University of Southern Queensland

Faculty of Engineering and Surveying

Assessment of Crop Health In Relation to Competition from Weeds: Using Balloon-borne Images and Spectrometer Data

A dissertation submitted by

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towards the degree of

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Abstract

Remote sensing is increasingly being applied to agricultural applications. It offers the ability to quickly and efficiently supply information about the spatial variability that occurs within fields. Recently remote sensing technology has been successfully applied to identify and mapping weeds within crops. Weeds pose a serious threat to crop health and can adversely affect yield. The opportunity exists to explore new applications of remote sensing in the agricultural setting particularly measuring crop health.

This study covers the application of remote sensing to detect weed-induced stress in grain crops. The aim of the study was to determine the ability of spectral data, captured by a low cost balloon-borne camera system and a spectroradiometer, to discriminate between a healthy and stressed crop. Spectral data was collected from a weed trial site that contained several sorghum varieties planted at different planting densities and with or without weeds. Discriminant function analysis was conducted on the data captured by the two sensors to analyse the ability of spectral data to be used to differentiate between the crop containing weeds and the crop without weeds. The results of the analysis indicate that the spectral data from both sensors can be used to distinguish between the healthy and stressed crop. These results provide sufficient cause to suggest further research is warranted into the application of remote sensing as a tool for measuring crop health.

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Certification

I certify that the ideas, design and experimental work, results, analyses and conclusions set out in this dissertation are entirely my own effort, except where otherwise indicated and acknowledged.

I further certify that the work is original and has not been previously submitted for assessment in any other course or institution, except where specifically stated.

Shawn Geoffrey Darr

Student Number: 0019821066

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Signature

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Date

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My sincerest thanks go to Dr Armando Apan, of the University of Southern Queensland, for his guidance, support, encouragement and help in the execution of this project. Thanks must also be extended to my co-supervisor, Troy Jensen from the Queensland Department of Primary Industry and Fisheries, who supplied the balloon-borne camera system and provided, advice, encouragement, and support.

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I would also like to thank my fellow GIS and Surveying students, namely Cameron McGregor, Akchousanh Rasphone, Charmaine Hebbard and David Bligh, for their support and camaraderie throughout this project and my studies.

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Glossary Of Terms And Abbreviations

Agronomy	The applied Aspects of soil science and several plant sciences often limited to crops.
Anthesis	The time of a flower's opening.
Band	A wavelength interval within the electromagnetic spectrum.
Cultivar	Plant variety produced by cultivation.
Digital Number	Value assigned to a pixel in a digital image, commonly from 0 to 255.
DPI&F	Department of Primary Industries and Fisheries.
Geometric Correction	The process of mapping a remotely sensed image onto a chosen projection such as latitude longitude or a coordinate system.
GIS	Geographic Information System, is a set of tools for collecting, storing, retrieving at will, transforming and displaying data from the real world for a set of

purposes (Burrough, 1986).

Reflectance The ratio of radiant energy reflected by a body to the energy incident upon it. Reflectance is independent of units.

Spectrum Continuous sequence of electromagnetic energy arranged according to wavelength or frequency.

Wavelength The distance between adjacent peaks or troughs, measured in the direction of propagation, in harmonic wave.

Georeferencing/Registration See geometric correction.

Root Mean Squared Error The error is calculated for each transformation performed and indicates how good the derived transformation is.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Weeds pose a serious threat to the health of crops. They compete directly with crops, act as host for crop disease and pests and contaminate harvests. The Cooperative Research Centre for Australian Weed Management (2003) indicates that Farmers spend approximately $70 per hectare per annum on weed management and the total cost of weeds to the Australian agriculture industry now exceeds $4 billion per year.

Effective weed control is required to maximise crop yields, prevent weed seed contamination at harvest, ensure good water use efficiency, and reduce weed seed banks (DPI&F 2002). With a move away from conventional tillage to zero till practices over the past decades, farmers have seen an enormous increase in the use and reliance on herbicides to control weed populations (DPI&F 2002). This has caused concern over the effect herbicides are having on the environment and the resistance that weeds are developing to herbicide use. To reduce the reliance on herbicides farmers are moving to integrated weed management practices. Integrated weed management systems are designed to reduce weed numbers with minimal herbicide use. This is achieved by implementing other control practices such as biological control, crop rotation, planting configurations and densities, and other techniques.

The CRC for Australian Weed Management (2003) is advocating research be conducted into developing new technologies that will assist farmers to reduce weed populations. Some of this research is being directed at opportunities remote sensing provides in detecting and measuring spatial variation on a broad scale.

1.2 Statement of the Problem

Research into agricultural applications of remote sensing has been conducted since at least the 1970's. Since that time remote sensing technology has been applied to many agricultural applications. This process continues today with innovative remote sensing technology being employed to detecting weeds within crops, through real-time detection and weed mapping.

Current research into weeds and crops appears to be concentrating on the discrimination of weeds and crops. Little evidence has been found of research being conducted into measuring stress in crops caused by the presence of weeds or other environmental factors. With the incentives being provided by the CRC for Australian Weed Management and other agricultural bodies to conduct innovative research into new technologies that will allow farmers to better manage weeds and other crop stress, the opportunity exists to research new methods of applying remote sensing technology to these situations.

1.3 Rationale of the Study

This project was established with the assistance of the DPI&F, in the aim to measure spatial variability within crops. In particular, to use remote sensing to detect and identify areas of crop stress so as to provide the ability to alter crop management in-season. This study will attempt to achieve these goals through the use of cost effective remote sensing, image processing techniques and statistical analysis.

1.4 Objectives

The broad objective of this study is to ascertain whether remote-sensing techniques can be used to differentiate between healthy and stressed crop. For the purpose of these objectives, healthy crop is considered a crop without weeds, and a stressed crop a crop with weeds.

The specific objectives of this project were to:

1) Obtained spectral data of the two crop types using a spectroradiometer and low cost aerial images;

2) Determine the ability of the spectral data captured by the spectroradiometer to discriminate between healthy and stressed sorghum crops;

3) Determine the ability of the data extracted from the aerial images to discriminate between healthy and stressed sorghum crops; and

4) Determine if correlation exists between the two data sources.

1.5 Scope and Limitations of the Study

This project has been substantially limited by the spectral data captured particularly for the spectroradiometer. Two trial sites were identified as potential research sites for this project. The research has been conducted on the second of these two trial sites. This site however was not the first choice.

A site located near the township of Brookstead was considered the most favourable site. Spectral data was captured at this site with the spectroradiometer on the 27 January 2004. Over two hundred spectral samples were taken at the site along with observations about plant maturity and weed and plant density. Spectral data capture was to occur within the week for the Balloon-borne camera system. However due to time constraints and unfavourable weather, data capture could not occur with the balloon-borne camera system.

During this time data capture for both sensors did occur at the Kingsthorpe trial site. It was not anticipated that this data would be used and the quantity and quality of data reflect this situation.

After realising the window for data capture for the balloon-borne camera had passed, it was decided to progress with the spectral data from the second site even with its limitations.

1.6 The Organisation of the Dissertation

This dissertation is organised into six main chapters plus ancillary material. Chapter 1 introduces the study, including project aims and objectives, rationale of the study and the scope and limitation of the study. Chapter 2 comprises a literature review. It introduces the concepts and theory relevant to the study. Chapter 3 outlines the research methodology. It describes the study area, data capture, image pre-processing and the statistical analysis employed.

Chapter 4 presents the results of the discriminant function analysis for both sensors, the regression analysis and other statistical results. Chapter 5 discusses the results of this study. This discussion is presented in four sections. The first section discusses the results of the discriminant function analysis for the spectroradiometer. The second discusses the results of the discriminant function analysis for the aerial images. The third compares the results of the discriminant function analysis for both sensors. Finally the results of the regression analysis are discussed.

Chapter 6 presents the conclusions derived from this study and makes suggestions for application of this research and recommendations for further research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter outlines the background information that was reviewed in order to conduct this project. It starts by introducing the effect weeds have on plants. This is followed by a brief outline of the characteristics of sorghum, which is the crop the spectral samples were collected from. A brief review of precision agriculture is supplied along with the remote sensing techniques used to detect weeds. A review of vegetation spectral responses is presented followed by a review of the previous studies that have been conducted into detecting vegetation stress with remote sensing techniques. Finally, insights into previous studies undertaken to detect plant stress were sought to provide direction and indicate were gaps in knowledge occurred for the application of remote sensing to detecting weed stress in crops.

2.2 Weeds

Weeds are plants that interfere with the development or harvest of crops, or reduce the value of harvested crops (de Kantzow & Sutton 1988). The Weed Society of America (1967) simply defines weeds as a “plant that is growing where it is not desired”.

Weeds can be categorised as direct competitors, indirect competitors, or contaminants (de Kantzow & Sutton 1988). This project is concerned with the effect of direct competitors, which compete directly with the crop for space, light, nutrients and water and thereby reduce yield.

Competition between crops and plants occurs when nutrient, water or light supplies falls below the combined demand of both species. Crops and plants compete for nutrients and water when roots explore the same soil mass, and they compete for light when weed or crop leaves shade the other (de Kantzow & Sutton 1988). Competition for nutrients, light and water between weeds and crops results in yield loss for both species (de Kantzow & Sutton 1988; Zimdahl 1999).

The competition between weeds and crops for nutrients, light and water is an interrelated relationship. If the accessibility of one of these factors is reduced so is the availability of the others due to the limiting factor of the reduced resource (Zimdahl 1999). Thus if the competition between weeds and the crop reduces the amount of light the crop receives than the crops ability to compete for nutrients and water will in turn be reduced. The effect a weed has on a crop is generally in proportion to the amount of light, water and nutrients weeds use at the expanse of crops (Zimdahl 1999).

Zimdahl (1999) states that weeds in nearly all cases are far more efficient and effective at obtaining nutrients from the soil than crops. Increasing the availability of nutrients does not reduce the completion for nutrients. Rather increased application of fertiliser stimulates weed growth and causes competition for light. So at lower fertility competition is primarily for nutrients but at high fertility competition is for light.

Lack of water is often the primary environmental factor limiting crop production and is probably the most critical requirement for plant growth (King 1966). Weeds tend to use water more efficiently than crops, have a greater capacity to consume water and are often more successful at acquiring water (Zimdahl 1999). The reason for this is that weeds generally have a greater rooting depth and have a larger feeding diameter and volume (Zimdahl 1999).

Light regulates many aspects of plant growth and development. Competition between crop and weeds for light is most rigorous when there is high fertility and adequate moisture. Plants with large leaf area indices have a competitive advantage and normally out compete plants with smaller leaf area (Zimdahl 1999).

2.3 Sorghum

Grain sorghum is the main summer grain crop grown in most regions of North-Eastern Australia. Approximately sixty percent of the crop is grown in Queensland and the remainder in northern New South Wales. Sorghum plays a key role in providing feed grains to the beef, dairy, pig and poultry industries (DPI&F 2004). Sorghum is not used for human consumption in Australia, but is a staple food for many people living in the developing nations in the semi-arid tropical areas of Africa and Asia (Grundon, Edwards, Takkar, Asher & Clarklow 1987).

Sorghum requires a warm, summer growing period of about 4-5 months. Planting times are usually between September to January. The crop is highly drought tolerant, but responds well to rainfall.

The total area of sorghum planted in northern Australia has been increasing, with the 2000-2001 crop totaling 818,000 ha (DPI&F 2004). Farm yields vary with the avarage yield for the north-eastern cropping region being approxmatley 2 t/ha, and maximum yields may reach 6 t/ha (DPI&F 2004).

The major limiting factor to production is water stress during grain fill, which can result in reduced yield. If not properly managed, weeds will compete with sorghum for water and nutrients which can lead to crop stress and yield loss. In-crop weeds must be controlled within 4 to 5 weeks of a crops life to avoid significant yield loss.

2.4 Precision Agriculture

The development of precision agriculture, based on remote sensing and geographic information systems (GIS), is beginning to revolutionise the way farmers manage their crops. Instead of managing their farm on a field-by-field basis, farmers are now able to manage resources and limitations such as the presence of weeds on an infield basis.

The aim of precision agriculture or site-specific crop management is to vary management practices according to the spatial variation within fields. Unlike conventional agricultural practices where uniform application of fertilisers, herbicides or even irrigation occurs, precision agriculture concentrates on delivering variable application within the field. The result of this technique is that inputs are delivered proportionally to the capability or limitations of the land.

By using variable infield management, precision agriculture has the ability to increase efficiency and productivity. This is achieved by minimising inputs, through more efficient application of resources and by maximising yields by overcoming site-specific limitations (Kelly & Jensen 2003).

2.5 Weed Detection

There has been considerable research into distribution of weeds within crops. Much of this research has determined that weeds are not distributed uniformly but form aggregated spatial patterns (Rew & Cussans 1995; Nordmeyer, Hausler & Niemann 1997). Weed patches through surveys have been demonstrated to cover from 80 percent to as little as a few percent (Brown et al 1990). The concept of precision agriculture is now being developed to incorporate the management of weeds. Two methods for site-specific weed control are being concurrently investigated and developed. These are real-time detection where weed assessment and spraying are carried out simultaneously, and using weed maps created prior to the spraying operation (Nordbo, Christensen, Kirstensen & Walter 1994).

Walter, Hiesel and Christensen (1997) suggest weed mapping has a number of advantages over real-time detection. First, it can be used for planning treatment maps that integrate crop-weed competition. Secondly the optimum time to detect weeds may not coincide with the optimum time to spray. Finally, weed maps are more appropriate for mapping multi-species weed populations in cereal crops. Lamb & Brown (2001) also suggest that weed maps give farm managers the ability to monitor the effectiveness of past or current weed management strategies.

Weed maps can be generated by a number of methods. Either through manual surveying, which is labour intensive and suffers from the operator's subjectiveness, or by machine assisted/automatic techniques.

The latter method incorporates remote sensing and weed discrimination by image analysis. Research has progressed significantly in this area, with a number of researches reporting success at discriminating weeds. Jurado-Exposito, et al.

(2003) were able to discriminate between sunflower, wheat stubble, and weed species in a controlled trial. Problems were experienced in distinguishing particular weed species from other species, but three groups of species were able to be distinguished.

Whilst research has focused on developing techniques to identify weeds, little or no research has been conducted into discriminating the impact of weed stress on crop performance using remote sensing.

2.6 Spectral Response of Vegetation

Lamb & Brown (2001) suggest that there are two requirements necessary for remote sensing to detect and map weeds. These are suitable differences in spectral reflectance and that the remote-sensing instrument has appropriate spatial and spectral resolution to detect the presence of weeds. These two requirements are equally valid for detecting weed-induced stress in crops. The following section investigates the ability of weed-induced stress to be detected through changes in spectral response.

The spectral reflectance curve of healthy green vegetation almost always has the "peak-and-valley" configuration (Lillesand & Kiefer 1994) that is represented in Figure 2.1. The valleys in the visible portion of the spectrum are primarily caused by the chemical compound chlorophyll (Campbell 1996; Lillesand & Kiefer

1994). Chlorophyll is contained in plant leaves and used in the process of photosynthesis. Chlorophyll absorbs a greater proportion of radiation in the red and blue wavelengths for use in the photosynthesis process than green wavelengths (Campbell 1996). The higher reflectance of green wavelengths gives healthy vegetation their green appearance and is responsible for the peak in the spectral reflectance curve around the 500-578 nm wavelength range.

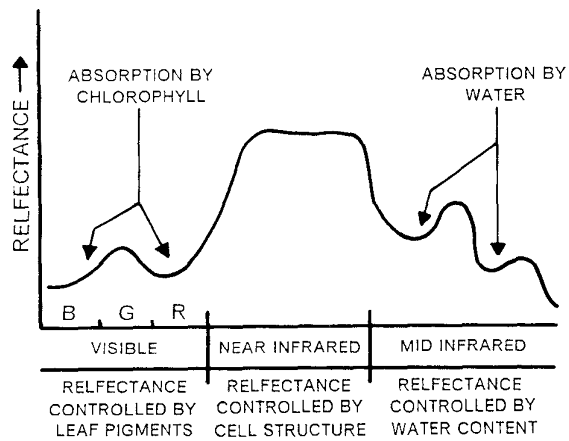


Figure 2.1 Major Influences On The Spectral Properties Of Healthy Green Vegetation

(Source: Campbell, J.B. 1996, *Introduction to Remote Sensing*, 2nd edn, The Guilford Press, New York. p. 458)

The infrared portion of the spectrum is not influenced by chlorophyll but by the tissue structure within the leaf. The internal structure of healthy leaves provides near ideal diffuse reflection of infrared wavelengths (CCRS 2003). In the range from 700 to 1300 nm a plant leaf typically reflects 40 to 50 percent of incident radiation (Lillesand & Kiefer 1994), which accounts for the second peak in the spectral curve in Figure 2.1.

Because plant structure is highly variable between plant species, the infrared portion of the spectrum allows discrimination between different plant species even though the visible spectrum for plants may be very similar (Lillesand & Kiefer 1994).

2.7 Spectral Response of Stressed Vegetation

As plants mature or are subjected to stress by disease, insect attack or water deficiency, the spectral characteristics of the plant leaf may change (Campbell 1996). Both the visible and infrared regions are generally affected concurrently by these changes but changes in the infrared reflectance are often more noticeable (Campbell 1996).

The infrared reflectance is reduced as a result of a deterioration of cell walls, whilst visible reflection is affected by reduced chlorophyll presence in the plants leaves. A reduction of chlorophyll presence in plant leaves results in less absorption and proportionately more reflection of the red wavelengths (CCRS 2003), this results in plant leaves turning yellow (combination of red and green wavelengths) and reduces the valley in the spectral reflection curve, typically seen for healthy vegetation.

Changes in vegetative vigour, maturity and plant stress can all be detected by changes in both visible and infrared reflection (Lillesand & Kiefer 1994;

Campbell 1996). Infrared reflection however has greater differentiation capability due to the greater amount of energy reflected than the visible region. In the infrared range 40-50 % of incident energy is reflected, whereas in the visible range only 5-15 % is reflected with the majority being absorbed as part of the photosynthesis process (Lillesand & Kiefer 1994).

The above discussion appears to provide a confident assessment for the ability to separate weed induced stressed plants from healthy plants spectrally. With the basic findings suggesting that stressed plants will broadly have lower reflectance across the entire spectrum. This is however challenged by Guyot’s research into the effect of leaf water content. Guyot (1990) suggests that the leaf water content has a direct effect on the optical properties of leaves in the middle infrared region and an indirect effect on the visible and near-infrared reflectance. Guyot (1990) stated, based on laboratory conditions, that a reduction of the leaf water content induces an increasing reflectance over the whole spectrum, and in particularly the middle infrared portion. Guyot did however state that it would be necessary to have severe water stress to effect leaf optical properties for infield crops.

Whilst Guyot’s research does not contradict the previous findings, it does cloud what we might expect to see from spectral response of weed induced stress depending on the stress type the crop is experiencing, e.g. nutrient, water or light stress.

2.8 Previous Studies using Remote Sensing for Detecting Weed Stress

An exhaustive search into previous studies that may have used remote sensing techniques to detect weed-induced stress in crops has failed to unearth any such research. A number of interrelated titles were searched based on plant stress however these either provided no further information than that discussed in previous sections or were unavailable. This has led me to conclude that there is a dearth of research into this particular area and that research is warranted into the ability of remote sensing to be employed to detect weed induced stress in crops.

2.9 Summary

Weeds compete with crops on many levels causing a reduction of yield quality and quantity. In an attempt to manage weeds within crops more efficiently than traditional methods, a number of techniques have been successfully applied to detecting and mapping the in-crop variability of weeds.

Remote sensing is one such technique that has been able to be employed because of its ability to discriminate between different plant types based on distinctive spectral responses. Research has also indicated that the spectral response for healthy vegetation and stressed vegetation differs allowing the possibility of discriminating between the two. Research into the applicability of remote sensing to detecting weed induced stress in crops has either not been conducted or is inaccessible at the time of this research. This provides the incentive and opportunity for this project to investigate the possibility of using remote sensing techniques to discriminate between healthy vegetation and vegetation that has been stressed due to the presence of weeds based on differing spectral responses.

CHAPTER 3

RESEARCH METHODS

3.1 Introduction

This chapter outlines the design of the research employed in this study. The methodologies employed in the analysis and processes of this project are expanded upon. The chapter begins with a brief introduction to the study area and outlines the experimental plan that this project is based on. The data capture procedures are then described. This is followed by an explanation of the pre-processing required prior to analysis. The methods used to analyse that data are then described. The final part of this chapter presents a discussion of the accuracy assessment of the data used.

3.2 Study Area

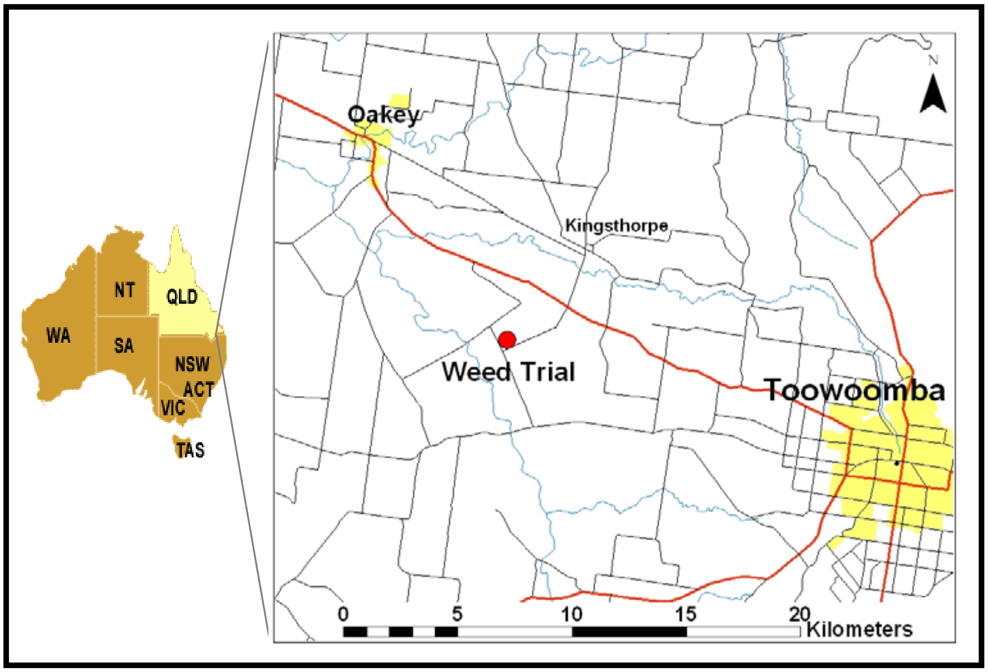


Figure 3.1 Location of the Study Area

The study area is located at 151° 46” 41’ E and 27 ° 30” 51’ S, and lies 20 km northwest of the city of Toowoomba (Figure 3.1). The area is part of the broad-acre farming region of the Darling Downs, which is part of the northern grain-growing region of Australia. The research project focuses on area that is being used for a weed trial by the Queensland Department of Primary Industries and Fisheries (Figure 3.2). This weed trial area is referred to as “Kingsthorpe”.

Figure 3.2 Kingsthorpe Weed Trial Site

The Kingsthorpe study area contained two weed trials, the first was a variety and density trial, and the second was a row spacing trial. This project is concerned solely with the variety and density trial.

The DPI&F's objective for the variety and density trial was to determine if sorghum agronomy (crop density and cultivar characteristics) could be manipulated to improve crop competition on weeds. The treatments in this trial were:

- **6 Sorghum Cultivars**
  - Pioneer 85G83 (83)
  - Pioneer 86G87 (87)
  - Pioneer Bonus MR (BO)
  - Pacific MR Buster (BU)
  - Pacific MR Goldrush (GO)
  - Pacific MR43 (43)

- **3 Seeding Rates**
  - 45,000 established plants/ha (45K)
  - 60,000 established plants/ha (60K)
  - 75,000 established plants/ha (75K)

- **2 Weed Free Controls**
  - Pacific MR Buster (BU) planted at 3 seeding rates
  - Pacific MR Goldrush (GO) planted at 3 seeding rates

- **3 Replications**

All plots were sown with 1 meter row spacing as solid plantings. The size of each plot was 4 x 15 m (4 rows of 15 meters). Japanese millet (*E. crus-galli*) was used as a model weed to mimic barnyard grass. Planting began on the 5 November 2003 with the millet planted first, followed by sorghum. Irrigation was applied to germinate the crop and 'weeds'. Treatments were randomised in the replications as can be seen in **Figure 3.3**.

Figure 3.3 Sorghum Cultivar Density Trial Layout

This project concentrated solely on Replication 1. Within Replication 1, the plots containing weed free controls and the corresponding plots with weeds were identified as "Comparable Pairs". These comparable pairs were used for determining if a spectral distinction could be made between the health of the crop based on whether the crop did or did not contain weeds. These plots contained the varieties Pacific MR Buster and Pacific MR Goldrush, at the three seeding rates mentioned above. These comparable pairs have been identified in **Figure 3.3** and highlighted red. Table 3.1 lists the six comparable pairs identified, along with the plot identification number.

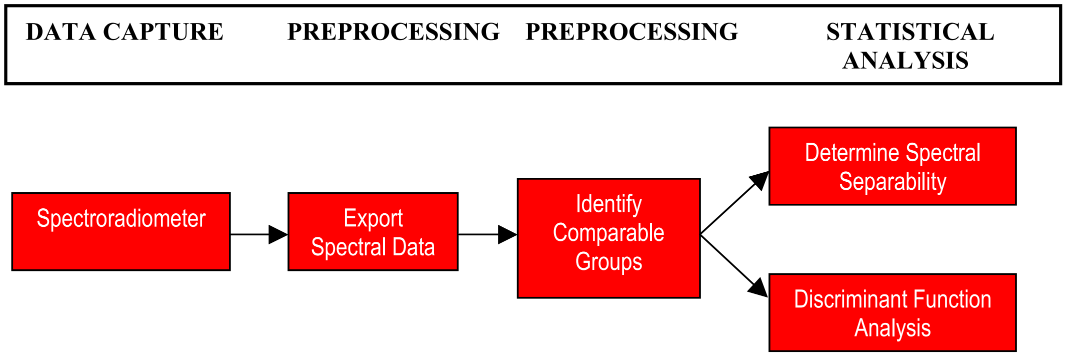
Table 3.1 Comparable Pairs

Comparable Pair (Variety / Sowing rate)	Plot Without Weeds (Plot ID)	Plot With Weeds (Plot ID)
Buster – 45K	19	13
Buster – 60K	20	14
Buster – 75K	21	15
Goldrush – 45K	22	16
Goldrush – 60K	23	17
Goldrush – 75K	24	18

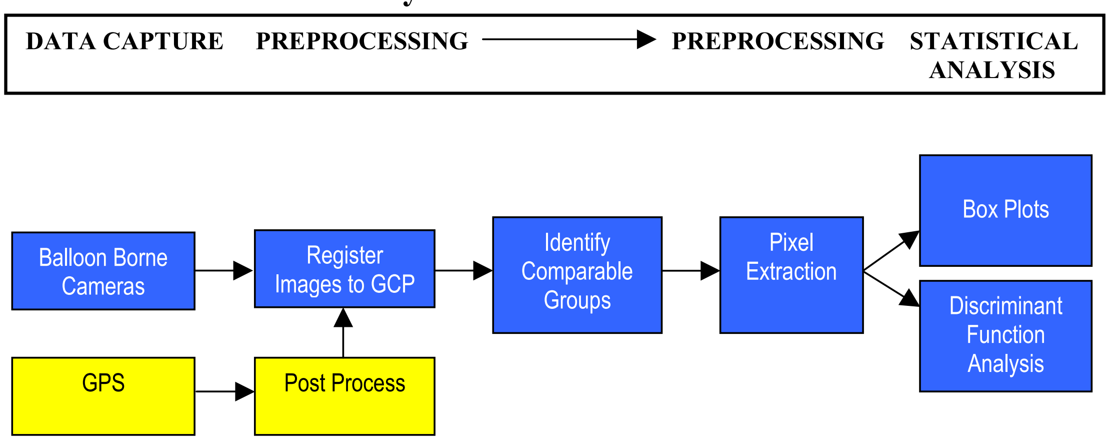
3.3 Methodology Flow Chart

The data capture, post processing and analysis steps taken for this project are outlined in Figure 3.4. The following sections provide a description of each step.

Spectroradiometer



Balloon-borne Camera System



Correlation Analysis

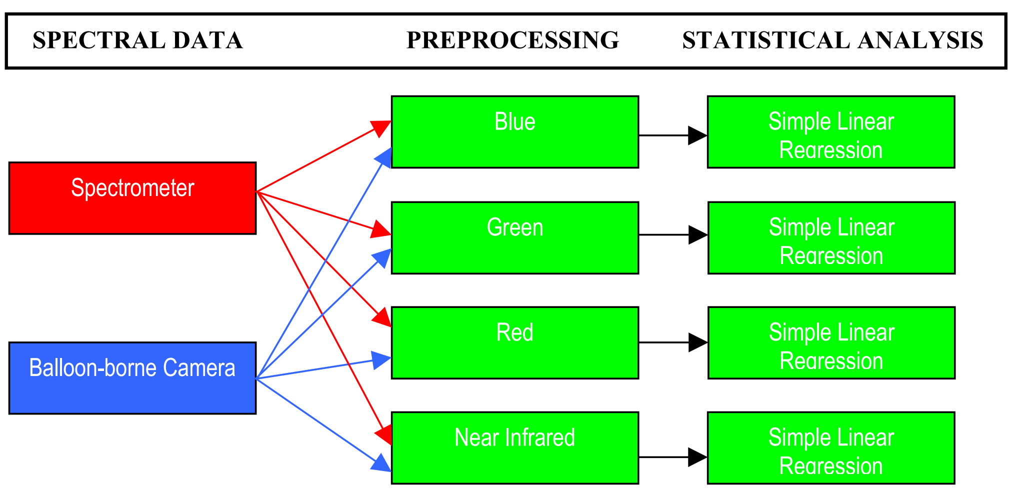


Figure 3.4 Methodology Flow Chart

3.4 Data Capture and Acquisition

3.4.1 Introduction

Spectral data capture took place on the 28 January 2004. The sky was predominately cloud free and the conditions were regarded as good. The crop growth stage at the time of acquisition was not uniform. The most mature plants had reached anthesis whilst in the less mature pants the heads had only recently extended through the flag-leaf sheath.

3.4.2 Balloon-borne Digital Images

Low cost aerial images were acquired for the study area using a balloon-based digital camera system. The images were acquired between the hours of 10.00 am and 11.30am. The balloon-borne camera system uses two one mega-pixel cameras; this system can be seen in Figure 3.4. The first camera captures the visible spectrum over the blue, green and red regions. The second camera has an infrared filter placed over the lens, allowing it to capture the near infrared spectrum over the range of 700 nm to 900 nm. The infrared wavelengths are collected on three bands. These bands correspond to the three visible bands found in all

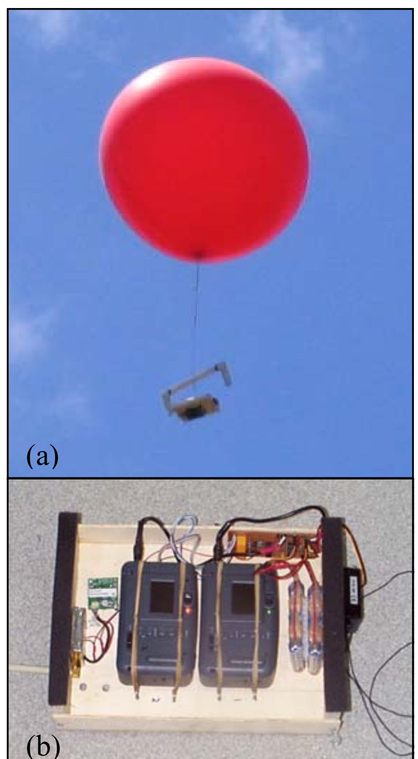


Figure 3.4 Balloon-Borne Camera System

conventional photographic cameras. This results in differing proportions of the infrared spectrum being collected on each band. This is because of the different relative sensitivity of each band. Figure 3.5 provides an example of the typical relative sensitivity of the three bands found in most conventional cameras.

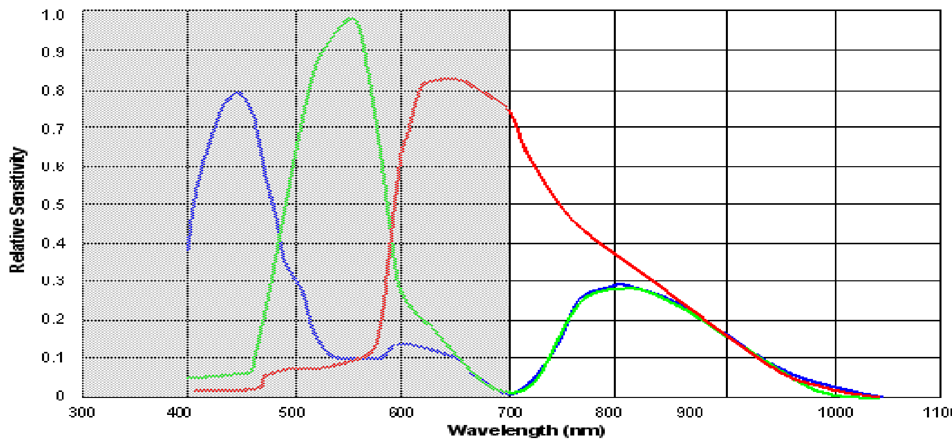


Figure 3.5 Relative Sensitivity of Photographic Camera Bands

The camera system is suspended underneath a helium filled balloon and positioned over the target by the use of two fishing lines tethered to the frame of the camera system. An example of the imagery taken from the balloon-borne camera system is presented in Figure 3.6.

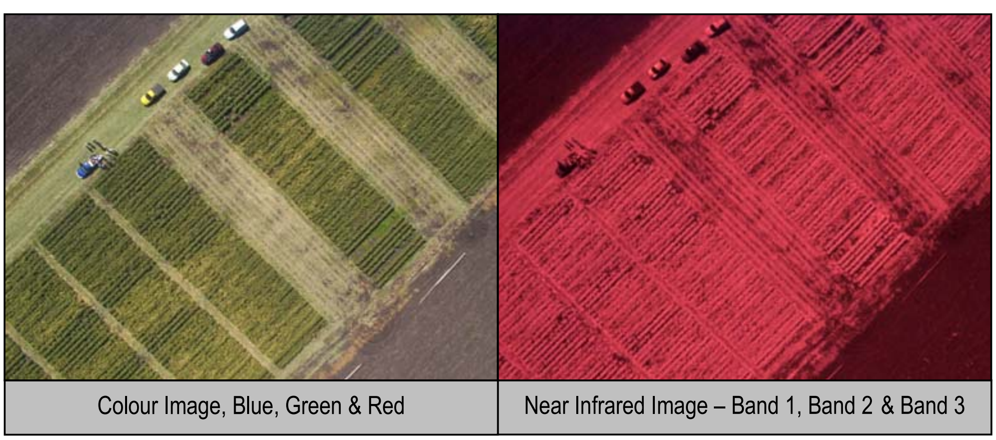


Figure 3.6 Balloon-Borne Imagery of the Kingsthorpe Weed Trial Site

3.4.3 Spectroradiometer

Spectroradiometer readings of the variety and density trial were taken immediately after the balloon-borne imagery capture. Readings were only taken from Replication 1.

Figure 3.7 Spectroradiometer

The spectral readings were taken with a FieldSpec® UV/VNIR HandHeld Spectroradiometer (Figure 3.7). This instrument captures reflected light energy over the range of 325 – 1075 nm, in wavelength intervals of 1.6nm (Analytical Spectral Devices, 2002). This data is automatically resampled to provide 750 bands at a 1nm bandwidth (Analytical Spectral Devices, 2002). The captured range incorporates ultraviolet light, the visible spectrum, and the very near infrared portion of the electromagnetic spectrum.

The foreoptic device used to collect the reflected light energy was the "Bare Head". The Bare Head has a conical view subtending an angle of 25 degrees (Analytical Spectral Devices, 2002). The field of view can be determined by the following equation:

$$\textbf{FOV} = \textbf{2 (height} \times \textbf{tan } \boldsymbol{\alpha}\textbf{)}$$

Where FOV = Field of View

Height = mean height above the target

α = ½ the subtending angle of the foroptic

Readings were taken approximately 50cm above the heads of the crop, therefore the field of view would have been approximately 22 cm.

The spectrometer readings were taken at approximately 1.5 m in from the start of each row, this distance varied for each sampling as heads were chosen visually for similar maturity stages, although this was not possible on all occasions. Every second row was sampled in Replication 1, providing two samples per plot. Figure 3.8 shows the spectrometer sampling pattern.

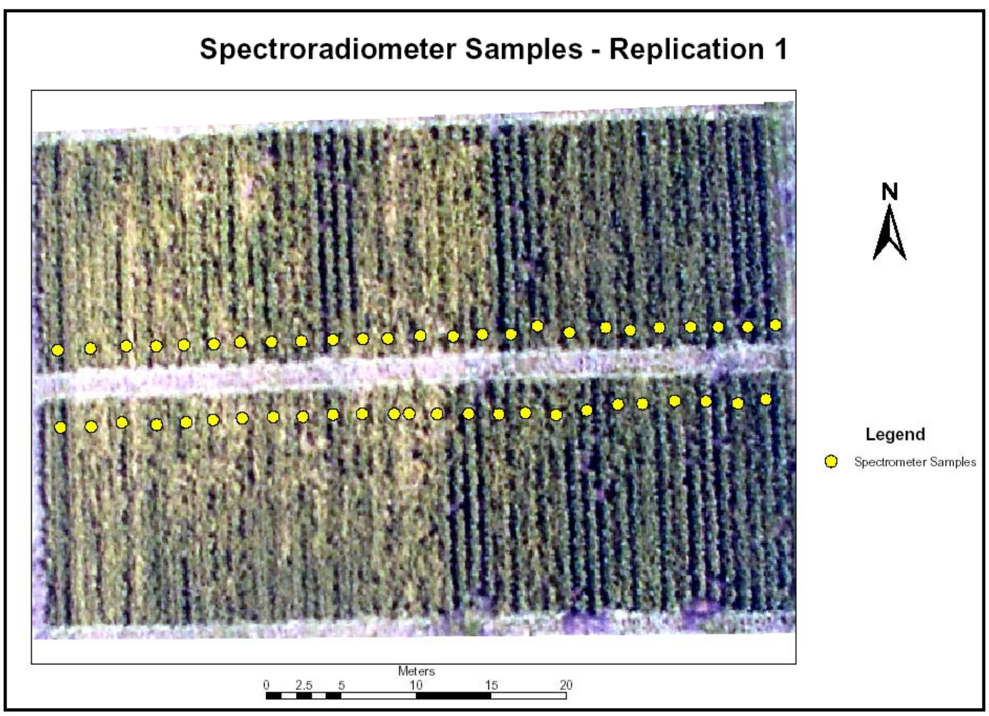


Figure 3.8 Location of Spectrometer Sampling in Replication 1

3.4.4 Global Positioning System

The position of ground control points was acquired on the 9 March 2004 using a Trimble GeoExporer 3. Ground control points were acquired over both trial sites to allow for georeferencing of the captured images.

3.5 Software and Hardware Used

The System hardware and software configuration used during pre-processing and analysis are outlined below:

Hardware:

IBM ThinkPad

Processing	1300MHz CPU; Intel Pentium M.
Memory	256MB RAM.

Dell

Processing	1.60 GHz CPU; Intel Pentium 4.
Memory	128MB RAM.

Hewlett-Packard Pavilion

Processing	2.66 GHz CPU; Intel Pentium 4.
Memory	192MB RAM

Software:

ESRI – *ArcGIS* Version 8.3 for Windows

ERDAS – *Imagine* Version 8.6

Microsoft – *Excel2000*

Analytical Spectral Devices - *ViewSpec Pro*

SPSS Inc. - *SPSS* Student Version 12.0 for Windows

3.6 Data Pre-processing

3.6.1 GPS

The GPS data collected was post-processed by Mr Peter Gibbings (USQ) using Trimble's GPS Pathfinder Office software. The rover file containing ground control points was differentially corrected with the base files from USQ's base station. The differential correction resulted in the accuracy of the ground control points being improved from approximatley 5.9 meters horizontally accuracy to 0.8m to 1.0m horizontal accuracy. Vertical accuracy was not considered. Figure 3.9 is a screen capture of the post processing process.

The post-processed data was exported as a shape file with a UTM projection of WGS84. This was later converted to Map Grid of Australia 1994 (MGA 94) using the Geocentric Datum of Australia 1994 (GDA 94) in ArcGIS.

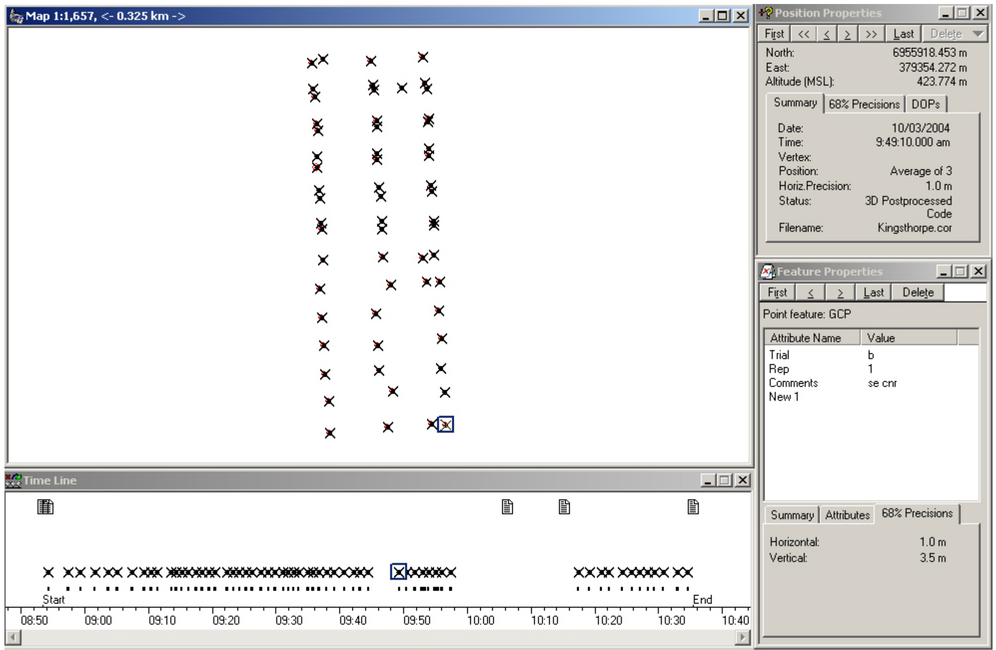


Figure 3.9 Post Processing of Ground Control Points Collected with a GeoExplorer 3 GPS Unit.

3.6.2 Spectroradiometer

The data collected by the spectroradiometer was opened using ViewSpec Pro®, a proprietary software of Analytical Spectral Devices, the manufactures of the spectroradiometer. ViewSpec Pro® was used to export the spectral data in ASCII format.

This data was imported into Excel and then organised into "comparable groups". The groups were created by grouping samples according to their membership to the comparable pairs that were identified previously. This resulted in samples being grouped based on each sample being of the same cultivar and planted at the same density. The only variable to change between comparable groups was the presence of weeds. Table 3.2 shows the six comparable groups that were assembled together for comparison. The name of each group is taken from the comparable pair they belong too.

Table 3.2 Spectroradiometer Comparable Groups

Comparable Group (Variety / Sowing rate - established plants per hectare)	Number of Samples in plots with weeds	Number of Samples in plots with no weeds	Total Number of samples in the group
BU 45K	2	2	4
BU 60K	2	2	4
BU 75K	2	2	4
GO 45K	2	2	4
GO 60K	2	2	4
GO 75K	2	2	4

3.6.3 Balloon-borne Digital Images

3.6.3.1 Image Registration

The images captured by the balloon-borne digital cameras were visually inspected for there suitability for further analysis. A single colour image and the corresponding infrared image were chosen to use for analysis. This selection was based on the coverage the images provided of Replication 1 and for the vertical orientation of the cameras at the time of capture.

The colour image was registered to the ground control points collected by GPS using ERDAS® Imagine 8.6. The process involved geometrically correcting the image using a polynomial geometric model of order one, the resampling method used was nearest neighbour. The root means squared (RMS) error for this process was 5.4765 and the pixel size produced by the registration was 0.065224 meters. Figure 3.10 is a screen capture of this process.

Registration of the images was required to allow the images to be overlayed so both the colour image and the infrared image corresponded exactly with one another. This allows pixels to be extracted from both images from precisely the same position. Additionally by registering the images to real world coordinates it allowed measurements to be made from the images.

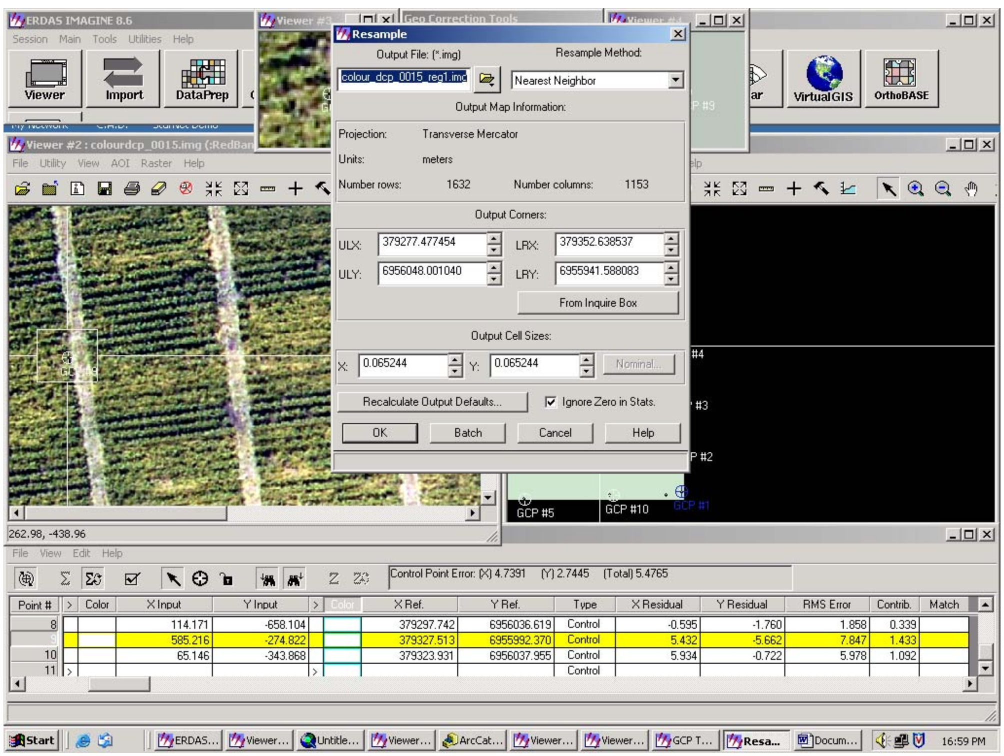


Figure 3.10 Geometric Correction of the chosen colour image

The corresponding infrared image, was then registered to the geometrically corrected colour image, using the same process. The RMS error for this process was 0.8467 and the pixel resolution once again was 0.065224 meters. Figure 3.11 is a screen capture of this process. These registered images were then subset in Imagine 8.6 using an area of interest so that only Replication 1 is present in the images.

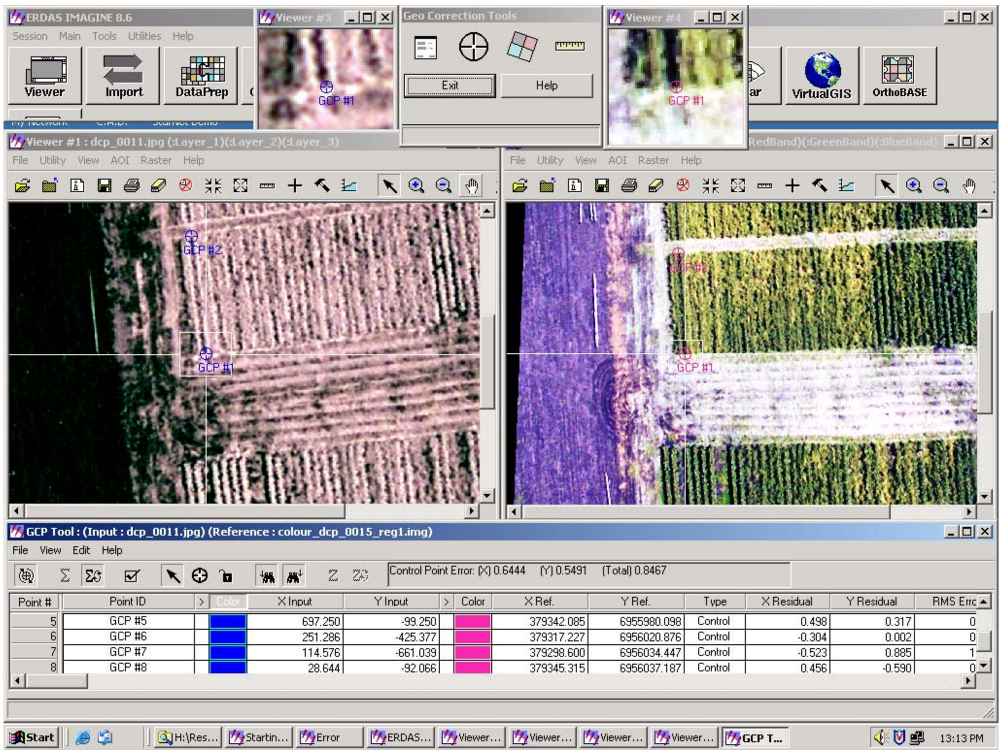


Figure 3.11 Geometric Correction of the selected infrared image.

After assessing the control point error, the accuracy of the GPS ground control points and the pixel resolution of the georeferenced image, it was decided that the GPS control points had an insufficient accuracy to proceed with the use of these registered images.

An artificial plot layout was developed based on the GPS ground control points and the original images were registered to this grid. The construction of this artificial plot layout and accuracy issues are discussed in a later section entitled Validation Accuracy Assessment.

The registration of the colour image to the artificial plot layout achieved an RMS error of 1.6859 and a pixel size of 0.066749 m (Figure 3.12). The infrared image was then registered to the geometrically corrected colour image. An RMS error of 0.3392 resulted and the pixel size was identical to the colour image (Figure 3.13). These registered images were then subset in Imagine 8.6 using an area of interest so that only Replication 1 was present in the images (Figure 3.14).

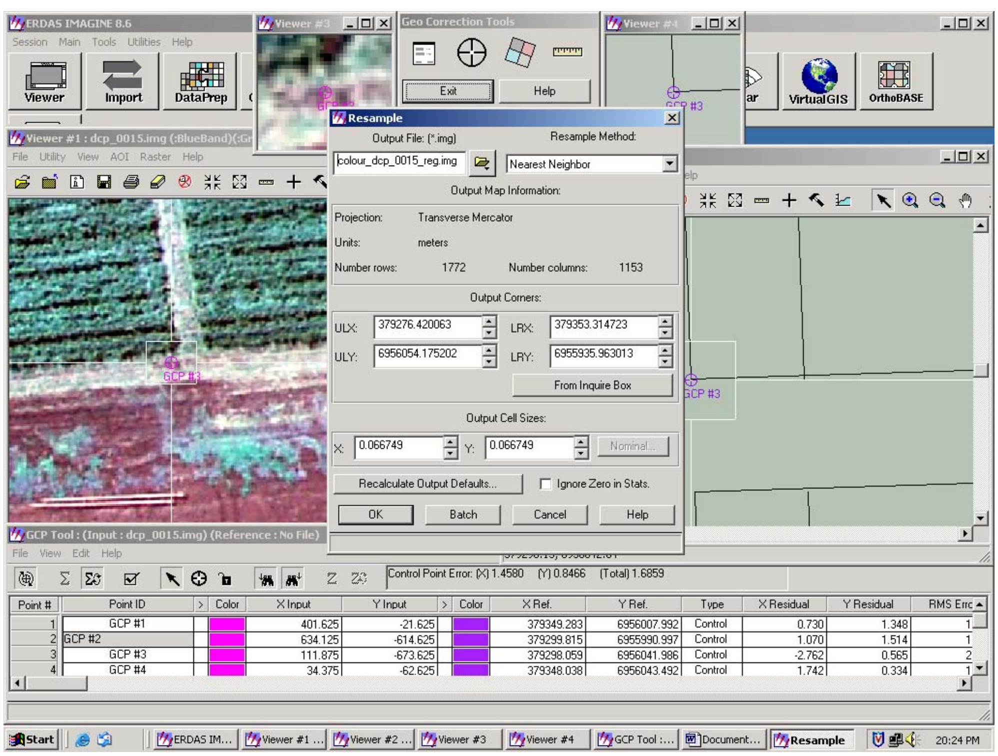


Figure 3.12 Georeferencing of the Colour Image to the Artificial Plot Layout

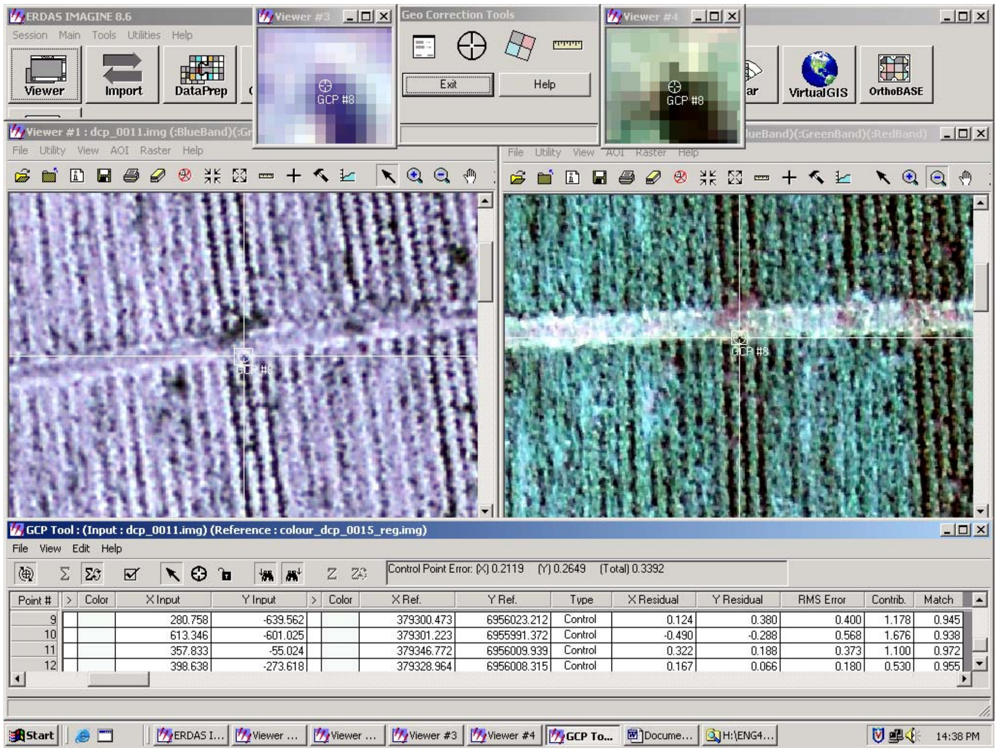


Figure 3.13 Georeferencing of the Infrared Image to the Developed Grid

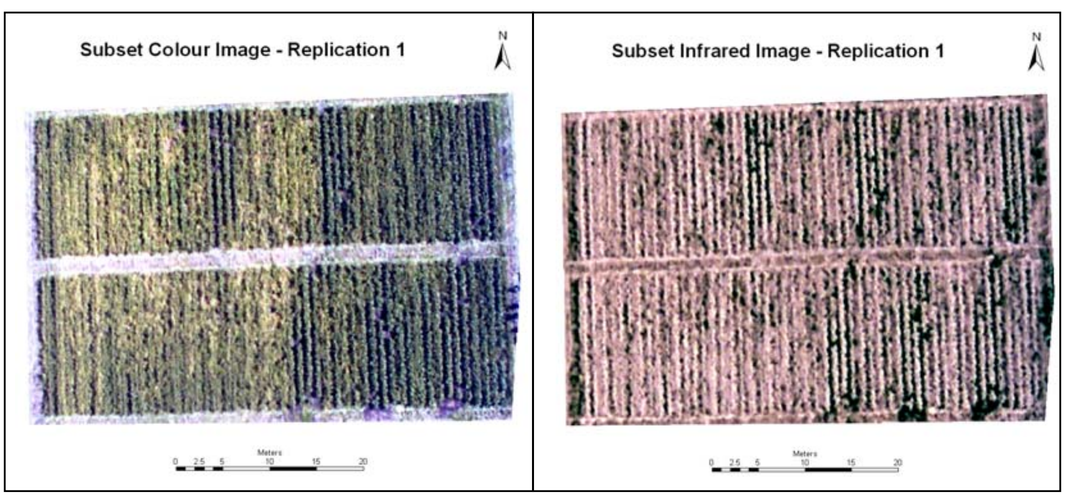


Figure 3.14 Subset Images of Replication 1

3.6.3.2 Pixel Extraction

Pixel extraction occurred for two purposes. The first was to establish if the pixel values within the balloon-borne images could be used to discriminate between the health of the crop in relation to the competition of weeds. This required a number of samples to be taken from within each plot that corresponded to the comparable pairs identified earlier. The second purpose was so that the pixel values could be compared to the spectroradiometer data to determine if a correlation existed. This required pixel values to be extracted from exactly the same location that the spectroradiometer samples were taken.

To enable pixels to be extracted for the comparable pairs it was first necessary to identify the plots that corresponded to the comparable pairs. This was achieved by using ArcGIS to create polygons around the relevant plots. Figure 3.15 shows the polygons overlayed on the registered colour image.

A sampling grid was then developed in ArcGIS (Figure 3.16). This sampling grid was created by generating a set of lines to represent the centre of each row. This was accomplished by manually identifying the first row and then offsetting this row consecutively at a distance of 1 meter to correspond to the planting width. Lines were then generated perpendicular to the row centre lines. The initial lines were placed 1.5 meters from the end of each plot. This distance approximately corresponded to the position that the spectroradiometer samples were taken. The approximate position spectroradiometer were taken from can be seen Figure 3.16. Lines were then placed consecutively at 3 meters spacings between the two lines.

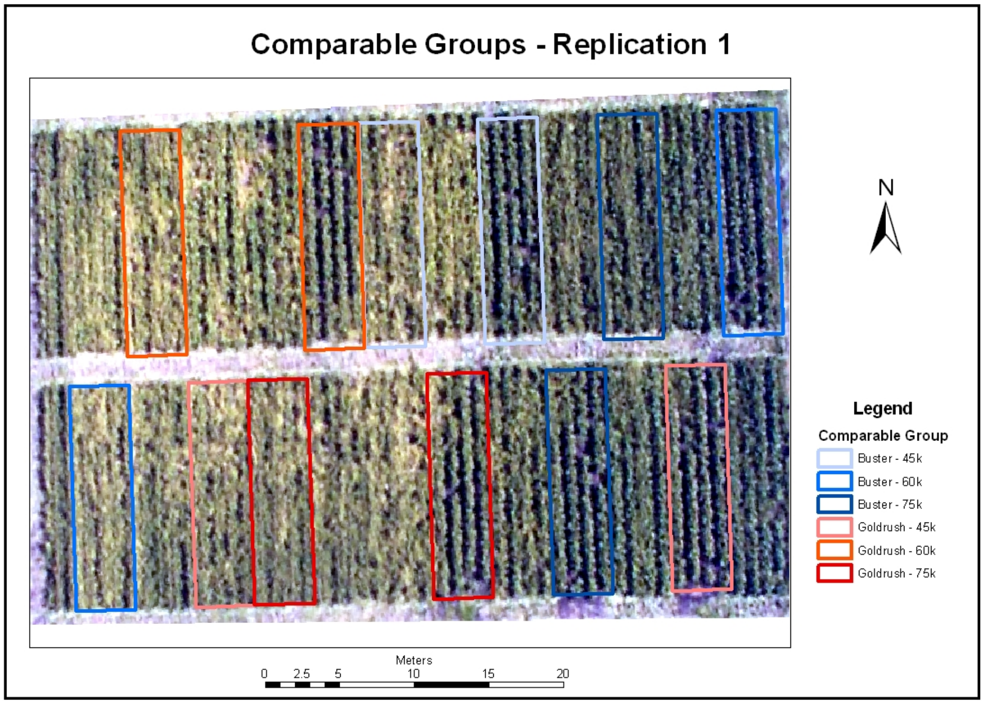


Figure 3.15 Comparable Groups for Replication 1

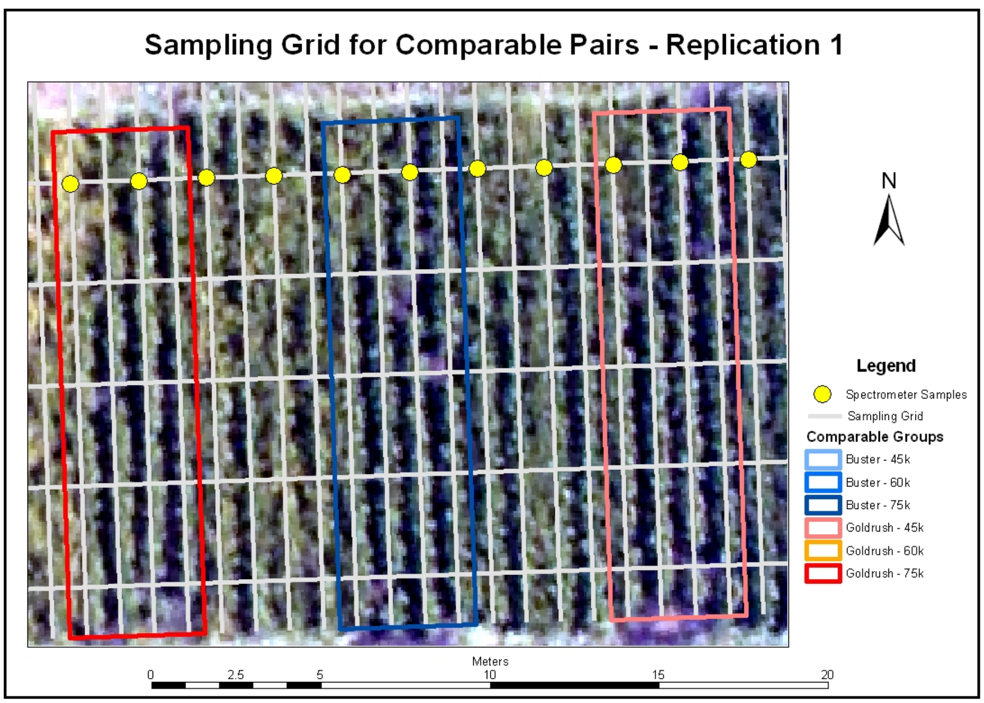


Figure 3.16 Sampling Grid for Comparable Pairs

The grid resulted in 20 intersections occurring within each plot. The intersections that occurred within the plots for comparable pairs were used to create areas of interest in Imagine 8.6. These areas of interest were used to extract the digital values of pixels in the image.

The grid was also used to extract pixels for the correlation analysis between the balloon-borne images and the spectroradiometer. Areas of interest were created by using the sampling grid to approximate the position that the spectroradiometer measurements were taken.

Areas of interest were created using 3x3 kernels. This size was chosen to approximate the field of view of the spectroradiometer. As mentioned earlier the sampling height of 50 cm above the crop gave the spectroradiometer a field of view of approximately 22 cm, this equates to a circular coverage of 380 cm^2. A 3x3 kernel on the registered images has the square dimensions of 20 × 20cm and coverage of 400 cm^2.

As mentioned above, the identification of areas of interest was based on the intersections created by the sampling grid. However creating areas of interest at the intersection could not be strictly adhered to. Problems resulted from missing plants in rows, plants growing at angles, and rows not being planted at exactly 1 meter spacings. To combat this, areas of interest were chosen so that they were as close as practical to the intersection point but still centred on a plant. Figure 3.17 shows the typical placement of areas of interest for the colour image.

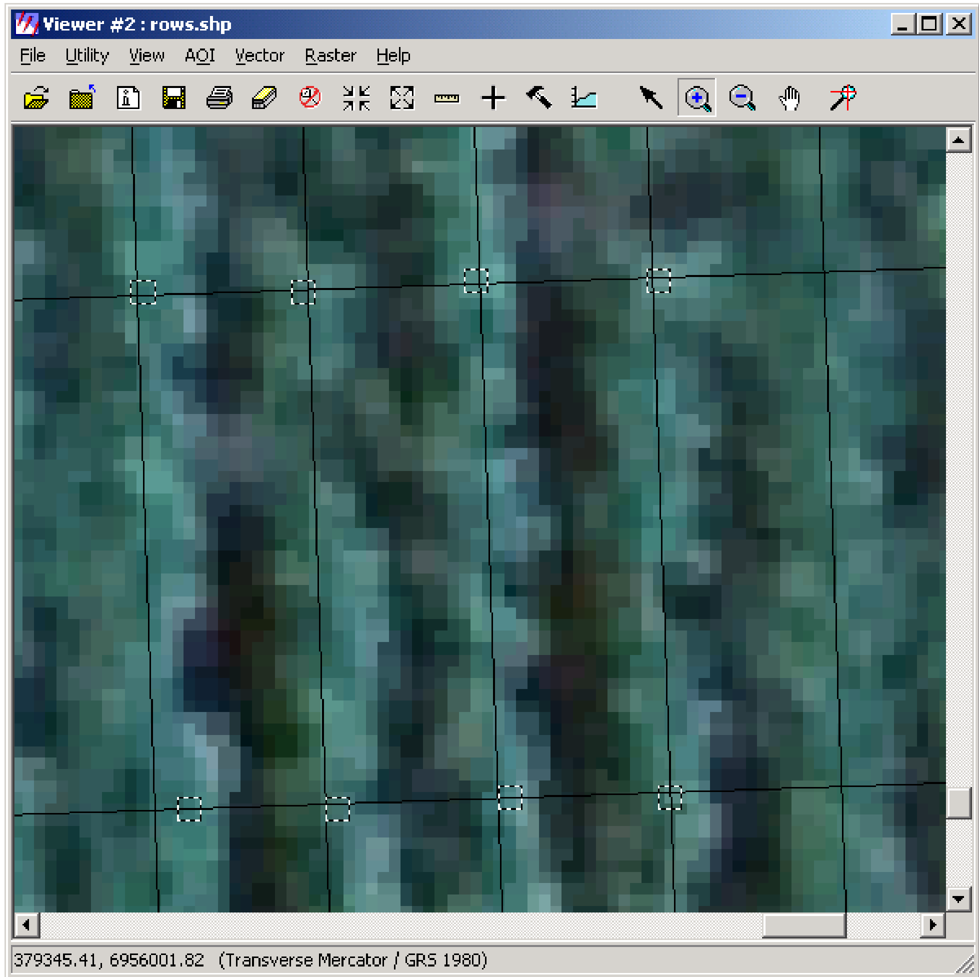


Figure 3.17 Areas of Interest Based on the Sampling Grid

The areas of interest created were used to export the digital numbers for the pixels contained in those areas of interest. Imagine 8.6 provides the ability to export digital numbers for each band of the image in an ASCII format. This procedure was carried out for both the coloured image and the infrared image.

The exported digital values were imported into Excel. The median value for each 3x3 kernel was calculated to provide a single value, which could be used for statistical analysis. The median value was chosen to remove the effect any outliers may have on the measure of centre.

The median values for the three bands of the infrared image were added to the three bands of the colour image. These median values were then arranged into comparable groups. Table 3.3 provides a summary of the comparable groups formed and the number of samples in each group.

Table 3.3 Balloon-borne Camera Comparable Groups

Comparable Group (Variety / Sowing rate - established plants per hectare)	Number of Samples in plots with weeds	Number of Samples in plots with no weeds	Total Number of samples in the group
BU 45K	20	20	40
BU 60K	20	20	40
BU 75K	20	20	40
GO 45K	20	20	40
GO 60K	20	20	40
GO 75K	20	20	40

3.7 Initial Statistical Analysis

For convenience sake, from this point forward samples taken from plots with weeds will be referred to as "stressed samples" and samples taken from plots with no weeds will be referred to as "healthy samples".

Prior to performing the discriminant function analysis an attempt was made to determine the spectral regions of highest separation for the two different treatments (weeds vs. no weeds) as well as the direction of the separation i.e. do samples from plots with weeds have higher reflectance than plots with no weeds. The varying sample sizes for the two different sensors necessitated two different approaches to be taken for this analysis.

As indicated in the previous section there were only a small number of spectroradiometer samples taken, this precluded conventional statistical analysis such as using boxplots to compare the distribution of grouped samples. Instead, samples were analysed based on comparable groups ability to be separated visually and arithmetically.

The balloon-borne data contained many more samples than the spectroradiometer, this allowed conventional statistical methods to be applied to this data. Boxplots were created for each comparable group to allow a comparison to be made of the separability and direction of separation for the two treatments based on spectral responses.

Consideration was given to repeating the process used to determine the spectral separability of the spectroradiometer data. This would have been impractical because of the large number of calculations involved and the difficulty in interpreting the equally large number of results.

3.7.1 Separability of Spectroradiometer Spectral Responses

After forming the comparable groups, each group was graphed together in ViewSpec Pro. These graphs were examined visually for the degree of separability of the samples based on the presence or absence of weeds.

Analysis was then conducted using Excel to determine the spectral regions of greatest separation. This analysis was based on finding the absolute difference between the reflectance of each sample. This was conducted on a comparable group basis and was performed for each wavelength measured. These values were averaged to provide a single figure for the separation of reflectance values for each wavelength. These average values were then converted to a percentage of the total reflectance of the band.

The average values provide the ability to make comparisons between the different wavelengths based on the absolute separability of the two treatments for each spectral wavelength. The percentage values provide the ability to make comparisons between the different wavelengths based on the proportion of the separation that occurs for each wavelength.

Within each spectral region, the section of wavelengths that provided the highest separation was then determined. This range was determined by locating the band having the single highest average separation as a percentage and then including other bands that had a separation within 10 percent of this band.

A table was constructed based on these values. The table contains each comparable group, the spectral regions of the spectroradiometer, a separation rank based on the absolute separation, the section of highest separation for each spectral region and the average difference in separation as a percentage.

3.7.2 Direction of Separation of Spectral Responses

It was considered important to know the direction that the separation occurred for each wavelength and whether this separation was maintained for the entire spectral region. This was achieved in Excel by subtracting the reflected value of the healthy samples from the stressed samples. This resulted in four measurements, two for the comparison of the healthy samples with the first stressed sample, and two for the comparison of the healthy samples with the second stressed sample. For this comparison the magnitude of the separation was not important but the direction of the separation was, i.e. positive or negative. The values of the subtraction were converted into either a value of 1, 0 or –1, where 1 represented a positive value, 0 no difference and –1 a negative value.

These values were then averaged for each spectral region that the spectroradiometer captures. The resulting values were than classified into the following classes (Table 3.4).

Table 3.4 Classes For Direction of Spectral Separation For Spectrometer Samples

Value	Classification	Description
1	Higher	Indicates every portion of the spectral curve taken from the plot with weeds had a higher reflection than the plot without.
0.99 – 0.01	Partially Higher	Indicates the majority of the spectral curve taken from the plot with weeds had a higher reflection than the plot without.
0	No Difference	Indicates no difference in spectral curves.
-0.01 – -0.99	Partially Lower	Indicates the majority of the spectral curve taken from the plot with weeds had a lower reflection than the plot without.
-1	Lower	Indicates every portion of the spectral curve taken from the plot with weeds had a lower reflection than the plot without.

3.7.3 Separability of Balloon-borne Spectral Responses

Side-by-side boxplots provide a concise way of comparing the distribution of a quantitative variable for two or more groups, “weeds” or “no weeds” in this case. Side-by-side boxplots provide the benefit of allowing a direct comparison to be made on the basic shape, centre and spread of the distribution of two or more groups (De Veaux & Velleman 2004).

Boxplots for the balloon-borne data were created in SPSS. The six comparable groups were included for each of the six camera bands. The samples for each comparable group were “grouped” on the basis of the presence or absence of weeds.

3.8 Discriminant Function Analysis

Discriminant function analysis was the statistical tool employed to test the ability of the spectral response measured by both the spectrometer and balloon-borne images to discriminate between the crop experiencing weed-induced stress and healthy crop (no weeds). Discriminant function analysis was chosen as the appropriate statistical procedure to use on the basis of the advice of the supervisor.

Discriminant function analysis is used to model the value of a dependent categorical variable based on its relationship to one or more predictors (SPSS 2003). In this case the dependent variables are the presence or absence of weeds while the predictors are the spectral responses of the crop measured by either the spectroradiometer or the balloon-borne images. Discriminant function analysis models the ability to separate groups (crop with or without weeds) based on the independent variables (spectral response) by finding linear combinations of those variables that best separate the groups of classes (SPSS 2003). These combinations are called discriminant functions and have the form displayed in the following equation (SPSS 2003):

$$d_{ik} = b_{0k} + b_{1k} x_{i1} + \ldots + b_{pk} x_{ip}$$

Where d_{ik} is the value of the k^{th} discriminant function for the i^{th} case

p is the number of predictors

b_{jk} is the value of the j^{th} coefficent of the k^{th} function

x_{ij} is the value of the i^{th} case of the j^{th} predictor

The number of functions equals min(#groups –1, #predictors)

The procedure is conducted by choosing the first function that will separate the groups as much as possible. The procedure then adds further functions based on their ability to further separate the groups as much as possible until reaching the maximum number of functions as determined by the number of predictors and categories in the dependent variable (SPSS 2003).

3.8.1 Spectroradiometer

The spectrometer data was the first to be analysed in SPSS using discriminant function analysis. After importing the data from Excel, some minor formatting was required such as transposing the data and setting the dependent groups values to “Weeds” or “No Weeds”. The transform function was then used to seed a random number that allowed the random selection of cases to be replicated in the analysis. The transform function was then used to create the selection variable for validation. A Bernoulli distribution was used with a probability parameter of 0.7. This results in the validation variable randomly taking on the value of 1, approximately 70% of the time , and a value of zero on all other occasions. These validation values were used to define the cases that were used to create the model. This means that approximately 70% of cases were selected at random to be used to develop the discriminate function. The remaining cases were used to validate the model results.

SPSS provides the opportunity to select statistics and tables that can be generated with discriminant function analysis results. These statistics can provide useful information about the performance of the discriminant analysis. The statistics selected to be included in this research were means and the Fishers function coefficients (Figure 3.18). From the classification menu the summary table was the only option selected (Figure 3.19).

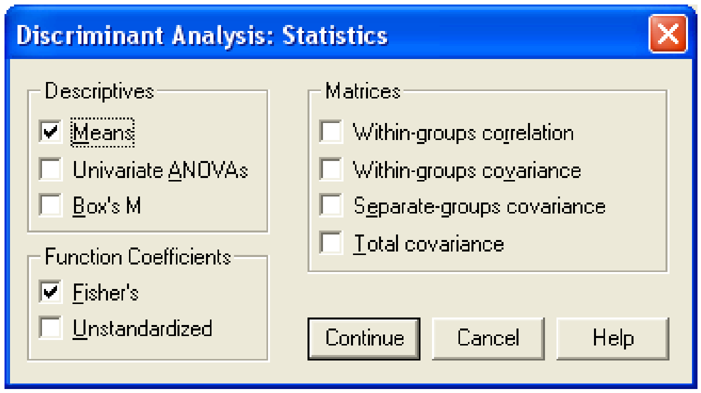


Figure 3.18 Statistical Selection for Discriminant Function Analysis

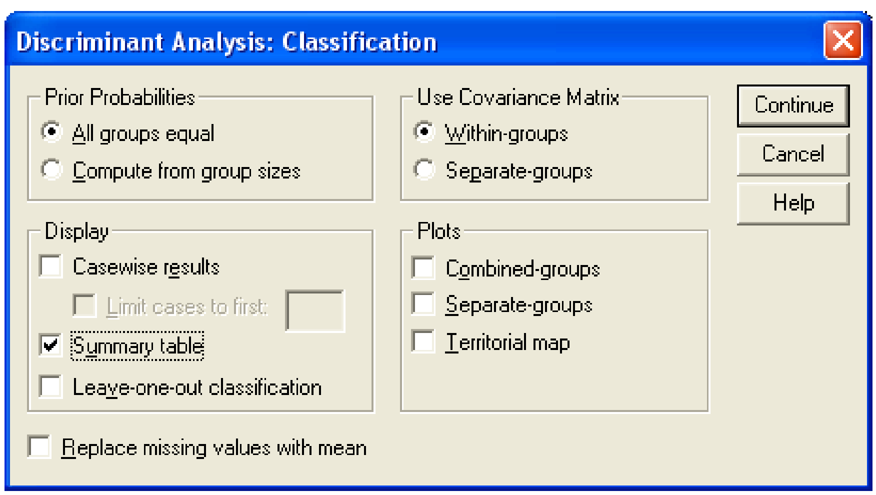


Figure 3.19 Classification Selection for Discriminant Function Analysis

The spectrometer data was analysed based on the following categorisation of the samples shown in Table 3.5. These categories differ from the comparable pairs grouping discussed earlier because of the small sample size of each group. The small sample size was insufficient to enable sound statistical analysis. Thus comparable groups were created to provide greater sample sizes.

Table 3.5 Spectrometer Comparable Groups used for Discriminant Function Analysis

Comparable Group	Description	No. of Samples
All BU	Samples taken from Buster plots at all planting rates.	12
All GO	Samples taken from Goldrush plots at all planting rates.	12
All Variables	Samples taken of both Buster and Goldrush plots at all planting rates.	24

3.8.2 Balloon-Borne Data

Upon completing the discriminant analysis of the spectrometer data, the balloon-borne data was analysed using the same procedure. The balloon-borne data analysis was based on the comparable groups formed earlier. The categories used for the spectrometer data were also included to allow a cross comparison between the two sensors. The groupings used for the analysis of the balloon-borne imagery are shown in Table 3.6.

Table 3.6 Categorisation of Balloon-Borne Data for Discriminant Function Analysis

Comparable Group	Description	No. of Samples
BU 45k	Samples taken from Buster plots with a planting rate of 45,000 plants/ha	40
BU 60k	Samples taken from Buster plots with a planting rate of 60,000 plants/ha	40
BU 75k	Samples taken from Buster plots with a planting rate of 75,000 plants/ha	40
GO 45k	Samples taken from Goldrush plots with a planting rate of 45,000 plants/ha	40
GO 60k	Samples taken from Goldrush plots with a planting rate of 60,000 plants/ha	40
GO 75k	Samples taken from Goldrush plots with a planting rate of 75,000 plants/ha	40
All BU	Samples taken from Buster plots at all planting rates	120
All GO	Samples taken from Goldrush plots at all planting rates	120
All Variables	Samples taken of both Buster and Goldrush plots at all planting rates	240

3.9 Simple Linear Regression

To determine if a correlation existed between the spectral responses measured by the spectroradiometer and the corresponding data for the balloon-borne cameras, scatterplots were created using SPSS. A matrix of scatterplots was produced and then from this matrix individual scatterplots were identified for closer inspection. A regression line was then calculated for each scatterplot.

The data used included all spectrometer data collected from Replication 1. The matching balloon data was paired to this spectrometer data. The matching of spectrometer data and the balloon data resulted in 50-paired samples being used.

These pairs were then analysed based on the balloon camera bands, such that the blue band was compared to the bands corresponding to the blue range of the visible spectrum for the spectrometer i.e. 446 nm to 500 nm and so on for the other bands. Table 3.7 shows the range of the spectrometer bands compared to each band from the balloon-borne cameras.

Table 3.7 Ranges of values from the spectrometer used to compare with balloon-borne camera bands.

Spectrometer Wavelength Range (nm)	Balloon-borne Camera Band
446 - 500	Blue
500 - 578	Green
620 - 700	Red
700 - 900	Infrared Band 1
700 - 900	Infrared Band 2
700 - 900	Infrared Band 2

3.10 Validation Accuracy Assessment

3.10.1 GPS and Image Registration

After assessing the RMS error, the accuracy of the GPS ground control points and the pixel size of the georeferenced image it was decided that the GPS control points had an insufficient accuracy to allow satisfactory registration of the images. The 1 meter accuracy of the GPS reflects very poorly when compared to the pixel resolution obtained for the images of 0.065m. This restricts the accuracy level that can be obtained in the image registration to an error of no better than one meter. This represents an accuracy error of 15 times the magnitude of the pixel resolution. This was deemed unacceptable.

A further problem associated with the GPS ground control points was a large amount of wander in the direction of the inaccuracy. The wandering is highlighted in Figure 3.20 by the misalignment of the points. At the map scale in Figure 3.20 the points on the eastern and western boundaries should appear straight, this is however far from the case. The spacings between plots vary dramatically also.

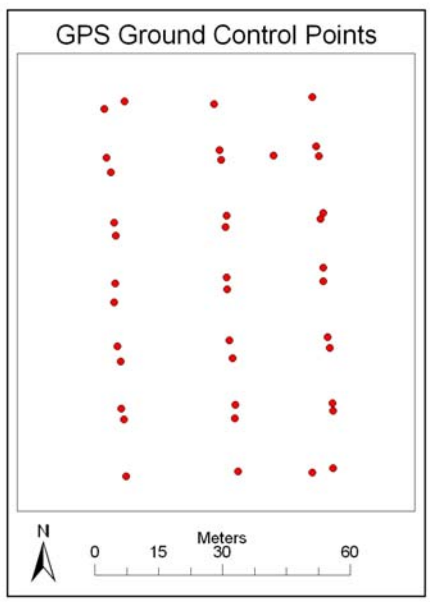


Figure 3.20 Locations of Ground Control points collected by GPS.

To improve the registration of the images an artificial plot layout was created in ArcGIS (Figure 3.21). The artificial plot layout was based on the GPS ground control points and the dimensions of the plots in the experiment. The layout was developed by using a single GPS control point, the most south-eastern point to provide the location of the grid. A second point, the most north-easterly point, was used to give the orientation. The dimensions of the trial plots were then used to fill in the grid. This artificial layout overcame much of the inaccuracies associated with the GPS ground control points as well as providing for additional control points to use during the registration process. The colour image was registered to the artificial plot and like the initial attempt the infrared image was then georeferenced to the registered colour image. The artificial plot layout was able to increase the accuracy of the registration process from a control point error of 5.4765 to 1.69859 for the colour image and from 0.8467 to 0.3392 for the infrared image.

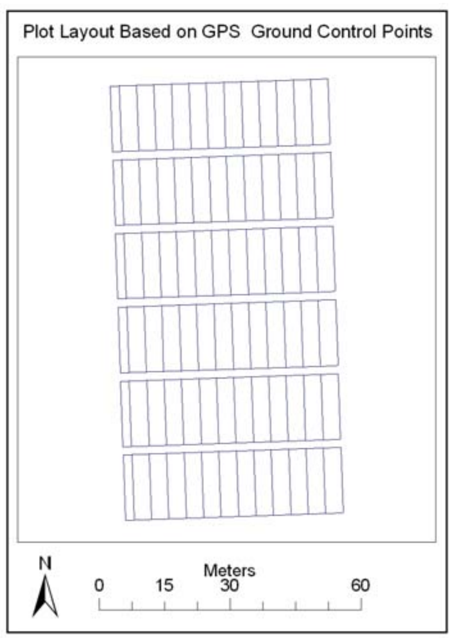


Figure 3.21 Artificial plot layout created from GPS control points and the dimensions of the trial plots

3.10.2 Balloon Images

Apart from the registration issues discussed previously, the other issues involving the balloon images was the angle of the cameras relative to the ground at the time of capture and the orientation of the cameras to the target. Of the fifteen photographs taken a majority of the photos were oblique, thus ruling out the possibility of registration with the available software. Of the remaining photos only two covered the study area and both provided only partial coverage. Replication 1 was the only replication to achieve full coverage for the density/cultivar trial.

3.10.3 Spectroradiometer

Spectrometer samples were only acquired for Replication 1 of the density/cultivar trial and the number of samples is small, only two per plot. Whilst this has consequences for the analysis that can be conducted a further problem exists. The general shape of the spectral curve below approximately 750 nm takes on the expected shape for vegetation, above this value however the shape of the curve has large spikes and is generally erratic, as can be seen in Figure 3.22. The cause of this spiking or noise is unknown. An approach has been made to Analytical Spectral Devices as to the likely cause of the spiking but the cause remains unresolved at the time of writing this report.

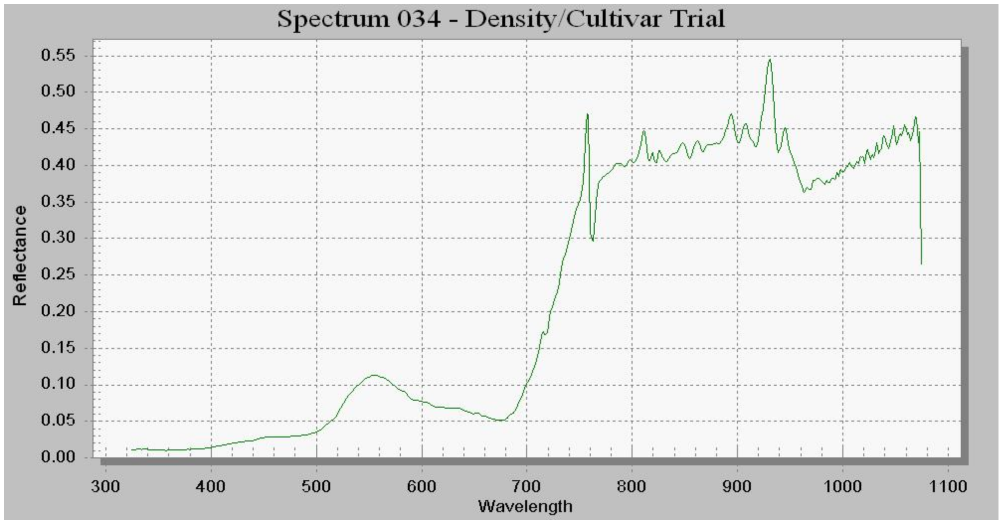


Figure 3.22 Typical Spectral Curve For The Samples Taken At Kingsthorpe Density/Cultivar Trial

3.10.4 Positional Accuracy of Pixel Extraction

The correlation analysis requires a spectral sample from the spectroradiometer and the balloon-borne camera to be acquired from the exact same location. This has not been able to be achieved. During data capture the spectroradiometer position relative to the end of each row varied considerably. The aim was to sample 1.5 meters from the end of each row. This was not possible on all occasions largely because of gaps in the rows. No record was taken of when samples varied from the 1.5 meter distance, making it impossible to extract pixels from the aerial images at the exact location the spectroradiometer sample was taken.

CHAPTER 4

RESULTS

4.1 Introduction

This Chapter presents the results of the analysis. The order of the presentation of the results follows that of the methodology. The initial statistical results are provided first. These results encompass the separability analysis of the spectroradiometer samples and the boxplots of the balloon-borne camera data. This is followed by the results of the discriminant function analysis results. The spectroradiometer results are presented first and this is followed by the results of the balloon-borne camera system. The final section presents the results of the correlation analysis.

4.2 Spectroradiometer

4.2.1 Graphs of Spectroradiometer Spectral Curves

The graphed spectral curves for the spectroradiometer data are presented in Figures 4.1 to 4.6. These graphs show no general trend for the reflectance of samples taken from plots with weeds to have either higher or lower reflectance over any spectral region than those samples that were taken of plots with no weeds.

The general pattern of all graphs is that the spectral curves have very little separation in the ultraviolet part of the spectrum. The samples become mildly separated in the blue section of the spectrum and appear to further separate in the green and red portions of the spectrum. The greatest separation occurs in the infrared segment of the spectral curves.

The graphs of the samples taken from plots containing BU 45K, BU 75K and GO 75K show that plots containing weeds, generally have higher reflectance in the near infrared region. There appears to be no other pattern in the visible spectrum.

In the graphs of the other plots (BU 60K, GO 45K and GO 60K) the reverse situation occurs. In these graphs, plots containing no weeds generally have higher reflectance in the near infrared region. Again in the visible part of the spectrum no pattern is apparent.

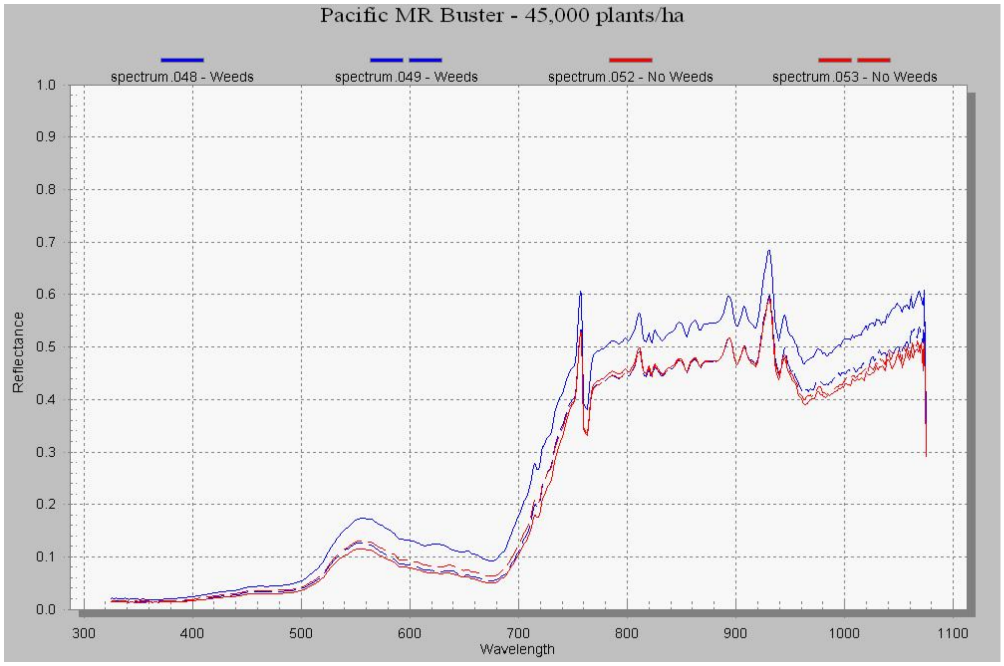


Figure 4.1 Spectral Curves Of Comparable Group BU 45K

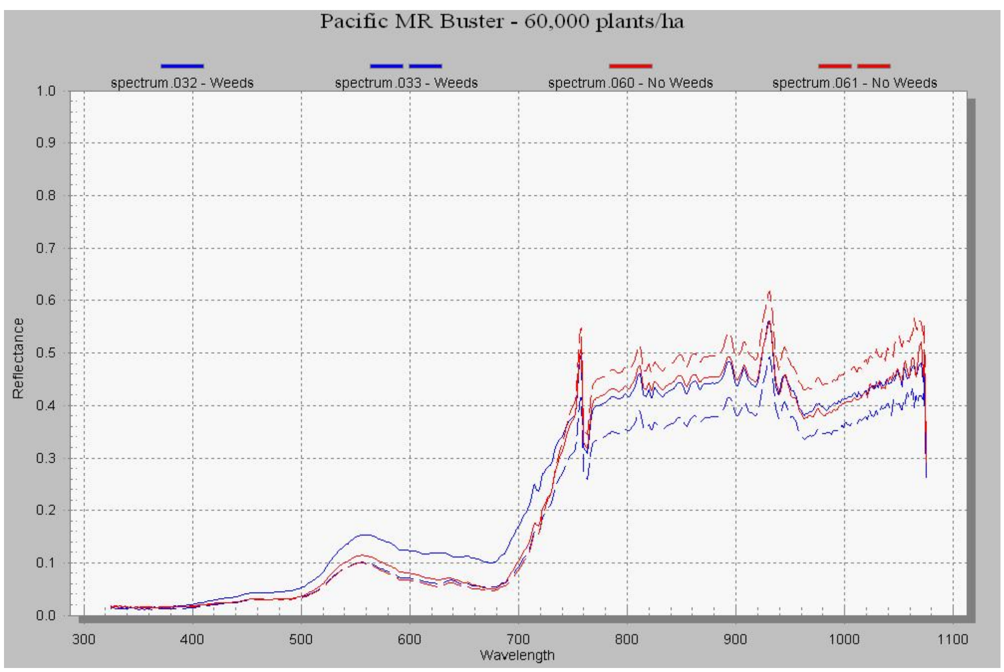


Figure 4.2 Spectral Curves Of Comparable Group BU 60K

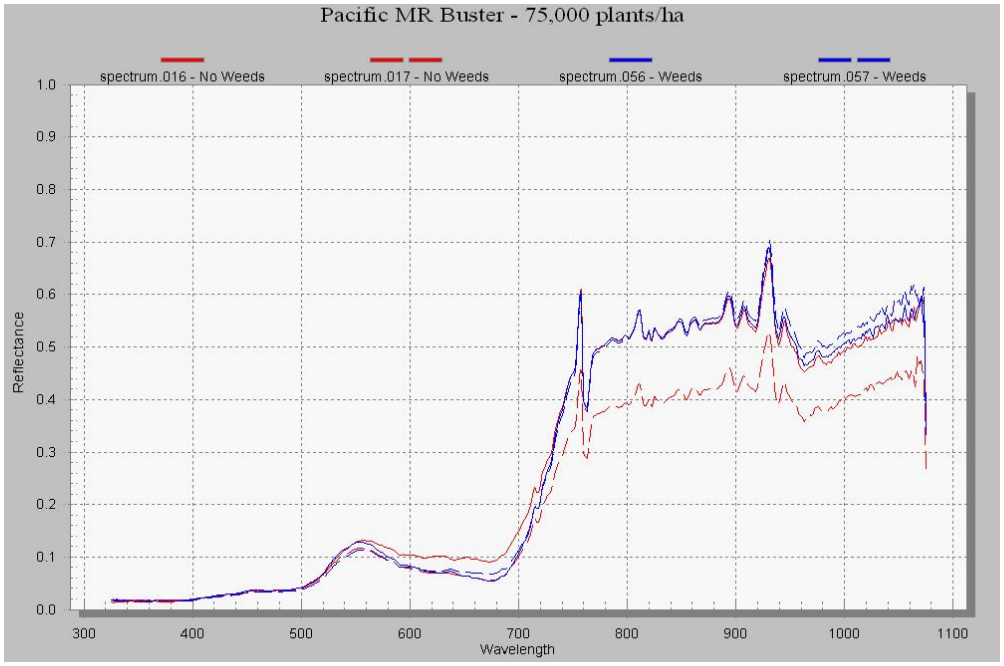


Figure 4.3 Spectral Curves Of Comparable Group BU 75K

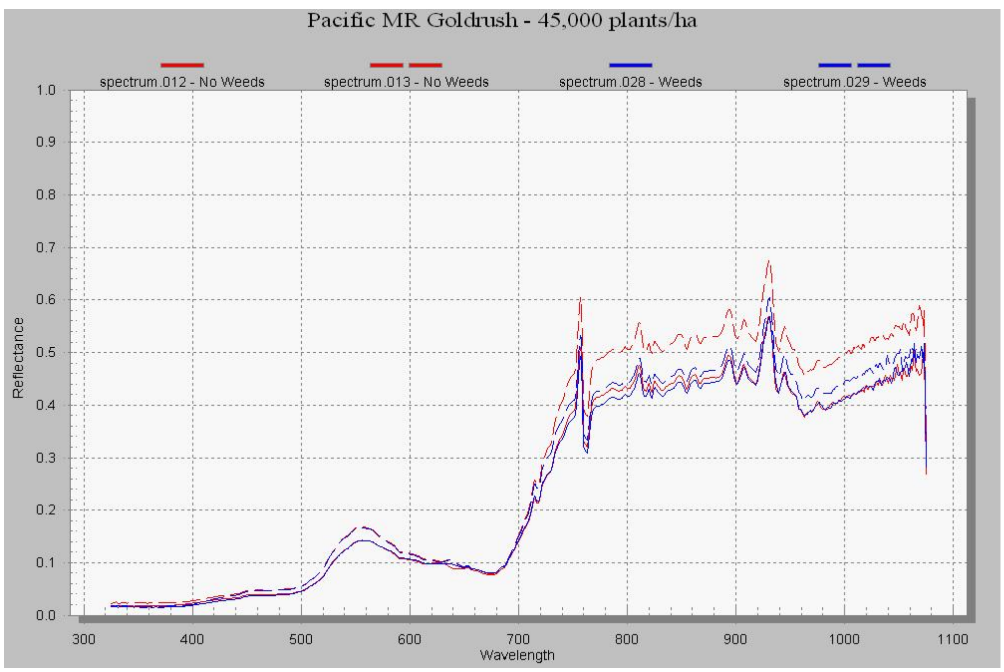


Figure 4.4 Spectral Curves Of Comparable Group GO 45K

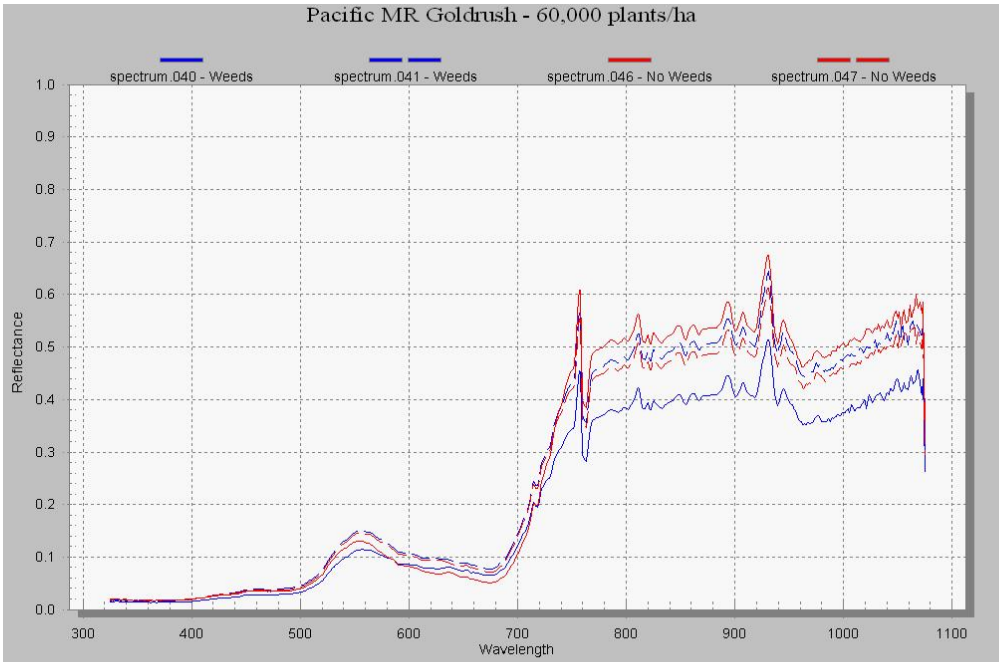


Figure 4.5 Spectral Curves Of Comparable Group GO 60K

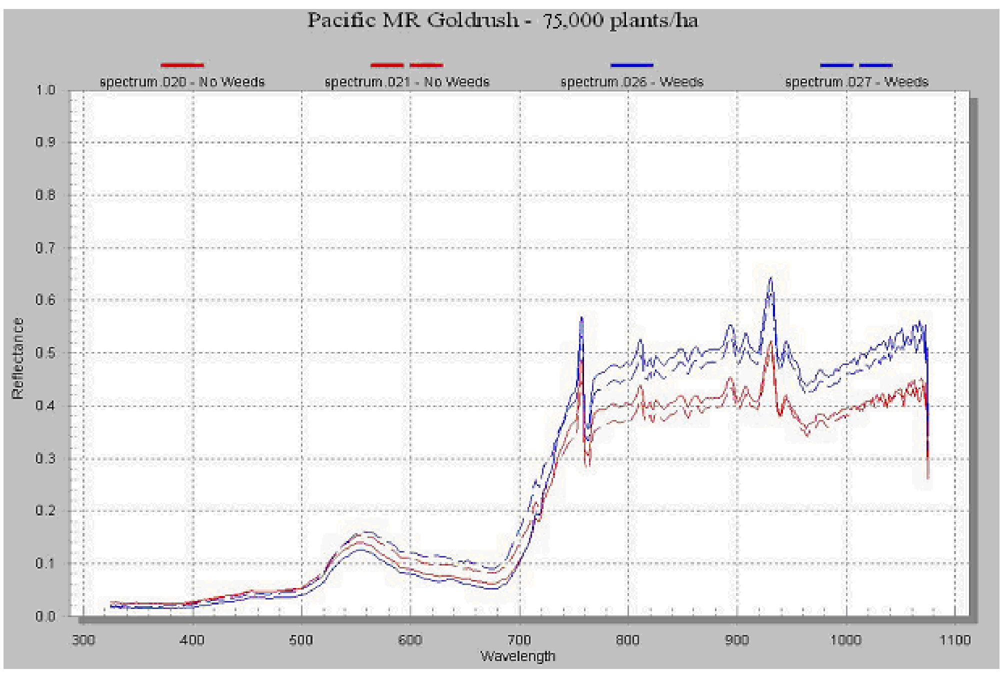


Figure 4.6 Spectral Curves Of Comparable Group GO 75K

4.2.2 Separability of Spectral Curves

4.2.2.1 Absolute Difference of Spectral Responses

The degrees to which the spectroradiometer samples can be separated based on the absolute difference in the value of wavelengths are presented in Table 4.1. The results in this table show that the highest degree of absolute separation occurs in infrared wavelengths. The separation is classified as either high or medium-high for these wavelengths for all six comparable groups. The highest separation for the near infrared portion of the spectrum commonly fell at the extreme range of its spectrum at 690 to 700nm. Only one of the comparable groups, GO 45K, did not coincide with this region. The highest range for GO 45K was 726 to 817nm, for the other comparable groups this area was commonly the area of the second highest separation.

The spectral regions green, yellow, orange and red provided medium to medium-low absolute separation. For the green section of the spectrum, the region of 560 to 578nm generally provided the highest separation. For yellow, virtually its entire range (578 to 592nm) provided uniform separation. A similar pattern occurred for the orange portion of the spectrum, but the range 610nm to 620nm, provided the greatest separation. The red component of the spectrum had its highest separation at the range from 660 to 690nm on five out of six occasions.

Table 4.1 Separability of Spectroradiometer Samples for the Ultraviolet, Colour and Infrared Spectral Regions

Comparable Group	Spectral Region *	Separation Rank†	Section of Highest Separation (nm)	Proportion of Separation (%)	Comparable Group	Spectral Region	Separation Rank	Region of Highest Separation (nm)	Proportion of Separation (%)
BU 45K	Ultra Violet	Low	387-399	23.7	GO 45K	Ultra Violet	Low	361-394	24.6
	Violet	Low	400-425	23.6		Violet	Low	400-406	20.4
	Blue	Low-Medium	460-500	23.0		Blue	Low	446-448	15.8
	Green	Medium	567-578	25.9		Green	Low-Medium	501-558	13.4
	Yellow	Medium	579-592	27.9		Yellow	Low-Medium	579-587	8.4
	Orange	Low-Medium	608-619	32.3		Orange	Low	593-606	7.3
	Red	Low-Medium	647-690	35.5		Red	Low	637-641	8.7
	Near Infrared	Medium-High	691-699	37.7		Near Infrared	Medium-High	726-817	11.4
BU 60K	Ultra Violet	Low	333-334	21.2	GO 60K	Ultra Violet	Low	326-327	19.2
	Violet	Low	400-445	20.4		Violet	Low	421-445	15.8
	Blue	Low-Medium	487-500	24.7		Blue	Low	446-500	16.7
	Green	Medium	570-578	31.4		Green	Low-Medium	501-574	16.7
	Yellow	Medium	579-592	34.6		Yellow	Low-Medium	574-592	15.6
	Orange	Medium	613-619	41.1		Orange	Low-Medium	613-619	19.2
	Red	Medium	620-632	44.8		Red	Low-Medium	649-690	21.5
	Near Infrared	Medium-High	691-700	42.7		Near Infrared	High	691-696	20.4
BU 75K	Ultra Violet	Low	327-328	20.2	GO 75K	Ultra Violet	Low	327-328	28.6
	Violet	Low	421-430	7.2		Violet	Low	400-405	25.2
	Blue	Low	446-461	6.1		Blue	Low	446-500	17.7
	Green	Low-Medium	570-578	12.2		Green	Low-Medium	571-580	20.2
	Yellow	Low-Medium	582-592	14.2		Yellow	Low-Medium	579-592	23.1
	Orange	Low-Medium	614-619	19.6		Orange	Low-Medium	617-619	29.9
	Red	Low-Medium	662-690	30.4		Red	Low-Medium	650-690	32.8
	Near Infrared	High	691-696	27.1		Near Infrare	High	691-699	32.3

* The spectral region used for each colour is Ultraviolet (325 - 400nm), Violet (400-446nm), Blue (446 - 500nm), Green (500 - 578 nm), Yellow (578 - 592nm), Orange (592 - 620nm), Red (620 - 700 nm), and Near Infrared (690 - 1075nm) (CCRS, 2004).

† Separation was ranked according to the following: Low (0 – 0.009), Low-Medium (0.01 – 0.029), Medium (0.03 – 0.049), Medium-High (0.05 – 0.069) and High (0.07 and above) (units: absolute reflectance)

The blue portion of the spectrum had low to medium-low separation. On all occasions, the highest separation consistently occurred over the range of 460 to 500nm.

For violet and ultraviolet light the separation was low on all occasions. The range of the highest separation for the ultraviolet commonly occurs over the range of 327 to 330nm. Twice this area did not correspond to the highest region of separation, on those occasions the range was from 380 to 399nm. The violet section of the spectrum had a common range within the range of 400 to 425nm for almost all comparable groups.

These results have been summarised into Table 4.3, which can be found below. The table has been constructed by summarising the separation rank and the common region of the highest spectral separation for the ultraviolet, colour, and infrared spectral regions that the spectroradiometer captures.

Table 4.2 Summary Of The Spectral Separability Of Spectrometer Samples

Spectral Region	Separation Rank	Common Region of Highest Separation (nm)
Ultra Violet	Low	327-330
Violet	Low	400-425
Blue	Low	460-500
Green	Low-Medium	560-578
Yellow	Low-Medium	578-592
Orange	Low-Medium	610-620
Red	Low-Medium	660-690
Near Infrared	High/Medium-High	690-700

If a comparison is made of the size of the highest separation that occurred between the stressed and healthy samples as a proportion of the total reflectance of the band, a different result is found then the rank given in the separation rank. Infrared maintains the highest separation with a range of values from 11 to 40 percent, with the separation on average in the 30 percent range. Red typically has the next highest proportional separation, with a fluctuating range from 9 to 45 percent. The remaining spectral regions have similar proportional separations, which are approximately in the 20 percent range. These values fluctuate for all but the ultraviolet region, which consistently has a proportional separation of just above 20 percent.

4.2.2.2 Direction of Spectral Response Separations

The table created for the direction of separation is provided below (Table 4.3). The near infrared range has been divided into two sections because of its size in comparison to the other spectral regions. This table shows in the ultraviolet, near infrared 900-1075nm and near infrared 690-900 regions the spectral curves consistently separate in one direction. For ultraviolet, eighteen of the twenty-four comparisons resulted with samples from plots with weeds having lower reflectance than the samples taken from plots without weeds. For near infrared 900-1075nm and near infrared 690-900 regions of the spectrum, 17 and 18 of the comparisons respectively resulted in samples from plots with weeds having a higher reflectance than the samples taken from plots without weeds.

Table 4.3 Direction of Separation of Spectral Responses

Comparable Group	(Weeds Sample # - No Weeds Sample #)	Ultra Violet 325-400nm	Violet 400-446nm	Blue 446-500nm	Green 500-578nm	Yellow 578-592 mn	Orange 592-600nm	Red 620-690nm	Near Infrared 690-900nm	Near Infrared 900-1075nm
BU 45K	1 vs 1	Higher	Higher	Higher	Higher	Higher	Higher	Higher	Higher	Higher
	1 vs 2	Higher	Higher	Higher	Higher	Higher	Higher	Higher	Higher	Higher
	2 vs 1	P/Higher	Higher	Higher	Higher	Higher	Higher	Higher	P/Lower	Higher
	2 vs 2	P/Lower	Lower	Lower	Lower	Lower	Lower	Lower	P/Lower	P/Higher
BU 60K	1 vs 1	P/Higher	Higher	Higher	Higher	Higher	Higher	Higher	P/Lower	Higher
	1 vs 2	P/Lower	Higher	Higher	Higher	Higher	Higher	Higher	P/Lower	Lower
	2 vs 1	Lower	Lower	Lower	Lower	Lower	Lower	P/Lower	Lower	Lower
	2 vs 2	Lower	Lower	P/Lower	Higher	Higher	Higher	Higher	P/Lower	Lower
BU 75K	1 vs 1	Lower	P/Higher	Higher	P/Higher	Lower	Lower	Lower	P/Higher	P/Higher
	1 vs 2	Higher	Higher	Higher	Higher	Higher	Higher	P/Higher	Higher	Higher
	2 vs 1	Lower	Lower	Lower	Lower	Lower	Lower	Lower	P/Lower	Higher
	2 vs 2	P/Higher	P/Higher	P/Lower	Lower	P/Lower	Higher	Higher	Higher	Higher
GO 45K	1 vs 1	Lower	Lower	Lower	P/Lower	Higher	P/Higher	P/Higher	P/Lower	P/Higher
	1 vs 2	Lower	Lower	Lower	Lower	Lower	Lower	P/Lower	Lower	Lower
	2 vs 1	P/Lower	P/Higher	Higher	Higher	Higher	Higher	Higher	Higher	Higher
	2 vs 2	Lower	Lower	Lower	Lower	Lower	Lower	P/Lower	Lower	Lower
GO 60K	1 vs 1	Lower	Lower	Lower	Lower	P/Higher	Higher	Higher	P/Lower	Lower
	1 vs 2	Lower	Lower	Lower	Lower	Lower	Lower	Lower	Lower	Lower
	2 vs 1	P/Lower	Higher	Higher	Higher	Higher	Higher	Higher	P/Lower	Lower
	2 vs 2	Lower	P/Higher	Higher	Higher	Higher	Higher	Higher	Higher	P/Higher
GO 75K	1 vs 1	Lower	Lower	Lower	Lower	Lower	Lower	Lower	P/Higher	Higher
	1 vs 2	Lower	Lower	Lower	Lower	Lower	Lower	Lower	P/Higher	Higher
	2 vs 1	Lower	Lower	Lower	P/Higher	Higher	Higher	Higher	Higher	Higher
	2 vs 2	P/Lower	Lower	Lower	P/Higher	Higher	Higher	Higher	Higher	Higher
	Total*	6 of 24	11 of 24	10 of 24	13 of 24	14 of 24	15 of 24	16 of 24	17 of 24	18 of 24

The following classes are used for the classification of the direction of separation:

Higher	- Indicates every portion of the spectral curve taken from the plot with weeds had a higher reflection than the plot without.
P/Higher	- (Partially Higher) Indicates the majority of the spectral curve taken from the plot with weeds had a higher reflection than the plot without.
No Difference	- Indicates any difference in spectral curves.
P/ Lower	- (Partially Lower)Indicates the majority of the spectral curve taken from the plot with weeds had a lower reflection than the plot without.
Lower	- Indicates every portion of the spectral curve taken from the plot with weeds had a lower reflection than the plot without.

* Total- refers to the number of times samples taken from plots with weeds have a higher reflectance than samples taken from plots with no weeds.

The only other significant result occurred for the red part of the spectrum. Sixteen of the comparisons resulted in the samples from the plots with weeds having a higher reflectance than the samples taken from the plots without weeds. The other results provide almost equal chance of the reflectance being higher or lower.

4.3 Balloon-borne Data

4.3.1 Boxplots

The boxplots for the visible bands (Figure 4.7 to 4.12) show very similar characteristics. The median for the plots with weeds is usually higher than the medians of plots without weeds for all six comparable groups. Only BU 75K and GO 75K consistently have lower median values and the degree, to which the median values of these two comparable groups differ, is very small. Whereas for the other four comparable groups the median values differ noticeably.

The Interquartile Ranges (IQR) of the two groups (weeds and no weeds) follows a similar pattern and the IQRs generally have similar spreads and often overlap. The distribution of the digital numbers for a number of the comparable groups is skewed either to the right or left. The distribution of GO 60K with weeds tends to be skewed to the left and the distribution of GO 75K with weeds is skewed to the right. No other pattern for skewness repeats for the other comparable groups. High outliers are indicated in all three boxplots for the visible bands.

The pattern for the three boxplots of the near infrared bands is reversed to the pattern for the boxplots of the visible bands. The median of the digital numbers for the plots with weeds is almost always lower. Again BU 75K goes against this trend but the median values are very similar. For the remainder of the comparable groups there is an obvious difference between median values for the plots with weeds and plots without. Generally low outliers are present in these boxplots.

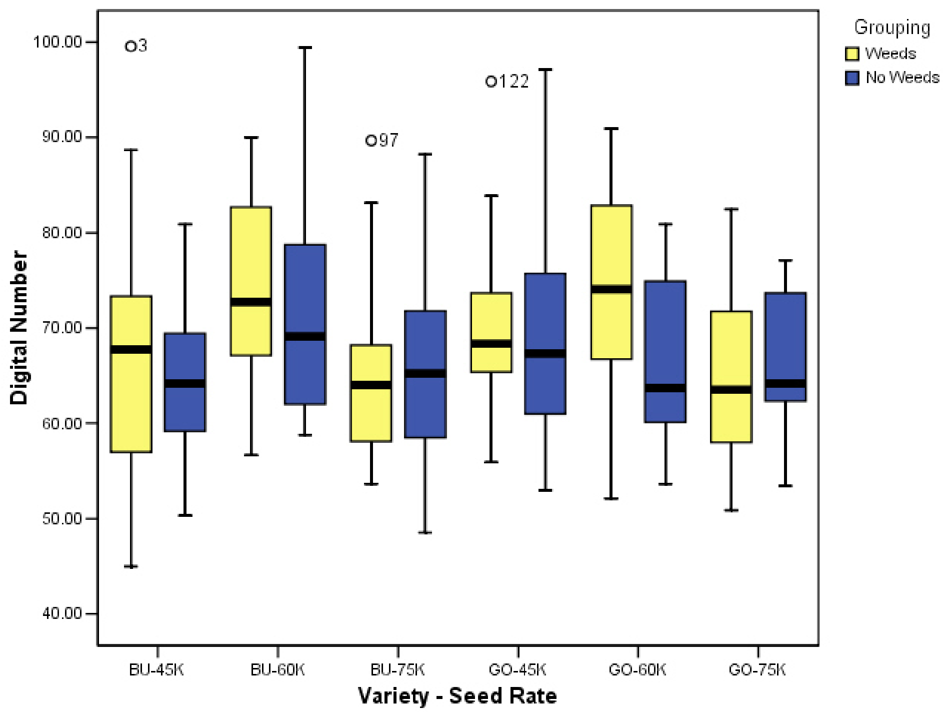


Figure 4.7 Boxplots of Balloon-Borne Data – Blue Band

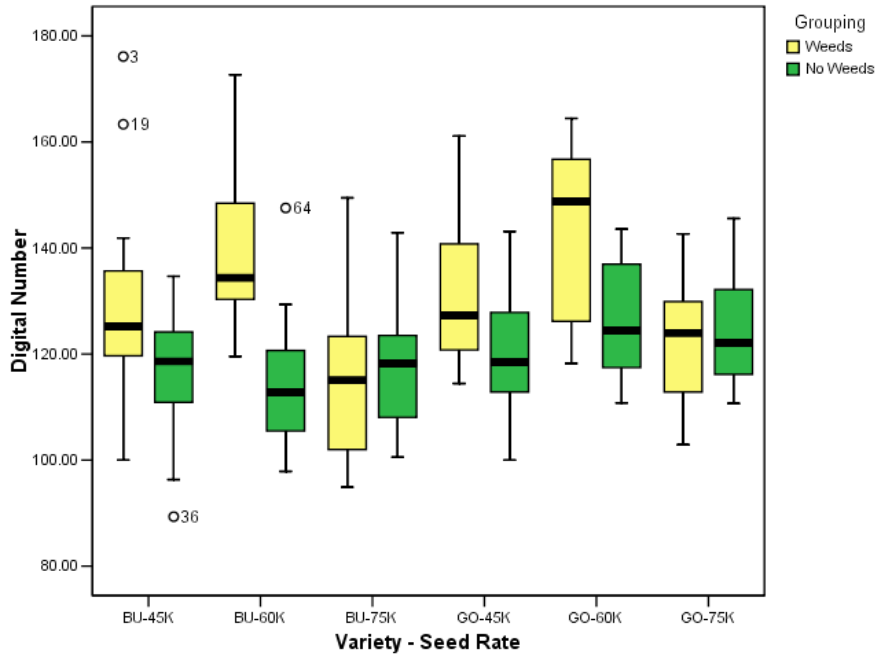


Figure 4.8 Boxplots of Balloon-Borne Data – Green Band

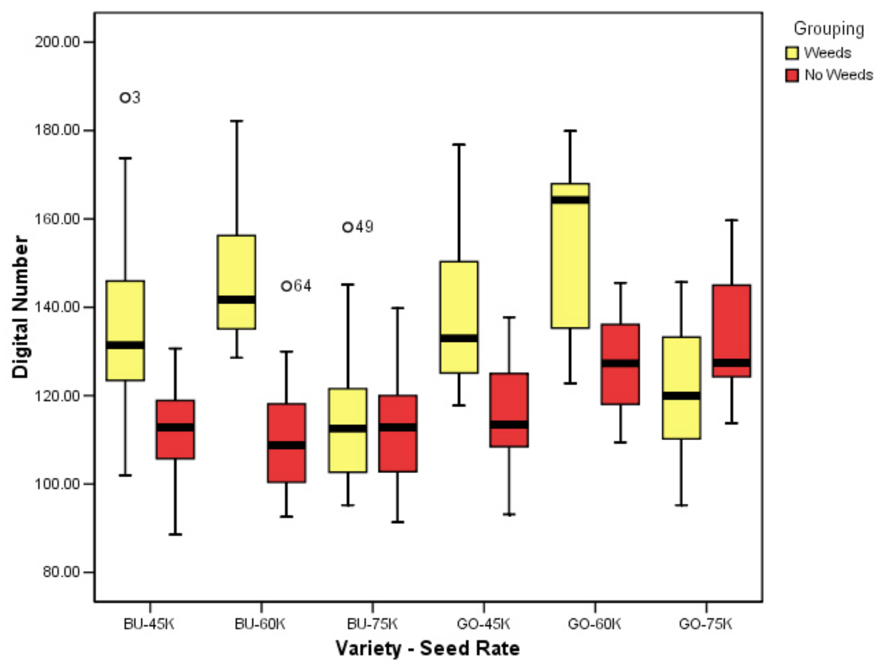


Figure 4.9 Boxplots of Balloon-Borne Data – Red Band

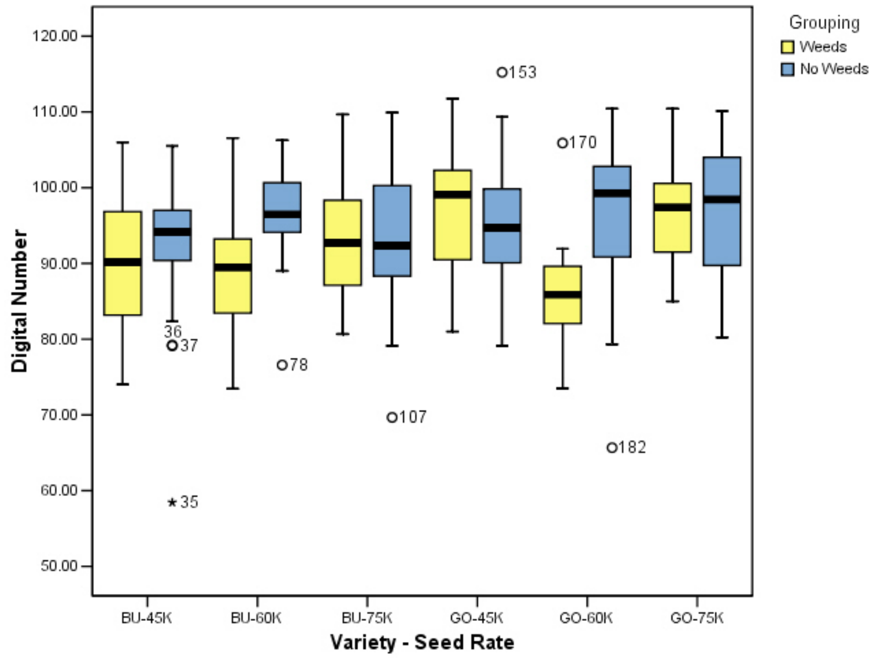


Figure 4.10 Boxplots of Balloon-Borne Data – Infrared Band 1

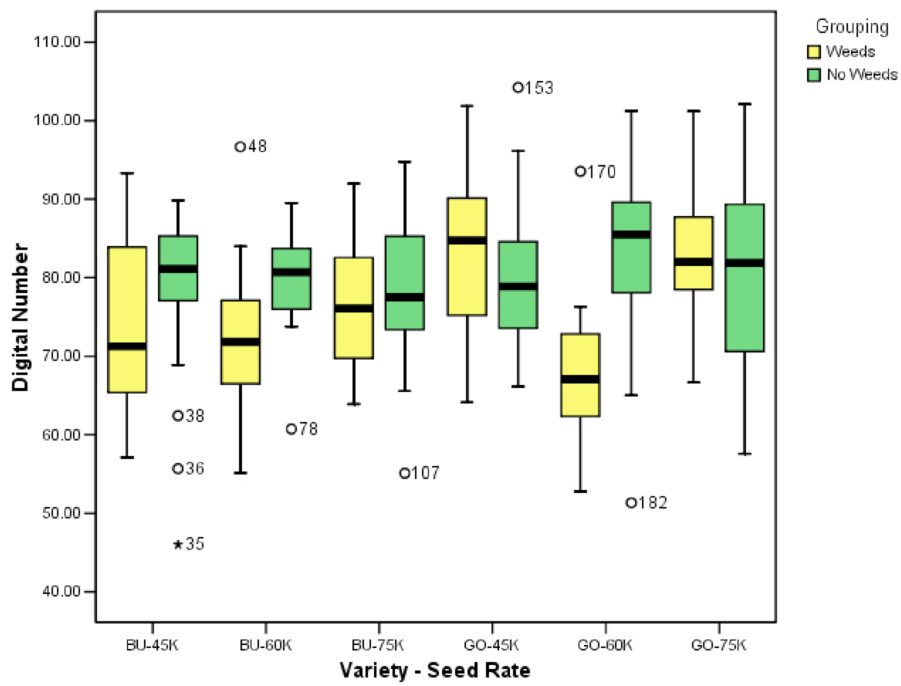


Figure 4.11 Boxplots of Balloon-Borne Data – Infrared Band 2

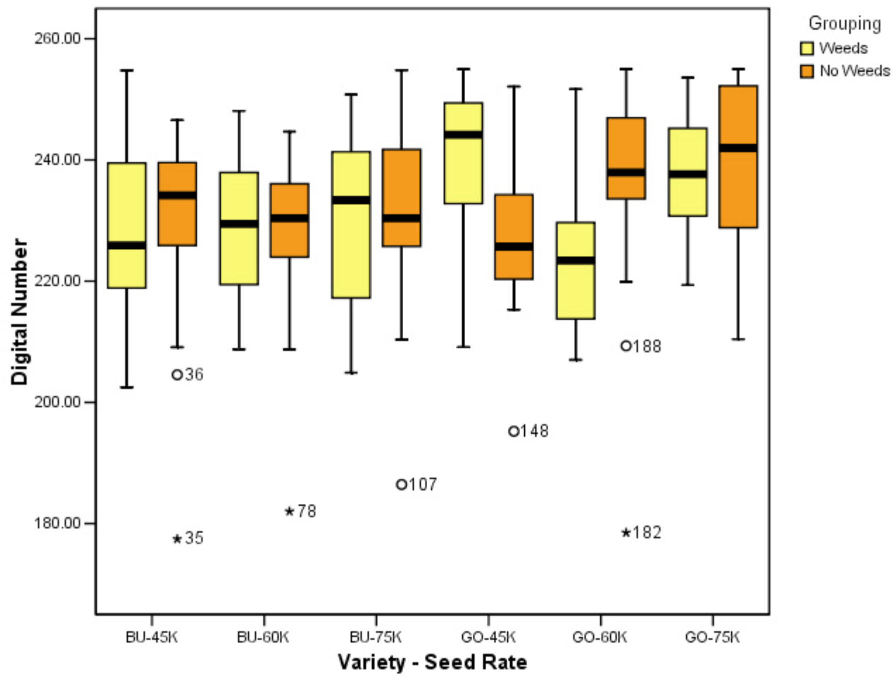


Figure 4.12 Boxplots of Balloon-Borne Data – Infrared Band 3

4.4 Results of Discriminant Function Analysis

The following sub-paragraphs detail the statistical results for the discriminant function analysis performed for both sensors. Not all statistics relevant to discriminant function analysis were interpreted in this study. A selection of the most useful is presented below. The entire output of the relevant discriminant function analysis statistics and tables for the spectroradiometer and balloon-borne images are included in Appendix B and C respectively.

4.4.1 Spectroradiometer

4.4.1.1 Canonical Correlation

The canonical correlation is the most useful measure of the tables when there are two groups (SPSS 2003). The canonical correlation is equivalent to Pearson's correlation between the discriminant scores and the groups. Pearson's correlation measures the degree to which the relationship between two variables can be described by a straight line (SPSS 2003). A value of 1 indicates a strong linear association and a value of 0 indicates no relationship (De Veaux & Velleman 2004).

The canonical correlations for the spectrometer samples can be seen in the summarised table below (Table 4.4). This table show the canonical correlation is above 95% in all cases.

Table 4.4 Spectrometer Samples Canonical Correlations

Comparable Group	Canonical Correlation
BU All	.957
GO All	.994
All Variables	.992

4.4.1.2 Wilks' Lambda

Wilks' lambda is a measure of how well each function separates cases into groups. It is equal to the proportion of the total variance in the discriminant scores not explained by differences among the groups. The value of Wilks' lambda ranges between 0 and 1, smaller values of Wilks' lambda indicate greater discriminatory ability of the function.

Table 4.5 contains the Wilks’ lambda values for the spectroradiometer samples. The values for Wilks’ lambda vary a little but they indicate that the functions have a high discriminating ability.

Table 4.5 Spectroradiometer Wilks’ Lambda Values

Comparable Group	Wilks’ Lambda
BU All	.129
GO All	.017
All Variables	.084

4.4.1.3 Standardized Canonical Discriminant Function Coefficients

The standardized coefficients allow you to compare variables measured on different scales. Coefficients with large absolute values correspond to variables with greater discriminating ability (SPSS 2004). The standardized canonical discriminant function coefficients results for the spectroradiometer are summarised in Table 4.7 below. These coefficients indicate the discriminant model relies heavily on ultraviolet wavelengths to classify the cases. The model created to classify All Variables required many more wavelengths to be able to classify the data.

Table 4.6 Spectrometer Standardized Canonical Discriminant Function Coefficients

BU All		GO All		All Variable	
K_325	.178	K_325	-1.340	K_325	17.991
K_326	6.345	K_326	5.724	K_326	-5.539
K_327	.039	K_327	9.084	K_327	9.533
K_328	5.715	K_328	-30.506	K_328	-13.077
K_330	-8.821	K_330	13.790	K_330	-8.515
K_331	10.584	K_334	.382	K_331	.758
K_340	-13.891	K_346	3.852	K_333	-7.835
				K_335	-4.347
				K_336	.114
				K_338	-3.407
				K_342	8.616
				K_351	17.288
				K_363	-13.942
				K_729	3.463

* K refers to the wavelength

4.4.1.4Classification Function Coefficients

The classification functions are used to assign cases to groups. A separate function is produced for each group. This function is then used to calculate a classification score for each case. The discriminant model then assigns the case to the group whose classification function obtained the highest score.

The classification function coefficients are included below in Tables 4.8 to 4.10. The results of these tables are very similar to standardized canonical discriminant function coefficients results.

Table 4.7 Spectrometer Classification Function Coefficients for BU All

	Group	
	Weeds	No Weeds
K_325	-6676.108	-6777.836
K_326	66617.769	62868.117
K_327	66936.758	66908.510
K_328	48638.618	44867.157
K_330	146197.60	151059.560
K_331	-149833.2	-155747.11
K_340	-151210.0	-142896.99
(Constant)	-253.919	-241.526

Fisher's linear discriminant functions

Table 4.8 Spectrometer Classification Function Coefficients for GO All

	Group	
	Weeds	No Weeds
K_325	259664.478	267283.638
K_326	-86989.471	-114730.507
K_327	-169857.300	-211986.876
K_328	25995.646	189942.717
K_330	34127.862	-34436.475
K_334	45656.165	43702.440
K_346	-64238.675	-84647.286
(Constant)	-459.517	-603.115

Fisher's linear discriminant functions

Table 4.9 Spectrometer Classification Function Coefficients for All Variables

	Group	
	Weeds	No Weeds
K_325	174020.004	137337.147
K_326	-67974.711	-56800.355
K_327	102996.185	85563.291
K_328	-141374.166	-117174.213
K_330	-16950.960	-1799.726
K_331	-50672.178	-52084.917
K_333	-41157.115	-24770.404
K_335	-5323.765	3212.497
K_336	-81177.945	-81402.527
K_338	3578.116	10957.084
K_342	99059.611	81972.905
K_351	177862.259	142577.425
K_363	-164419.977	-135905.183
K_729	3854.231	3079.051
(Constant)	-420.762	-285.789

Fisher's linear discriminant functions

4.4.1.5 Classification Results

The classification table shows the practical results of the discriminant model (SPSS 2003). The *a* value at the bottom of the table provides the proportion of cases correctly classified that were used to create the model. These classification results generally provide overly optimistic assessments of how well the model performed. A better measure of the models performance is the *b* result of the classification (SPSS 2004). The *b* value gives the percentage of cases correctly classified that were not used in the modeling process and provides a realistic measure of the overall success of the model. The classification results for the spectrometer samples are listed in the following tables (Tables 4.11 to 4.13).

Table 4.10 Spectroradiometer Classification Results for All BU

			Group	Predicted Group Membership: Weeds	Predicted Group Membership: No Weeds	Total
Cases Selected	Original	Count	Weeds	4	0	4
			No Weeds	0	5	5
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	1	1	2
			No Weeds	0	1	1
		%	Weeds	50.0	50.0	100.0
			No Weeds	.0	100.0	100.0

a. 100.0% of selected original grouped cases correctly classified.

b. 66.7% of unselected original grouped cases correctly classified.

Table 4.11 Spectroradiometer Classification Results for All GO

			Group	Predicted Group Membership: Weeds	Predicted Group Membership: No Weeds	Total
Cases Selected	Original	Count	Weeds	4	0	4
			No Weeds	0	5	5
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	1	1	2
			No Weeds	0	1	1
		%	Weeds	50.0	50.0	100.0
			No Weeds	.0	100.0	100.0

a. 100.0% of selected original grouped cases correctly classified.

b. 66.7% of unselected original grouped cases correctly classified.

Table 4.12 Spectroradiometer Classification Results for All Variables

			Group	Predicted Group Membership: Weeds	Predicted Group Membership: No Weeds	Total
Cases Selected	Original	Count	Weeds	6	0	6
			No Weeds	0	10	10
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	3	3	6
			No Weeds	0	2	2
		%	Weeds	50.0	50.0	100.0
			No Weeds	.0	100.0	100.0

a. 100.0% of selected original grouped cases correctly classified.

b. 62.5% of unselected original grouped cases correctly classified.

The *a* values in the above tables indicate that the models were able to correctly classify those cases used to create the model at a success rate of 100% on each occasion. They also show that the *b* value for each table is much lower with only two thirds of cases not used in the model correctly classified.

4.4.2 Balloon-borne Camera

4.4.2.1 Canonical Correlation Balloon-borne Images

The canonical correlations for the balloon-borne imagery can be seen in the following compilation of Eigenvalues (Table 4.13). For the comparable groups with only one variable changing, i.e. Buster 45K, Buster 60K, etc, the canonical correlation ranges from 0.704 to 0.947 with an average value of approximately 0.90. For the grouping where the second variable, planting density, is introduced (i.e. Buster All and Goldrush All) the canonical correlation is reduced to 0.747

and 0.530 respectively. The canonical correlation further falls to 0.557 when all variables are measured together, i.e. All Variables.

Table 4.13 Eigenvalues for Balloon-borne Images

Comparable Group	Function	Eigenvalue	% of Variance	Culmative %	Canonical Correlation
Buster 45K	1	4.175[a]	100.0	100.0	.898
Buster 60K	1	11.700[a]	100.0	100.0	.960
Buster 75K	1	.985[a]	100.0	100.0	.704
Goldrush 45K	1	8.769	100.0	100.0	.947
Goldrush 60K	1	4.169[a]	100.0	100.0	.898
Goldrush 75k	1	2.096[a]	100.0	100.0	.823
Buster All	1	1.262[a]	100.0	100.0	.747
Goldrush All	1	.390[a]	100.0	100.0	.530
All Variables	1	.451[a]	100.0	100.0	.557

[a.] First 1 canonical discriminant functions were used in the analysis.

4.4.2.2 Wilks Lambda

The Wilks' lambda values have been summarised in Table 4.15. These values vary and range from .079 to .719, this indicates that the functions developed from the ballon-borne data have moderate to low discriminating ability.

Table 4.14 Balloon-borne Cameras Wilks' Lambda

Comparable Group	Wilks' Lambda
BU 45K	.193
BU 60K	.079
BU75K	.504
GO 45K	.102
GO 60K	.193
GO 75k	.323
BU All	.442
GO All	.719
All Variables	.689

4.4.2.3 Standardized Canonical Discriminant Function Coefficients

Table 4.16 below has been created to summarise the results for standardized canonical discriminant function coefficients for each comparable group. The absolute value has been replaced with the variables rank, so as to improve and aid the comprehension of the table.

Table 4.16 shows that the red band has the highest discriminating ability followed by the green band. The results of the remaining bands are rather inconsistent. However, from the remaining bands blue and infrared band 1 provide the next level of discrimination, followed by infrared bands 2 and 3 with the least discriminating ability.

Table 4.15 Balloon-Borne Data – Ranked Standardized Canonical Discriminant Function Coefficients

Comparable Group	Red	Green	Blue	Infrared Band 1	Infrared Band 2	Infrared Band 3
BU 45K	1st	5th	2nd	3rd	6th	4th
BU 60K	2nd	3rd	1st	4th	5th	6th
BU75K	1st	2nd	5th	6th	3rd	4th
GO 45K	1st	3rd	5th	2nd	6th	4th
GO 60K	1st	4th	6th	5th	3rd	2nd
GO 75k	2nd	1st	5th	3rd	4th	6th
BU All	1st	2nd	4th	6th	3rd	5th
GO All	5th	1st	4th	2nd	6th	3rd
All Variables	1st	5th	2nd	3rd	4th	6th

4.4.2.4 Classification Function Coefficients

The classification functions scores are summarised below in Table 4.16. The results indicate that the classification score for the red band on seven of nine occasions was higher for the weeds group. The classification score for the green band favoured the no weeds group six out of nine times and the blue band favoured the no weeds group eight out of nine times. The infrared classification scores only slightly favoured the no weeds group.

Table 4.16 Classification Function Coefficients

Comparable Group	Group	Red	Green	Blue	Infrared - Red	Infrared - Green	Infrared - Blue	(Constant)
BU 45K	Weeds	-1.23	0.668	2.443	6.676	-9.158	1.195	-516.217
	No Weeds	-2.021	0.874	3.219	7.071	-9.271	0.581	-520.152
BU 60K	Weeds	-2.277	3.183	1.331	8.922	-8.308	-0.297	-808.962
	No Weeds	-3.419	2.944	2.633	9.101	-8.235	-0.274	-775.835
BU 75K	Weeds	-0.275	-0.801	2.321	4.282	-4.998	-0.201	-306.778
	No Weeds	-0.857	-0.22	2.413	4.247	-4.586	-0.566	-304.054
GO 45K	Weeds	3.474	-1.88	2.196	11.026	-7.178	-5.007	-978.802
	No Weeds	2.098	-0.621	2.107	9.755	-7.216	-3.417	-808.303
GO 60K	Weeds	-3.611	4.386	-0.646	8.07	-6.187	-3.416	-550.418
	No Weeds	-4.211	4.702	-0.442	8.487	-5.497	-4.424	-578.581
GO 75K	Weeds	-6.943	1.741	12.763	17.947	-12.45	-11.921	-1142.45
	No Weeds	-6.114	0.652	12.894	18.091	-12.62	-11.809	-1152.42
BU ALL	Weeds	-0.973	0.599	1.021	3.906	-6.249	1.386	-287.193
	No Weeds	-1.303	0.789	1.212	3.885	-6.019	1.182	-277.113
GO ALL	Weeds	-3.031	3.197	1.842	5.881	-6.509	-0.709	-465.288
	No Weeds	-2.986	3.011	1.951	5.789	-6.447	-0.579	-450.696
All Variables	Weeds	-1.679	1.487	1.581	4.552	-5.96	0.469	-358.97
	No Weeds	-1.794	1.523	1.67	4.508	-5.899	0.489	-351.344

Fisher's linear discriminant functions

4.4.2.5 Classification Results

The results of the discriminate models classification of cases has been summarised into a single table below (Table 4.17) This is followed by the individual tables for each comparable group (Table 4.19 to 4.27). The results indicate that the discriminate analysis performed better for the comparable groups that contained only a single variable that changed. As more variables were introduced the number of successful classifications reduced. Overall the models performed well with a high proportion of unselected cases successfully classified.

Table 4.17 Summary of Classification Results of Balloon-Borne Imagery

Comparable Group	Percentage of selected original grouped cases correctly classified.	Percentage of unselected original grouped cases correctly classified.
Buster 45K	100.0	93.3
Buster 60K	100.0	100.0
Buster 75K	85.2	76.9
Goldrush 45K	100.0	100.0
Goldrush 60K	96.3	76.9
Goldrush 75k	96.33	92.3
Buster All	86.4	89.7
Goldrush All	70.4	59.0
All Variables	72.5	70.0

Table 4.18 Spectroradiometer Classification Results for BU 45K

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	13	0	13
			No Weeds	0	12	12
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	6	1	7
			No Weeds	0	8	8
		%	Weeds	85.7	14.3	100.0
			No Weeds	.0	100.0	100.0

a 100.0% of selected original grouped cases correctly classified.
b 93.3% of unselected original grouped cases correctly classified.

Table 4.19 Spectroradiometer Classification Results for BU 60K

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	13	0	13
			No Weeds	0	14	14
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	7	0	7
			No Weeds	0	6	6
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0

a 100.0% of selected original grouped cases correctly classified.
b 100.0% of unselected original grouped cases correctly classified.

Table 4.20 Spectroradiometer Classification Results for BU 75K

			Group	Predicted Group Membership Weeds	Predicted Group Membership No Weeds	Total
Cases Selected	Original	Count	Weeds	12	1	13
			No Weeds	3	11	14
		%	Weeds	92.3	7.7	100.0
			No Weeds	21.4	78.6	100.0
Cases Not Selected	Original	Count	Weeds	5	2	7
			No Weeds	1	5	6
		%	Weeds	71.4	28.6	100.0
			No Weeds	16.7	83.3	100.0

a 85.2% of selected original grouped cases correctly classified.
b 76.9% of unselected original grouped cases correctly classified.

Table 4.21 Spectroradiometer Classification Results for GO 45K

			Group	Predicted Group Membership Weeds	Predicted Group Membership No Weeds	Total
Cases Selected	Original	Count	Weeds	13	0	13
			No Weeds	0	14	14
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	7	0	7
			No Weeds	0	6	6
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0

a 100.0% of selected original grouped cases correctly classified.
b 100.0% of unselected original grouped cases correctly classified.

Table 4.22 Spectroradiometer Classification Results for GO 60K

			Group	Predicted Group Membership		Total
				Weeds	No Weeds	
Cases Selected	Original	Count	Weeds	12	1	13
			No Weeds	0	14	14
		%	Weeds	92.3	7.7	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	5	2	7
			No Weeds	1	5	6
		%	Weeds	71.4	28.6	100.0
			No Weeds	16.7	83.3	100.0

a 96.3% of selected original grouped cases correctly classified.
b 76.9% of unselected original grouped cases correctly classified.

Table 4.23 Spectroradiometer Classification Results for GO 75K

			Group	Predicted Group Membership		Total
				Weeds	No Weeds	
Cases Selected	Original	Count	Weeds	12	1	13
			No Weeds	3	11	14
		%	Weeds	92.3	7.7	100.0
			No Weeds	21.4	78.6	100.0
Cases Not Selected	Original	Count	Weeds	5	2	7
			No Weeds	1	5	6
		%	Weeds	71.4	28.6	100.0
			No Weeds	16.7	83.3	100.0

a 85.2% of selected original grouped cases correctly classified.
b 76.9% of unselected original grouped cases correctly classified.

Table 4.24 Spectroradiometer Classification Results for BU All

			Group	Predicted Group Membership		Total
				Weeds	No Weeds	
Cases Selected	Original	Count	Weeds	31	8	39
			No Weeds	3	39	42
		%	Weeds	79.5	20.5	100.0
			No Weeds	7.1	92.9	100.0
Cases Not Selected	Original	Count	Weeds	17	4	21
			No Weeds	0	18	18
		%	Weeds	81.0	19.0	100.0
			No Weeds	.0	100.0	100.0

a 86.4% of selected original grouped cases correctly classified.
b 89.7% of unselected original grouped cases correctly classified.

Table 4.25 Spectroradiometer Classification Results for GO All

			Group	Predicted Group Membership		Total
				Weeds	No Weeds	
Cases Selected	Original	Count	Weeds	27	12	39
			No Weeds	12	30	42
		%	Weeds	69.2	30.8	100.0
			No Weeds	28.6	71.4	100.0
Cases Not Selected	Original	Count	Weeds	13	8	21
			No Weeds	8	10	18
		%	Weeds	61.9	38.1	100.0
			No Weeds	44.4	55.6	100.0

a 70.4% of selected original grouped cases correctly classified.
b 59.0% of unselected original grouped cases correctly classified.

Table 4.26 Spectroradiometer Classification Results for All Variables

			Group	Predicted Group Membership		Total
				weeds	No Weeds	
Cases Selected	Original	Count	weeds	58	23	81
			No Weeds	21	58	79
		%	weeds	71.6	28.4	100.0
			No Weeds	26.6	73.4	100.0
Cases Not Selected	Original	Count	weeds	27	12	39
			No Weeds	12	29	41
		%	weeds	69.2	30.8	100.0
			No Weeds	29.3	70.7	100.0

a 72.5% of selected original grouped cases correctly classified.
b 70.0% of unselected original grouped cases correctly classified.

4.5 Results of Regression

The matrices created for the four bandwidths of the balloon-borne cameras and the associated bandwidths for the spectrometer, yielded a very large table that is difficult to interpret and will not be displayed. The scatter plots and regression lines are presented below for the spectrometer camera bands that yielded the highest correlation (Figure 4.13 to 4.18). The scatter plots on all occasions exhibited no correlation between the spectroradiometer data and the balloon-borne camera data.

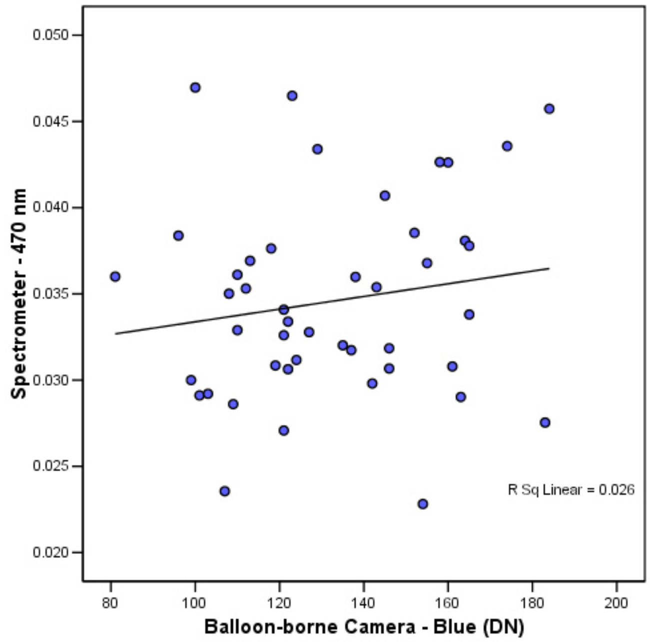


Figure 4.13 Scatterplot And Regression Line For Blue Correlation

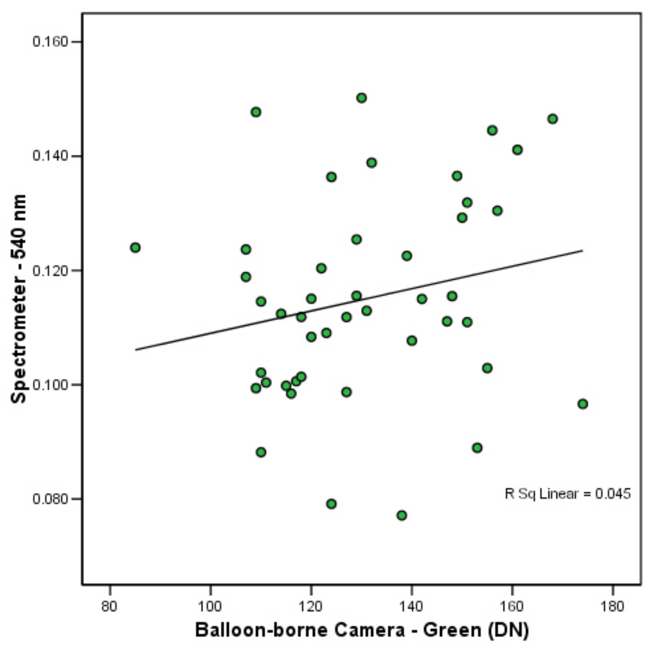


Figure 4.14 Scatterplot And Regression Line For Green Correlation

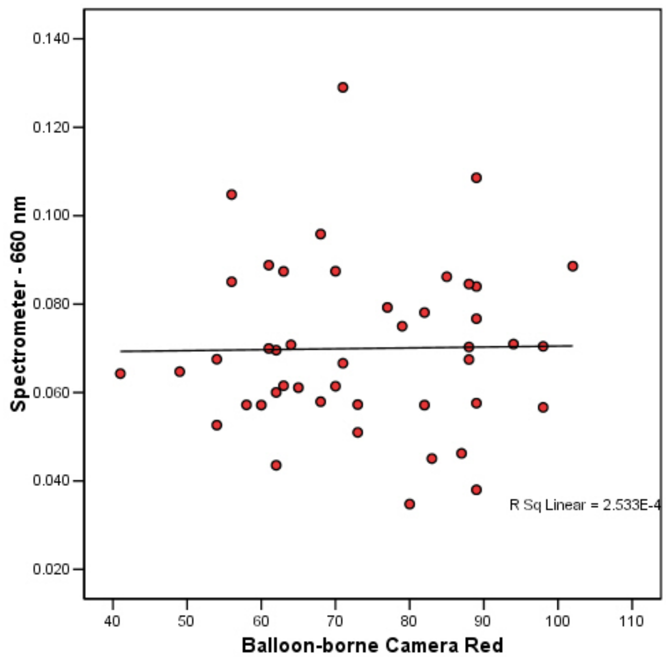


Figure 4.15 Scatterplot And Regression Line For Red Correlation

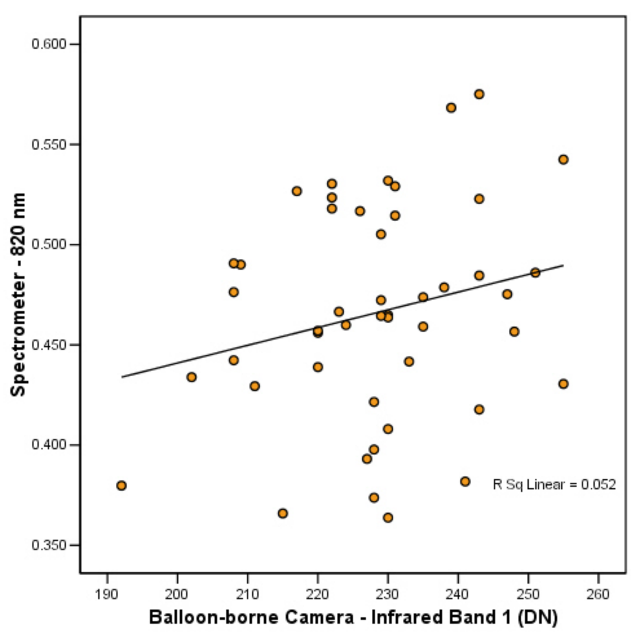


Figure 4.16 Scatterplot And Regression Line For Infrared Band 1 Correlation

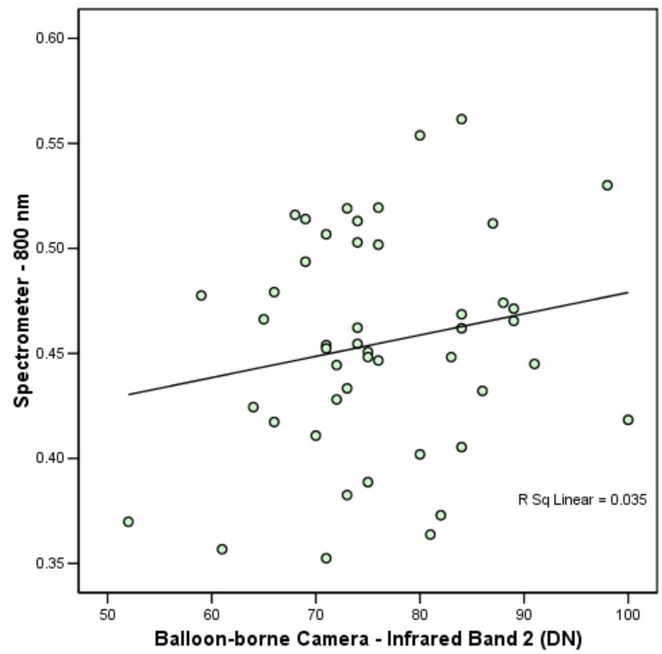


Figure 4.17 Scatterplot And Regression Line For Infrared Band 2 Correlation

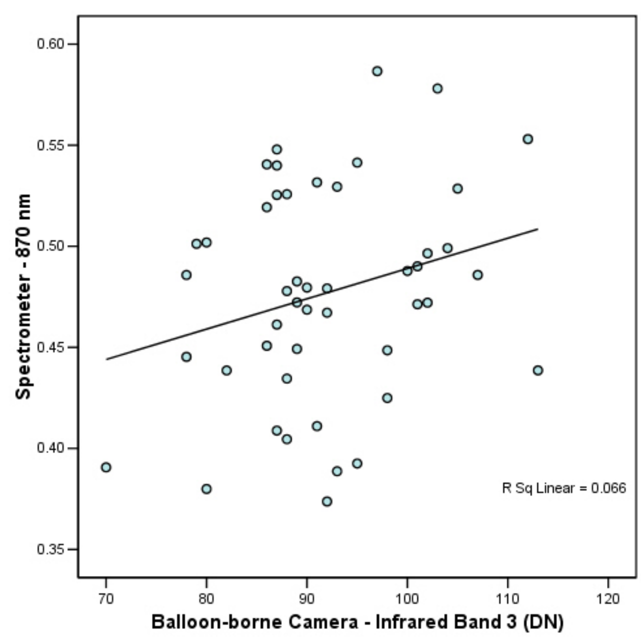


Figure 4.18 Scatterplot And Regression Line For Infrared Band 3 Correlation

4.6 Summary

The results of the discriminate function analysis for the balloon-borne camera and the spectroradiometer have revealed that the spectral data collected by these instruments is able to successfully discriminate between healthy and stressed crop. The initial analysis has provided some clues as to why certain spectral regions provide a greater opportunity to discriminate between the two crop types. This will be further explored in the following section.

The regression analysis failed to provide any evidence of a correlation between the data collected by the two sensors. This will also be discussed in the following section.

CHAPTER 5

DISCUSSION

5.1 Introduction

This chapter presents the discussions raised as a result of this project. A discussion of the discriminant function analysis results is presented first. The discussion commences by analysing the results of the spectroradiometer data, this is then followed by an in-depth discussion of the discriminant analysis results of balloon-borne camera system. The results of the classification results are discussed first, this is then followed by a discussion of the most relevant other statistics included in SPSSs discriminant function analysis output. The initial statistical analysis performed on the two data sets is also included in this discussion. The following section compares the results of the discriminant function analysis for the two sensors. This discussion will solely focus on a comparison of the comparable groups that allow direct comparison. Finally the correlation analysis will be discussed.

5.2 Discriminant Function Analysis

5.2.1 Spectroradiometer

It must be stated at the outset of this discussion of the results for the spectroradiometer, that the sample size is to small to draw conclusions with any conviction. Only having two samples per plot and 24 samples in total, limits the statistical analysis that can be performed. The statistical analysis that has been performed cannot be used to draw inferences about the wider population or be taken to be a true representation of the situation at the Kingsthorpe trial. For this reason the analysis will only be brief. Having said this the statistical analysis of the data can be used to directly compare the data for the samples taken. For that reason alone, the following discussion is presented.

5.2.1.1 Classification results

The classification results indicate that the model performs well when classifying the cases used to create the model. This is to be expected, as these cases were used to develop the model and therefore the model is based on the properties of these cases. Because of this these classification results are often over optimistic. A better measure of the models performance is the results of the classification of the cases not used in the model.

The results show that for the three comparable groups a success rate of approximately 66% was achieved when the model was applied to those cases not used to create the model. This suggests that overall the model is correct two out of three times. This represents a satisfactory result, as the model was required to deal with a number of variables, these were planting density and plant variety.

The canonical correlation confirms the strength of the models. The canonical correlation for all three comparable groups was greater than 90% indicating a strong correlation between the discriminant scores and the groups.

5.2.1.2 Other Statistics

The standardised canonical discriminant function coefficients used to create the model are almost exclusively for the ultraviolet range. To understand why ultraviolet wavelengths plays such a significant role in the model we can look at the initial statistical analysis conducted on this data. Table 4.1 in Chapter 4 indicates that the ultraviolet had the lowest separation based on the absolute difference between spectral curves of different groups. The column containing the difference in separation as a percentage indicates that the ultraviolet portion of the spectrum does in fact exhibit a large separation when considered as a proportion of the measured spectral values. The region of highest separation also corresponds approximately to those bands used in the discriminant model.

Another factor that may influence the ability of the ultraviolet wavelengths to be able to discriminate between weeds and no weeds is that the proportion of the separation remains relatively constant at approximately twenty percent for all comparable groups. This is in contrast with the other wavelengths whose separation fluctuates.

A further clue as to why ultraviolet wavelengths feature prominently in the model can be seen in the table showing the direction of the separation. Ultraviolet wavelengths have the equal highest consistency in the direction of separation. Eighteen out of twenty-four comparisons resulted in plots with weeds having a lower reflectance. For the Goldrush samples all twelve comparisons resulted in plots with weeds having a lower reflectance. This points to why the ultraviolet region of the spectrum is relied so heavily on by the discriminant model.

The other wavelengths to feature prominently in the direction of separation table are both the divisions of the near infrared spectrum, and the red wavelengths to a lesser degree. For the near infrared and the red regions of the spectrum the degree of separation as a percentage is quite high with the separation of approximately 30% common. However this separation does fluctuate and is as low as 10% for both regions on one occasion. These may indicate why these spectral regions are not prominent in the discriminate model. It is likely however that these two spectral regions would likely provide the next level of discriminating ability after ultraviolet.

5.3 Balloon-borne Camera Data

Unlike the situation with the spectroradiometer, the balloon data does allow the ability to draw inferences from the sample data. The greater sampling size provides the ability to closely examine the results. For this reason this section will provide a more in depth discussion of the statistical results.

This section will only examine the classification results of the comparable groups derived from the original comparable pairs identified in the early part of Chapter 3. The results of the comparable groups that contained more than one variable (variety and multiple planting densities) will be discussed in a later section when a comparison is made between the two sensors.

5.3.1 Classification results

The classification results indicate the models were able to achieve a high proportion of success for individual treatments. The models were successfully applied to the unselected cases and achieved near similar results for the classification of the cases used to create the model. This verifies that the models were significantly robust to enable the models to be successfully applied to unfamiliar data.

For the cases used to create the classification model, the model incorrectly classified three of these cases from the one group on two occasions. On both these occasions the cases belonged to no weeds group but were classified as belonging to the weeds group. Both these misclassifications occurred for the higher planting density of 75,000 plants per hectare.

A possible explanation for the misclassification of cases from higher planting densities is that as planting density increases plant competition also increases. This can lead to plants becoming stressed if there is an inadequate supply of resources to meet the plants requirements (Starr & Taggart 1989). If this were the case then plants from both groups would have exhibited some signs of stress.

When the model was applied to those cases not used to create the model to verify the models performance, the models predictive abilities showed a bias towards the no weeds category. Seven cases were incorrectly classified as no weeds when in fact the cases belonged to the weeds group. This compares to only three no weeds cases being incorrectly classified. This suggests the model over emphasizes the characteristics used to classify the no weeds group.

Eight of the ten incorrectly classified cases occurred at the higher planting densities, suggesting the higher competition for resources resulted in plants having similar spectral characteristics. If the higher planting densities caused the crop without weeds to compete with other plants in the crop than it would have become stressed and therefore had similar spectral properties as the plants that were competing with the weeds and the other crop.

The misclassification could be caused by the reverse argument. If the crops planted at higher planting densities were able to out compete, and limit the establishment and growth of the weeds, then the effect of the weeds on the crop would have been limited. This would have resulted in the plants from both groups having similar growing conditions and therefore similar spectral characteristics. However this may not be the case as a recent study into crop and weed completion indicates that crop seeding rates had minimal impact on weed numbers (Osten 2003).

An investigation into the recommended planting densities revealed that both varieties have a recommended planting density of 40,000 to 70,000 plants per hectare (Pacific Seeds 2004). This implies that the higher planting densities used in the experiment approaches or exceeds the recommended planting densities. This may suggest the original proposition is more likely, that as planting density increases so does the inter-crop completion, thus causing the crop to become stressed whether weeds are present or not.

5.3.2 Canonical Correlation and Wilks Lambda

The results of Wilks' lambda indicate that as the planting density increase the Wilks' lambda values also increase. As already stated smaller values of Wilks' lambda indicate greater discriminatory ability of the function. Therefore as the planting density increases the ability to discriminate between the two groups diminishes. This provides further evidence to the suggestion above that at higher planting densities the crop becomes stressed whether there are weeds present or not.

The common trend for the canonical correlation is for the values to decrease when the planting density increases. This signifies that as planting density increases the correlation between the discriminant scores decreases. This adds even further evidence to the proposition that as planting density increases the health of the crop with or without weeds becomes increasingly similar and so to do the spectral properties.

5.3.3 Other Statistics

The results of the standardized canonical discriminant function coefficients indicate that the visible bands have the highest discriminating ability. In particular the results provide clear evidence that the red band has the highest discriminating ability followed by the green band. The results of the remaining bands are rather inconsistent but generally the near infrared bands have the least discriminating ability.

By examining the classification function coefficients of these bands we can gain some understanding of why the bands performed well or poorly when discriminating between the crops with or without weeds.

5.3.3.1 Red Band

The results indicate that the coefficients for red are higher in the majority of cases for the plots with weeds. This signifies that the red wavelengths have a greater ability to classify the plots with weeds. This may indicate that as the health of the plant deteriorates the amount of light reflected in these wavelengths increases. This point is well supported by past research that indicates that plant stress will cause a reduction in plant chlorophyll, which reduces the amount of red and blue light absorbed and thus increases the amount of light reflected in those wavelengths from the surface of the plant (CCRS 2003).

The boxplots created for the red band support this view. The boxplots clearly shows that in almost all cases there is higher reflectance in the red band for the plots with weeds.

5.3.3.2 Green Band

This same phenomena can be used to explain the higher coefficients in the green band for plots with no weeds. In healthy vegetation chlorophyll absorbs a greater proportion of radiation in the red and blue wavelengths as part of the photosynthetic process. This leads to a higher proportion of green wavelengths being reflected and is what gives healthy plants their green appearance (Campbell 1996).

These results however are not supported by the boxplots for the green band. The boxplots indicate that the plots with weeds generally have a higher reflectance in the green band. This disagreement in results is somewhat confounding. It may be possible that the extracted pixels may contain both the crop and the weed, which increases the reflection of green wavelengths. Although this suggestion is plausible it has not been tested and I am unsure how this fits within the model.

5.3.3.3 Blue Band

The coefficients for the blue band also pose interesting questions. It was thought that the coefficients for the blue band would follow the same pattern as the red band, because chlorophyll has a similar influence on both bands. The boxplots of the blue band indicate that the median value for plots with weeds is generally higher, thus giving rise to the expectations that the green band would have a greater discriminating ability for plots with weeds. The results were the reverse of the expectations however. The coefficients demonstrated that the blue wavelengths have a marginally higher discriminating ability for the plots without weeds.

If the classification function coefficients are examined on a singular basis and compared with the respective boxplots no evidence is forthcoming to support the fact that the classification functions favours the discrimination of plots without weeds. The comparison shows that in several cases (BU 45K, BU 60K and GO 60K) the classification functions favours the discrimination of plots without weeds when the reflectance for plots with weeds is higher. For other cases (BU 75K, GO 75K, BU 60K) the classification functions again favours the discrimination of plots without weeds but the reflectance in these plots is lower.

5.3.3.4 Infrared Bands

Campbell (1996) suggests that in stressed vegetation the infrared reflectance is reduced as a result of a deterioration of cell walls. We would therefore expect the infrared to have higher reflectance in the plots without weeds. The boxplots for all three infrared bands supports this, with thirteen of eighteen clusters having higher reflectance for the plots with no weeds. The coefficients from the table however are evenly spread, with half the coefficients indicating the infrared bands have a higher discriminating ability for plots with weeds and the other half indicating the infrared bands have a higher discriminating ability for plots without weeds.

As already mentioned higher planting densities can lead to plant stress. This stress is often in the form of water stress (Starr & Taggart 1989). Guyot (1990) stated that a reduction of the leaf water content induces an increasing reflectance over the whole spectrum. It was therefore decided to investigate if higher planting densities for plots with weeds resulted in higher reflectance of near infrared and therefore causing come of the coefficients to favour the discrimination of plots with weeds. The coefficients where compared to the near infrared reflectance on a planting density basis to see if a pattern might emerge. The coefficients and reflectance values for different planting densities however yielded no such pattern. Again the coefficients were evenly split between the two groups.

5.4 Discriminant Function Analysis Comparison

During this comparison only the result of the comparable groups, BU All, GO All and All Variables, are compared. These groups where chosen because the spectroradiometer data was limited to these three groups and the balloon-borne camera was selected to match these groups to enable a direct cross comparison.

Analysing the classification results of the discriminant analysis show that two sensors achieved comparable results. The spectroradiometer successfully classified two out of three unselected cases whereas the spectroradiometer on average classified seventy percent of unselected cases correctly.

The canonical correlations for the sensors differed significantly in favour of the spectroradiometer. The spectroradiometer's canonical correlation exceeded 90% for all three comparable groups. The best correlation for the balloon data only achieved a value of 75% for BU All, the other two only had moderate correlations of approximately 55%.

The spectroradiometer also out performed the balloon-borne camera for the Wilks' lambda values. The Wilks' lambda values for the balloon data ranged from 0.44 to 0.69 indicating each discriminant function performed poorly when separating cases into groups. This is not evident in the classification of the unselected cases however. The results for the spectroradiometer ranged from 0.02 to 0.13, which indicates that each function performed well at separating cases into groups.

The classification results suggest that the models created from both sets of data achieve comparable result. The accompanying statistics however suggest that the balloon-borne camera data did not have the discriminating ability of the spectroradiometer. This may be attributed to the spectrometers ability to capture the ultraviolet portion of the spectrum. The models created from the spectroradiometer data relied heavily on this data to create its discriminant functions. The spectroradiometer also captured many more bands over much narrower bandwidths, providing the opportunity to measure spectral variation more accurately. This greater flexibility in the discriminating ability of narrow bands is evident in the standardized canonical discriminant function coefficients, which are almost exclusively in the same region of the spectrum.

The models performed better when confined to two changing variables and were not as successful when a third additional variable was introduced. This situation is not unexpected as each additional variable that is introduced to the comparable group needs to be modelled by the discriminant model. This can lead to a restriction in the discriminating ability of the model because of reduced window of opportunity to discriminate.

5.5 Regression

The regression analysis failed to provide any evidence of an association between the reflectance values captured by both sensors. This however does not mean there is no correlation. There are a number of reasons why this is the case.

The first and most convincing reason relates to the lack of positional accuracy when acquiring samples for the two sensors. Whilst some effort was made to sample from the same location, this could not be guaranteed. The reasons for this have been explained previously. The result of this situation is that some if not all of the samples were taken from different locations. This inevitably makes it exceedingly difficult to establish a correlation when the comparison is being made on different plants.

The second factor is a common problem that occurs in statistical analysis. Outliers can affect the results of any analysis but particularly regression analysis. The results of the boxplots indicate that there are a number of outliers contained in the balloon data and there certainly would be outliers for the spectrometer data. An attempt was made to identify the outliers and remove them from the analysis. This bought about a marginal improvement in the r-square value but was not considered sufficient to include in the results.

The final factor is less obvious. A number of different treatments were involved in the correlation analysis for each band, i.e. planting density, variety and the health of the crop. The presence of these variables may have affected the results. This suggestion cannot be tested however because of a lack of spectroradiometer data.

5.6 Summary

The models created for the discriminant function analysis successfully classified cases as weeds or no weeds generally four out of five times for the balloon data and two out of three times for the spectroradiometer. As the planting densities increased the accuracy of classification was affected for the balloon data, indicating that as plant density increases the crop health becomes more homogenous, regardless of whether weeds are present or not.

The balloon data had comparable results for the groups that allowed cross comparison between the two sensors. However statistics such as the canonical correlation and Wilks' lambda suggest that the models created from the balloon data lack the discriminating ability of the spectroradiometer.

The correlation analysis suggests there is no linear association between the two sensors. There were a number of mitigating factors involved in measuring the relationship between the spectral responses captured by the two sensors. It is more than likely these factors adversely affected the possibility of determining a correlation existed.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter presents the conclusions drawn from the results of this project with respect to the projects objectives that were defined in Chapter 1. It describes the success of the analysis of both sensors and concludes on their ability to discriminate between the spectral response of healthy crops and stressed crops. Recommendations for improvements to the study are made. Recommendations for practical applications of the research along with opportunities for future research are also mentioned.

6.2 Conclusions

The methods and analysis presented in this dissertation provide an ability to distinguish between healthy and stressed crops. Both sensors have the capacity to spectrally discriminate between the two crop types.

No real difference was found in the success rate of classification of the two sensors. The spectroradiometer with its hyperspectral ability proved to have a greater discriminating ability than the multispectral balloon-borne camera system, however this did not translate in to better classification results. The balloon-borne camera system provided very similar classification results and was able to capture a greater amount of information in a shorter period. This indicates that the balloon-borne camera system can readily be applied to other situations that require fast low-cost capture of spectral data on field by field basis.

No correlation was found between the two data sources but this is not to say that an association does not exist. The sampling technique and a lack of spectroradiometer data significantly contributed to the opportunity to assess if a correlation existed between the two sensors.

Improvements could be made to the sampling process, which would allow a better opportunity to analyse the ability of the spectroradiometer data to discriminate between healthy and stressed crops.

From the results of this research there is there is reason to believe that the spectral data provided by both sensors could be used to quantify the effect of the weeds and other causes of stresses on crops.

6.3 Recommendations for Practical Applications

Presently this technology provides the opportunity to discriminate between healthy and stressed crops. The value of this technology in it current state to farm managers is unclear. The results of this research do however provide the incentive to pursue further research into the ability of the sensors to quantify the effect the weeds have on plant growth and yield. If this could be realised the technology would become an invaluable tool to farmers, particularly in measuring the environmentally factors affecting plant growth and yield. Further research is required before practical applications could be realised. A practical application other than sought by this study may arise from further research and wider application of this technology.

6.4 Recommendations for Future Research

Further work that could enhance and augment the methods presented in this dissertation include:

1. Investigate the ability of the sensors to detect plant stress at an earlier growth stage when management practices are more feasible.

2. Investigate the ability to quantify the plant stress caused by the presence of weeds.

3. Investigate the ability of different platforms to distinguish plant stress.

4. Investigate if these techniques can be applied to other situations such as identify nutrient inadequacies such deficiencies in nitrogen, potassium, etc.

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APPENDIX A

PROJECT SPECIFICATION

University of Southern Queensland
Faculty of Engineering and Surveying

ENG 4111/412 Research Project
PROJECT SPECIFICATION

FOR:	**Shawn DARR**
TOPIC:	Assessment of Crop Health In Relation to Competition from Weeds: Using Balloon-borne Images and Spectrometer Data
SUPERVISOR:	Dr Armando Apan
ASSOCIATE SUPERVISOR:	Troy Jensen, DPI&F
SPONSOR:	Queensland Department of Primary Industries and Forestry
PROJECT AIM:	This project will seek to identify and quantify the influence that weeds have on broad acre agricultural crops. The project will use spectral data obtained from spectroradiometer measurements and low cost aerial images to identify weed-induced stress in sorghum crops.

PROGRAMME: Issue A, March 2004

1. Conduct literature review on using spectral data for crop condition monitoring, particularly the effects of weeds.
2. Acquire spatial data sets, i.e. aerial imagery.
3. Collect spectroradiometer and GPS data.
4. Perform pre-processing operations on aerial images, e.g. image registration and image sub-scene selection.
5. Determine the spectral separability of crop planted with weeds vs. without weeds for the handheld spectrometer data.
6. Determine the spectral separability of the corresponding data for the aerial imagery.
7. Conduct correlation analysis of spectral response for handheld spectrometer vs. aerial imagery.
8. Generate conclusions and recommendations.
9. Write and submit dissertation.

AGREED: ______________ (Student) ______________ (Supervisor)

DATE: 22/03/04 22/03/04

Sponsor: Queensland Department of Primary Industries and Forestry
Predictive Precision Systems, Tor Street, Toowoomba
Phone (07) 4688 1307
Troy.Jensen@dpi.qld.gov.au

APPENDIX B

Spectroradiometer
Discriminant Function Analysis
Output

Spectrometer – BU All

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		9	75.0
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	3	25.0
	Total	3	25.0
Total		12	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.684(a)	100.0	100.0	.637

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.594	1.825	7	.969

Standardized Canonical Discriminant Function Coefficients

	Function
	1
K_325	.178
K_326	6.345
K_327	.039
K_328	5.715
K_330	-8.821
K_331	10.584
K_340	-13.891

Structure Matrix – This table has been removed because of size restrictions.

Functions at Group Centroids

Group	Function 1
Weeds	.653

No Weeds	-.816

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		12
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		12

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	5	5.000
No Weeds	.500	4	4.000
Total	1.000	9	9.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
K_325	-6676.108	-6777.836
K_326	66617.769	62868.117
K_327	66936.758	66908.510
K_328	48638.618	44867.157
K_330	146197.608	151059.560
K_331	-149833.222	-155747.111
K_340	-151210.087	-142896.998
(Constant)	-253.919	-241.526

Fisher's linear discriminant functions

Classification Results(a,b)

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	3	2	5
			No Weeds	0	4	4
		%	Weeds	60.0	40.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	0	1	1
			No Weeds	0	2	2

%	Weeds	.0	100.0	100.0
	No Weeds	.0	100.0	100.0

a 77.8% of selected original grouped cases correctly classified.
b 66.7% of unselected original grouped cases correctly classified.

Spectrometer – GO All

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		9	75.0
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	3	25.0
	Total	3	25.0
Total		12	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	58.717[a]	100.0	100.0	.992

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.017	14.314	7	.046

Standardized Canonical Discriminant Function Coefficients

	Function
	1
K_325	-1.340
K_326	5.724
K_327	9.084
K_328	-30.506
K_330	13.790
K_334	.382
K_346	3.852

Structure Matrix – This table has been removed because of size restrictions.

Functions at Group Centroids

Group	Function 1
Weeds	7.556
No Weeds	-6.044

Unstandardized canonical discriminant functions evaluated at group means

Classification Processing Summary

Processed		12
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		12

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	4	4.000
No Weeds	.500	5	5.000
Total	1.000	9	9.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
K_325	259664.478	267283.638
K_326	-86989.471	-114730.507
K_327	-169857.300	-211986.876
K_328	25995.646	189942.717
K_330	34127.862	-34436.475
K_334	45656.165	43702.440
K_346	-64238.675	-84647.286
(Constant)	-459.517	-603.115

Fisher's linear discriminant functions

Classification Results(a,b)

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases	Original	Count	Weeds	4	0	4

Selected			No Weeds	0	5	5
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	1	1	2
			No Weeds	0	1	1
		%	Weeds	50.0	50.0	100.0
			No Weeds	.0	100.0	100.0

a 100.0% of selected original grouped cases correctly classified.
b 66.7% of unselected original grouped cases correctly classified.

Spectrometer – All variables

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		16	66.7
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	8	33.3
	Total	8	33.3
Total		24	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	10.848(a)	100.0	100.0	.957

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.084	17.305	14	.240

Standardized Canonical Discriminant Function Coefficients

	Function
	1
K_325	17.991
K_326	-5.539
K_327	9.533
K_328	-13.077
K_330	-8.515
K_331	.758
K_333	-7.835
K_335	-4.347
K_336	.114
K_338	-3.407
K_342	8.616
K_351	17.288
K_363	-13.942
K_729	3.463

Structure Matrix – This table has been removed because of size restrictions.

Functions at Group Centroids

	Function
Group	1
Weeds	3.977
No Weeds	-2.386

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		24
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		24

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	6	6.000
No Weeds	.500	10	10.000
Total	1.000	16	16.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
K_325	174020.00	137337.147

	4	
K_326	-67974.711	-56800.355
K_327	102996.185	85563.291
K_328	-141374.166	-117174.213
K_330	-16950.960	-1799.726
K_331	-50672.178	-52084.917
K_333	-41157.115	-24770.404
K_335	-5323.765	3212.497
K_336	-81177.945	-81402.527
K_338	3578.116	10957.084
K_342	99059.611	81972.905
K_351	177862.259	142577.425
K_363	-164419.977	-135905.183
K_729	3854.231	3079.051
(Constant)	-420.762	-285.789

Fisher's linear discriminant functions

Classification Results(a,b)

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	6	0	6
			No Weeds	0	10	10
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	3	3	6
			No Weeds	0	2	2
		%	Weeds	50.0	50.0	100.0
			No Weeds	.0	100.0	100.0

a 100.0% of selected original grouped cases correctly classified.
b 62.5% of unselected original grouped cases correctly classified.

APPENDIX C

Balloon-borne Camera System
Discriminant Function Analysis
Output

Balloon-borne Camera – BU 45K

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		25	62.5
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	15	37.5
	Total	15	37.5
Total		40	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	4.175(a)	100.0	100.0	.898

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.193	32.875	6	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Red	3.016
Green	-.730
Blue	-2.065
Infrared - Band 1	-1.341
Infrared - Band 2	.294
Infrared - Band 3	1.337

Structure Matrix

	Function
	1
Red	.489
Green	.272
Infrared - Band 2	-.121

Infrared - Band 3	-.113
Blue	.079
Infrared - Band 1	-.054

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

	Function
Group	1
Weeds	1.883
No Weeds	-2.040

Unstandardized canonical discriminant functions evaluated at group means

Classification Processing Summary

Processed		40
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		40

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	13	13.000
No Weeds	.500	12	12.000
Total	1.000	25	25.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
Red	-1.230	-2.021
Green	.668	.874
Blue	2.443	3.219
Infrared - Band 1	6.676	7.071
Infrared - Band 2	-9.158	-9.271
Infrared - Band 3	1.195	.581
(Constant)	-516.217	-520.152

Fisher's linear discriminant functions

Classification Results(a,b)

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	13	0	13
			No Weeds	0	12	12
		%	Weeds	100.0	.0	100.0

			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	6	1	7
			No Weeds	0	8	8
		%	Weeds	85.7	14.3	100.0
			No Weeds	.0	100.0	100.0

a 100.0% of selected original grouped cases correctly classified.
b 93.3% of unselected original grouped cases correctly classified.

Balloon-borne Camera – BU 60K

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		27	67.5
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	13	32.5
	Total	13	32.5
Total		40	100.0

Group Statistics

Group		Mean	Std. Deviation	Valid N (listwise)	
				Unweighted	Weighted
Weeds	Red	143.12821	9.83609	13	13.000
	Green	135.71795	10.23817	13	13.000
	Blue	71.27350	9.48907	13	13.000
	Infrared Band 1	228.39316	10.38394	13	13.000
	Infrared Band 2	71.71368	9.95595	13	13.000
	Infrared Band 3	88.45513	7.96331	13	13.000
No Weeds	Red	110.25397	10.78887	14	14.000
	Green	114.48413	9.12201	14	14.000
	Blue	70.96032	10.25113	14	14.000
	Infrared Band 1	230.29107	9.11110	14	14.000
	Infrared Band 2	80.87679	4.72254	14	14.000
	Infrared Band 3	96.86280	4.81331	14	14.000
Total	Red	126.08230	19.57137	27	27.000
	Green	124.70782	14.38324	27	27.000
	Blue	71.11111	9.70187	27	27.000

	Infrared Band 1	229.37726	9.60239	27	27.000
	Infrared Band 2	76.46492	8.86946	27	27.000
	Infrared Band 3	92.81466	7.69278	27	27.000

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	11.700(a)	100.0	100.0	.960

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.079	55.916	6	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Red	-1.792
Green	-.350
Blue	1.955
Infrared Band 1	.264
Infrared Band 2	.085
Infrared Band 3	.023

Structure Matrix

	Function
	1
Red	-.483
Green	-.333
Infrared Band 3	.196
Infrared Band 2	.181
Infrared Band 1	.030
Blue	-.005

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

Group	Function 1
Weeds	-3.416
No Weeds	3.172

Unstandardized canonical discriminant functions evaluated at group means

Classification Processing Summary

Processed		40
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		40

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	13	13.000
No Weeds	.500	14	14.000
Total	1.000	27	27.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
Red	-2.277	-3.419
Green	3.183	2.944
Blue	1.331	2.633
Infrared Band 1	8.922	9.101
Infrared Band 2	-8.308	-8.235
Infrared Band 3	-.297	-.274
(Constant)	-808.962	-775.835

Fisher's linear discriminant functions

Classification Results(a,b)

			Group	Predicted Group Membership		Total
				Weeds	No Weeds	
Cases Selected	Original	Count	Weeds	13	0	13
			No Weeds	0	14	14
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	7	0	7
			No Weeds	0	6	6
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0

a 100.0% of selected original grouped cases correctly classified.
b 100.0% of unselected original grouped cases correctly classified.

Balloon-borne Camera – BU 75K

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		27	67.5
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	13	32.5
	Total	13	32.5
Total		40	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.985[a]	100.0	100.0	.704

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.504	15.085	6	.020

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Red	-3.658
Green	3.386
Blue	.423
Infrared - Band 1	-.250
Infrared - Band 2	1.911
Infrared - Band 3	-1.601

Structure Matrix

	Function
	1
Green	.298
Infrared - Band 2	.180
Blue	.171
Infrared - Band 1	.089
Red	.087
Infrared - Band 3	.051

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

Group	Function 1
Weeds	-.991
No Weeds	.920

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		40
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		40

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	13	13.000
No Weeds	.500	14	14.000
Total	1.000	27	27.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
Red	-.275	-.857
Green	-.801	-.220
Blue	2.321	2.413
Infrared - Band 1	4.282	4.247
Infrared - Band 2	-4.998	-4.586
Infrared - Band 3	-.201	-.566
(Constant)	-306.778	-304.054

Fisher's linear discriminant functions

Classification Results(a,b)

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	12	1	13
			No Weeds	3	11	14
		%	Weeds	92.3	7.7	100.0
			No Weeds	21.4	78.6	100.0

Cases Not Selected	Original	Count	Weeds	5	2	7
			No Weeds	1	5	6
		%	Weeds	71.4	28.6	100.0
			No Weeds	16.7	83.3	100.0

a 85.2% of selected original grouped cases correctly classified.
b 76.9% of unselected original grouped cases correctly classified.

Balloon-borne Camera – GO 45K

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		27	67.5
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	13	32.5
	Total	13	32.5
Total		40	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	8.769(a)	100.0	100.0	.947

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.102	50.143	6	.000

Standardized Canonical Discriminant Function Coefficients

	Function 1
Red	3.629
Green	-2.710
Blue	.171
Infrared - Band 1	3.156
Infrared - Band 2	.068
Infrared - Band 3	-2.521

Structure Matrix

	Function
	1
Red	.320
Green	.217
Infrared - Band 1	.128
Blue	.050
Infrared - Band 2	.006
Infrared - Band 3	-.005

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

	Function
Group	1
Weeds	2.957
No Weeds	-2.746

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		40
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		40

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	13	13.000
No Weeds	.500	14	14.000
Total	1.000	27	27.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
Red	3.474	2.098
Green	-1.880	-.621
Blue	2.196	2.107
Infrared - Band 1	11.026	9.755
Infrared - Band 2	-7.178	-7.216
Infrared - Band 3	-5.007	-3.417
(Constant)	-978.802	-808.303

Fisher's linear discriminant functions

Classification Results(a,b)

			Group	Predicted Group Membership Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	13	0	13
			No Weeds	0	14	14
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	7	0	7
			No Weeds	0	6	6
		%	Weeds	100.0	.0	100.0
			No Weeds	.0	100.0	100.0

a 100.0% of selected original grouped cases correctly classified.
b 100.0% of unselected original grouped cases correctly classified.

Balloon-borne Camera – GO 60K

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		27	67.5
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	13	32.5
	Total	13	32.5
Total		40	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	4.169(a)	100.0	100.0	.898

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.193	36.139	6	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Red	2.406
Green	-1.166
Blue	-.537
Infrared - Band 1	-1.118
Infrared - Band 2	-1.406
Infrared - Band 3	1.833

Structure Matrix

	Function
	1
Infrared - Band 2	-.486
Red	.385
Infrared - Band 3	-.378
Infrared - Band 1	-.371
Green	.244
Blue	.089

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

	Function
Group	1
Weeds	2.039
No Weeds	-1.893

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		40
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		40

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	13	13.000
No Weeds	.500	14	14.000
Total	1.000	27	27.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
Red	-3.611	-4.211
Green	4.386	4.702
Blue	-.646	-.442
Infrared - Band 1	8.070	8.487
Infrared - Band 2	-6.187	-5.497
Infrared - Band 3	-3.416	-4.424
(Constant)	-550.418	-578.581

Fisher's linear discriminant functions

Classification Results(a,b)

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	12	1	13
			No Weeds	0	14	14
		%	Weeds	92.3	7.7	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	5	2	7
			No Weeds	1	5	6
		%	Weeds	71.4	28.6	100.0
			No Weeds	16.7	83.3	100.0

a 96.3% of selected original grouped cases correctly classified.
b 76.9% of unselected original grouped cases correctly classified.

Balloon-borne Camera – GO 75K

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		27	67.5
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	13	32.5
	Total	13	32.5
Total		40	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	2.096(a)	100.0	100.0	.823

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.323	24.861	6	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Red	4.016
Green	-4.314
Blue	.382
Infrared - Band 1	.582
Infrared - Band 2	-.576
Infrared - Band 3	.282

Structure Matrix

	Function
	1
Infrared - Band 1	.224
Red	.198
Infrared - Band 3	.191
Infrared - Band 2	.067
Green	-.014
Blue	-.002

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

Group	Function 1
Weeds	-1.446
No Weeds	1.342

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		40
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		40

Classification Function Coefficients

	Group	
	Weeds	No Weeds
Red	-6.943	-6.114
Green	1.741	.652
Blue	12.763	12.894
Infrared - Band 1	17.947	18.091
Infrared - Band 2	-12.450	-12.620
Infrared - Band 3	-11.921	-11.809
(Constant)	-1142.454	-1152.423

Fisher's linear discriminant functions

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	13	13.000
No Weeds	.500	14	14.000
Total	1.000	27	27.000

Classification Results(a,b)

			Group	Predicted Group Membership		Total
				Weeds	No Weeds	
Cases Selected	Original	Count	Weeds	12	1	13
			No Weeds	0	14	14
		%	Weeds	92.3	7.7	100.0
			No Weeds	.0	100.0	100.0
Cases Not Selected	Original	Count	Weeds	6	1	7
			No Weeds	0	6	6
		%	Weeds	85.7	14.3	100.0
			No Weeds	.0	100.0	100.0

a 96.3% of selected original grouped cases correctly classified.
b 92.3% of unselected original grouped cases correctly classified.

Balloon-borne Camera – BU All

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		81	67.5
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0

	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	39	32.5
	Total	39	32.5
Total		120	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.262(a)	100.0	100.0	.747

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.442	62.035	6	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Red	2.585
Green	-1.317
Blue	-.937
Infrared - Band 1	.143
Infrared - Band 2	-1.027
Inrared - Band 3	.860

Structure Matrix

	Function
	1
Red	.525
Green	.321
Infrared - Band 2	-.182
Inrared - Band 3	-.127
Infrared - Band 1	.029
Blue	.017

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

	Function
Group	1
Weeds	1.151
No Weeds	-1.069

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		120
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		120

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	39	39.000
No Weeds	.500	42	42.000
Total	1.000	81	81.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
Red	-.973	-1.303
Green	.599	.789
Blue	1.021	1.212
Infrared - Band 1	3.906	3.885
Infrared - Band 2	-6.249	-6.019
Inrared - Band 3	1.386	1.182
(Constant)	-287.193	-277.113

Fisher's linear discriminant functions

Classification Results(a,b)

				Predicted Group Membership		
			Group	Weeds	No Weeds	Total
Cases Selected	Original	Count	Weeds	31	8	39
			No Weeds	3	39	42
		%	Weeds	79.5	20.5	100.0
			No Weeds	7.1	92.9	100.0
Cases Not Selected	Original	Count	Weeds	17	4	21
			No Weeds	0	18	18
		%	Weeds	81.0	19.0	100.0
			No Weeds	.0	100.0	100.0

a 86.4% of selected original grouped cases correctly classified.
b 89.7% of unselected original grouped cases correctly classified.

Balloon-borne Camera – GO All

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		81	67.5
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	39	32.5
	Total	39	32.5
Total		120	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.390(a)	100.0	100.0	.530

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.719	25.041	6	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Red	-.643
Green	2.005
Blue	-.868
Infrared - Band 1	1.132
Infrared - Band 2	-.583
Infrared - Band 3	-.992

Structure Matrix

	Function
	1
Red	.700
Green	.637
Infrared - Band 2	-.322
Infrared - Band 3	-.319
Blue	.254
Infrared - Band 1	-.098

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

Group	Function 1
Weeds	.640
No Weeds	-.595

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		120
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		120

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Weeds	.500	39	39.000
No Weeds	.500	42	42.000
Total	1.000	81	81.000

Classification Function Coefficients

	Group	
	Weeds	No Weeds
Red	-3.031	-2.986
Green	3.197	3.011
Blue	1.842	1.951
Infrared - Band 1	5.881	5.789
Infrared - Band 2	-6.509	-6.447
Infrared - Band 3	-.709	-.579
(Constant)	-465.288	-450.696

Fisher's linear discriminant functions

Classification Results(a,b)

			Group	Predicted Group Membership		Total
				Weeds	No Weeds	
Cases Selected	Original	Count	Weeds	27	12	39
			No Weeds	12	30	42
		%	Weeds	69.2	30.8	100.0
			No Weeds	28.6	71.4	100.0
Cases Not Selected	Original	Count	Weeds	13	8	21

Selected		No Weeds	8	10	18
	%	Weeds	61.9	38.1	100.0
		No Weeds	44.4	55.6	100.0

a 70.4% of selected original grouped cases correctly classified.
b 59.0% of unselected original grouped cases correctly classified.

Balloon-borne Camera – All Variables

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		160	66.7
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Unselected	80	33.3
	Total	80	33.3
Total		240	100.0

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.451(a)	100.0	100.0	.557

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.689	57.693	6	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Red	1.604
Green	-.409
Blue	-.693
Infrared - Band 1	.490
Infrared - Band 2	-.482
Infrared - Band 3	-.136

Structure Matrix

	Function

	1
Red	.706
Green	.510
Infrared - Band 2	-.223
Infrared - Band 3	-.201
Blue	.104
Infrared - Band 1	.028

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

Functions at Group Centroids

Group	Function 1
weeds	.659
No Weeds	-.676

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		240
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		240

Prior Probabilities for Groups

Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
weeds	.500	81	81.000
No Weeds	.500	79	79.000
Total	1.000	160	160.000

Classification Function Coefficients

	Group	
	weeds	No Weeds
Red	-1.679	-1.794
Green	1.487	1.523
Blue	1.581	1.670
Infrared - Band 1	4.552	4.508
Infrared - Band 2	-5.960	-5.899
Infrared - Band 3	.469	.489
(Constant)	-358.970	-351.344

Fisher's linear discriminant functions

Classification Results(a,b)

			Group	Predicted Group Membership		Total
				weeds	No Weeds	
Cases Selected	Original	Count	weeds	58	23	81
			No Weeds	21	58	79
		%	weeds	71.6	28.4	100.0
			No Weeds	26.6	73.4	100.0
Cases Not Selected	Original	Count	weeds	27	12	39
			No Weeds	12	29	41
		%	weeds	69.2	30.8	100.0
			No Weeds	29.3	70.7	100.0

a 72.5% of selected original grouped cases correctly classified.
b 70.0% of unselected original grouped cases correctly classified.