Skidmore, 2007; Pullanagari et al., 2012; Ramoelo et al., 2013), limited attention is being given to airborne imaging due to its limited availability and complexity in data analysis. Skidmore et al. (2010) successfully mapped forage quality, protein and polyphenol concentrations for trees and grass, of savannahs using AHI (HyMap, Australia). Similarly, Knox et al. (2011) conducted an experiment to map forage nutrients, such as nitrogen, phosphorus and fiber, during dry the season in an African savannah system using the Carnegie Airborne Observatory (CAO alpha imaging spectrometer). Axelsson et al. (2012) verified the possibility of predicting biochemical properties (N, P, K, Ca, Mg and Na) of mangroves in the Berau Delta, Indonesia, using airborne imaging spectrometer (HyMap, Australia). Beeri et al. (2007) also used HyMap to successfully map forage quality and quantity across two grassland regions for the Northern Great Plains, USA. Among those biochemicals only N was estimated satisfactorily and the other properties were poorly explained. Many attempts have been made to map N variation across landscapes and ecosystems, though other nutrients which are also essential for vegetation growth have received less attention. Canopy reflectance is a function of vegetation optical properties, biophysical, such as leaf area index (LAI) and leaf orientation and biochemical attributes, such as nitrogen level, water content, as well as soil background, illumination conditions, viewing geometry, and atmospheric scattering (Asner et al., 1998; Curran, 1989; Jacquemoud et al., 1992). Despite these confounding effects on canopy reflectance, statistical techniques have been used to derive canopy biochemistry.

Multispectral and hyperspectral sensors collect reflectance information in multiple bands, where multispectral sensors collect a smaller number of broad bands that are often used together to form vegetation indices, e.g. the Normalized Difference Vegetation Index (NDVI), the simple ratio (SR), the optimized soil adjusted vegetation index (OSAVI) (Mutanga and Skidmore, 2004). Hyperspectral sensors collect spectral data in few hundreds or thousands of narrow bands which offer the possibility to investigate optimized narrow band vegetation indices by exploring all possible band combinations. Optimized narrow band indices have shown improved performance over broad band indices for extracting variables of interest from vegetation (Mutanga and Skidmore, 2004). However, the models based on vegetation indices are case often specific and lack the ability to be generally applied due to environmental conditions (Verrelst et al., 2015). Conversely, multivariate regression approaches have been proposed to utilize the information from the full spectrum. Extensive research has been conducted to explore the multivariate statistical relationships between in-situ biochemistry and reflectance values of vegetation (Mutanga et al., 2005; Phillips et al., 2013; Pullanagari et al., 2012). In early remote sensing studies the stepwise multiple linear regression (SMLR) method was typically used to extract biochemical information from spectra (Kokaly, 2001; Mutanga et al., 2005). However these methods can lead to over-fitting because they cannot effectively handle the multicollinearity that exists in the data which is common in hyperspectral remote sensing data (Grossman et al., 1996). Alternatively partial least squares regression (PLSR) method reduces the spectral data into fewer orthogonal components, and yields robust and accurate models hence it is now widely used in spectroscopy and remote sensing studies (Atzberger et al., 2010; Pullanagari et al., 2012; Phillips et al., 2013). However, when the relationship between vegetation variables and reflectance data is complex and non-linear, PLSR is not the optimum choice for hyperspectral data analyses (Arenas-Garcia and Camps-Valls, 2008). Advanced non-linear regression methods (also known as machine learning approaches) have recently been applied for the retrieval of biophysical variables such as LAI (Arenas-Garcia and Camps-Valls, 2008; Verrelst et al., 2012) and classification studies (Omer et al., 2015). These achived signficant improvement of accuracy over traditional methods (Verrelst et al., 2012), and may improve predictions of macro and micro nutrients in pasture. We aimed to evaluate these methods of analysis. Specifically, based on the literature, we chose to compare partial least squares regression (PLSR), kernel PLSR, support vector regression (SVR) and random forest regression (RFR) to determine prediction accuracy of macro and micro nutrient concentrations for New Zealand pastures.

2. Materials and methods

2.1. Study area and ground sampling

This study investigated the variability of pasture nutrient concentrations on a 600 ha hill country farm, situated in the North Island of New Zealand (Fig. 1). The study area comprised of 80 sampling locations (Fig. 1) used as ground calibration sites which were identified based on a stratified random design. The locations were equally distributed over the farm to cover the range of physical conditions present. A stratified sampling framework was created using a combination of GIS (geographic information system) layers in ArcGIS software. These layers were slope angle, slope aspect and soil types. The study area was categorized based on the slope categories of 0–8°; 8–16°; 16–25° and 25°<, the aspect categories of North, South, East and West, and the soil types of allophanic, brown, podzol, recent and oxidic. The slope and aspect values were obtained from 8 meter spatial resolution DEM (digital elevation model) provided by Land Information New Zealand (https://data.linz.govt.nz/). Soil data was obtained from S-map project (http://www.landcareresearch.co.nz/databases/smap.asp). Each location being selected from all group combinations and constrained by accessibility. Each of the 80 sampling sites had 5 sample plots, of 0.5×0.5 m chosen randomly. These 400 sample points were georeferenced with Real-Time Kinematic–Global Positing System (RTK GPS). The chemical results of the 5 plots were averaged and considered as one reading in the data analysis. It is assumed that these conditions represent a diverse array of canopy chemistry and botanical composition. The pastures are mainly mixed species; perennial ryegrass (*Lolium perenne* L.), white clover (*Trifolium repens* L.) and a less dominant proportion of brown top (*Agrostis capillaries*) and crested dogs tail (*Cynosurus cristatus*). The presence of a wide range of vegetation types and vegetation dynamics introduced significant heterogeneity. In addition, the specific spatial pattern of grazing animals considerably influenced the