

## IDENTIFYING GRASS SPECIES USING HYPERSPECTRAL SENSING

**Cushnahan, T.A., Yule, I.J., Pullanagari, R. and Grafton, M.C.E.**

*New Zealand Centre for Precision Agriculture, Massey University,  
Palmerston North 4442, New Zealand*

### **Abstract**

Current hill farming practices rely on the skill of the farmer and previous experience to guide key elements of the operation such as stocking rates. The use of remotely sensed hyperspectral data raises the possibility to reduce some of the guesswork from the system by identifying pasture species being farmed and use that information to raise net returns. The diurnal and seasonal variations in plant reflectance were investigated using hyperspectral proximal sensing, this paper examines if these techniques were sufficiently robust to be practically useful.

The primary difficulty in application of remote sensing technology to the hill farm environment is the potential spatial and temporal variability of species in different regions of New Zealand. Monoculture plots of a number of turf species were used to ascertain the level of daily and seasonal variability within the species groups and to investigate how it might impact species identification.

Spectral data was collected from the plots using an ASD FieldSpec® with CAPP which collects spectral reflectance from 350nm to 2500nm in the electromagnetic spectrum. This was completed over a one year period. The species on the chosen plots were monocultures of 7 species with different cultivars for two species. Linear discriminant analysis (LDA) and partial least squares regression (PLSR) were carried out on the full spectrum data.

A U test was used to identify the most effective wavebands to use where data reduction was necessary; however where data processing is less limited the optimum number of bands for discrimination were identified. Where the instrument collecting the data is not limited there is an advantage in using a larger number of wave bands. In this experiment it was found that including up to 400 wavebands over the VIS/NIR SWIR range was useful.

The techniques used were successful in identifying the species with a high level of accuracy. The diurnal and seasonal changes within the plants were clearly detectable by LDA although they did not affect the ability to discriminate between species.

### **Introduction**

The sheep and beef sector contributed \$5.4 billion (2.5%) to the New Zealand economy in 2013 (*Statistics, 2013*). New Zealand hill farms where much of this production takes place are characterised by varied, often steep, terrain which limits the possibilities for pasture improvements such as reseeded. Hill farm pasture is often an eclectic mixture of many species with variable feed values.

Regardless of the pasture type, information on distribution and quality is crucial for maximising outputs and managing inputs. Primary to the question of feed quality is species composition. The feed value of different grass species varies (*Jackson et al., 1996*) so

knowing which species dominates a sward would enable better management practices to be developed. Intensive ground based data collection is physically difficult and cost prohibitive on hill farm locations. It is thus essential that we develop techniques to gather the necessary information remotely.

The benefit to farming in general and hill farming in particular, to have site specific information on pasture composition is difficult to overstate. It could inform better feed budgeting, stock management and fertiliser management and all would contribute to fiscal savings and maximising returns for the farmer.

Hyperspectral sensors collect light reflected from objects such as vegetation in a series of contiguous bands. They can have hundreds or thousands of bands which vastly improves the spectral resolution of the sensors compared to their multispectral counterparts. This increased definition in the spectral resolution allows them to identify a greater range of materials (*Goetz, Vane, Solomon, & Rock, 1985*). They provide better vegetation classification results than multispectral sensors and their narrow bands allow for selection of bands and creation of narrowband indices for a range of biophysical and biochemical properties (*Galvão, Epiphany, Breunig, & Formaggio, 2011*).

A number of studies have looked at identification of species from hyperspectral reflectance readings (*M. Cho, Sobhan, Skidmore, & de Leeuw, 2008; M. A. Cho et al., 2010; Ghasemloo, Mobasheri, & Rezaei, 2011; Prospere, McLaren, & Wilson, 2014; Vaiphasa, Skidmore, de Boer, & Vaiphasa, 2007; Zomer, Trabucco, & Ustin, 2009*). The approaches taken to solve the problem are as varied as the applications for which the information is intended.

The output from hyperspectral sensors carries a lot of information from nutrient content to species composition (*Bin, Ostland, Peng, & Ruiliang, 1999; M. I. Sobhan, 2007; Tarpley, Reddy, & Sassenrath-Cole, 2000*). A large proportion of the data from hyperspectral sensors can be redundant (*Pal & Foody, 2010; Thenkabail, Lyon, & Huete, 2011*). The problem with the vast amount of data that hyperspectral sensors gather is that having too many dimensions in the data can reduce rather than improve accuracies (*Hughes, 1968; Pal & Foody, 2010*). This naturally leads to exploration of techniques to reduce the dimensionality. Use of various indices or selection of a limited number of important bands that carry the relevant information while reducing classification error has become the norm (*Liu & Motoda, 1998; Pal & Foody, 2010; Schmidt & Skidmore, 2003; Thenkabail et al., 2011*). Those studies that choose bands rather than use prescribed indices must determine which carry the most or most important information (*Pullanagari et al., 2012; M. I. Sobhan, 2007*). A great number of statistical techniques have been adapted or developed for this task.

The primary pigment in plants is chlorophyll which enables the plant to convert light energy into carbohydrate. There are a number of other pigments that assist and protect this process including xanthophyll cycle carotenoids. (*B. Demmig-Adams & Adams, 1992; Jahns & Holzwarth, 2012*) and are known to have diurnal fluctuations (*Barbara Demmig-Adams & Adams Iii, 1996*). The expression and use of these pigments is shown not to be species specific (*Barbara Demmig-Adams & Adams, 1996*) Gamon, Peñuelas, and Field (1992) created a physiological reflectance index (PRI) to study the diurnal changes in pigment concentrations under various stress conditions. Their index was able to track changes in plant physiology associated with photosynthetic efficiency. The goal of photosynthesis is to produce carbohydrate/starch for night time utilisation (*Graf, Schlereth, Stitt, & Smith, 2010*). The concern is that the steady build-up of this carbohydrate reserve and changes in plant pigments through the day could complicate species identification.

There are a number of problems associated with discriminating species using reflectance, such as the spectral similarity of some vegetation and the spectral variability within a species (Price, 1994; Roth, Dennison, & Roberts, 2012). The mixed nature of plant communities adds another level of complexity to the information contained within reflectance data. Zomer et al. (2009) found heterogeneous mixed communities were more difficult to delineate and required prior knowledge from field data and/or the use of spectral matching or unmixing. The strength of diurnal or seasonal biochemical or biophysical changes within the plant could have a major impact on the practical application of this technology to hill farming situations.

## Materials and Methods:

This paper investigates the potential changes in reflectance on a diurnal and seasonal level and their impact on species identification. We explore the practicality of identifying various species from hyperspectral reflectance data. We examined the potential for the natural daily changes within the plant to alter the reflectance and examined if these subtle changes could be detected.

### Site Location

The trial plots were located just outside Palmerston North, New Zealand at the offices of The New Zealand Sports Turf Institute (NZSTI). Managed monoculture plots of turf species were used to standardise the conditions and limit the variables for the experiments. Most plots were managed identically including mowing (25mm), irrigation and fertiliser application. Irrigation negated the seasonal drying of the plant and coupled with mowing prevented the grass from going to seed. *Cotula* is primarily used for bowling greens so was mown at 5mm.

### Data Collection

Hyperspectral reflectance data was collected from eleven different fine turf areas using an ASD FieldSpec® pro (ASD Spectral devices, Boulder Colorado) with attached CAPP probe (Sanchez, 2009). The species were chosen both for their purity and to represent a mixture of Family, genus, species and variety. All but one species was mown at around 25mm. The access to relatively pure swards negated the need for spectral unmixing. The consistent management regimes for the plots reduced variability from grass height and soil water content. The chosen plots were;

- |                    |   |
|--------------------|---|
| ○ Cotula           | <i>Leptinella dioica</i> cv. Pahia                  |
| ○ Couch            | <i>Cynodon dactylon</i> cv. Agridark                |
| ○ Kikuyu           | <i>Pennisetum clandestinum</i> cv. Regal Stay Green |
| ○ Egmont           | <i>Agrostis capillaris</i> var. Egmont              |
| ○ Browntop         | <i>Agrostis capillaris</i> cv. Arrowtown            |
| ○ Rye '4600'       | <i>Lolium perenne</i> cv. 4600                      |
| ○ Rye 'Bizet'      | <i>Lolium perenne</i> cv. Bizet                     |
| ○ Rye 'Premier 2'  | <i>Lolium perenne</i> cv. Premier 2                 |
| ○ Blue Fescue      | <i>Festuca</i> sp.                                  |
| ○ Chewing's Fescue | <i>Festuca rubra</i> subsp. <i>Commutata</i>        |

### Reflectance Data Collection

Reflectance spectra were collected at 0800, 1000, 1200, 1400 and 1600hrs on the 3<sup>rd</sup> and 5<sup>th</sup> of September (Southern Hemisphere Spring) to ascertain if daily fluctuations in plant chemistry were detectable. Each site was identified and marked so that each subsequent sample could be collected from the exact same location. Both days were bright and sunny with no cloud at any time.

Upon completion of the initial experiment spectra from each plot were collected every 4 to 6 weeks (weather dependant) for the remainder of the year. Unfortunately the plot that contained the *Cynodon* sample was removed towards the end of the trial period. Data continued to be collected for the other plots.

### ***Primary Data Subsets***

Three subsets of the data were created; the first data subset collated each species to investigate the fluctuations in diurnal reflectance over the various collection times. A total of 40 samples were collated for each of the 5 time periods. Each sample was made up from the average of 10 readings. The results were used to answer the question; “Can we predict the time a sample was taken from the sample reflectance”?

The second dataset was collated to investigate the differentiation of season. The samples were split into four groups for each species. The results were used to answer the question; “Can we predict the season a sample was taken from the sample reflectance”?

The final subset collated all the data to investigate the separability of the various species and to look at reducing the dimensionality of the data via band selection. The results were used to answer the question; “What is the optimal number of bands for the best results in species identification”?

### ***Data handling***

The spectra were corrected for variations in the internal sensors using the Viewspec software supplied with the instrument and exported to Matlab® or R statistical software via Excel. The first and last 50 bands (350nm – 400nm and 2400nm – 2450nm) were excised due to obvious signal to noise problems leaving 2050 bands from 400nm to 2450nm.

## **Statistics:**

### ***Pre-Processing***

The raw spectral data was transformed in two ways; Standardisation ( $(x) - \text{Mean}(x) / \text{Std}(x)$ ) and conversion to 1<sup>st</sup> derivative. The derivative was calculated by application of the Gap-segment algorithm after filtering with a Savitzky-Golay filter. The filter with a window size of 11 followed by gap segment derivative with a segment size of 10 was carried out using the ‘prospectr’ package in ‘R’ (*Stevens & Ramirez-Lopez, 2014*).

### ***Band Selection***

A Partial Least Squares Regression (PLSR) and Mann–Whitney U test (U test) were carried out in Matlab® to identify bands that were sensitive to species discrimination. PLSR is a multivariate regression technique that is capable of analysing data where the variables have a high degree of correlation, are highly noisy and may have missing components (*Wold, Sjöström, & Eriksson, 2001*).

The U Test compared median values of each wavelength to determine if the between species variation was greater than the within species variation. The U test does not require a specific distribution (*McKnight & Najab, 2010*) so is more robust when normality cannot be confirmed. The process is systematically repeated for each wavelength and for every combination of species in turn. The 10 species in this trial required 45 iterations of the process to run. The result for each band combination is either a one (signifying a statistical difference) or zero and when collated can be graphed to view the bands where a difference was found most often (figures 2 & 3).

### Testing

A Linear Discriminant Analysis (LDA) projects a line that is orthogonal to the overall class variance and best separates the classes (Welling, 2005). The approach is applicable with numerical data and is a good approach for classification (Bhardwaj & Verma, 2015). The LDA was used here to examine each of the questions around collection time, season and subsequent species identification. The data was separated into training and test sets (80/20) prior to running the test. The LDA for the species was first carried out using a selection of 12 of the most prominent bands as predicted by the U test. The number of bands used was increased and the accuracy plotted to identify the optimal number for highest accuracy. This approach was repeated for both standardised and derivative data.

### Results:

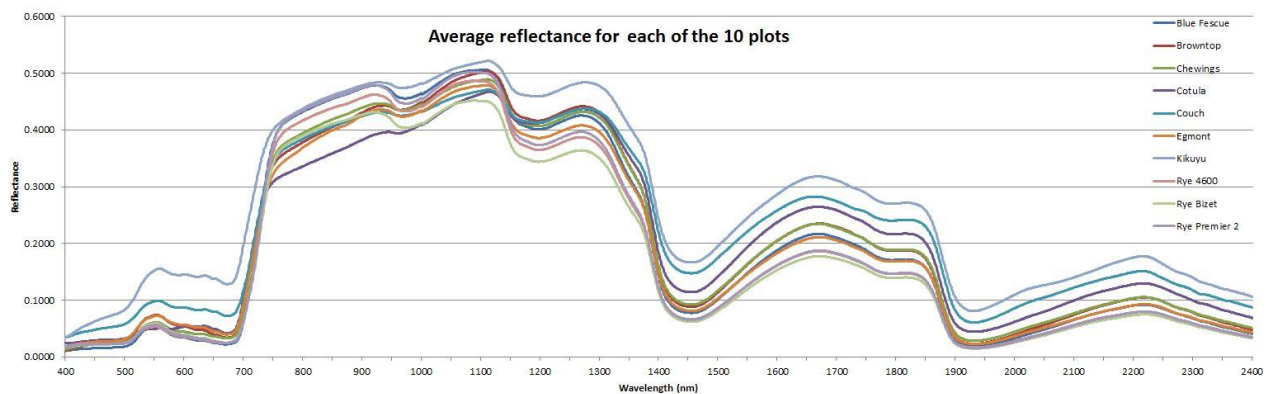


Figure 1: Graph of average reflectance for each of the 10 plots.

After a favourable comparison with Partial Least Squares Regression (PLSR) the U test was chosen for band selection because of its simplicity and ease of application. Results from the U test changed markedly from the standardised and 1<sup>st</sup> derivative data as depicted in figures 2 & 3.

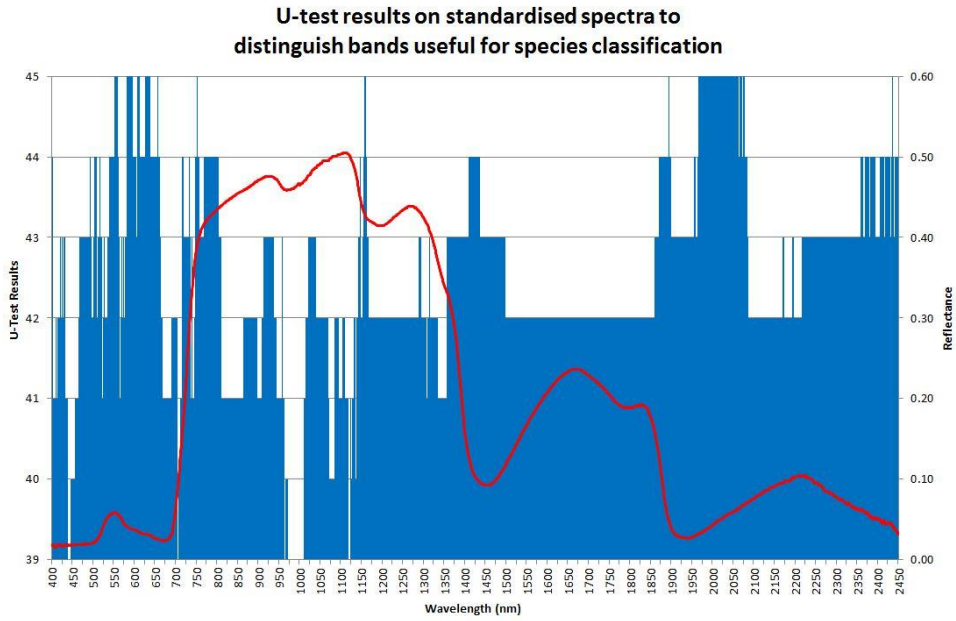


Figure 2: U test results from standardised data with reflectance curve of Blue Fescue overlaid for visualisation purposes. The y axis represents the cumulative total of positive results when each species is compared against every other species.

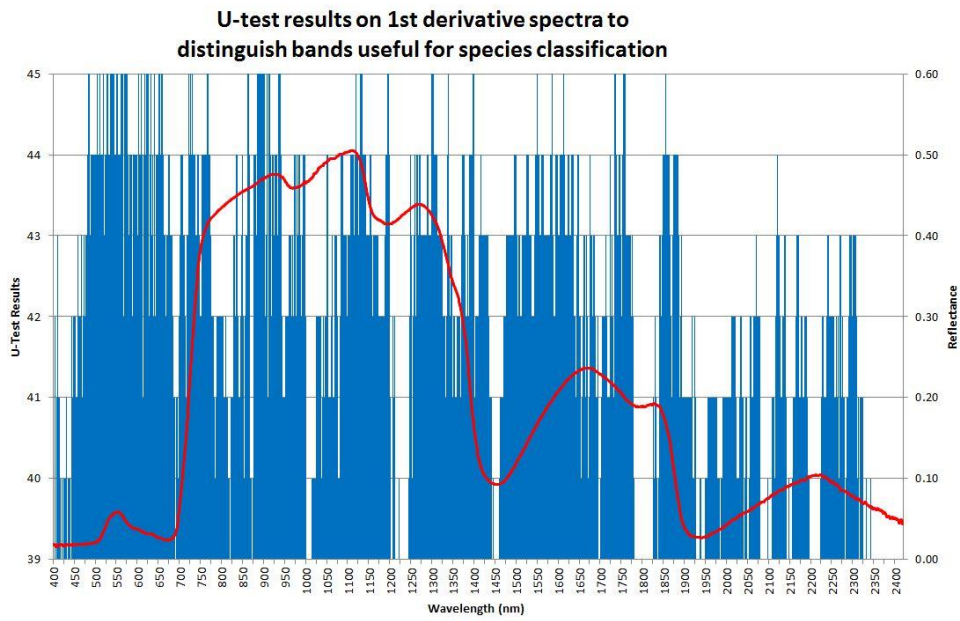


Figure 3: U test results from derivative data with reflectance curve of Blue Fescue overlaid for visualisation purposes. The y axis represents the cumulative total of positive results when each species is compared against every other species.



The U test from the derivative data indicated a higher importance of visible and NIR bands when compared to the standardised data which highlighted more bands in the SWIR. M. A. Cho et al. (2010) did not include any bands from the SWIR region for their study on savannah tree species. They suggested that some bands in the SWIR might have improved their results. I. Sobhan, Vaiphasa, and Skidmore (2007) also found important bands for discrimination in the visible part of the spectrum but noted a reduced number of bands in the NIR. They found important bands for species discrimination in a number of regions including the SWIR and concluded that bands within these regions ‘share’ information to discriminate species.

**Collection Time**

The LDA was able to predict the collection time for each species with high accuracies. Collection time was predicted for Cotula, Couch and the three varieties of Ryegrass with 100% accuracy. Some reduced accuracy (95% to 97.5%) was seen with Blue Fescue, Browntop, Chewings fescue, Egmont and Kikuyu. In all instances the inaccuracy manifested at the end of the day where the test showed some difficulty in deciding between 2pm and 4pm for those species.

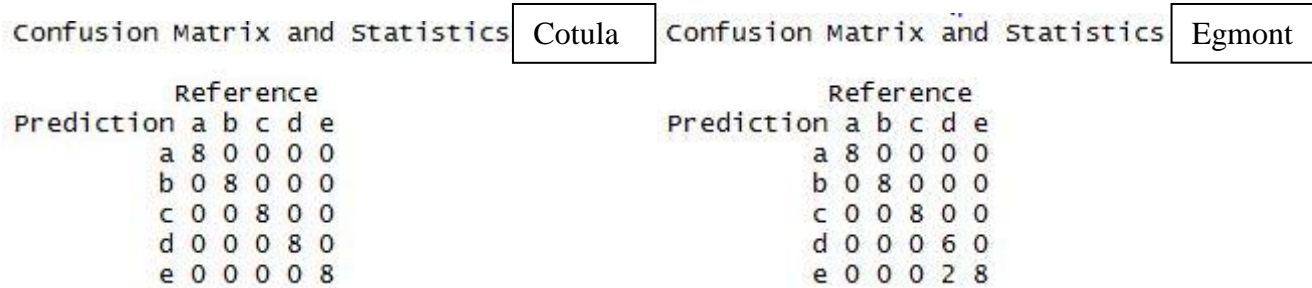


Figure 4: Confusion matrix for Cotula and Egmont for prediction of sample collection times a)08.00 b)10.00 c)12.00 d)14.00 e)16.00.

## Season

The LDA was able to predict the season and species with an overall accuracy of 92%.

Predicti	Referen																																					
	Blue Fescue Autumn	Blue Fescue Spring	Blue Fescue Summer	Blue fescue Winter	Browntop Autumn	Browntop Spring	Browntop Summer	Browntop Winter	Chewing Summer	Chewings Autumn	Chewings Spring	Chewings Winter	Cotula Autumn	Cotula Spring	Cotula Summer	Cotula Winter	Egmont Autumn	Egmont Spring	Egmont Summer	Egmont Winter	Kikuyu Autumn	Kikuyu Spring	Kikuyu Summer	Kikuyu Winter	Rye '4600' Summer	Rye 'Bizet' Summer	Rye 'Premier 2' Summer	Rye '4600 Autumn	Rye '4600 Spring	Rye '4600 Winter	Rye bizet Autumn	Rye Bizet Spring	Rye Bizet Winter	Rye Premier 2 Spring	Rye Premier 2 Winter	Rye premier2 Autumn		
Blue Fescue Autumn	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Blue Fescue Spring	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Blue Fescue Summer	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Blue fescue Winter	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Autumn	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Spring	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Summer	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Browntop Winter	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewing Summer	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Autumn	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Spring	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chewings Winter	0	0	0	0	0	0	0	0	1	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Autumn	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cotula Winter	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Egmont Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Egmont Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Egmont Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Egmont Winter	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kikuyu Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kikuyu Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kikuyu Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kikuyu Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0
Rye '4600' Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0
Rye 'Bizet' Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Rye 'Premier 2' Summer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
Rye 4600 Autumn	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0
Rye 4600 Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0
Rye 4600 Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0
Rye bizet Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	1	0
Rye Bizet Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0
Rye Bizet Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0
Rye Premier 2 Spring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	8	0	0	0	
Rye Premier 2 Winter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5	0	0
Rye premier2 Autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0

Figure 5: Confusion matrix for predicted and actual season and species. The quantities in each group vary because the LDA training and test groups were randomly chosen.

## Species

The LDA accuracy for standardised and derivative data reached peak accuracy at 96.96% and 98.04% respectively. The number of bands needed to achieve that accuracy was 404 and 266 respectively. Both datasets performed well and showed an improved accuracy when a portion of the spectral signature was used instead of the entire spectral signature. Table 2 shows improved accuracies using the bands selected with derivative data. The improved accuracies are evident when smaller quantities of bands are used but the differences shrink when the numbers of bands used increases.

Table 1: LDA accuracy results using standardised data with various numbers of bands chosen via the U test. Accuracy is seen to peak at 404 bands.

LDA for Bands Selected via U-Test From Standardised Data									
Bands	12	76	150	200	404	800	914	1740	2050
Accuracy	82.14%	89.82%	91.61%	93.75%	96.96%	96.07%	94.82%	92.14%	93.04%
Kappa	80.16%	88.69%	90.67%	93.06%	96.63%	95.63%	94.25%	91.27%	92.26%



Table 2: LDA accuracy results using derivative data with various numbers of bands chosen via the U test. Accuracy is seen to peak at 266 bands.

LDA for Bands Selected via U-Test From Derivative Data								
Bands	11	50	110	266	422	814	1177	1665
Accuracy	81.25%	95.54%	96.61%	98.04%	97.68%	96.96%	96.07%	94.82%
Kappa	79.17%	95.04%	96.23%	97.82%	97.42%	96.63%	95.63%	94.25%

Table 3: LDA accuracy using numbers of bands selected randomly from the entire spectrum of standardised data.

LDA for Random Bands From Standardised Data				
Bands	12	76	150	200
Accuracy	78.21%	97.50%	95.71%	98.21%
Kappa	75.79%	97.22%	95.24%	98.02%

Randomly selected bands proved every bit as useful and predictive especially when larger numbers were used. This corresponds well with the other data that showed improved performance with greater numbers of bands. The problem with the random selection of bands is the possible variability of results and problems with replication.

### ***Spectral regions descriptive capability***

The U test with standardised reflectance data predicted bands in the visible and SWIR as primary to species identification which corresponds well with I. Sobhan et al. (2007). The LDA using the derivative data contradicted this by predicting less influence from the SWIR and more in the NIR. To help clarify the relationship spectra from each region was analysed separately to ascertain their comparative discrimination power. Standardised data was used for the comparison rather than the derivative data. The LDA of the visible (400-750nm) predicted species with 97.68% accuracy, NIR (750-1250nm) 93.39% and the SWIR (1250-2450nm) 79.46%.

### **Discussion/Conclusion:**

The ability of the LDA to distinguish collection time and season was impressive although not altogether unexpected as the variability of plant physiology due to environmental factors is well known (Magney, Vierling, Eitel, Huggins, & Garrity, 2016). The difficulty the test encountered identifying the collection time with some species was interesting primarily because it consistently occurred in each case at the end of the day. The fact that not all the species exhibited this trait points to a possible divergence in species physiology. Apart from Kikuyu the species that proved more difficult to categorise in the later part of the day are less adapted to high growth competition situations. This leads us to believe that the criteria that change the spectra through the day (and therefore allow identification of the collection time) must have reached an asymptote in some species. This is feasible given the high light conditions experienced during the trial. It is speculated that this could relate to a build-up of xanthophyll cycle pigments, carbohydrate storage or a combination of biophysical properties. The samples were collected in early spring which may help to explain the inclusion of Kikuyu in this group as Kikuyu is much less active at that time of year (Betteridge & Haynes, 1986). The results are based on limited data but raise intriguing questions around species competition strategies that hyperspectral data may be able to assist with answering. Further examinations during days where cloud reduces light levels and on days where sunlight hours are longer (Summer) might be a good follow-up study. Seasonal fluctuations in plant reflectance were clearly identified with 92% classification which infers that each species changes in a measurable way over the year. The differences in plant reflectance both diurnally and

seasonally did not restrict the capability for the LDA to identify the species. This classification was however limited by the fact that the species were managed; irrigated, fertilised and mown which only addresses part of the story of how plant reflectance can change through the year (*Asner, 1998*). There is little doubt that we can separate species when they are sampled at similar points in time. The question of whether we can distinguish a particular species from samples taken under different growth and stress conditions is yet to be fully answered. Price (*1994*) gave a concise list of reasons why it may be difficult or impossible to always distinguish any given species from spectra alone and it has been suggested by others (*Cole, McMorro, & Evans, 2014; M. I. Sobhan, 2007*) that identification may need to be defined by spectra taken at a particular time or growth period to be most effective.

The number of bands necessary for discrimination varied with the pre-processing method although both datasets ended up with similar prediction maxima. This difference in sensitivity however has little to do with the pre-processing method. The pre-processing method influenced the U test band selection. Standardised data indicated a larger number of predictive bands in the SWIR while the derivative data did not. The subsequent regional sensitivity test supported the U test from the derivative data by showing a lesser predictive power of SWIR bands for species. The derivative data proved a better indicator of the bands where species level differences were located. Subsequently bands chosen with this data had improved predictive power. This does not mean the transformation made the species easier to discriminate; it merely meant that the bands chosen carried more information than those chosen with standardised data. The importance of this fact becomes greater when fewer bands are chosen or when fewer bands are necessary due to processing restrictions. Tables 1 and 2 illustrate this point very well with 266 bands from derivative and 404 bands from standardised data needed to reach maximal prediction.

The bands carrying the pertinent information will vary depending on the species (*Asner, 1998*). An understanding of this can assist with band selection but should be corroborated, where possible, with preliminary testing especially when a smaller number of bands are required.

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<https://www.mpi.govt.nz/funding-and-programmes/primary-growth-partnership/primary-growth-partnership-programmes/pioneering-to-precision-application-of-fertiliser-in-hill-country/>

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