Hyperspectral Assessment for Legume Content and Forage Nutrient Status in Pastures

著者	LIM Jihyun, KAWAMURA Kensuke, YOSHITOSHI Rena, YAYOTA Masato, OGURA Shinichiro
journal or publication title	Journal of Integrated Field Science
volume	14
page range	67-75
year	2017-03
URL	http://hdl.handle.net/10097/00121227

JIFS, 14 : 67 − 75 (2017)

Hyperspectral Assessment for Legume Content and Forage Nutrient Status in Pastures

Jihyun LIM[1],*, Kensuke KAWAMURA[2], Rena YOSHITOSHI1, Masato YAYOTA[3] and Shin-ichiro OGURA[4]

[1]Global Career Design Center, Hiroshima University, Japan
[2]International Research Center for Agricultural Sciences (JIRCAS), Japan
[3]Faculty of Applied Biological Science, Gifu University, Japan
[4]Graduate School of Agricultural Science, Tohoku University, Japan

Correspondence: Jihyun LIM
Tel: +81-82-424-4588
e-mail: limjihyun7@gmail.com

Keywords: grazing management, hyperspectral remote sensing, legume content, partial least squares (PLS) regression, vegetation indices (VIs)

Abstract

The spectral assessment of pasture biomass and nutrient status is influenced by floristic composition. The accurate estimation of the nutrient status in a pasture throughout the growing season is challenging and a critical step to establish a site-specific management strategy for the improvement of productivity and profitability as well as the mitigation of the environmental impact. Remote sensing technologies have been widely applied to vegetation surveys because they can quickly retrieve the *in situ* biophysical and biochemical information of a field. Recent advances in sensing technologies, especially in a hyperspectral sensor system that has a higher spectral resolution of less than 10-nm bandwidth, have significantly improved predictive ability for the estimated biomass quantification in comparison with the conventional broad-band sensor system. Not only the biomass quantification but also other information about the pasture, such as forage nutrient content and the floristic composition, can also be estimated using its abundant spectral information, which is difficult to achieve on a broad-band sensor system. In this mini-review, we discuss the use of hyperspectral assessment to estimate the forage parameters of a pasture. Recent improvements in the analysis methodology of hyperspectral data have been reviewed and include (i) a univariate statistical approach based on narrow-band vegetation indices, (ii) multivariate statistical approaches, especially using partial least squares (PLS) regression, (iii) waveband selection to enhance the predictive performance of PLS regression, and (iv) the spatial interpolation of predicted values from ground-based hyperspectral measurements.

1. Introduction

Grassland ecosystems have spatial and temporal dynamics in the biotic factors such as floristic composition, forage nutrients (*e.g.*, protein, minerals and energy) and plant productivity (Bailey *et al.*, 1996; Vallentine, 2000), and there are interactions between the dynamics and the grazing distribution of animals during the growing seasons with abiotic factors such as the slope, elevation, aspect (Govender *et al.*, 2007) and distance from water sources (Yoshitoshi *et al.*, 2016). The timely and accurate quantification of the biotic factors in a grazed paddock, particularly the biophysical and biochemical characteristics of the pasture and its spatial distribution are essential to facilitate the decision-making process to enable adequate agronomic operation, such as controlling the grazing intensity, adjusting the fertilizer level and determining the best time for mowing, throughout the growing season.

Remote sensing techniques provide such information on vegetation in rangeland and agricultural crop fields in a non-destructive, quick, and inexpensive manner compared to the conventional destructive method such as wet chemistry; they also require less labor and have reduced environmental impacts.

Remote sensing techniques using the optical region that includes the visible and near-infrared (NIR) portions of the electromagnetic spectrum have been successfully used to quantify the biophysical characteristics of vegetation based on their optical properties in past decades (Gates et al., 1965; Allen et al., 1969; Tucker, 1980; Gamon et al., 1995; Cohen et al., 2003). However, these conventional broadband remote sensing approaches for estimating the vegetation biochemical characteristics within the optical region have a limitation due to their lower spectral resolution, which leads to the loss of critical vegetation information associated with the absorption features located in specific narrow bands (Curran, 1989; Blackburn, 1998; Thenkabail et al., 2000). Recent advances in sensing technologies in the spectral resolution, from multispectral sensors to hyperspectral sensors with less than 10-nm spectral resolution (Asner, 1998), enable the detection of narrow absorption features (Fig. 1), and allow more accurate quantification of not only the biophysical characteristics of the vegetation in the pasture but also other information. Recently, it has been demonstrated that ground-based hyperspectral measurement can estimate the floristic composition such as legume content (Biewer et al., 2009; Sanches, 2009; Kawamura et al., 2013) and forage nutrients of a pasture (Mutanga and Kumar, 2007; Zhao et al., 2007; Kawamura et al., 2009; Pullanagari et al., 2012,) with improved temporal frequency and lower cost than spaceborne or airborne instruments, and such enhanced performance highlights the spatial variability of the pasture characteristics within a field as well as differences between fields (Kawamura et al., 2008a, Lim et al., 2015b).

This review describes the necessity and potential of field hyperspectral assessment for the estimation of forage nutrient status and legume content in the pasture. Recent improvements in the analytical methodology of hyperspectral data are described based on statistical approaches, and widely applied methods are described. For this aim, (i) a univariate statistical approach using narrow band vegetation indices, (ii) multivariate statistical approaches, especially using partial least squares (PLS) regression, (iii) waveband selection to enhance the predictive performance of PLS regression and (iv) the spatial interpolation of predicted values from field hyperspectral measurements were described.

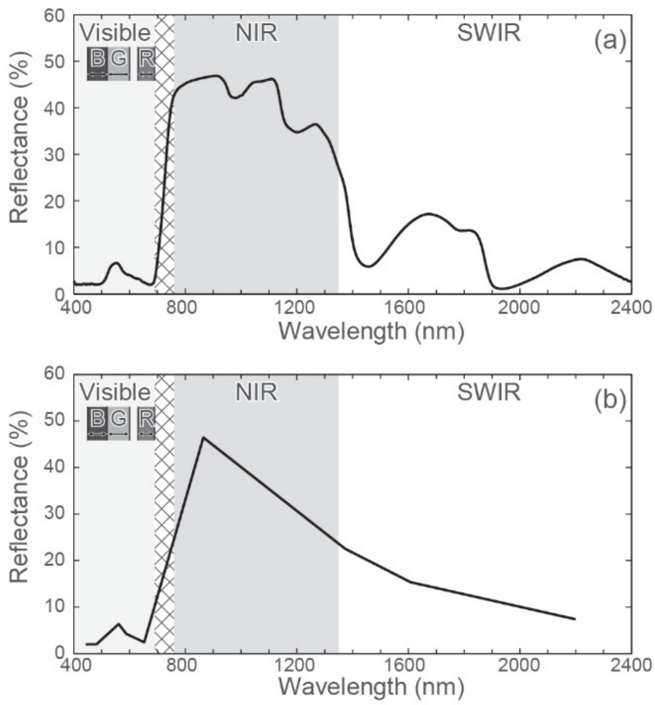

Fig.1. (a) Hyperspectral reflectance of healthy mixed-sown pasture (average canopy reflectance of grazing pasture measured by an ASD FieldSpec Pro radiometer) in the optical region ranging from visible (blue (B), green (G) and red (R)) and near-infrared (NIR) to short-wave infrared (SWIR) and the spectral response with the Landsat 8 band-setting as an example of broad-band remote sensing.

2. Narrow vegetation indices

One of the most common approaches to estimate the vegetation properties from remotely sensed data is making an empirical regression model. Such a statistical approach involves univariate or multivariate regression analysis. In conventional broadband remote sensing, vegetation indices (VIs), which are computations of the spectral response in two or more bands such as simple ratios (SR) and the normalized difference vegetation index (NDVI) (Rouse *et al.*, 1974), have been widely applied to find relations between the characteristics of vegetation via univariate regression analysis. To date, various VIs have been developed and successfully used to quantify plant biophysical properties (Rouse *et al.*, 1974; Huete, 1988; Roujean and Breon, 1995; Chen, 1996; Gitelson *et al.*, 1996). Most of these conventional VIs are based on the contrast between two or more spectral bands. For example, NDVI, one of the most widely used VIs, defined as (R_{NIR}-R_{red}) / (R_{NIR}+R_{red}), uses low reflectance in the red band related to chlorophyll absorption and high reflectance in the NIR due to multiple scattering effects to predict the greenness of vegetation (Rouse *et al.*, 1974). However, NDVI approaches generally saturate asymptotically under conditions of moderate to high biomass (Gitelson, 2004, Lim *et al.*, 2015a) due to decreasing sensitivity at the NIR band, which faces difficulty related to the distinguishability of the temporal and spatial variabilities of the pasture characteristics in the different growing stages.

Considerable efforts have been expanded to find new combinations of narrow bands of NDVI (Mutanga and Skidmore, 2004b; Cho *et al.*, 2007; Kawamura *et al.*, 2011) and SR (Fava *et al.*, 2009) derived data from hyperspectral measurements. These new combinations of VIs have exhibited improved predictive ability for quantifying biophysical and biochemical variables than the conventional red-NIR band combination in the grassland environment. It has been reported that the critical waveband combinations vary with the parameters (Mutanga and Skidmore, 2004b; Cho *et al.*, 2007; Kawamura *et al.*, 2011; Lim *et al.*, 2012) and growth stage (Fava *et al.*, 2009) ,which suggests the potentials to develop parameter specific indices (Gamon *et al.*, 1992). For instance, an experiment conducted on a sheep-grazed pasture exhibiting various levels of fertility (Betteridge *et al.*, 2010) (n = 25) using the narrow-band normalized difference spectral index (NDSI), based on the traditional equation of NDVI defined as (R_{Band1}–R_{Band2}) / (R_{Band1}+R_{Band2}), demonstrated much better performance in estimating the herbage biomass (R^2 = 0.42 to 0.83) and the concentrations (% of dry matter [DM]) of nitrogen (N) (R^2 = 0.46 to 0.73) and phosphorus (P) (R^2 = 0.11 to 0.86) than the standard NDVI as measured by the coefficient of determination (R^2) values using hyperspectral measurements ranging from 400 to 2500 nm. The wavelength regions that were regarded as critical, showing higher R^2 values, for estimating the pasture properties were different in each parameter (Fig. 2), and this showed better predictive accuracy than the red-NIR combination which is generally employed in broad-band VIs.

3. Multivariate statistical approach - partial least squares (PLS) analysis

Multivariate statistical approaches have been proposed to utilize high spectral dimensionality such as multiple linear regression (MLR) (Curran, 1989; Kokaly and Clark, 1999; Zhao *et al.*, 2007), principal component regression (PCR) (Peñuelas *et al.*,

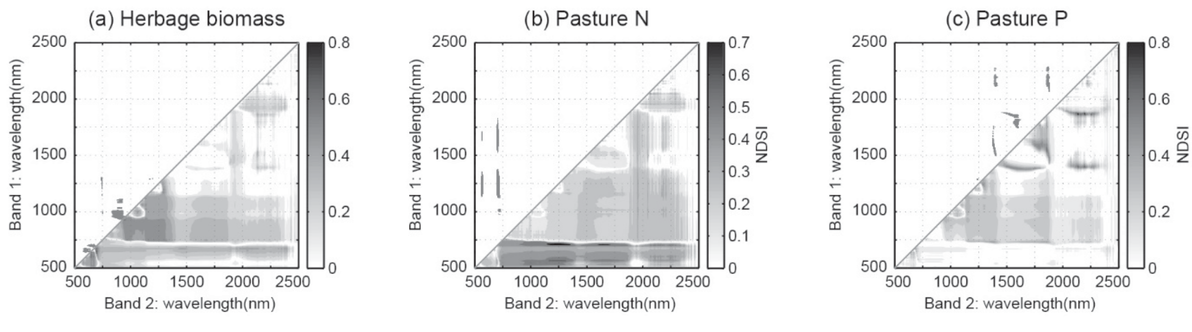

Fig.2. Narrow band normalized-difference spectral index (NDSI) and critical wavelength region to estimate (a) herbage biomass and concentrations of (b) nitrogen and (c) phosphorous of a sheep-grazed paddock (n = 25).

1993),partial least squares (PLS) regression (Geladi and Kowalski, 1986; Hansen and Schjoerring, 2003), support vector machines (SVMs) (Vapnik, 2013), and neural networks (Mutanga and Skidmore, 2004a) using the original hyperspectral response or transformations of the spectra such as first derivative reflectance (FDR) (Dawson and Curran, 1998, Kawamura *et al.*, 2010) and continuum removed absorption features (CRDR) (Mutanga *et al.*, 2004). These approaches have demonstrated their potential for vegetation parameter estimation. PLS regression is the most widely used bi-linear method and is able to include all available waveband information in the model (Wold *et al.*, 2001) due to its superiority for multi-collinear data processing. PLS regression is a fundamental method that has long been used in laboratory near-infrared spectroscopy (NIRS) calibration and has been increasingly used in - field assessment of forage quantity and quality parameters such as crude protein (CP = N×6.24), metabolic energy, acid detergent fiber (ADF) and reported good performance (Schut et al., 2005; Schut et al., 2006; Zhao et al., 2007; Biewer et al., 2009b; Pullanagari et al., 2012).

3.1 Wavebands selection to improve the predictive ability of the PLS model

The complete canopy spectra of the in situ vegetation contains redundant information such as the mechanical noise, soil background effects and water absorption in the atmosphere (Gates *et al.*, 1965; Woolley, 1971; Vanderbilt *et al.*, 1985). Moreover, some researchers have reported that no significant improvement in the vegetation parameter estimations was discovered in a comparative study with PLS using the full spectrum (FS-PLS) between the optimized narrow-band VIs for rice (Nguyen and Lee, 2006; Inoue *et al.*, 2008) and wheat (Hansen and Schjoerring, 2003). Recently, developing a PLS model with wavelength region selection has been regarded as a promising way to improve the prediction power of the model (Darvishzadeha *et al.*, 2008). To date, various approaches have been developed to eliminate useless wavebands or to select informative wavebands, such as moving-window PLS (MW-PLS) (Jiang *et al.*, 2002), iterative stepwise elimination PLS (ISE-PLS), uninformative variable elimination PLS (UVE-PLS) (Centner *et al.*, 1996), and genetic algorithm PLS (GA-PLS) (Leardi *et al.*, 1992).

There was significant improvement of the PLS model with spectral subset selection to estimate the pasture nutritional quality as well as biomass (*e.g.*, Fig. 3). The concentrations of the macronutrients (*e.g.*, phosphorus, potassium, calcium and magnesium) which are mainly responsible for the plant development and determine the forage nutritional quality (Schmidtlein and Sassin, 2004; Darvishzadeha *et al.*, 2008; Kawamura *et al.*, 2008b; Kawamura *et al.*, 2010), fiber (Kawamura *et al.*, 2010) and legume content (Kawamura *et al.*, 2013) can be estimated using the *in situ* hyperspectral spectra of the pasture. Kawamura et al. (2013) reported that only less than 10% of the wavebands remain from the complete canopy reflectance data (400–2350 nm) to discriminate legumes, and less than 20% of wavebands are used for the determining the forage nutritional concentration in the experiment conducted on cattle-grazed pasture of different growth stages. This suggests that the complete spectral information with high dimensionality also contains redundant information that can be a disturbance or otherwise not contribute to the estimation of the pasture characteristics.

In spite of the agreement and demands to the developing the integrated calibration model of field hyperspectral measurement for the assessment of forage quality and floristic composition of pasture, further investigation to clarify the critical wavelength region for each forage parameter and application to multivariate statistical approaches such as PLS is still required. Past studies have been devoted to clarify the wavelength regions which are attributed from photosynthetic pigment absorption in visible region to red-edge such as chlorophyll centered on 430, 460, 520, 550, 640, 680 and 690 nm (Curran, 1989; Chappelle et al., 1992; Thenkabail et al., 2004; Chan and Paelinckx, 2008). The red-edge region (Horler et al., 1983; Peñuelas et al., 1993; Thenkabail et al., 2000; le Maire et al., 2008; Chan and Paelinckx, 2008) which is strongly associated with protein (N) and carotenoids (Car) bands is related to physiological status centered on 470 nm (Blackburn, 1998) and 510 nm (Gitelson *et al.*, 1996). More consideration should be demonstrated to determine the wavelength region for macronutrients (e.g., phosphorus, potassium, calcium and magnesium) known as potentially located in short-wave infrared region (Mutanga and Kumar, 2007; Pimstein *et al.*, 2011; Ramoelo *et al.*, 2011).

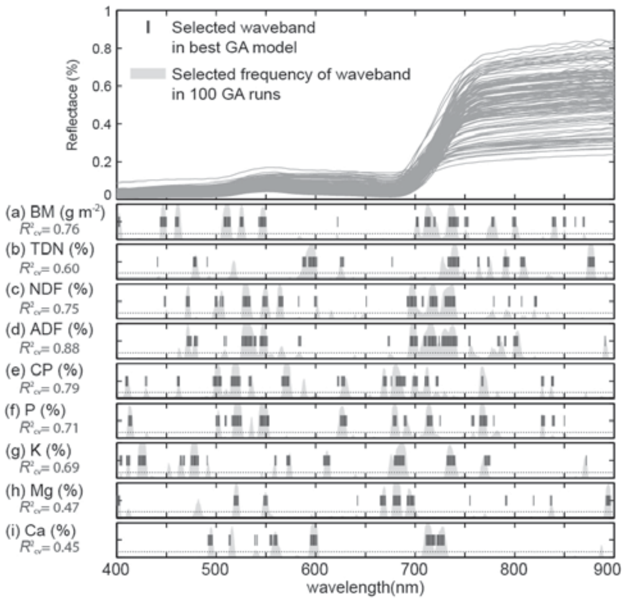

Fig. 3. Selected wavebands by the best GA-PLS model in 100 runs (black line) and the selection frequency of each wavelength by 100 runs of GA-PLS (grey solid) to estimate the herbage biomass (BM) and concentration of total digestible nutrients (TDN), neutral detergent fiber (NDF), acid detergent fiber (ADF), crude protein (CP), phosphorus (P), potassium (K), magnesium (Mg) and calcium (Ca) using the genetic algorithm partial least squares (GA-PLS) and cross-validated R^2 in a cool-season Italian ryegrass meadow field. (Edited from Lim et al)

3.2 Application: Spatial interpolation of field hyperspectral assessment

Lim *et al*. (2015b) reported that the improved prediction power of the GA-PLS model (Fig. 3) resulted in the efficient elimination of redundant spectral information. Using this GA-PLS model, forage parameters (*e.g.*, total digestible nutrients (TDN)) were estimated non-destructively based on the in-field canopy hyperspectral measurement data collected with 10m interval (Lim *et al.*, 2015a) and the map generated by the spatial interpolation of the estimated parameters. From the map, the growth development and nutritive status of the grass can be monitored throughout the two consecutive growing seasons. Especially nutritive changes of pasture such as the timing to leach the peak of nutritive values and its spatial and temporal distributions in the Italian ryegrass field have been distinguished within filed inherently as well as between fields and seasons (Fig. 4) under different fertilization controls (Lim *et al.*, 2015a). The results suggest the possibility of 'real-time' monitoring of the pasture, especially forage nutritive values which is invisible, troughout a growing season without destructive manners. Such information may contribute to determining the timing for maintaining the fertility level or cutting with fine-scale to produce high-quality forage during the growing season in real time.

4. Potential of Hyperspectral Assessment for Legume Content and Forage Nutrient Status in Pasture

Field hyperspectral assessment has enabled significant advances for determining the forage nutrient concentration and discriminating the floristic composition (*e.g.*, legume) of a pasture as well as biomass refining informative wavelength region approaches with narrow-band hyperspectral VIs and multivariate statistical approaches (*e.g.*, PLS) quickly and non-destructively. However, limited studies have been performed to determine the critical wavelength region to estimate the pasture characteristics, especially the concentrations of forage nutrients (*e.g.*, P, K, calcium and energy), and legumes and the results are time- and site-specific, except for biomass and nitrogen which are known to be strongly associated with chlorophyll content. More efforts should be made to define the waveband and its integral application on various grassland environments.

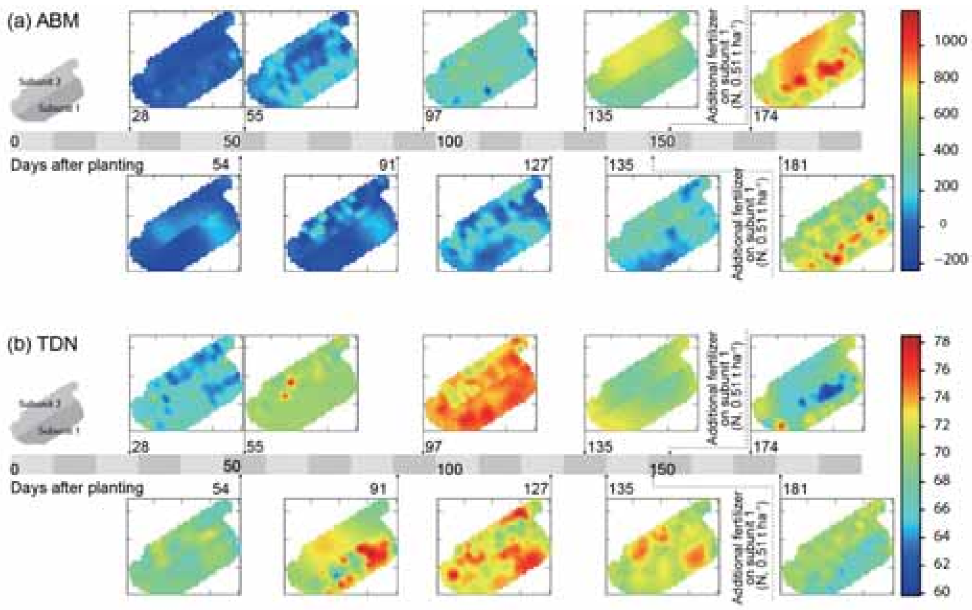

Fig. 4. Spatial distribution maps (5 m grid) of an Italian ryegrass meadow field obtained by ordinary kriging for (a) ABM, (b) NDF, (c) TDN and (d) CP by days after planting (DAF) (Lim *et al.*, 2015b).

Acknowledgements

This study was partially supported by the Japan Society for the Promotion of Science (JSPS), KAKENHI (Grant number. 26850174). We are grateful to all the staff of the Setouchi Field Science Center, Saijo Station, Hiroshima University, and AgResearch, New Zealand for their assistance in the field experiments.

References

Allen, W.A., H.W. Gausman, A.J. Richardson and J.R. Thomas (1969) Interaction of isotropic light with a compact plant leaf. JOSA, 59: 1376–1379.

Asner, G.P. (1998) Biophysical and biochemical sources of variability in canopy reflectance. Remote Sensing of Environment, 64: 234–253.

Bailey, D.W., J.E. Gross, E.A. Laca and et al. (1996) Mechanisms that result in large herbivore grazing distribution patterns. Journal of Range Management, 49: 386–400.

Betteridge, K., D. Costall, S. Balladur, M. Upsdell and K. Umemura (2010) Urine distribution and grazing behaviour of female sheep and cattle grazing a steep New Zealand hill pasture. Animal Production Science, 50: 624–629.

Biewer, S., S. Erasmi, T. Fricke and M. Wachendorf (2009a) Prediction of yield and the contribution of legumes in legume-grass mixtures using field spectrometry. Precision Agriculture, 10: 128–144.

Biewer, S., T. Fricke and M. Wachendorf (2009b) Development of canopy reflectance models to predict forage quality of legume-grass mixtures. Crop Science, 49: 1917–1926.

Blackburn, G.A. (1998) Quantifying chlorophylls and caroteniods at leaf and canopy scales: An evaluation of some hyperspectral approaches. Remote Sensing of Environment, 66: 273–285.

Centner, V., D.L. Massart, O.E. De Noord, S. De Jong, B.M. Vandeginste and C. Sterna (1996) Elimination of uninformative variables for multivariate calibration. Analytical Chemistry, 68: 3851–3858.

Chan, J.C.W. and D. Paelinckx (2008) Evaluation of Random Forest and Adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. Remote Sensing of Environment, 112: 2999–3011.

Chappelle, E.W., M.S. Kim and J.E. Mcmurtrey (1992) Ratio analysis of reflectance spectra (RARS): an algorithm for the remote estimation of the concentrations of chlorophyll a, chlorophyll b, and carotenoids in soybean leaves. Remote Sensing of Environment, 39: 239–247.

Chen, J.M. (1996) Evaluation of vegetation indices and a modified simple ratio for boreal applications. Canadian Journal of Remote Sensing, 22: 229–242.

Cho, M.A., A.K. Skidmore, F. Corsi, S.E. Van Wieren and I. Sobhan (2007) Estimation of green grass/herb biomass from airborne hyperspectral imagery using spectral indices and partial least squares regression. International Journal of Applied Earth Observation and Geoinformation, 9: 414–424.

Cohen, W.B., T.K. Maiersperger, S.T. Gower and D.P. Turner (2003) An improved strategy for regression of biophysical variables and Landsat ETM+ data. Remote Sensing of Environment, 84: 561–571.

Curran, P.J. (1989) Remote sensing of foliar chemistry. Remote Sensing of Environment, 30: 271–278.

Darvishzadeha, R., A.K. Skidmore, M. Schlerf, C. Atzberger, F. Corsi and M. Cho (2008) LAI and chlorophyll estimation for a heterogeneous grassland using hyperspectral measurements. ISPRS Journal of Photogrammetry and Remote Sensing, 63: 409–426.

Dawson, T. and P. Curran (1998) Technical note. A new technique for interpolating the reflectance red edge position.

Fava, F., R. Colombo, S. Bocchi and et al. (2009) Identification of hyperspectral vegetation indices for Mediterranean pasture characterization. International journal of applied earth observation and geoinformation, 11: 233–243.

Gamon, J., J. Penuelas and C. Field (1992) A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. Remote Sensing of Environment, 41: 35–44.

Gamon, J., C.B. Field, M.L. Goulden and et al. (1995) Relationships between NDVI, canopy structure, and photosynthesis in three californian vegetation types. Ecological Applications, 5: 28–41.

Gates, D.M., H.J. Keegan, J.C. Schleter and V.R. Weidner (1965) Spectral properties of plants. Applied Optics, 4: 11–20.

Geladi, P. and B.R. Kowalski (1986) Partial least-squares regression: a tutorial. Analytica Chimica Acta, 185: 1–17.

Gitelson, A.A. (2004) Wide dynamic range vegetation index for remote quantification of biophysical characteristics of vegetation. Journal of Plant Physiology, 161: 165–173.

Gitelson, A.A., Y.J. Kaufman and M.N. Merzlyak (1996) Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of Environment, 58: 289–298.

Govender, M., K. Chetty and H. Bulcock (2007) A review of hyperspectral remote sensing and its application in vegetation and water resource studies. Water Sa, 33.

Hansen, P.M. and J.K. Schjoerring (2003) Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. Remote Sensing of Environment, 86: 542–553.

Horler, D.N.H., M. Dockray and J. Barber (1983) The red edge of plant leaf reflectance. International Journal of Remote Sensing, 4: 273–288.

Huete, A.R. (1988) A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25: 295–309.

Inoue, Y., G. Miah, E. Sakaiya, K. Kaneko and K. Kawamura (2008) NDSI map and IPLS using hyperspectral data for assessment of plant and ecosystem variable : With a case study on remote sensing of grain protein content, chloropyll content and biomass in rice. Journal of the Remote Sensing Society of Japan, 28: 317–330.

Jiang, J.H., R.J. Berry, H.W. Siesler and Y. Ozaki (2002) Wavelength interval selection in multicomponent spectral analysis by moving window partial least-squares regression with applications to mid-infrared and near-infrared spectroscopic data. Analytical Chemistry, 74: 3555–3565.

Kawamura, K., K. Betteridge, D. Costall, I.D. Sanches, M. Tuohy and Y. Inoue (2008a) Hyperspectral canopy reflectance as a potential tool to estimate and map pasture mass and quality.

Kawamura, K., K. Betteridge, I.D. Sanches, M.P. Tuohy, D. Costall and Y. Inoue (2009) Field radiometer with canopy pasture probe as a potential tool to estimate and map pasture biomass and mineral components: a case study in the Lake Taupo catchment, New Zealand. New Zealand Journal of Agricultural Research, 52: 417–434.

Kawamura, K., A.D. Mackay, M.P. Tuohy, K. Betteridge, I.D. Sanches and Y. Inoue (2011) Potential for spectral indices to remotely sense phosphorus and potassium content of legume-based pasture as a means of assessing soil phosphorus and potassium fertility status. International Journal of Remote Sensing, 32: 103–124.

Kawamura, K., N. Watanabe, S. Sakanoue and Y. Inoue (2008b) Estimating forage biomass and quality in a mixed sown pasture based on PLS regression with waveband selection. Grassland Science, 54: 131–146.

Kawamura, K., N. Watanabe, S. Sakanoue, H.J. Lee, Y. Inoue and S. Odagawa (2010) Testing genetic algorithm as a tool to select relevant wavebands from field hyperspectral data for estimating pasture mass and quality in a mixed sown pasture using partial least squares regression. Grassland Science, 56: 205–216.

Kawamura, K., N. Watanabe, S. Sakanoue, H.J. Lee, J. Lim and R. Yoshitoshi (2013) Genetic algorithm-based partial least squares regression for estimating legume content in a grass-legume mixture using field hyperspectral measurements. Grassland Science, 59: 166–172.

Kokaly, R.F. and R.N. Clark (1999) Spectroscopic determination of leaf biochemistry using band-depth analysis of absorption features and stepwise multiple linear regression. Remote Sensing of Environment, 67: 267–287.

Leardi, R., R. Boggia and M. Terrile (1992) Genetic algorithms as a strategy for feature selection. Journal of Chemometrics, 6: 267–281.

Le Maire, G., C. François, K. Soudani and et al. (2008) Calibration and validation of hyperspectral indices for the estimation of broadleaved forest leaf chlorophyll content, leaf mass per area, leaf area index and leaf canopy biomass. Remote Sensing of Environment, 112: 3846–3864.

Lim, J., K. Kawamura, H.J. Lee and et al. (2015a) Evaluating a hand-held crop-measuring device for estimating the herbage biomass, leaf area index and crude protein content in an Italian ryegrass field. Grassland Science, 61: 101–108.

Lim, J., K. Kawamura, R. Yoshitoshi, K. Betteridge and D. Costall (2012) "Hyperspectral proximal sensing as a tool for estimating herbage biomass and forage nutrient status in grassland, New Zealand". Proceeding of The 3rd Australian and New Zealand Spatially Enabled Livestock Management Symposium: 13–14.

Lim, J., K. Kawamura, R. Yoshitoshi, Y. Kurokawa and N. Watanabe (2015b) Mapping forage quantity and quality in Italian ryegrass field during growing season using proximal sensing. Grassland Sicences, 61(ext.): 2.

Mutanga, O. and L. Kumar (2007) Estimating and mapping grass phosphorus concentration in an African savanna using hyperspectral image data. International Journal of Remote Sensing, 28: 4897–4911.

Mutanga, O. and A.K. Skidmore (2004a) Integrating imaging spectroscopy and neural networks to map grass quality in the Kruger National Park, South Africa. Remote Sensing of Environment, 90: 104–115.

Mutanga, O. and A.K. Skidmore (2004b) Narrow band vegetation indices overcome the saturation problem in biomass estimation. International Journal of Remote Sensing, 25: 3999–4014.

Mutanga, O., A.K. Skidmore and H. Prins (2004) Predicting in situ pasture quality in the Kruger National Park, South Africa, using continuum-removed absorption features. Remote Sensing of Environment, 89: 393–408.

Mutanga, O. and L. Kumar (2007) Estimating and mapping grass phosphorus concentration in an African savanna using hyperspectral image data. International Journal of Remote Sensing, 28: 4897–4911.

Nguyen, H.T. and B.W. Lee (2006) Assessment of rice leaf growth and nitrogen status by hyperspectral canopy reflectance and partial least square regression. European Journal of Agronomy, 24: 349–356.

Peñuelas, J., J.A. Gamon, K.L. Griffin and C.B. Field (1993) Assessing community type, plant biomass, pigment composition, and photosynthetic efficiency of aquatic vegetation from spectral reflectance. Remote Sensing of Environment, 46: 110–118.

Pimstein, A., A. Karnieli, S.K. Bansal and D.J. Bonfil (2011) Exploring remotely sensed technologies for monitoring wheat potassium and phosphorus using field spectroscopy. Field Crops Research, 121: 125–135.

Pullanagari, R.R., I.J. Yule, M.P. Tuohy, M. Hedley, R.A. Dynes and W.M. King (2012) In-field hyperspectral proximal sensing for estimating quality parameters of mixed pasture. Precision Agriculture, 13: 351–369.

Ramoelo, A., A.K. Skidmore, M. Schlerf, R. Mathieu and I.M.A. Heitkönig (2011) Water-removed spectra increase the retrieval accuracy when estimating savanna grass nitrogen and phosphorus concentrations. ISPRS Journal of Photogrammetry and Remote Sensing, 66: 408–417.

Roujean, J.L. and F.M. Breon (1995) Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. Remote Sensing of Environment, 51: 375–384.

Rouse, J.W., R.H. Haas, J.A. Schell and D.W. Deering (1974) Monitoring vegetation systems in the Great Plains with ERTS. In S. C. Freden, E. P. Mercanti, & M. Becker (Eds.), Third Earth Resources Technology Satellite–1 Symposium. NASA SP-353, 1: 309–317.

Sanches, I.D.A. (2009) Hyperspectral proximal sensing of the botanical composition and nutrient content of New Zealand pastures: a thesis presented in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Earth Science. In: Hyperspectral proximal sensing of the botanical composition and nutrient content of New Zealand pastures: a thesis presented in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Earth Science. Massey University, Palmerston North, New Zealand, 219

Schmidtlein, S. and J. Sassin (2004) Mapping of continuous floristic gradients in grasslands using hyperspectral imagery. Remote Sensing of Environment, 92: 126–138.

Schut, A.G.T., C. Lokhorst, M. Hendriks, J. Kornet and G. Kasper (2005) Potential of imaging spectroscopy as tool for pasture management. Grass and Forage Science, 60: 34–45.

Schut, A.G.T., G.W.a.M. Van Der Heijden, I. Hoving, M.W.J. Stienezen, F.K. Van Evert and J. Meuleman (2006) Imaging spectroscopy for on-farm measurement of grassland yield and quality. Agronomy Journal, 98: 1318–1325.

Thenkabail, P.S., R.B. Smith and E. De Pauw (2000) Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. Remote Sensing of Environment, 71: 158–182.

Thenkabail, P.S., E.A. Enclona, M.S. Ashton and B. Van Der Meer (2004) Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. Remote Sensing of Environment, 91: 354–376.

Tucker, C.J. (1980) A critical review of remote sensing and other methods for non-destructive estimation of standing crop biomass. Grass and Forage Science, 35: 177–182.

Vallentine, J.F. (2000) Grazing management, Elsevier.

Vanderbilt, V., L. Grant, L. Biehl and B. Robinson (1985) Specular, diffuse, and polarized light scattered by two wheat canopies. Applied Optics, 24: 2408–2418.

Vapnik, V. (2013) The nature of statistical learning theory, Springer Science & Business Media.

Wold, S., M. Sjöström and L. Eriksson (2001) PLS-regression: a basic tool of chemometrics. Chemometr. Intell. Lab., 58: 109–130.

Woolley, J.T. (1971) Reflectance and transmittance of light by leaves. Plant Physiology, 47: 656–662.

Yoshitoshi, R., N. Watanabe, T. Yasuda and. (2016) Methodology to predict the spatial distribution of cattle dung using manageable factors and a Bayesian approach. Agriculture, Ecosystems & Environment, 220: 135–141.

Zhao, D., P.J. Starks, M.A. Brown, W.A. Phillips and S.W. Coleman (2007) Assessment of forage biomass and quality parameters of bermudagrass using proximal sensing of pasture canopy reflectance. Grassland Science, 53: 39–49.