



## THE USE OF OPTICAL SENSORS TO ESTIMATE PASTURE QUALITY

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***Abstract-*** Optical remote sensing tools are being used in a number of agricultural applications by recording an object's transmission of electromagnetic energy from reflecting and radiating surfaces. This unique spectral information is used to characterize the features of green vegetation. With the development of proximal sensing tools, vegetation or crop health can be determined and monitored in real-time. This information provides an opportunity for precise management of input resources to optimise plant growth and reduce the potential for an adverse environmental effect.

Pasture management is of major importance in New Zealand. This paper describes the operation of multispectral (Crop Circle<sup>™</sup> and CROPSCAN<sup>™</sup>) and hyper spectral sensors (ASD Field Spec<sup>®</sup> Pro) to explore the pasture quality and quantity. The ability to manage these factors is an important component in grazing, livestock management, and a key driver of animal performance and productivity. The results indicate that these sensors have the potential to assess vegetation characteristics.

**Index terms:** electromagnetic energy, optical remote sensing, pasture management, multispectral, hyperspectral

## **I. INTRODUCTION**

During the last twenty years New Zealand has seen a significant expansion of the dairy industry both in terms of the area being farmed under dairying and the productivity of the industry. The dairy industry contributes about 7 per cent to New Zealand's GDP, to the New Zealand economy, it has secured it as a world leader in dairy exports [1]. In order to improve the current system of dairy farming, pasture, grazing and livestock management need to be continually improved. Not only must more pasture to be grown economically but the quality of the pasture which directly influences milk production and livestock performance [2] must also be improved. Hence, monitoring the quality of pasture is an important operation to improve efficiency. Traditional laboratory techniques are sometimes used to estimate the pasture quality, but these procedures are expensive, laborious and time consuming, and the results of measurement often come back to the farmers after the pasture has been grazed, hence significantly reducing any benefit to the farmer in terms of feed management and budgeting for his animals. Therefore, rapid and non-destructive tools, and techniques are required to assess the pasture quality in the field giving near instant results.

Since the advent of remote sensing technologies many researchers have studied the potential of remote sensing devices to monitor green vegetation health [3], [4] and [5] . They developed robust and significant relationships between sensor derived measurements and ground truth vegetation measurements such as biophysical and biochemical variables. So far, in remote sensing, these optical sensing tools tend to operate from suborbital aircraft and satellites, and are used for describing green vegetation features. Although there are advantages of speed from surveying using space and airborne sensors, it involves extremely expensive equipment, complex processing, and suffers from frequent cloud cover, meaning no images can be collected. To overcome these problems ground or field based optical sensing tools (or proximal sensors) are emerging and are commercially available. These have been used to evaluate vegetation and field crops characteristics. In addition, proximal sensors provide real-time information for decision making.

This paper presents the description of optical (multispectral and hyperspectral) sensors and the potential to estimate pasture quality, and outlines methods for developing robust relationships between spectral reflectance and pasture quality variables.

## II. THEORETICAL BACKGROUND

The principle of optical remote sensing originated from spectroscopy, which is the study of the interaction between electromagnetic radiation and matter. In contrast to spectroscopy, remote sensing focuses on reflectance rather than absorbance.

According to the Beer-Lambert law [6], in Figure 1, when energy hits the object (leaf) it can be absorbed, transmitted and reflected. The fraction of energy reflected at a particular wavelength varies for different features. Additionally, the reflectance of features varies at different wavelengths. Thus, two features that are indistinguishable in one spectral range may be very different in another portion of the spectrum. Therefore, this essential property of matter allows different features to be identified and separated by their spectral signatures.

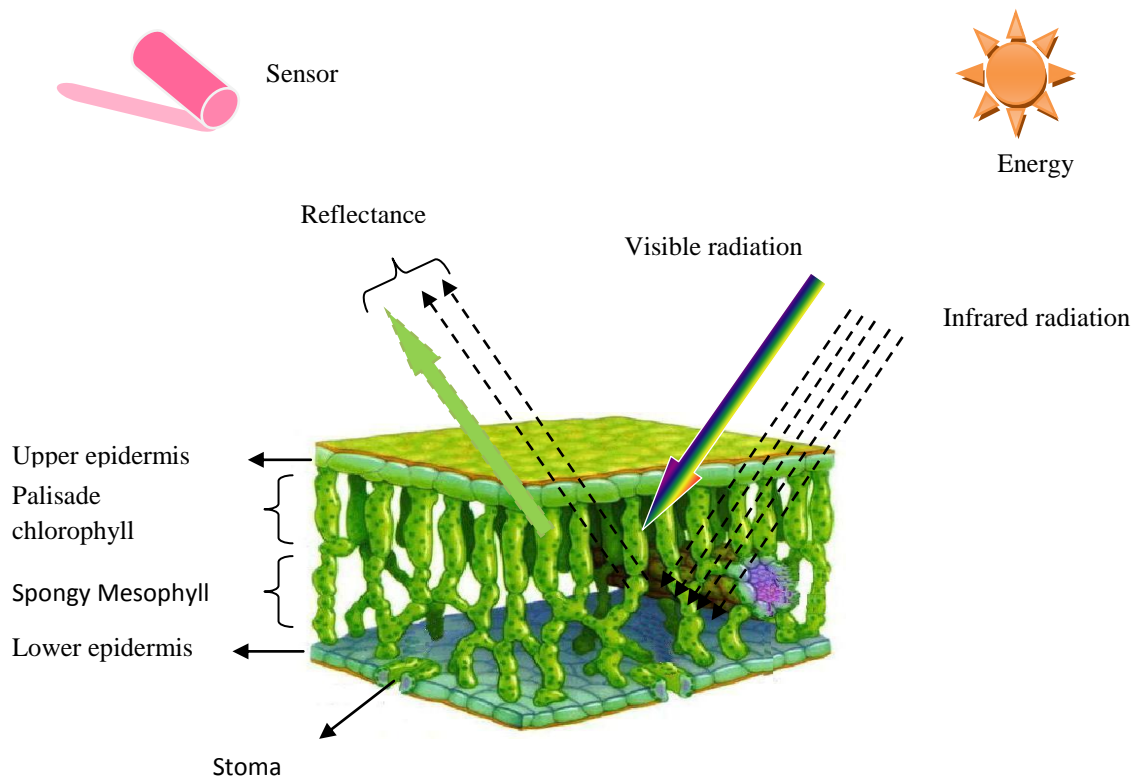


Figure 1. Interaction between energy source, leaf structure and spectral sensor [7].

	Biochemical	Wavelength (nm)
1	Chlorophyll and Nitrogen	350-750 (Visible region)
2	Protein	910, 1020, 1730, 1980, 2130, 2240, 2300
3	Lignin	1120, 1420, 1690
4	Cellulose	1490, 1736, 1780, 1820, 1924, 2100, 2270, 2340, 2350
5	Starch	990, 1450, 1530, 1580, 1900, 2000, 2100, 2250, 2340
6	Sugar	1450, 1490, 1940, 1960, 2080, 2270

Table 1. Absorption features related to common quality components [9].

The spectral reflectance defined as the ratio of the reflected radiation to the total radiation falling upon the surface and the mathematically definition [8]:

$$\rho_{\lambda} = \frac{E_R(\lambda)}{E_I(\lambda)} = \frac{I_o}{I_t}$$

Where  $\rho_{\lambda}$ - spectral reflectance of  $\lambda$  wavelength;  $I_o$  -energy of wavelength reflected from the object;  $I_t$  - energy of wavelength incident upon the object.

Spectral response of vegetation is primarily influenced by physical structure of the plants and canopy. Figure 1 indicates the interaction between cells structure of leaf and electromagnetic energy [1]. Most of the visible radiant flux of the electromagnetic energy absorbed by palisade cells, which contain chlorophyll pigments and green light, is reflected back, which is why green leaves appear green in colour (Figure 1). However, the NIR radiation is not affected by the palisade cells and penetrates to the spongy mesophyll.

The typical reflectance of green vegetation shown in Figure 2; healthy vegetation has high absorption in visible region and low absorption in infrared region while the stressed vegetation has lower absorption in visible region and higher absorption in infrared region, thus, these unique spectral signatures can be used to determine vegetation health.

The unique spectral signatures of green vegetation from visible region of the electromagnetic spectrum allow quantifying biomass, dry matter, chlorophyll, nitrogen and vegetative fraction etc. While infrared radiation of the electromagnetic spectrum is also responsible for determining the other biochemical concentrations. These infrared (near and shortwave infrared) signatures originates from the energy transition of the molecular vibration (rotation, bending and stretching) of the C-H, N-H, O-H, C-N and C-C bonds, which are the primary constituents of the organic compounds of plant tissues. Therefore, the reflectance from the infrared region is a function of chemical composition. For instance, Table 1 describes that each quality component has its own spectral signature as absorption peaks at specific wavelength [9].

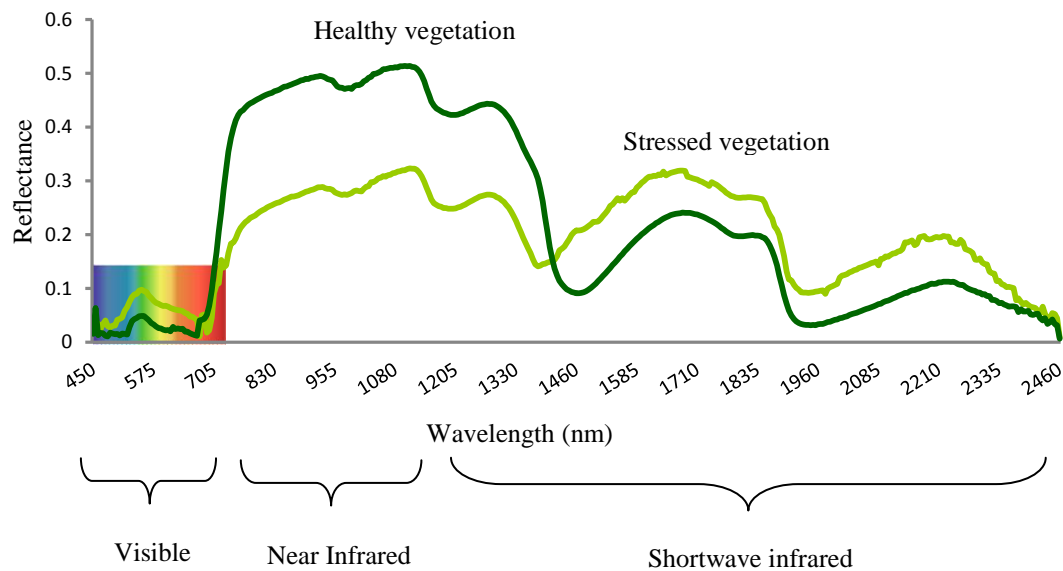


Figure 2. Reflectance of green vegetation across the electromagnetic spectrum [1].

### III. DESCRIPTION OF THE SENSORS

There are a wide range of optical sensors available, based on their spectral properties they classified as multispectral and hyperspectral spectral sensors.





CROPSCAN™



ASD Field Spec® Pro



Crop Circle™

Figure 3. The sensors being used in a field experiment

A multispectral sensor (Crop Circle<sup>TM</sup> and CROPSCAN<sup>TM</sup>) has wide spectral resolution with a limited number of wavebands used to describe a limited number of features such as nitrogen [10] and biomass variation, and leaf area index [11] while hyperspectral sensors such as the ASD Field Spec<sup>®</sup> Pro offer fine spectral resolution with numerous and contiguous wavebands across the electromagnetic spectrum which provides detailed information about the object such as detailed biophysical and biochemical information. The importance of high spectral resolution sensor in quantifying the various features with high precision and accuracy is highlighted in [12]. Based on the source of light, these sensors are classified into active and passive sensors. Active sensors such as the Crop Circle<sup>TM</sup> ACS-470 from Holland Scientific Inc., uses its own light source and can be used to collect data within a range of lighting conditions or even darkness making it much more usable to growers. In contrast, passive sensors, for example: CROPSCAN<sup>TM</sup> (Rochester, Minnesota), completely depends upon natural light (sun radiation) for radiant flux and used to collect information on the level of that varying natural light.

Table 2 describes the technical specifications of the multispectral and hyper spectral sensors which were used in this study. Investigating the spectral resolution and spectral range of the optical sensors was a critical component for the study because of each feature can be characterised by specific wavebands (Table 1) with optimum resolution.

S.No	Specification	Hyper Spectral Sensor	Multi Spectral Sensor	
1	Name	ASD Field Spec <sup>®</sup> Pro	CROPSCAN <sup>TM</sup>	Crop Circle <sup>TM</sup>
2	Sensor type	Passive	Passive	Active
3	Spectral range	350-2500	440-1680	450-880
4	Spectral Bands	2150	16	3
5	Spectral Resolution	1-2 nm	10 nm	10-20
6	Detectors	Silicon (300-1000nm) TE cooled, InGaAs (1000-2500 nm)	Silicon and Germanium	Silicon
7	Foot print	20 cm	60 x 60 cm	5×60 cm
8	FOV	8°,18°,25°	28°	32°/6°
9	Distance from target	1 m	1.2 m	0.6-1.2 m

Table 2. Sensor Specifications for example hyperspectral and multispectral sensors

#### IV. COMPUTATION

Several computational and statistical approaches have been developed to build a robust relation between spectral reflectance data and variables of interest. Of which, univariate regression and multivariate regression approaches have been widely used [13].

Due to the ease of establishing and interpretation of univariate regression models, these have commonly been used in predicting the required variables. For developing univariate regression, reflectance data uses either individual wavebands or a combination of bands: subsequently calculated as vegetative indices. Usually, these vegetative indices use a combination of visible and near infrared reflectance data to reflect the reflectance values as a single value. Tremendous efforts have been done in order to improve sensitivity of the vegetation indices to the required properties and as a result of this, numerous vegetation indices are being reported in the literature [14]. Among that natural difference vegetative index (NDVI) is best-known indice and has been widely used in remote sensing, it is calculated as [15]:

$$NDVI = \frac{NIR - VIS}{NIR + VIS}$$

To develop a model, reflectance values of individual bands or vegetative indices are regressed against the reference values, standard measured values. These spectrally derived univariate models may describe limited information such as, green biomass, dry matter, leaf area index and nitrogen concentration etc. and differ with species and site.

In order to improve the accuracy and stability of prediction models, and to define more finite features, multivariate regression approaches have been developed which utilise a higher number of spectral wavebands. The prominent multivariate regression techniques are; step wise regression, principle component analysis (PCA) [16] and partial least square regression (PLSR) [17], all previously used in remote sensing [13].

The analysis of hyperspectral data usually involves manipulation steps followed by statistical treatment [17], described in Figure 3.



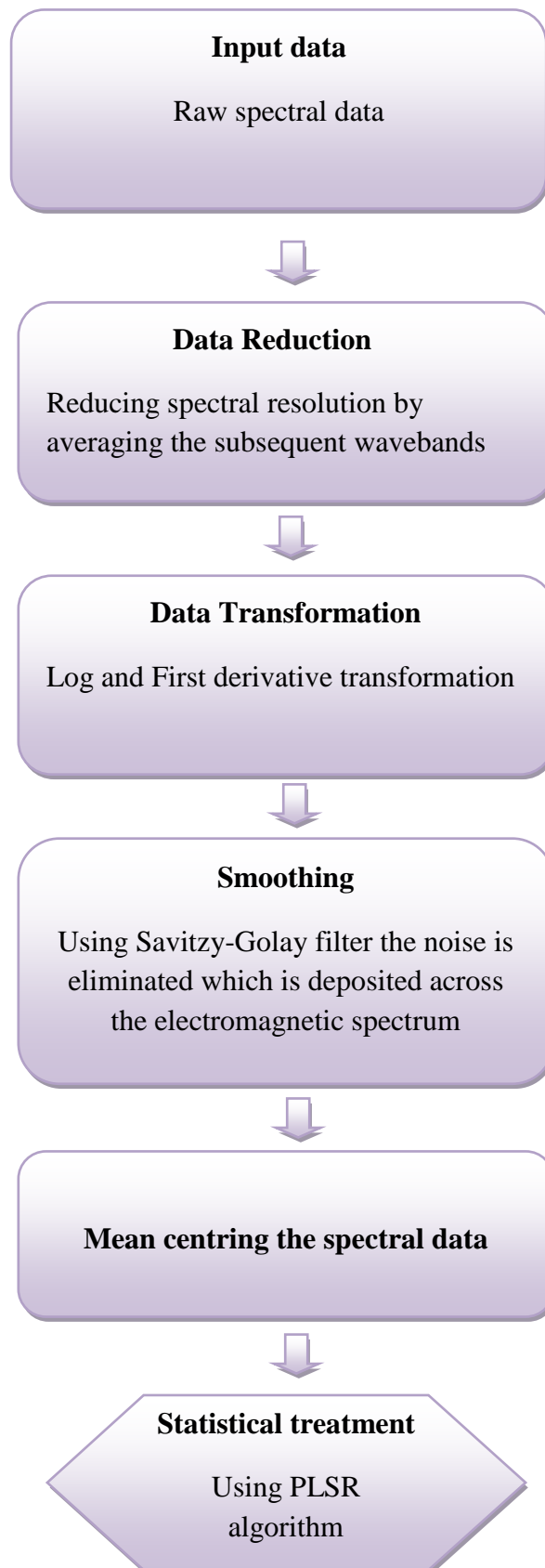


Figure 4. Flow chart of hyperspectral data analysis

## V. RESULTS

Multispectral (Crop Circle<sup>®</sup> and Crop Scan<sup>™</sup>) and hyperspectral sensors (ASD Field Spec<sup>®</sup> Pro) were used to collect spectral signatures from pastures.

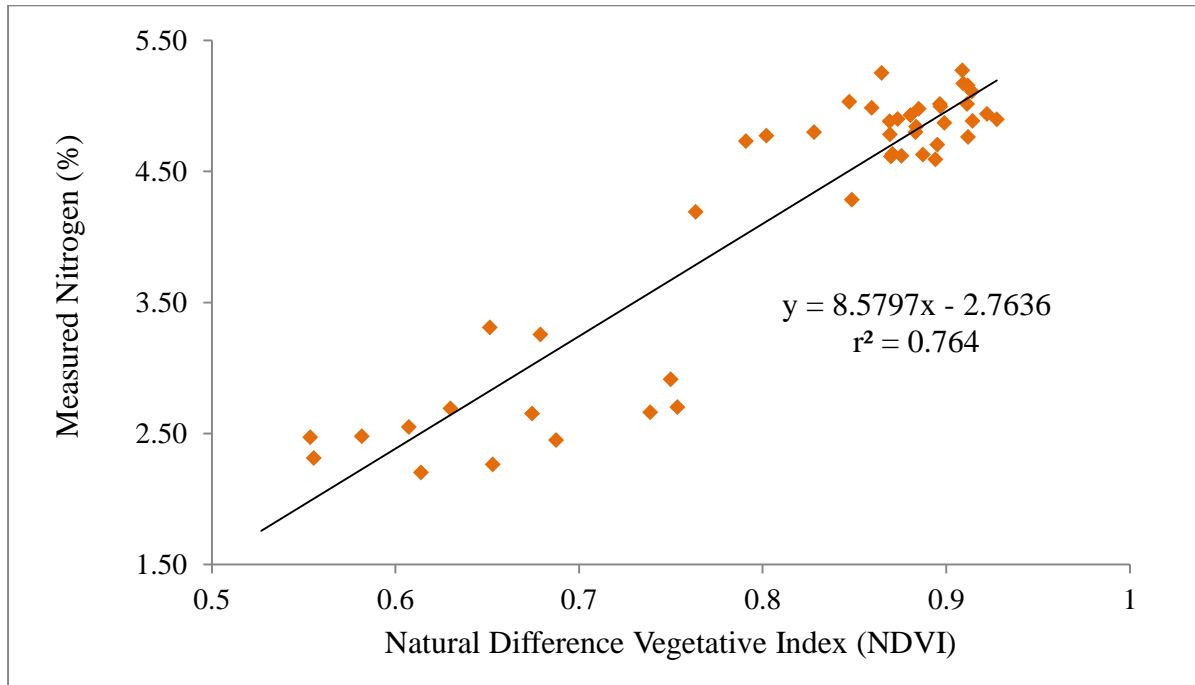


Figure 5 Regression model showing the relation between measured nitrogen and sensor (Cropcircle<sup>™</sup>) derived reflectance readings as natural difference vegetative index (NDVI)

In a nitrogen fertilizer experiment, conducted by Landcare, Palmerston North, a Crop Circle sensor (ACS-470) was used to acquire reflectance from plots which received different nitrogen treatments, with the purpose of being able to predict nitrogen content of the pasture from the reflectance readings. The captured reflectance was calculated as NDVI from a combination of the visible (670/22 nm) and near infrared regions (760/LWP). The sites used were cut and the nitrogen concentration in the pasture measured. A significant correlation between the measured nitrogen percentage and reflected readings as NDVI with a coefficient of determination ( $r^2$ ) of 0.764 was obtained (Figure 4).

In order collect hyperspectral readings, various experimental sites were used to create a wide range of biochemical variations and environmental conditions. Typically, the ASD Field Spec<sup>®</sup> Pro is a passive sensor, but, artificial illumination was provided using a standard

canopy pasture probe (CAPP)-top grip coupled with 50 Watt tungsten-quartz-halogen lamp [18].

After obtaining spectral signatures, concurrent ground truth samples were harvested and then immediately sent to the FeedTech (AgResearch Grasslands, Palmerston North) laboratory for near infrared spectroscopy analysis which is used extensively for determining chemical composition of dried ground samples.

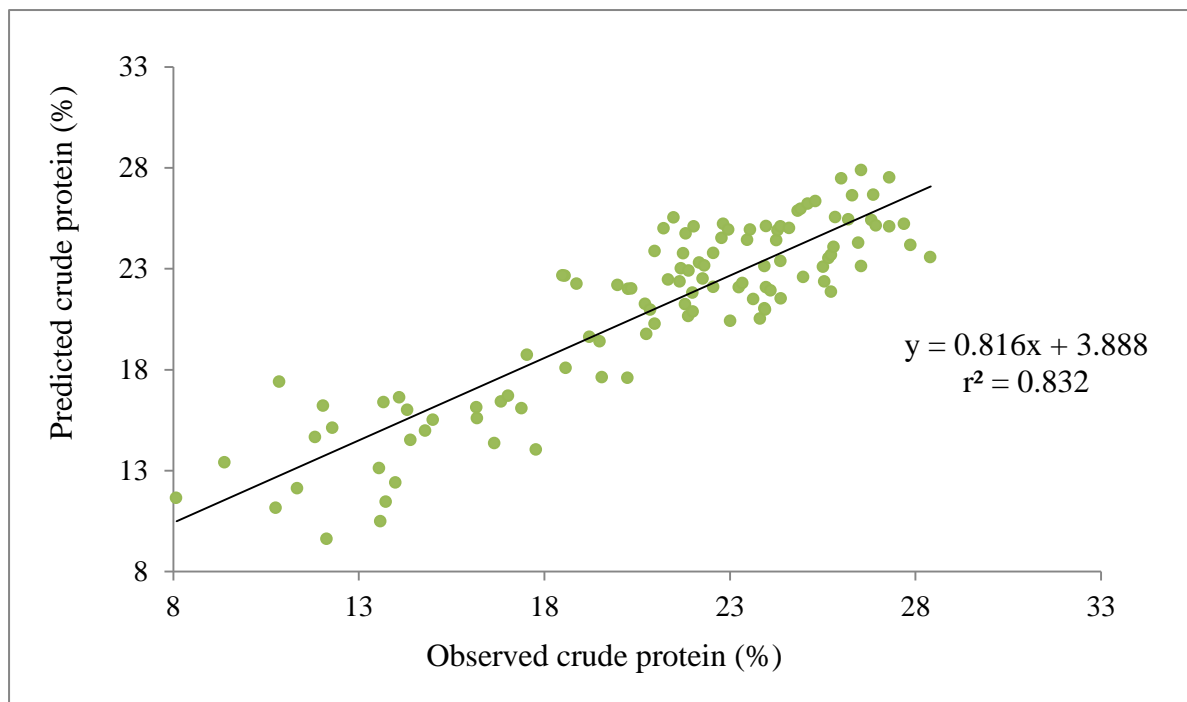


Figure 6. Scatter diagram showing the relation between observed and predicted observations [19]

Prior to data analysis the data manipulations steps illustrated in Figure 3 were used to process the data, PLSR algorithms were then applied for statistical analysis. Then as part of the calibration of the model the measured crude protein concentrations were plotted against the predicted levels, satisfactory results were obtained with an  $r^2$  value of 0.832. The prediction accuracy of the hyperspectral sensor is greater than the multispectral sensor and wide had wide range of applicability.

## VI. CONCLUSION

These research findings demonstrate that there is potential in using optical sensors to provide a practical solution for providing greater accuracy in pasture quality measurement in the field. This takes optical technology out of the laboratory and onto the farm to give near real-time information to the farmer. When proximal sensors are coupled with global positioning system (GPS) pasture quality spatially can be monitored spatially which allows the relationships between environment and production inputs such as fertiliser to be further optimised. This is currently possible with a small range of sensors using two or three channels to estimate crop biomass in crops such as wheat, the information from these sensors is used to make decisions around the fertiliser application to the crop. The advantage of crops such as wheat is the paddock is usually around the same growth stage, weeds are suppressed and so variability is limited. In pasture the situation is somewhat different; the pasture has been subject to grazing and highly variable (N) application through urination events from cows, in addition to other environmental factors relating to topography and soil. The maturity of the sward also changes throughout the year, as does species composition, and calibrations achieved at one part of the season may not be relevant to later stages. Clearly further work needs to be completed to establish robust calibration models and methodologies to operate over a range of conditions.

If this technology were applied to pasture management, the results from pasture measurement would make a significant difference to farmer's decision making on such issues as fertilizer application, pasture and grazing management. This should lead to better productivity for farmers but also better environmental outcomes as a result of reduced error margins in current farm practices and better informed management decisions.

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## VIII. REFERENCES

- [1] MAF. (2003, *Contribution of the Land-based Primary Industries to New Zealand's Economic Growth*. Available: <http://www.maf.govt.nz/mafnet/rural-nz/profitability-and-economics/>
- [2] C. W. Holmes, *et al.*, *Milk production from pasture*. Palmerston North, N.Z. :: Butterworths of New Zealand Ltd., 2002.
- [3] R. Houborg and E. Boegh, "Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data," *Remote Sensing of Environment*, vol. 112, pp. 186-202, 2008.
- [4] J. L. Hatfield, *et al.*, "Application of Spectral Remote Sensing for Agronomic Decisions," *Agronomy Journal*, vol. 100, 2008.
- [5] E. R. Hunt, *et al.*, "Applications and Research Using Remote Sensing for Rangeland Management," *PHOTOGRAMMETRIC ENGINEERING AND REMOTE SENSING*, vol. 69, pp. 675-694, 2003.
- [6] P. Williams and K. Norris, *Near-infrared technology in the agricultural and food industries*. MN 55121, USA: American Association of Cereal Chemists, Inc., 1987.
- [7] Drew, "Leaf structure," in <https://dbscience3.wikispaces.com/Drew>, ed.
- [8] Y. Ozaki, *et al.*, "Spectral analysis," in *Near infrared spectroscopy in food science and technology*, Y. Ozaki, *et al.*, Eds., ed New Jersey: Wiley-Interscience, John Wiley & Sons, Inc.: Hoboken 2005.
- [9] O. Mutanga, "Hyperspectral remote sensing of tropical grass quality and quantity," PhD, Wageningen University, Wageningen, The Netherlands, 2004.
- [10] D. Roberts, *et al.*, "Optimization of Crop Canopy Sensor Placement for Measuring Nitrogen Status in Corn," *Agronomy Journal*, vol. 101, p. 140, 2009.
- [11] R. Darvishzadeh, *et al.*, "Hyperspectral vegetation indices for estimation of leaf area index," in *Remote Sensing: From Pixels to Processes*, Enschede, Netherlands, 2006.
- [12] G. Chattopadhyay, "Sensor technology at submillimeter wavelengths for Space Applications," *International Journal on Smart Sensing and Intelligent Systems*, vol. 1, pp. 1-20, March, 2008.
- [13] J. R. J. Jungho Im, "Hyperspectral Remote Sensing of Vegetation," *Geography Compass*, vol. 2, pp. 1943-1961, 2008.
- [14] R. R. Pullanagari and I. Yule, "Use of Reflectance Sensors to Optimise Nutrient Management," in *Nutrient Management in a Rapidly Changing World*, Palmerston North, New Zealand, 2009, pp. 70-79.
- [15] J. Rouse, *et al.*, "Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation.," Greenbelt, Md, USA October 1973 1974.
- [16] M. Lieschnegg, *et al.*, "Non-invasive characterization of total hip arthroplasty by means of passive acceleration measurement," *International Journal on Smart Sensing and Intelligent Systems*, vol. 3, pp. 75-87, March, 2010.
- [17] R. A. Viscarra Rossel, "ParLeS: Software for chemometric analysis of spectroscopic data," *Chemometrics and Intelligent Laboratory Systems*, vol. 90, pp. 72-83, 2008.
- [18] I. D. Sanches, "Hyperspectral Proximal Sensing of the Botanical Composition and Nutrient Content of New Zealand Pastures," PhD, Soil and Earth Sciences, Massey University, Palmerston North, New Zealand, 2010.
- [19] I. J. Yule, *et al.*, "Technologies to improve productivity and reduce environmental impact of dairy systems," presented at the EcoTechs Conference: International workshop:Eco-design Methods and Tools for Agricultural Technologies, Clermont-Ferrand, France, 2010.

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