University of Southern Queensland

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Non-Contact Visual Soil Moisture Estimation

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Abstract

Drought in recent years has highlighted the importance of maintaining a sustainable water resource. Improvements in irrigation management can significantly increase water use efficiency and crop productivity for Australian agriculture. Measurement of Soil Moisture Content (SMC) is essential for improving irrigation management. Existing commercially-available SMC sensors require contact with the soil and measure only a single fixed point in a field. However, there can be significant spatial variability in soil properties and SMC within a field, and installation of multiple SMC sensors within a field is often not practical or economical. Non-contact methods reported in the literature for SMC estimation include satellite imagery of soil and plants. Satellite imagery approaches capture spectral bands in the visual, infrared and microwave wavelengths and then extract crop vigour to estimate SMC. However, this technology has a limited spatial resolution ($30m^2$) and temporal resolution (every 2-3 weeks). An alternative approach uses a ground-based camera that can be moved around the field on ground-based or aerial vehicles as required, providing high spatial and temporal resolution SMC estimation. A camera-based estimation system has been developed. Red and near infrared images of plants are processed using MATLAB® Image Processing Tool box and ColorWorker® software. A MATLAB® program has been developed that performs the following image analysis: (i) overlays images of different spectral bands; (ii) selects key regions in the visual image; (iii) selects key regions in the infrared image; and (iv) calculates reflectance in the visible and infrared bands. Multiple regression analysis has been conducted to analyse the calculated reflectance and develop a model that estimates SMC. The camera and image analysis system has been evaluated on chamomile, lettuce and lucerne plants. These plants were grown under three irrigation levels (20%, 30% and 40% VWC) and two soil types (loam and sand). Each sample was replicated twice, giving a total of 36 samples. Daily digital images were taken of plants with band pass filters in red and near infrared bands. An on-site weather station provides micro climate data which is used calibrate the models. Three spectral responses were derived from the images: (i) chlorophyll a/b ratio – Chl(a/b); (ii) Normalised Difference Vegetation Index – NDVI; and (iii) near infrared at 850 ηm – IR850. A soil moisture estimation model was derived for each plant and soil type which showed a significant correlation between one of the spectral responses of the plant and SMC. The Root Mean Squared Error RMSE value was used to test the accuracy of the estimation models. There were nine models which had a RMSE less than 5%. Two lucerne/sand models with NDVI response had RMSE value of 1.39% and 1.49% Volumetric Water Content (VWC), both replicates in each model were within 0.40%. Lucerne/sand was also sensitive in IR850 response, with a RMSE for replica 1 and 2 of 2.04% and 2.89% VWC respectively. Chamomile/loam was sensitive to IR850 response across all three irrigation levels, all RMSE values were below 2.89% VWC for the data obtained during August. Lettuce/loam was sensitive to IR850 response for data obtained during July. Replicates 1 and 2 had RMSE values of 1.9% and 2.56% VWC. There were no correllations for the chl(a/b) index. This research has shown that in some conditions SMC can be estimated from plant spectral response (NDVI and IR850) for chamomile, lettuce and lucerne. Further research is needed to understand the effects of what plant nutrition and disease have on the spectral response and SMC estimation.

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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.

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This project has been a rewarding and challenging exercise. The combination of the size of the project in terms of what had to be completed and the duration of project was testing at times. I have had great support around me, which has enabled me to complete this project. I would like to acknowledge Dr Alison McCarthy as the project supervisor and thank her for the guidance throughout the project. She has been generous with her time and encouragement. I could not have completed this project without the support of my wife and understanding of my children and close friends. Thank you.

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Chapter 1

Introduction

1.1 Background

Water is a valuable resource which society is dependent on for survival. According to the Australian Bureau of Statistics (2012) 6,596 GL of water was used for irrigation purposes across Australia during 2009 and 2010. Irrigation on its own made up 52% of the total water used during that same year. Therefore efficient use of water in agriculture is crucial to ensure its sustainability into the future.

An important part of efficient water use is to be able to effectively manage irrigation to optimise crop production and minimise over watering and wastage. Knowledge of soil moisture content (SMC) can be a tool to effectively manage irrigation.

Traditionally SMC has been measured via in situ techniques such as Time Domain Reflectometer (TDR), Capacitive Sensors and Standing Wave Sensors. These sensor types can produce accurate measurements by determining the dielectric constant of the soil, then deriving the soil moisture content. While accuracy is good, the process of measuring is labour intensive and only point measurements can be made. To get full coverage of a target area, a network of sensors would need to be installed.

An automatic non-contact based measurement would provide a cheap and quick evaluation of soil moisture. Therefore this would be more likely to be adopted as a common place tool to evaluate soil moisture, rather than relying on the farmer's experience and judgement to irrigation.

Past research has proved that soil moisture content can be inferred from remote imaging. The methods used have mostly utilised data which is from satellite mounted sensors operating in multiple bands of the electromagnetic spectrum. Some research has also used data from multiple satellites and sensors to mitigate against a gap in data due to heavy cloud cover. There are some aspects of satellite data which need to be considered, including cost of subscription, temporal/spatial resolution of the available data and coverage of the region being targeted.

SMC estimation using local data rather than satellite data would provide end users with more control over the temporal and spatial resolution of the data and reduce the effect of cloud cover. By providing greater detailed data it will give the end user the ability to monitor a particular crop due for irrigation. This could be performed at a time suited to the end user and not relying on when data has been made available to the subscriber of a particular product.

Existing methods of soil moisture estimation using satellite imagery could be adapted to a system which utilises data obtained at a local level. This includes methods such as Normalised Difference Vegetation Index (NDVI), near infrared analysis and visual techniques in the spectral range of 690 to 700 ηm.

1.2 Objectives

This report investigated methods of SMC estimation, from both in situ and remote sensed data. A suitable technique was selected from the findings of the literature review, to develop a visual based non-contact SMC estimation. The motivation behind this type of estimation is to provide the end user with increased spatial and temporal resolution. This will mean irrigation management will be more efficient, as the irrigator can check a particular area for a soil moisture status before irrigation is started. The technique will focus on obtaining data from plant canopy, this will be suitable to monitor crops, as monitoring the soil directly will be obscured. The soil moisture estimation needs to be autonomous in processing and interpreting the data to allow for an easy output of soil moisture content, without the need for specialist knowledge. The project specification (Appendix A) objectives are:

- Conduct literature review of visual plant and soil responses to soil moisture content.
- Review camera/sensor technology and image analysis techniques for capturing and automatically analysing visual plant responses to soil moisture.
- Design a method of obtaining accurate data of plant response to varying levels of soil moisture content.
- Collect plant image data at varying levels of soil moisture content using candidate camera system/s.
- Analyse data to extract plant features that indicate soil water status.
- Develop algorithm which can identify changes in plant reaction and estimate the value of soil moisture content.
- Evaluate algorithm performance on soil moisture content estimation.

As time and resources permit:

- Adapt and refine algorithm to estimate soil moisture for other plant types.
- Develop and evaluate a proof-of-concept non-contact visual soil moisture estimation system.

Chapter 2

Literature Review

2.1 Soil Moisture Content (SMC)

Soil moisture content is the amount of water held by the soil. SMC can be expressed as a ratio of moisture present in the soil compared to the soils capacity to hold water. All SMC values in this report will be stated in terms of volumetric water content (VWC) and expressed as a percentage. For completeness the soil moisture content can be measured in tension kPa. This is the pressure the plant needs to overcome to be able to extract water from the soil.

Not all water present in the soil is available for vegetation. The International Atomic Energy Agency (IAEA, 2008) describe the available water to plants as being the difference between the "wilting point" and "field capacity". The wilting point is the minimum SMC, at which point the moisture left in the soil cannot be extracted by the plants. The field capacity is the maximum SMC that can be held by the soil before water drains away.

2.2 Determining Soil Moisture Content

SMC measurement can be categorised as direct measurement and non-contact sensing. This project will be developing a non-contact method of SMC estimation, in the process a method of direct measurement will be utilised, which will provide a reference point for the project experiment. The reference will be analysed with plant visual data to determine if a relationship exists and to calibrate SMC prediction models. The measured SMC will also be used to verify the accuracy of the prediction models. The following review will look at different methods in each category.

2.2.1 Direct Measurement

Soil Moisture Content can be measured and expressed as a gravimetric or volumetric ratio or percentage. A common technique involves taking a soil sample, weighing it, drying the sample in an oven and then weighing it again. The difference in weight is directly related to the water content of the soil. According to International Atomic Energy Agency (IAEA, 2008), to express the result in gravimetric units, the result is normalised by dividing the result by the dried weight of the sample with the units Mg Mg^{-1}. For volumetric units m^3m^{-3}, the mass of water lost is converted to volume by dividing the mass by the water density (Equation 2.1), then the volume of water lost is divided by the volume of the sample. The process of measuring SMC directly is labour intensive and is a single point measurement only, which is useful for calibration of sensors.

$$Volumetric = \frac{WaterMass}{WaterDensity} \tag{2.1}$$

Time Domain Reflectometry (TDR) measures soil dielectric constant by generating a high speed electromagnetic pulse through a line of known length. The reflected pulse is measured and the travel time of the pulse is used to find the dielectric constant. This type of sensor has a high accuracy and a high cost (ICT International, 2014).

Neutron Probe is another direct method of measuring SMC. The probe is placed into an aluminium access tube where it emits neutrons into the soil. The probe then detects the speed of the neutrons as it collides with hydrogen atoms present in the soil. This collision causes the neutrons to slow and this is related to the soil moisture content. Giddings and Williams (2004) discuss the advantages of a Neutron probe method as being suitable for a large range of soil types and being able to produce a root zone profile. The disadvantages of this method is that it does utilise radiation to function, which is a potential health hazard and therefore the user must be registered. Another disadvantage is that the results begin to lose accuracy within 100mm of the surface.

Capacitive type sensors consist of two probes which are inserted into the soil. The soil properties determine the dielectric constant between the two probes. ICT International (2014) state by measuring the capacitor charge time, a linear relationship can be formed with the dielectric constant of the soil and therefore SMC. The cost of this type of sensor is low.

Gypsum Block uses electrical resistance to measure soil water tension. Department of Environment and Primary Industries (n.d.) describe the sensor as consisting of two electrodes surrounded by a gypsum block. The block is buried in the soil, where it will absorb moisture if soil is wet and releases moisture if the soil is dry. The electrical resistance will increase when moisture is low and decrease when soil moisture is high. The gypsum block is useful for monitoring dry soils in the range of 50 kPa and above.

Standing Wave also derives SMC for the dielectric constant of the soil. ICT International (2014) state that their brand of sensor uses an oscillator to generate a signal of which the amplitude of the reflected signal is measured and converted to SMC. The cost of this type of sensor is rated as moderate.

2.2.2 Non-Contact Sensing

Knowledge of **Plant Physiology and Spectral Response** is required to understand how remote SMC estimation works. Figure 2.1 depicts the cross section of a typical green leaf. The cross section shows the interaction of infrared, green, red and blue light with the palisade and mesophyll cells of the leaf. The red and blue light are absorbed in the palisade cells and used for photosynthesis, while the infrared radiation penetrates into the centre of the leaf or mesophyll layer. The level of reflected infrared radiation is influenced by the water content in the leaf. This illustrates the type of parameters which could be focussed on to develop a method of estimating SMC. Gibson and Power (2000) compares the response between healthy, stressed and soil measurements across the visible and IR range. Figure 2.2 shows that in the healthy vegetation there is a dip in the reflectance band around 700ηm. In the stressed vegetation the dip has decreased. The healthy vegetation also shows greater reflectance in the visible green and NIR parts of the spectrum compared to the stressed vegetation. This agrees with Carter, Cibula and Miller (1996) who state the leaf chlorophyll begins to decrease and therefore reflectance is increased in the $695 \pm 5\eta$m. Gibson (Gibson and Power, 2000) describes the NIR part of the spectrum as having the largest peak in reflectance compared to green in the visible spectrum.

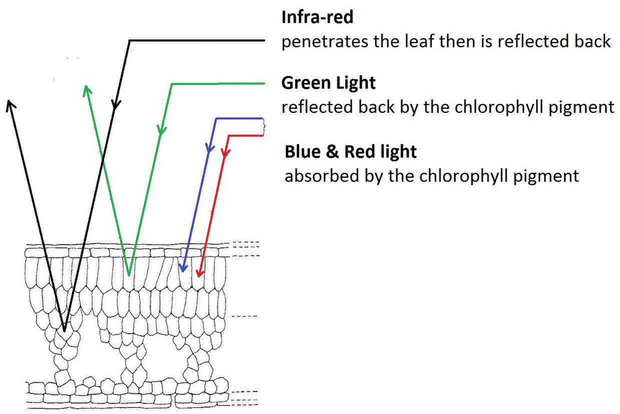

Figure 2.1: Plant Physiology

Source: (Gibson and Power, 2000)

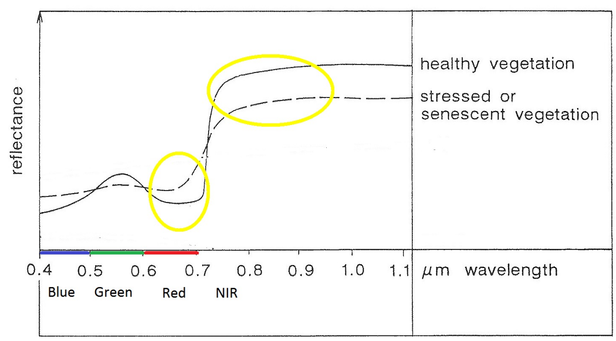

Figure 2.2: Plant Spectral Response

Source: (Gibson and Power, 2000)

Hyperspectral Sensors measure the spectral reflectance at high spectral resolution and can be either active or passive. This type of technology is available as a proximal or a remote device. White and Raine (2008) states the passive devices require constant calibration via a white object with known reflectance and at the same solar irradiance to the target object been measured. The cost and technical knowledge required to use this technique is prohibitive to the end user and therefore mainly used in research only. The unit of measure is a ratio of the maximum reflectance and has a value ranging from 0 to 1 for each measured spectral range.

Thermal sensing of crop canopy can determine plant transpiration rate through the temperature. Thermographs are visual images which indicate a thermal signature of the target. The use of thermal data of a crop canopy can detect the response of the plant to the current conditions. A plant has the ability to vary it's transpiration and therefore moisture loss, by changing the aperture size of the stomatal. As the stomatal size is reduced the amount of transpiration is reduced, which removes the evaporative cooling effect of the plant, and therefore the temperature of the plant increases. Carter, Cibula and Miller (1996) compared narrowband reflectance ratios of thermal images for use as an early detection of plant stress. They concluded that the canopy temperature from 800 to 1200 ηm band was not effective, as there was a negative effect from environmental conditions, such as wind and rain.

Thermal inertia is another approach to soil moisture estimation using thermal sensing to utilise thermal inertia of the surface. Kuenzer and Dech (2013) defines thermal inertia (I) as the resistance of an object to increase temperature by 1K. Thermal Inertia is dependent on three parameters, heat capacity (c) which is the energy required to increase temperature by 1K, density of material (p) and thermal conductivity of the material (K). These parameters and therefore thermal inertia can not be determined remotely. An approximation of thermal inertia, known as Apparent Thermal Inertia (ATI) can be calculated from thermal daytime and night time thermal and visual images. The equation for ATI is shown in Equation 2.2.

ATI technique is used in China North plain and gives the greatest correlation to SMC when the land surface is homogeneous and has a vegetation cover of constant agrotype (min Li, lin Liu, yu Zhang, Wang, Sun and xin Wang, 2004). ATI is affected by vegetation cover, min Li et al. (2004) used a correction formula and NDVI to adjust for the effect of vegetation cover. ATI is suitable for areas with only light vegetation cover (min Li et al., 2004; Kuenzer and Dech, 2013). For the application of crop canopy monitoring, the ATI approach would not be suited due to the heavy vegetation coverage.

$$ATI = \frac{(1-A)}{\Delta T} \tag{2.2}$$

Where A is the surface Albedo and ΔT is the difference in temperature between day and night time thermal images.

Microwave sensing is a common technique for measuring soil moisture. Alshikaili (2007) reports the advantages of not being effected by night time, cloud, smoke or precipitation. Microwave sensors can be either active or passive. Passive sensors detect natural radiation from the object, operating in the spectral band of 0.1mm to 3cm. Active sensors (radar) produce their own radiation and measure the reflected radiation from the target. Kuenzer and Dech (2013) state the limitation of microwave data is a 25 to 50 km spatial resolution.

Visible and NIR imaging has been used in numerous studies to remotely determine plant parameters. The visible spectrum can be used to analyses the colour of plant foliage. As shown in Figure 2.1, healthy vegetation will absorb red and blue light. The red and blue light is used by the chlorophyll pigment to convert energy during photosynthesis. Kriedemann (1999) reported in *Plants in Action: Adaptation in Nature, Performance in Cultivation* that Chlorophyll can be separated into chlorophyll a (CHla) and chlorophyll b (CHlb). Both CHla and CHlb are required for plant photosynthesis; however, each has a different function and the ratio (of a/b) varies with the condition the plant is exposed to. CHla is associated with processing energy absorbed where high light levels are present. Where low light levels are present, more resources of the plant are required to optimise light harvesting; therefore there is less of CHla and more of CHlb.

CHla and CHlb absorb energy from the blue and red parts of the visible spectrum. CHla has maximum absorption at wavelength 430 ηm and secondary peak at 660ηm, CHlb has maximum absorption at wavelength 450 ηm and secondary peak at 640ηm. By monitoring these narrow bands of the visible spectrum, the rate of chlorophyll content can be estimated and analysed with SMC. If a relationship between SMC and Chl(a/b) exists, this could be developed to predict SMC from the visual response of the plant.

Sarker, Rahman and Paul (1999) studied the effect of soil moisture on Retaliative Leaf Water Content RLWC and chlorophyll across four wheat varieties. It was found that soil moisture had a significant effect on chlorophyll a/b ratio. Pirzad, Shakiba, Zehtab-Salmasi, Abolghasem Mohammadi, Darvishzadeh and Samadi (2011) conducted an experiment on Matricaria chamomilla L and reported on the effect of water stress on RLWC, chlorophyll, proline and soluble carbohydrates. They concluded that water stress has a significant effect on chlorophyll. When irrigation levels were between field capacity and 55% chlorophyll varied with SMC. It was also noted that other measurements of proline and soluble carbohydrate were measured using a spectrophotometer and bands of 515 ηm and 625 ηm respectively. These additional parameters may play a role in discounting some unwanted variables in the future.

Xue and Yang (2009) studied the relationship between leaf chlorophyll content and plant indices derived from hyperspectral reflectance of leafy green vegetables. The vegetable varieties used were Lactuca sativa (Lettuce), Brassica chinensis L (Pakchoi) and Spinacia oleracea L (Spinach). The results proved a strong correlation with chlorophyll content.

The spectral response of the vegetation changes as the condition of the plant changes. When the plant begins to stress from deficiency in water or nutrient, or suffer from disease for example, the cell structure is altered and the spectral response is affected. There is generally a decrease in IR reflectance and an increase in visual reflectance (Gibson and Power, 2000).

While plant response in chlorophyll and therefore spectral response in the blue and red regions is not solely determined by soil moisture content, it is a starting point for use in non-contact SMC estimation. Other factors which influence the measurement will be isolated from this experiment and factored into the solution once the fundamental principle has been proven.

2.2.3 Vegetation Indices

Vegetation indices are used to estimate vegetation parameters from spectral reflectance at various wavelengths throughout the electromagnetic spectrum. Some of these indices are discussed below.

Normalised Difference Vegetation Index (NDVI) This index is used to remotely estimate the density of vegetation cover from sparse to dense being 0 to 1 respectively. The index is a ratio of NIR and visible (red) spectrum as show in Equation 2.3. The application of NDVI was extended by Schnur, Xie and Wang (2010) to estimate root zone SMC. The NDVI was derived from Moderate Resolution Imaging Spectroradiometer (MODIS). A correlation was found, however when the soil moisture was low the correlation did not exist.

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)} \tag{2.3}$$

Visible and Shortwave infrared Drought Index (VSDI) is an alternative to NDVI for real time drought monitoring. Zhang, Hong, Qin and Liu (2013) indicates that NDVI is not suitable from drought monitoring due to the time lag between drought and NDVI response. The equation for VSDI is shown in Equation 2.4.

$$VSDI = 1 - [(\rho_{SWIR} - \rho_{blue}) + (\rho_{red} - \rho_{blue})] \tag{2.4}$$

Where ρ is the reflectance of the shortwave infrared (SWIR), red and blue parts of the spectrum.

Zhang et al. (2013) states the VSDI can give a measurement of wetness across various surfaces by using the SWIR, blue bands and water absorbing indicator bands as a reference to gauge moisture variation. Zhang et al. (2013) indicate that NIR is not used in the VSDI, as it has no direct response to water stress and is effected by other factors such as leaf structure, plant density and plant structure. This view supports with Gibson (Gibson and Power, 2000) in that water content has a greater effect when the spectral range is above 1300 ηm.

Water Index (WI) is a ratio of two different spectral bands, namely 970ηm and 900ηm as used by Peñuelas, Pinol, Ogaya and Filella (1997) and is shown in Equation 2.5. The water absorption band of the spectrum is at 970ηm, while the reference band not influenced by water is 900ηm. Peñuelas et al. (1997) used this version of the WI to determine the variation in plant water content, the inverse of this equation can give the plant water deficiency.

$$WI = \frac{R900}{R970} \tag{2.5}$$

2.3 Project Area of Research

Based on the findings of the literature review and the areas not previously studied, this project will be focussed on finding a relationship between spectral response of plant canopy, obtained from a standard digital images, and testing for a relationship directly with SMC. Any significant correlations will be modelled and used to predict SMC from appropriate spectral response.

The literature review has identified research which has shown a correlation between SMC and chlorophyll (a/b) ratio of wheat (Sarker et al., 1999) and chamomile (Pirzad et al., 2011). This research used direct methods to measure chlorophyll content of the plant foliage. Research by Xue and Yang (2009) showed it was possible to estimate chlorophyll content from spectral analysis of plant leaves (lettuce) using a spectrometer, which still involved removing leaves from the plant. The first area of research for this project will investigate plant response in narrow bands of the electromagnetic spectrum which relate to chlorophyll (a/b) ratio. The method of analysis will use the candidate image capture system, to gain spectral data at plant canopy level in order to estimate the vegetation index of Chl(a/b) (Equation 2.6), and then analysis this with SMC data.

$$Chl(a/b) = \frac{R640}{R660} \tag{2.6}$$

The NIR part the spectrum has been identified by Gibson and Power (2000) as showing changes in absorption with changes in plant condition. This region is also used in the WI and used by Peñuelas et al. (1997) to determine plant water content. The second area of research for this project will be to analyse the plant response to the NIR part of the spectrum and to test for a correlation directly with SMC data.

NDVI vegetation index has been used by (Schnur et al., 2010) with some correlation being identified during certain conditions. A third area of research will include a NDVI derived from the chosen image capture system. This data will be obtained at plant canopy level as opposed to the satellite based MODIS NDVI.

The plants chosen for this project will be Chamomile and Lettuce as used by Pirzad et al. (2011) and Xue and Yang (2009) respectively. In addition, lucerne has been selected as the third plant to extend the research. Lucerne is a commonly irrigated crop in central Victoria where the experiment was conducted.

Table 2.1 displays a summary of plant types which have shown some correlation between a response in the plant to plant water status or varying irrigation regimes.

Scientific Name	Common Name	Correlation	Reference
Arbutus unedo	Strawberry Tree (tree)		
Quercus Coccifera	Kermes Oak (tree)		
Cistus albidus	Rock Rose (shrub)		
Cistus Monspeliensis	Montpelier Rock Rose (shrub)	WI with Plant Water Concentration	Peñuelas et al. (1997)
Phillyrea Angustifolia	Narrow-leaved mock privet (shrub)		
Pistacia Lentiscus	Mastic Tree (tree)		
Brachypodium Retusum	Not Known (grass)		
Matricaria chamomilla L	Wild chamomile (annual)	Water Stress with Chl a & b	Pirzad et al. (2011)
Triticum aestivum L	Bread Wheat (annual)	SMC with Chl a/b	Sarker et al. (1999)
Lactuca sativa L	Lettuce		
Brassica chinensis L	Pakchoi	Leaf Chl with hyperspectral reflectance	Xue and Yang (2009)
Spinacia oleracea L	Spinach		

Table 2.1: Summary of plants used in previous studies

Chapter 3

Proposed Estimation System

The Proposed Estimation System hardware will consist of a camera, optical filters, x-right colour checker, weather station and SMC meter. System software will consist of MATLAB®, ColourWorker® and Microsoft® Excel and will be used to perform image processing and modelling. Figure 3.1 shows the proposed system block diagram. The raw data is obtained from the standard digital camera detailed in Section 3.2. The three filters described in Section 3.2.2 will be used to produce a digital image at the target wavelength. SMC data will be measured daily with the Vegetronix capacitive probe (Section 3.1), and calculated daily with data from the weather station and irrigation quantity as discussed in Section 4.4.2.

The system will begin with obtaining digital images of the target wavelengths. Only the VIS image is processed with ColourWorker® for narrow band spectral response, where all images are imported into the MATLAB spectral reflectance block for reflectance estimation for each wavelength.

The narrow band spectral response utilises ColourWorker® to analyse each plant sample. The output is the spectral response between 400 and 700 ηm. This data is imported into Excel, where the specific wavelegnths of 640 and 660 ηm are identified and the Chl (a/b) ratio calculated.

The spectral reflectance is calculated in MATLAB® image processing as discussed in Section 3.4.2. The output is the estimated spectral reflectance for IR850 filter and the NDVI vegetation index.

Multiple regression is performed in MATLAB and uses inputs of Chl(a/b) and NDVI indices and IR850 spectral response. Weather data and SMC data are also inputs in the multiple regression block. The output of the multiple regression are the variables most significant to plant spectral response in IR850, Chl(a/b) and NDVI plant indices.

Model coefficients of determination are perform with the most significant variables. The output of this block is a series of prediction models for plant samples and reponses which have shown a significant relationship.

The final block in the system is the verification stage. The R^2 and root mean squared error RMSE (Chapter 6) are calculated for each model and for both calibration and verfication data as identified in Section 5.1.3.

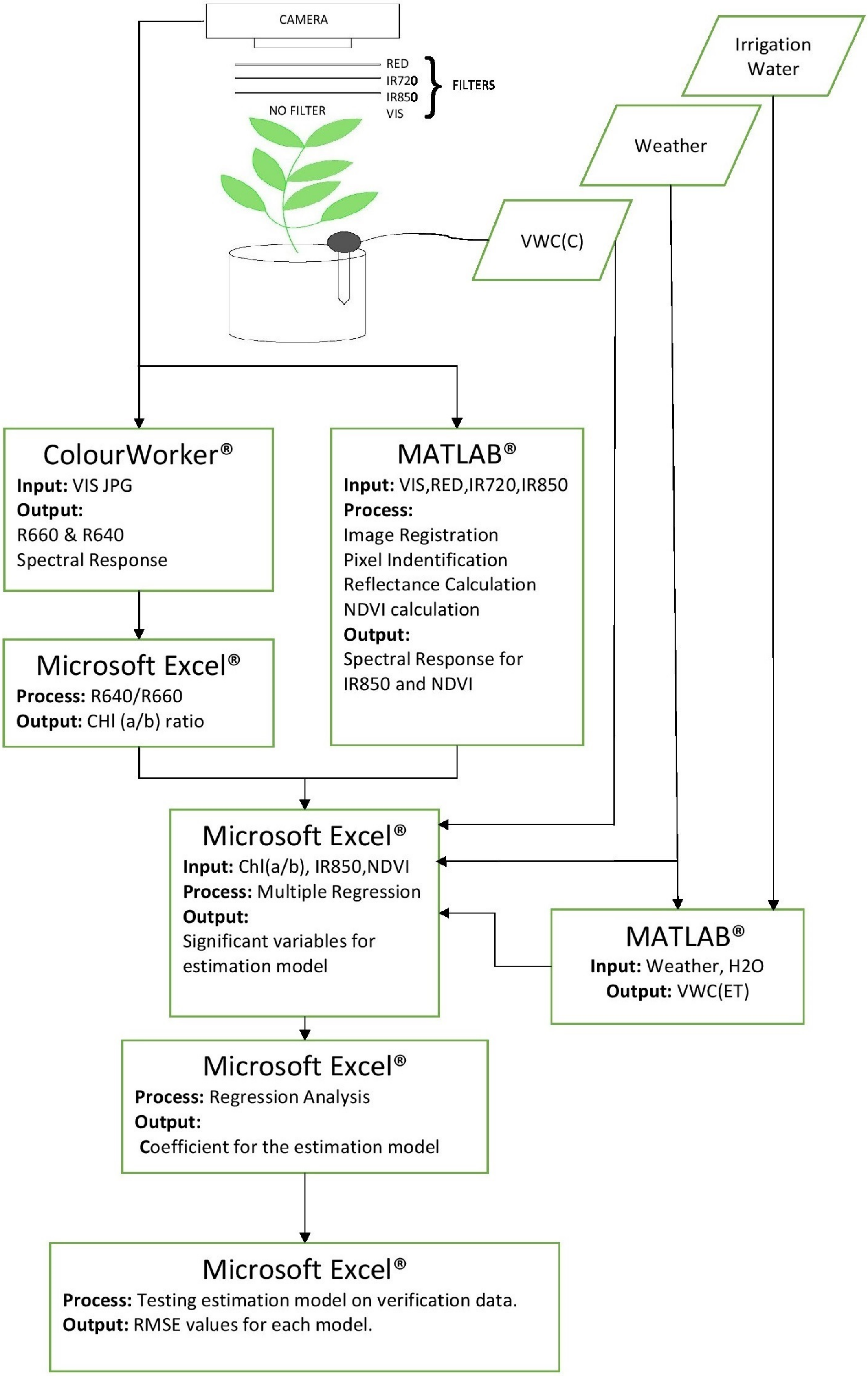

Figure 3.1: Estimation system block diagram

3.1 Review of Technology Required

The **Soil Moisture Meter** chosen for measuring SMC directly is a capacitive type probe. The manufacture is Vegetronix, model VG-METER-200. This model was chosen for its ease of use and it is relatively non destructive to the potting media. The VG-METER-200 also provide an option to measure the SMC in Volume Water Content (VWC) as a percentage. The unit has the capability to connect via serial USB to a PC to log values over time. Temperature, light level and time are also measured simultaneously. The VG-METER-200 meter is shown in Figure 3.2

Figure 3.2: Vegetronix VG-METER-200 Soil Moiture Meter

Source: (Vegetronix, n.d.)

The **Digital Camera** used for visual images is the Olympus mju 750. It has a 7.1MP CCD sensor and the output file is in JPEG format. The camera can sense into the NIR range, as tested against an infrared remote control LED.

Security cameras with a night time capability were considered as an option to capture an image in the NIR range. These cameras are common and are made by numerous manufactures. The cameras usually come fitted with IR LEDs to illuminate the area with infrared light. This camera will only be used in this project if the standard digital camera is not successful.

Thermal Imaging Cameras were considered for this project. They are commercially available and produced by many manufacturers with various resolutions and options. Generally speaking the standard spectral range is in the order of 7,500 ηm to 13,000 ηm. This range is outside the NIR and therefore not considered as suitable for this project.

3.2 Image Capture System

The Digital Camera used for capturing images is the Olympus mju 750. It has a 7.1MP CCD sensor and outputs a file in JPEG format. The camera can sense into the NIR range, as tested against an infrared remote control LED with a wavelength of 890nm.

3.2.1 Wavelengths to be analysed

The regions of the electromagnetic spectrum which are of interest in this project, range across the visible and NIR. As shown in the spectral response for healthy and senescent vegetation (Figure 2.2), there is a change in spectral response which is most prominent around the red edge and NIR, or wavelengths of 650 to 750nm and greater than 750nm respectively.

The exact wavelengths to be analysed in this project were determined by the available filters summarised in Table 3.1. The target wavelengths are listed below, in practice the various filters overlapped these wavelengths.

- 640ηm
- 660ηm
- 720ηm
- 850ηm

Remote visual SMC estimation will rely on the visual response of the plant foliage. The visual change will be too small to be obvious to the naked eye. It is proposed that the use of a commercially available digital camera and image processing will be able to detect changes related to SMC. Previous research performed by Pirzad et al. (2011) highlighted that irrigation had a significant effect on the chlorophyll a/b ratio for chamomile leaves. In a separate study, Xue and Yang (2009) successfully derived leaf chlorophyll content of green leafy vegetables, including lettuce, from hyper-spectral reflectance. Part of this experiment will look at the spectral response of chamomile and lettuce plants in a wavelength ratio 640/660 nm. This will equate to the chlorophyll (a/b) ratio.

Gibson and Power (2000) states in *Introductory Remote Sensing: Digital Image Processing and Applications*, that in general there is a decrease in IR reflectance as a plant stresses due to water or nutrient deficiency. The wavelength of 850nm was chosen to represent the NIR part of the electromagnetic spectrum. This wavelength is still within the range of the chosen camera and will provide NIR reference for use in NDVI measurements and WI (Peñuelas et al., 1997).

3.2.2 Optical Filters

A total of five images were taken each day. Interchanging external filters to the camera allowed each image to capture the response of the plant from a different part of the electromagnetic spectrum. The filters used are listed in Table 3.1 with spectral specifications.

Table 3.1: Optical filters used in experiment

Image No	Name	Details	Specification
1	VIS	No Filter	450 - 750 nm
2	RED	Roscolux #325	620 - 700 nm
3	IR720	Rocolax	40% at 720 nm
4	IR850	Citiwide Digital Experts	$>$ 850 nm
5	NEG	exposed/processed negative	70% at 800 nm (North Country Radio, 2011)

The IR720, IR850 and NEG filter required a change in camera settings from the standard visual images. The settings were determined from an initial trial. The optimum setting for this camera were an ISO setting of 1600 and white balance set on auto.

3.2.3 Image Analysis Techniques

Gilchrist (n.d.) explains in *A Simple Method to Determine Surface Albedo Using Digital Photography* that it is possible to obtain a relative albedo (A_{REL}) of a surface compared to a known surface, shown in Equation 3.1. Where the brightness of the reference and unknown surface (B_{REF} and B_{UN} respectively) are taken from the histogram of the digital image. The absolute albedo (A_{ABS}) of the unknown surface can then be determined by Equation 3.2.

$$A_{REL} = \frac{B_{UN}}{B_{REF}} \tag{3.1}$$

$$A_{ABS} = B_{REF} \times A_{REL} \tag{3.2}$$

Gilchrist (n.d.) used a lux meter to determine the initial Albedo of the reference surface. This was done by calculating the ratio of reflected to incident light of the reference surface. The results of this method agree with published Albedo values. Gilchrist reported that the results of the above method were within 3% of the values measured by the lux meter method. He noted that working with RAW image files would improve accuracy as brightness would not be compressed to 256 levels.

The ColourWorker® application was developed by Lane (n.d.) at the University of Sussex. It is based on the MATLAB® platform, and is used for reflectence measurements of coloured photos taken with standard digital cameras. This provides an economical method of obtaining accurate spectral measurements without the need for expensive lab equipment. The spectural range can be extended into the NIR with a compatible camera. ColourWorker® was created by Lane (n.d.) and the University of Sussex. The application is free for academic use.

The ColourWorker® application uses a colour standard in the form of the x-rite ColorChecker, as shown in Figure 3.3. The results can be exported as a .csv file for use in third party applications.

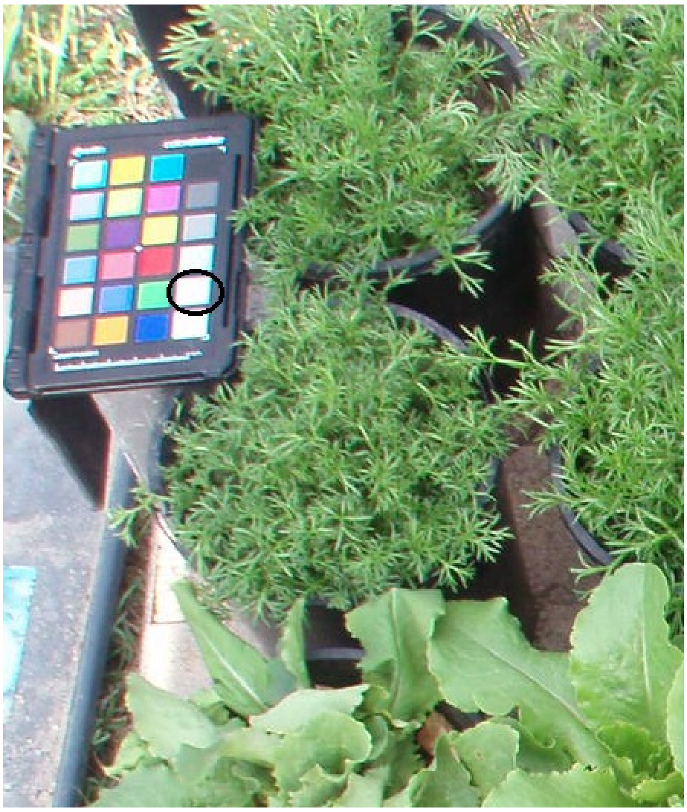

Figure 3.3: x-rite ColorChecker with reference patch circled

Source: (Watson, Paul. 2014)

3.2.4 Calibration of Colour Reference Chart

The x-right colour checker passport was placed in each image as a reference point for the ColourWorker software, and for the image analysis using MATLAB. The colour checker was used as a common reference object, to estimate the pixel intensity across varying degrees of ambient light.

Figure 3.3 show the patch selected to be the reference circled in black, this is the closest to the larger white balance card included on the reverse side. To calibrate the patch, the albedo of the white reference card was estimated. The colour checker was placed at the location of the experiment with the white balance patch facing up. Using a Dick Smiths Electronics Lux meter the incident lux L_i was measured 5 cm above the surface of the chart. The reflected lux L_r measurement was then taken 5 cm above the surface of the chart. This was performed by facing the lux sensor towards the chart (at a slight angle to avoid producing a shadow). The albedo A_r of the patch is calculated from Equation 3.3.

$$A_r = \frac{L_r}{L_i} = \frac{215}{1217} = 0.1766 \tag{3.3}$$

The albedo of the reference patch will be 18%. This value will be used as a reference to determine the albedo of the plants in the image. The sensitivity of this lux meter is optimum at 550 nm and has a normal distribution ranging across the visible part of the spectrum. The assumption has been made that NIR wavelengths will have a similar reflectance to visible wavelengths on the reference patch.

3.3 Data Collection and Management

The potted plants and x-right colour checker were grouped so that only one image per filter type was needed per day. A tripod was used to stabilise the camera and create a consistent distance from the experiment across all images taken.

Images were taken at the same time as SMC measurements. This data was collected daily at 8am. Due to external factors, the time of day moved from 8 am to 4 pm. During this time of year at the experiment location, the difference in temperature and ambient light between these times of day were not significant. The daily SMC data was manually recorded in a log book at the time of measurement and then entered into a Microsoft® Excel spreadsheet. To obtain images with consistent field of view and focus, all images were taken with a camera mount tripod and using the timing function on the camera. Digital images were transferred from the camera's XD card to a laptop computer and saved with a file name format yyyymmdd_XXX.JPG, where XXX is the filter type shown in Table 3.1.

As discussed in Section 4.3, the weather station recorded data at 30 minute intervals for the duration of the experiment. The weather station data was transferred from a csv file to an excel spreadsheet. At weekly intervals the file was replaced with updated data while keeping the same file name of download.xlxs. The weather station data was imported into MATLAB to perform daily ET, daily average temperature, relative humidity and wind speed calculations. The output of these calculations were used as independent variables in the regression analysis and for calculation of SMC from gravimetric method.

Spectral data from the ColourWorker software was transferred from a csv file to an excel spreadsheet named colourWorker.xlxs. The data for each visual image was assigned a sheet in the workbook titled with the relevant date. The first column contained the spectral value from 400 to 700 ηm and each of the 36 sample plants were assigned a column from 2 to 37. A separate excel sheet named summary compiled the relevant spectral data (including 640/660 ratio) for each plant sample.

Image processing was performed using MATLAB® as described in Section 3.4. The reflectance data produced was transferred to an Excel workbook titled filterData.xlsx. Each filter type was allocated a sheet titled with filter type. The date and 36 samples were allocated a column from 1 to 37.

The regression analysis was performed using an excel workbook named filterData.xlxs. Each sample type and filter type was allocated a sheet titled XX(FFF), where XX is the sample reference (Section 4.6) and FFF is the filter type (Section 3.2.2). Each sheet referred to external documents to import data as required.

3.4 Data Processing

Image processing will be performed on the raw images to extract reflectance information. An example of the raw images used in this project is shown in Figure 3.4. Two methods used for image processing will be discussed, ColourWorker® and MATLAB® image processing.

3.4.1 ColourWorker® Image Processing

Obtaining spectral data from plant foliage would usually require expensive spectrometers and other lab equipment. ColourWorker provides the ability to obtain spectral reflectance data from a standard digital image. The image does not need controlled lighting and has a resolution of 5ηm ranging from 400 to 700ηm. Figure 3.5 shows the selection and analysis of 36 samples in the one image. The chart in the top right corner is the spectral response for the first sample of chamomile grown in loam. The

a) b)

Figure 3.4: Sample images for 23rd August 2014 a) Visual Image b) IR850 Image

Source: (Watson, Paul. 2014)

flow chart in Appendix C.1 shows the process of image analysis using ColourWorker.

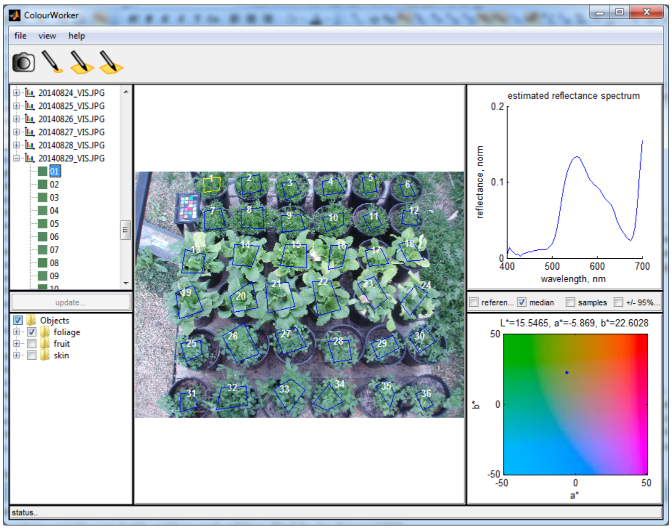

Figure 3.5: ColourWorker image analysis

(Source: Watson, Paul. 2014)

3.4.2 MATLAB® Image Processing

A program was designed using the MATLAB® platform and image processing toolbox, to individually analyse an image of 36 sample plants.The program listing is shown in Appendix B.1. The output is an average reflectance for each sample. There are three parts to the program; Part 1 loads the images and registers the images with each other. An example of image registration can be seen in Figure 3.6. Image registration is performed between the visual image and the filtered image. This enables the processing of the high resolution VIS image, identifying which pixels represent the plant foliage. The index of the relevant pixels are used to extract data from the filtered image. It can be seen in the raw images of Figure 3.4, that the IR850 image has less contrast and detail when compared to the VIS image. The flow chart for Part 1 can be seen in Appendix C.2.

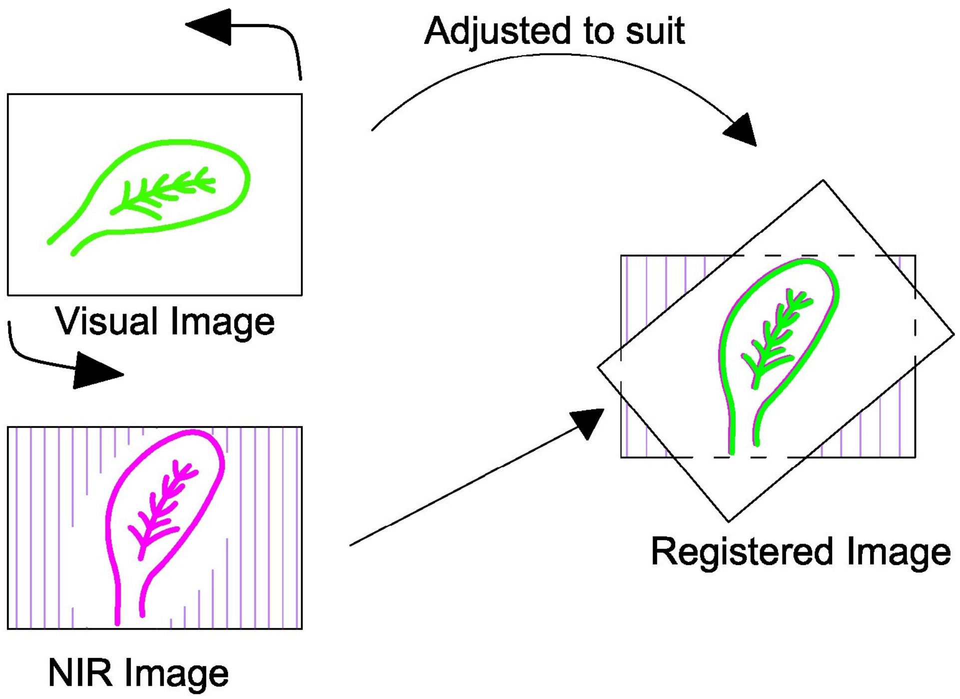

Figure 3.6: Diagram of image registration used to align two images of the same subject

Part 2 processes the registered image to allow for automatic extraction of pixels representing plant foliage. The flow chart for Part 2 is shown in Figure 3.7. Each step in the flow chart shows the effect on the image as the program progresses. The program follows the outline below:

1. **imcrop** crops the original image to display only the target sample identified in the cpselect stage.
2. **rgb2grey** converts the image to a grey scale or intesity image.
3. **imadjust** increases the contrast of the image by saturating the high and low intensity levels and remapping everything in between.
4. **greythresh** normalises the intensity values to a range of 0 to 1.

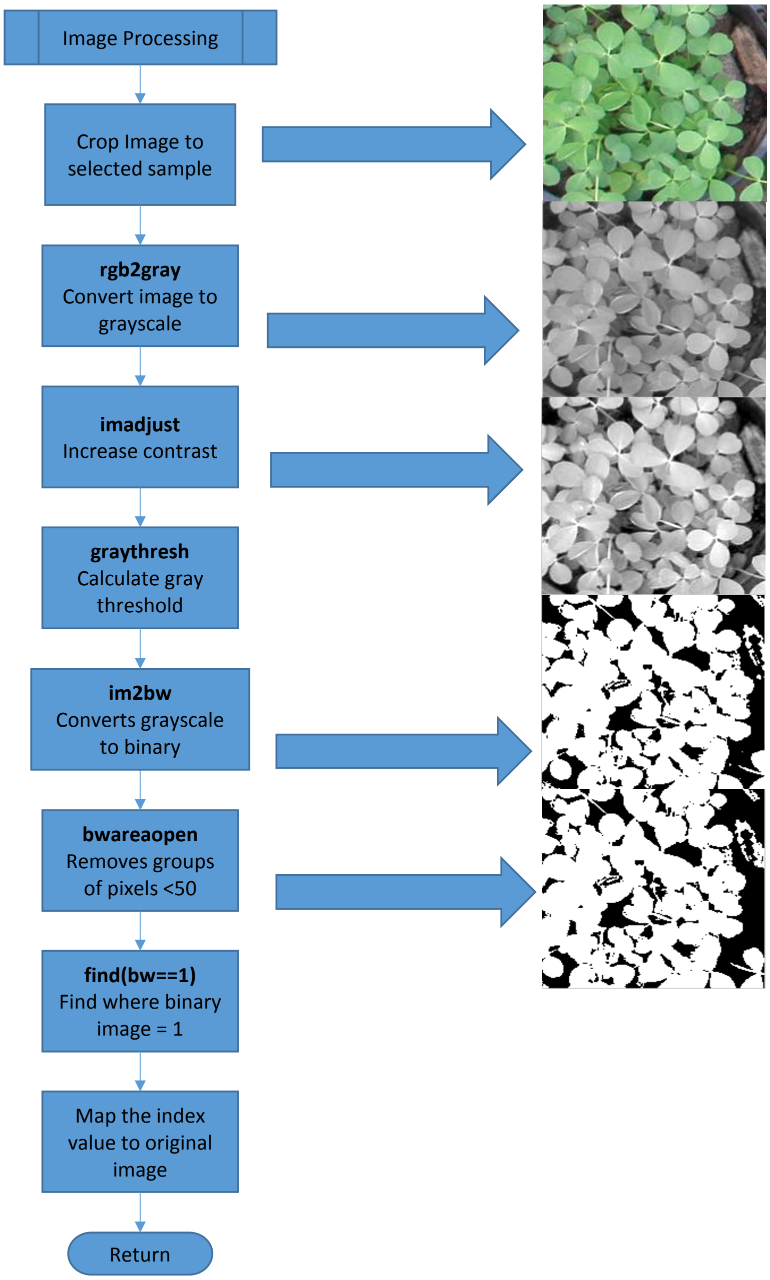

Figure 3.7: Image processing flow chart

5. **im2bw** converts the grey scale image to a binary image. Each pixel is assigned a 1 or 0 depending on if it is greater than or less than the threshold level. The output is a black and white image.

6. **bwareaopen** removes components of the binary image that have fewer than 50 connected pixels.

7. **find(bw==1)** records the index values of the pixels belonging to the plant foliage or where the pixels are black (equal to 1).

8. **mapping** of the recorded index values to the registered image is then performed. The index values are then confirmed to the user by displaying the original image with the relevent pixels blacked out. This also helps to keep track of which sample the analysis is up to.

Part 3 calculates the reflectance of the plant foliage. The flow chart is shown in Appendix C.3.

Chapter 4

Data Collection for Validation

4.1 Experiment objectives

The data required for this project was obtained through a fieldwork programme designed to control the growing conditions of the sample plants. This included controlled potting media discussed in Section 4.8, irrigation (Section 4.9) and exposure to the elements (excluding rain). The aim of the experiment was to obtain weather, soil moisture and plant visual response data for all samples on a daily basis. The objective of the experiment was to: (i) test and identify any parameters (visual response and weather data) which are sensitive to changes in SMC, (ii) develop a SMC estimation model and (iii) identify conditions that visual response could be used to estimate SMC.

4.2 Experiment Location

The experiment was carried out in Bendigo, Victoria. The geographical location is 36.75° South 144.26° East with altitude of 208 meters above sea level. The experiment was conducted in a private residential yard. The area had adequate space for exposure to wind and solar radiation. A weather station was placed at the site of the experiment to record local weather data. The specifications of the weather station are listed in 4.3.

4.3 Weather Station

The Davis Vantage Pro2 weather station was used to monitor and record air temperature, wind speed, relative humidity and global solar radiation (via additional sensor). The weather station has an on-board data logger and is powered by battery and solar panel. A wireless link to an indoor console provides connection to a laptop computer, via a USB cable. Data was accessed through WeatherLink software version 6.0.3. Data was recorded at 30 minute intervals for the duration of the experiment and was manually downloaded from the weather station as required.

4.4 Soil Moisture Measurement

4.4.1 Vegetronix Soil Moisture Meter

The Vegetronix (VG-Meter-200) soil moisture meter was chosen as an instrument to take point readings from each of the samples in the experiment. This is a capacitive type sensor with a 100mm sensor probe. The probe was set to measure at a depth of 65mm, at root zone of the seedlings. This sensor has the capability to stream data through a serial connection to a computer; however, this option was not used as there were 36 samples to be monitored. Instead each sample was tested individually on a daily basis.

A capacitive sensor measures the dielectric permittivity of the surrounding soil and can be correlated to VWC. There are some influencing factors which can affect the readings, these were listed by Prichard (n.d) as:

- Water content
- Soil temperature
- Soil porosity and bulk density
- Measurement Frequency
- Air Gaps in the sample soil

The volume of soil per pot is 805 cm^3. The relatively small sample size means there will be some disturbance to the soil as multiple reading are taken. Each time a measurement is made the probe will be inserted into the soil sample, which may affect the soil properties listed above. To ensure the soil moisture content readings are accurate, a gravimetric calculation will be conducted alongside the capacitive sensor. .

4.4.2 Gravimetric Measurement

A direct measurement of the soil moisture content of each sample was conducted to verify the measurements obtained from the capacitive sensor. The equipment required to perform direct measurement was an oven, thermometer, oven proof tins, scales with accuracy of 0.01g and a volumetric sampler. Equation 4.1 determines gravimetric water content as stated by White (n.d) in *BCG Soil Test Interpretation: Workshop Notes.*

$$GWC\% = \left(\frac{wetweight(g) - dryweight(g)}{dryweight(g)}\right) \times 100 \tag{4.1}$$

An additional SMC measurement was estimated using the gravimetric method. Each sample pot was irrigated with a measured quantity of water, refer to Section 4.9 for details. Using Equation 4.1 and 4.2 the starting VWC is known. With a pot depth of 10 cm, the VWC(C) in percentage is equal to VWC(C) in mm of water. This value can be reduced daily by the calculated ET (Section 4.5). The VWC(ET) is based on the full depth of the pot, compared to the capacitive probe VWC(C) measurement at a depth of 65mm.

4.4.3 Volumetric Measurement

To convert Gravimetric soil moisture measurements to volumetric Equation 4.2 used by White (n.d).

$$VWC\% = GWC\% \times BulkDensity(g/cm^3) \tag{4.2}$$

The baulk density of the two soil samples were calculated by taking a volumetric sample

Table 4.1: Sand and Loam Bulk Densities

Soil Type	**Weight** ($g/10cm^3$)	**Calculation**	**Baulk Density** (g/cm^3)
Loam	8.53	$\frac{8.53}{10}$	0.853
Sand	12.75	$\frac{12.75}{10}$	1.275

(10 cm^3) while maintaining the compactness of the soil. Weighing the sample and adjusting to the units of g/cm^3. The results of the two soil samples are listed in Table 4.1.

4.5 Evapotranspiration (ET)

Evapotranspiration describes the combined loss of water through evaporation and plant transpiration. The Davis weather station discussed in Section 4.3 has a built in ET calculation. There are different methods to calculate ET, the Davis weather station utilises the Californian Irrigation Management Information System CIMIS method and uses default un-calibrated atmospheric pressure in the calculation.

The Bureau of Meteorology (BOM) provides access to weather data including ET. The Penman-Monteith equation is use for the BOM calculation and is recommended by the United Nations Food and Agriculture Organisation. The Penman-Monteith equation will be used for this project, with the daily ET being re-calculated from the weather station data. A comparison of the weather station ET calculation and the Penman-Monteith equation was made to determine if there were any significant differences. The data for a 24 hour period on 15^{th} July 2014 (midnight to midnight) was used to calculate ET with the Penman-Monteith equation. The geographical location and elevation discussed in Section 4.2. Minimum and Maximum values of temperature, wind speed, relative humidity, atmospheric pressure and global solar radiation where obtained for that period. The ET values were then calculated using a MATLAB® function shown in Appendix D.1 and the Microsoft® Excel spread sheet created by Allen (2003). The Penman-Monteith Equation is shown in Equation 4.3.

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (4.3)$$

where:

ET_o	reference evapotranspiration [mm day^{-1}]
R_n	net radiation at crop surface [MJ m^{-2} day^{-1}]
G	soil heat flux density [MJ m^{-2} day^{-1}]
T	mean daily air temperature [$°C$]
U_2	wind speed at 2 meter height [m s^{-1}]
e_s	saturation vapour pressure [kPa]
e_a	actual vapour pressure [kPa]
$(e_s - e_a)$	saturation vapour pressure deficit [kPa]
D	slope vapour pressure curve [kPa $°C^{-1}$]
g	psychrometric constant [kPa $°C^{-1}$]

The ETo for 15^{th} July 2014 calculated with the Penman-monteith equation and the weather station calculation was 0.5 mm day^{-1} and 0.2 mm day^{-1} respectively. This verifies there is no significant difference between the two calculation methods. This conclusion was also reached by Bacci, Battista, Cardarelli, Carmassi, Rouphael, Incrocci, Malorgio, Pardossi, Rapi and Colla (2011).

The crop factor Kc is a ratio to adjust the ET from the reference crop of 20cm high well maintained grass cover, to the actual crop. British Columbia (2001) uses Equation 4.4 as an estimate for crops with an unknown Kc value.

$$Kc = \frac{Wp}{Wb} \quad (4.4)$$

Where:

Wp	Plant Width [cm]
Wb	Bed Spacing [cm]

The layout of the experiment has provided an air gap around the pots, which has increased circulation and provided more weight to the wind speed and temperature in the ET calculation. The plant width and bed width ration is close to 1. The crop factor has not been applied to the ET calculation to account for the increased effect of the pot drying out quicker.

4.6 Experiment Layout

The experiment had a layout as shown in Figure 4.1. Each sample in the experiment will be referenced by its location in the layout. A letter and number describes the row and column respectively. Using C5 as an example, this refers to replica number 1 of lettuce grown in loam with an irrigation level of 20%. Each sample is contained in a pot with a diameter of 10cm and samples are spaced 10cm apart.

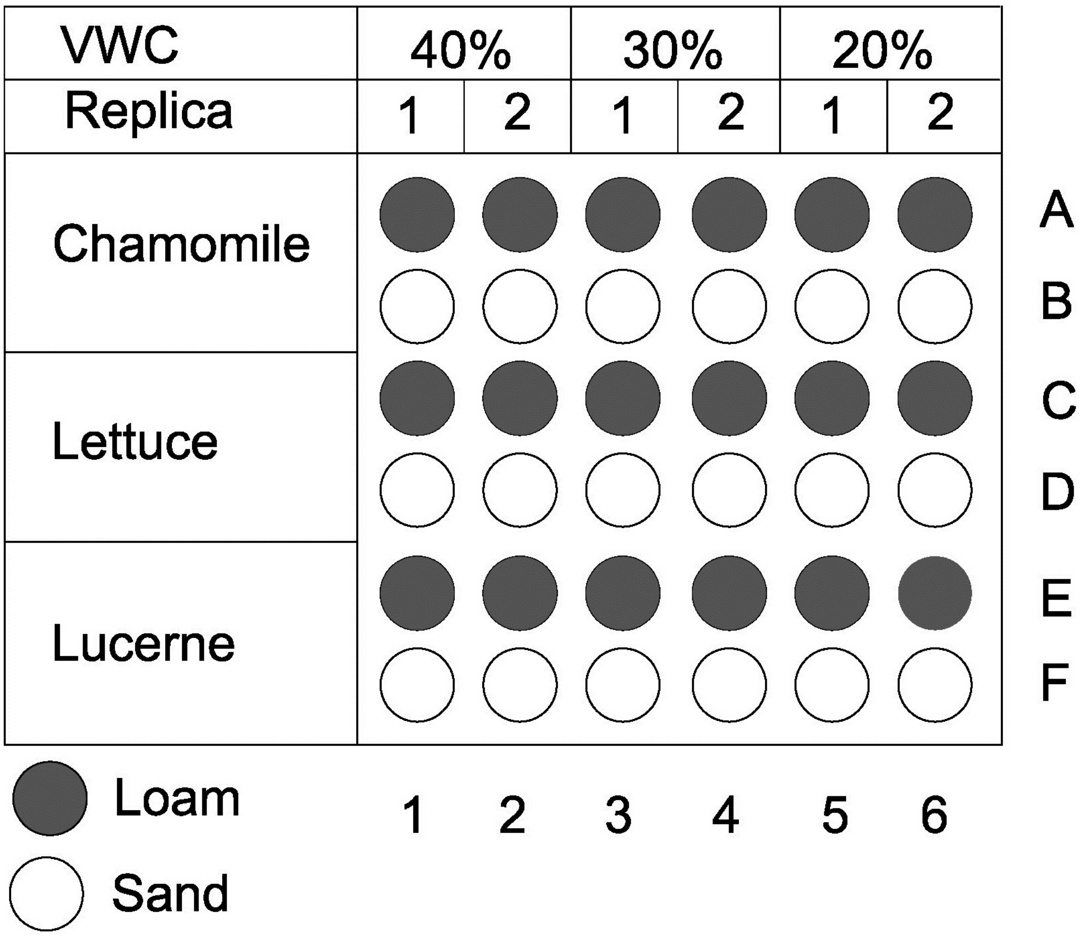

Figure 4.1: Experiment Layout

4.7 Plant Samples

The plants studied in this project were:

- Chamomile - Botanical Name Chamaemelum nobile,
- Lettuce - Botanical Name Lactuca sativa L, and
- Lucerne - Variety Sardi Seven (Winter Active).

The lettuce and lucerne were grown from seed and the chamomile was purchase as a 100mm plot. The data used for the experiment was collected throughout July and August. At the experiment location, July was typical Victorian winter weather with a temperature average of 8°C. During this time all plant samples were slow growing and the SMC of the pots took up to 20 days to dry out enough to require irrigation. As August approached there was an increase in the average temperature and sunlight hours. In this time plant growth across all samples increased.

4.8 Sample Preparation

The plants discussed in Section 4.7 were potted in a controlled way to ensure uniform samples. Each soil type was mixed in one batch before it was divided into samples pots. The makeup of the soil types consisted of a base mix with the addition of 30% sand for the loam mix, and 70% sand for the sand mix. Table 4.2 lists the quantities of the soil mixture.

Soil	**Mixture**	
Base Mix	75% general purpose potting mix	25% 50% compost 50% cow manure
Loam	70% Base Mix	30% washed sand
Sand	70% washed sand	30% base mix

Table 4.2: Soil Mixture

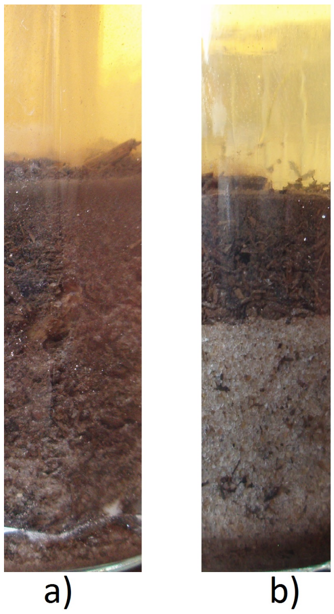

Figure 4.2: Soil Samples a) Loam b) Sand

Source: (Watson, Paul. 2014)

A side profile of both soil samples are shown in Figure 4.2. The samples were added to a glass jar of water and shaken, then allowed to settle for 24 hours. It can be seen that the sand mix (Figure 4.2b) had predominantly sand and a higher bulk density than the loam. The loam shows some air gaps even after settling time. The pots used in the experiment were recycled and made of black plastic with dimensions of 10cm in height by 10cm in diameter. The pots were sterilised before being filled with 850ml of soil.

4.9 Irrigation

The irrigation frequency for this experiment varied from 12 to 14 days in July down to 7 days during August, this was due to the rate at which water has been used. During July, the initial phase of the experiment used water at a slower rate than in August. This is due to plant growth and the transition from a Victorian winter towards spring. The irrigation frequency and amount of water is shown in Figure 4.3.

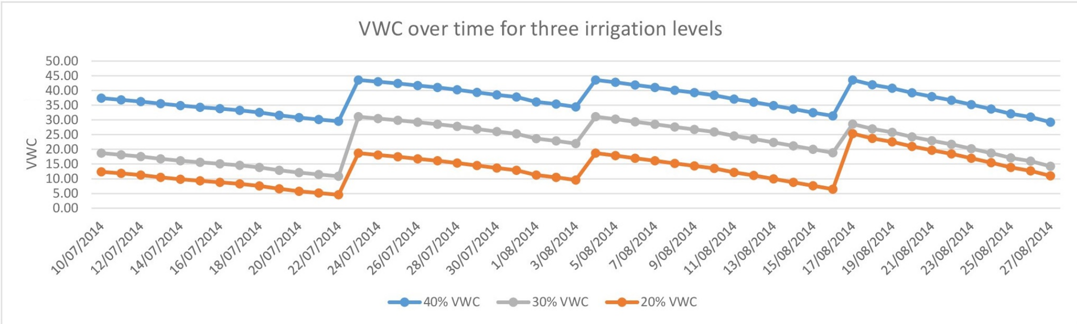

Figure 4.3: VWC of the three irrigation levels (20%, 30% and 40%) used in the experiment

Three irrigation levels were included in the experiment. Samples were irrigated at High, Medium and Low levels with 350mls (40%), 250mls (30%) and 150mls (20%) respectively of water added. The 40% irrigated samples were watered over a container to catch any run off or water which had drained through the first time. This water was returned to the pot until the soil had absorbed all the water. The medium and low irrigated samples both absorbed the water first time. Each irrigation included a general purpose plant food at a rate specified by the manufacture. This helped to keep the plant healthy and avoid nutrient deficiency.

Chapter 5

Soil Moisture Estimation Model

5.1 Model Development

Data analysis was performed by multiple linear regression using the regression tool from Microsoft® Excel's Data Analysis tool box. Multiple linear regression is a method which can model the relationship between a number of explanatory variables (independent variables) and the response variable (dependent variable). The output of the process is an Analysis of Variance (ANOVA) table. The table includes the prediction value (P) or the probability of the null hypothesis being true, and the coefficient of determination, or adjusted r^2 value which is a guide to the fitness of the model to the data. The r^2 ranges from 0 to 1, where 1 indicates a models good fit to the data. The ANOVA table also provides the regression coefficient for the intercept and each independent variable. The general form of the multiple linear regression model is shown in Equation 5.2.

$$y_i = \beta_0 + \beta_1 x_1 + \beta_n x_n \tag{5.1}$$

where:

y_i	Dependent variable
β_0	Regression coefficent of intercpt
β_n	Regresion Coefficient of independent variable
n	nth independent variable
x_n	value of nth independent variable

The objective of the data analysis is to create a model which can predict the SMC from the visual response of a plant canopy. There are two parts to the data analysis:

1. Identify parameters which have a significant relationship to plant visual response, and
2. Identify model coefficients and intercepts.

5.1.1 Identify Parameters with a Significant Relationship to Plant Visual Response

A parameter will be classed as having a significant relationship when the adjusted r^2 value for the ANOVA output is greater than 0.6. The hypothesis is that there is no significant correlation between the plant spectral response and any of the chosen independent variables listed in Table 5.1. The null hypothesis H_0 is that there is no significance between the dependent and independent variables. The alternative hypothesis H_a is that there is a significance between the two variables.

To quantify this statement the selection criteria will use a significance level of $\alpha = 0.05$, the hypothesis are listed in Equation 5.3:

$$\begin{aligned} H_0 &: \beta_n = 0 \\ H_a &: \beta_n \neq 0 \end{aligned} \tag{5.2}$$

The coefficient of the independent variable is β_n. The criteria for rejecting the null hypothesis is when the P-value $< \alpha$.

Dependent Variable	
Spectral Response	Estimated from digital images
	includes NDVI, IR850 and Chl a/b
Independent Variable	
Volumetric Water Content (VWC_C)	Measured with capacitive probe [%]
Volumetric Water Content (VWC_{ET})	Estimated from irrigation water and ET [%]
Days Since Irrigated (D)	Irrigated days = 0
Temperature (T)	Daily Average temperature [$°C$]
Relative Humidity (RH)	Daily Average Relative Humidity [%]
Wind (W)	Daily Average wind speed [km/hr]

Table 5.1: Variables used in analysis

The outcome of this test decides which independent variables will be suitable for the model and therefore used in the next part of the analysis. This analysis will also identify which SMC value has the most significant relationship to plant response. Both VWC(C) and VWC(ET) have been compared during this analysis.

5.1.2 Identify model coefficients and intercepts.

The second test will identify the model coefficients and intercepts using the parameters identified in Section 5.1.1. In this analysis the most significant SMC value will be the dependent variable. The other parameters identified in Section 5.1.1 will be the independent variables.

The hypothesis for this analysis is that there is no significant regression coefficient for the model parameters. The same significance level and criteria for rejecting the null hypothesis will be the same as in Section 5.1.1.

5.1.3 Defining Data for Model Calibration and Verification

The data for the experiment was collected from 24^{th} July 2014 to the 7^{th} September 2014. During July all plant samples were slow growing and there was 12 days between irrigation. August saw an increase in the average daily temperature by $1.2°C$. Bright sunshine hours (above 100 Wm^{-1}) for July and August were 180 and 230 hours respectively. The increase in temperature and bright sunshine hours saw the plant samples increase their growth rate and water use. There were 7 days between irrigation during August. With the change in conditions and plant stages occuring mid way through the project, the data was divided into three groups and analysed separately. This allowed for seasonal changes to be modelled. The data is categorised as follows:

1. July Data - 14^{th} July to 3^{rd} August
2. August Data - 4^{th} August to 24^{th} August
3. Verification Data - 25^{th} August to 7^{th} September

5.2 Chamomile Model

Identifying Parameters Significant to Plant IR850 Response.

Table 5.2 shows the coefficient of determination (r^2) for chamomile response to the IR850 filter and the variables listed in Table 5.1. An X indicates there was no correlation. Where the r^2 value is greater than 0.6, the relevant variables will be used in the next test, to determine regression coefficients and model intercepts.

The results for chamomile show a general relationship between spectral response in IR850 to independent variables across both soil types and all irrigation levels. There are two exceptions in the sand samples of the August data which did not show a correlation.

Table 5.2: Coefficient of determination (r^2) for chamomile response to the IR850 filter and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	0.65	0.66	0.64	0.6	0.69	0.79
	Sand	0.79	0.62	0.64	0.67	0.73	0.91
August Data	**Loam**	0.71	0.75	0.78	0.88	0.83	0.77
	Sand	0.75	X	X	0.75	0.75	0.82

Table 5.3 shows the coefficient of determination (r^2) for chamomile response to the Chl(a/b) ratio and the variables listed in Table 5.1. There is only the one significant relationship in sand irrigated at 40%, all other values are below 0.6 or have no correllation at all.

Table 5.3: Coefficient of determination (r^2) for chamomile response to the Chl(a/b) ratio and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	X	X	X	X	X	X
	Sand	0.27	X	X	0.39	X	0.37
August Data	**Loam**	X	X	X	X	X	X
	Sand	0.67	0.3	0.4	0.34	0.34	X

Table 5.4 shows the coefficient of determination (r^2) for chamomile response to NDVI and the variables listed in Table 5.1. The results show inconsistant r^2 values as there are no replicas showing similar values.

Table 5.4: Coefficient of determination (r^2) for chamomile response to NDVI and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	0.84	0.39	X	X	X	X
	Sand	X	X	0.9	X	X	X
August Data	**Loam**	0.36	0.83	X	X	X	X
	Sand	0.68	X	X	X	X	0.71

Identifying model coefficients and intercepts.

Table 5.5 shows the regression coefficients for the chamomile IR850 July data. The intercepts across all samples were consistent and each pair of replicas had values within 4% of each other. The value of the intercept coefficient decreased for each decrease in irrigation level. The IR850 coefficients were negative across all samples of soil type and irrigation levels. The IR850 coefficients ranged from -13.8 to -20.28. The negative relationship means when there is an increased reflection in the IR850 data, the SMC will fall. The independent variable Days since irrigated (D) was included in all sample models. The D coefficients were also negative, meaning as the number of days increased without irrigation, the SMC dropped. Relative humidity (RH) was included in four of the 12 samples. The RH coefficient was -0.02 for each model. Temperature (T) was included in sand at 22% irrigation level, with a coefficient of 0.038. The IR850 coefficients were the most significant variable in each of the sample models, followed by D coefficients.

Table 5.5: Chamomile IR850 July model coefficients and intercepts

			14^{th} July to 3^{rd} August						
Soil	**Irrigation**	**Replica**	**Intercept**	**IR850**	**D**	**T**	**RH**	**W**	r^2**(C)**
Loam	40%	1	49.36	-18.25	-0.87		-0.02		0.99
		2	47.35	-16.45	-0.848				0.99
	30%	1	34.01	-13.8	0.05				0.99
		2	34.76	-16.42	-0.87				0.99
	20%	1	22.28	-16.4	-0.85				0.99
		2	21.95	-14.76	-0.84				0.99
Sand	40%	1	44.12	-15.48	-0.84		-0.02		0.99
		2	42.29	-17.98	-0.86				0.99
	30%	1	31.84	-19.78	-0.89				0.99
		2	33.84	-20.28	-0.91		-0.02		0.96
	20%	1	20.09	-15.14	-0.86				0.99
		2	21.34	-14.41	-0.87	0.038	-0.02		0.99

Table 5.6 shows the performance of the chamomile IR850 August model. The intercept regression coefficient were similar between replicas for the samples grown in loam. The samples in loam at 30% irrigation had an intercept coefficients of -2.04 and 3.41, which is not consistent with coefficients at 40% and 20% which were 30.48 and 44.51 respectively. The IR850 coefficients were similar between replicas, all were within 7% of their counterpart. The IR850 coefficients for samples in Loam with 30% irrigation were at 212.34 and 197.91 respectively. As the irrigation reduced to 20% the relationship changed from positive to negative. The positive relationship is expected for healthy vegetation as this indicates IR wavelengths are being reflected from the foliage. The 20% irrigated samples have reflection coefficients of -182.99 and -192.10, which indicates the relationship between 850nm wavelengths and SMC changes with water deficient chamomile. The $r^2(C)$ values for the Loam samples were all greater than 0.91.

There were two samples with sand that did not have any correlation to SMC, these were replica 2 from the 40% and replica 1 from the 30% irrigation level. The intercept coefficients for the sand samples range between 0.44 and 71.52 and there is a large variation between replicas. The IR850 coefficients for the sand are also inconsistent with their replica counterpart. The D coefficients are consistent with each other ranging from

-1.0 to -1.46. The $r^2(C)$ values ranged from 0.8 to 0.99 which supports the variation in the model coefficients between replicas.

Table 5.6: Chamomile IR850 August model coefficients and intercepts.

			4^{th} August to 24^{th} August						
Soil	**Irrigation**	**Replica**	**Intercept**	**IR850**	**D**	**T**	**RH**	**W**	r^2**(C)**
Loam	40%	1	30.48	90.45	-1.13				0.97
		2	31.21	83.70	-1.13				0.97
	30%	1	-2.04	212.34	-1.07				0.91
		2	3.41	197.91	-1.03				0.96
	20%	1	44.51	-182.99	-1.12			0.71	0.97
		2	48.47	-192.10	-1.42				0.94
Sand	40%	1	0.44	225.05	-1.05				0.80
		2							
	30%	1							
		2	33.84	-20.28	-0.91		-0.02		0.99
	20%	1	71.52	-337.67	-1.46				0.94
		2	6.80	74.70	-1.0				0.98

5.3 Lettuce Model

Identifying Parameters Significant to Plant IR850 Response

Table 5.7 shows the coefficient of determination (r^2) for lettuce response to the IR850 filter and the variables listed in Table 5.1. The Loam July samples show strong r^2 values greater than 0.91. The sand July sample had two exceptions which had no correlation and a weak r^2 of 0.34. These values were for 30% and 40% respectively. The August data for loam shows a weaker r^2 with half of the sample below 0.6 or no correlation. The sand August r^2 values were also weak, ranging from 0.71 to 0.94, with the two 40% irrigated samples not showing a correlation.

Table 5.8 shows the coefficient of determination (r^2) for lettuce response to the Chl(a/b) ratio and the variables listed in Table 5.1. Only one sample in the July and August

Table 5.7: Coefficient of determination (r^2) for lettuce response to the IR850 filter and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	0.91	0.92	0.91	0.92	0.94	0.94
	Sand	0.34	0.92	X	0.96	0.95	0.95
August Data	**Loam**	0.81	X	0.56	0.88	0.75	X
	Sand	X	X	0.94	0.71	0.82	0.71

data show significance. This was sand August sample at 40% irrigation.

Table 5.8: Coefficient of determination (r^2) for lettuce response to the Chl(a/b) ratio and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	0.23	X	0.4	0.4	X	X
	Sand	X	X	X	X	0.38	X
August Data	**Loam**	0.56	0.39	X	X	X	0.51
	Sand	0.7	0.44	0.27	0.56	X	0.29

Table 5.12 shows the coefficient of determination (r^2) for lettuce response to NDVI and the variables listed in Table 5.1. The July data had only two significant samples for 40% irrigated in loam. These values were 0.92 and 0.94. In the sand samples there were four significant samples with an r^2 value ranging from 0.62 to .95. The August data only showed one significant sample for loam and sand. The r^2 values were 0.68 and 0.62, these values are only marginally significant.

Identifying model coefficients and intercepts.

Table 5.10 show results of lettuce model performance for IR850 July data. The regression coefficients for the intercepts across all samples were consistent, each pair of replicas had values within 10% of each other. The value of the intercept coefficient decreased for each decrease in irrigation level. The IR850 coefficients were negative across all samples of soil type and irrigation levels. The IR850 coefficients ranged from -12.2 to -16.01. The D coefficients were consistent across all samples ranging from -0.82

Table 5.9: Coefficient of determination (r^2) for lettuce response to NDVI and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	0.92	0.94	X	X	X	X
	Sand	0.95	0.81	0.64	0.36	0.62	0.43
August Data	**Loam**	X	0.68	X	X	0.39	0.5
	Sand	0.51	X	X	0.62	0.58	X

to -0.89. T coefficients were included in the loam sample irrigated to 40% and in sand samples irrigated at 30% and 20%. RH coefficients were included in 4 out of the 12 Lettuce models. T and RH coefficient values are only small contributors to the model equations.

Table 5.10: Lettuce IR850 July model coefficients and intercepts

14^{th} July to 3^{rd} August									
Soil	**Irrigation**	**Replica**	**Intercept**	**IR850**	**D**	**T**	**RH**	**W**	r^2**(C)**
Loam	40%	1	48.27	-13.28	-0.85	0.044	-0.02		0.99
		2	48.53	-13.99	-0.88	0.047	-0.02		0.99
	30%	1	34.99	-15.85	-0.88				0.99
		2	35.09	-16.01	-0.87				0.99
	20%	1	24.44	-14.87	0.89		-0.02		0.99
		2	22.70	-14.7	-0.84				0.99
Sand	40%	1	42.05	-14.92	-0.84				0.99
		2	42.40	-15.40	-0.88				0.99
	30%	1							
		2	32.20	-12.20	-0.86	0.05	-0.19		0.99
	20%	1	22.22	-15.97	-0.87	-0.02			0.99
		2	19.84	-13.57	-0.82				0.99

Table 5.11 shows results of the Lettuce models for IR850 August data. There were three samples which did not show a correlation between SMC and IR850 data, these are replica 2 of the 40% irrigated in loam and both samples in sand at 40% irrigation.

The intercept coefficients were inconsistent between replicas across the 12 samples. There is also inconsistency with variation in irrigation levels. The IR850 coefficients for the loam are 430.39 for 40% irrigation, 366.02 and 229.98 for 30% irrigation and -148.2 for the 20% irrigation. In sand the IR850 coefficients are -450.9 and -333.4 for 30% irrigation and 86.3 and -316.8 for 20% irrigation levels. The D coefficients are consistent across all models ranging from -0.99 to -1.49.

Table 5.11: Lettuce IR850 August model coefficients and intercepts

4^{th} August to 24^{th} August									
Soil	**Irrigation**	**Replica**	**Intercept**	**IR850**	**D**	**T**	**RH**	**W**	r^2**(C)**
Loam	40%	1	33.28	430.39	-1.49				0.77
		2							
	30%	1	-29.48	366.02	-1.11				0.99
		2	-8.74	229.98	-1.0				0.92
	20%	1	51.8	-148.20	-1.37				0.93
		2							
Sand	40%	1							
		2							
	30%	1	112.50	-450.90	-1.24				0.84
		2	31.08	-333.40	-1.40				0.87
	20%	1	1.48	86.30	-0.99	0.15			0.99
		2	72.88	-316.80	-1.60				0.84

5.4 Lucerne Model

Table 5.12 shows the coefficient of determination (r^2) for lucerne response to NDVI and the variables listed in Table 5.1. The July data for loam and sand have r^2 values all greater than 0.91. The August data has only one significant sample at 0.43, which is considered as a weak fit.

Table 5.12: Coefficient of determination (r^2) for lucerne response to the IR850 filter and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	0.93	0.94	0.96	0.93	0.95	0.95
	Sand	0.92	0.94	0.92	0.93	0.91	0.94
August Data	**Loam**	X	X	X	X	X	X
	Sand	X	X	0.43	X	X	X

Table 5.13 shows the coefficient of determination (r^2) for lucerne response to the Chl(a/b) ratio and the variables listed in Table 5.1. The results show a weak fit for both July and August data. There is only one marginally significant sample in the August data.

Table 5.13: Coefficient of determination (r^2) for lucerne response to the Chl(a/b) ratio and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	X	X	X	X	X	X
	Sand	X	X	X	X	X	0.44
August Data	**Loam**	0.19	0.67	X	X	0.29	0.4
	Sand	0.4	0.49	X	X	X	X

Table 5.14 shows the coefficient of determination (r^2) for lucerne response to NDVI and the variables listed in Table 5.1. The July data has r^2 values ranging from 0.62 to 0.95. Replica 1 at 40% irrigation for both loam and sand have no correlation in the July data. The August data is inconsistent with only three significant samples over the

loam and sand samples.

Table 5.14: Coefficient of determination (r^2) for lucerne response to NDVI and the independent variables from Table 5.1

	Irrigation (VWC)	40%		30%		20%	
	Replica	1	2	1	2	1	2
July Data	**Loam**	0.91	X	0.95	0.62	0.82	0.75
	Sand	X	0.81	0.93	0.94	0.93	0.9
August Data	**Loam**	0.71	X	X	X	0.47	0.75
	Sand	X	X	0.69	0.44	0.21	X

The Lucerne IR850 July data results are shown in Table 5.15. Replica 1 of 40% irrigation level in loam had no correlation between the 850nm wavelengths and SMC. The intercept coefficients are consistent between samples and decrease with reduced irrigation level. The IR850 coefficient are similar between replicas and are negative for all models. T coefficients were included in 7 out of the 11 models and range from 0.05 to 0.08. RH coefficients were included in 4 of the models with a value of -0.02 in each model. T and RH variable have the lowest weight in the prediction models. The r^2(C) values were 0.99 for all models and r^2(V) values are greater than 0.98.

Lucerne models for the IR850 August data were not successful, only one correlation between 850ηm wavelengths and SMC was determined. The r^2 value for this model was 0.59.

Lucerne was the only plant sample which showed a correlation between SMC and the NDVI. There were two exceptions in the July data where there was no correlation, these were replica 1 for 40% irrigation level for loam and sand. Table 5.16 shows the results of the models for the July data. The intercept coefficients are consistent between replicates and reduce with the reduction in irrigation level. The IR850 coefficients are negative for all models and consistent between replicates. D coefficients are consistent between replicas with a range of -0.56 to -0.87. T coefficients were included for all 5 loam models and 4 of the 5 models for the sand. RH coefficients were included in 5 of the 10 models.

Table 5.15: Lucerne IR850 July model coefficients and intercepts.

			14^{th} July to 3^{rd} August						
Soil	**Irrigation**	**Replica**	**Intercept**	**IR850**	**D**	**T**	**RH**	**W**	r^2**(C)**
Loam	40%	1							
		2	45.90	-8.65	-0.78				0.99
	30%	1	37.11	-16.76	-0.92		-0.02		0.99
		2	34.89	-14.94	-0.87				0.99
	20%	1	23.20	-14.50	-0.84	0.08	-0.02		0.99
		2	23.25	-14.55	-0.85	0.06	-0.02		0.99
Sand	40%	1	41.80	-18.32	-0.79	0.06			0.99
		2	42.51	-20.35	-0.84	0.05			0.99
	30%	1	32.00	-21.36	0.871				0.99
		2	32.38	-15.59	-0.87	0.06			0.99
	20%	1	21.36	-18.11	-0.84	0.078	-0.02		0.99
		2	19.02	-15.65	-0.80	0.07			0.99

Table 5.16: Lucerne NDVI July model coefficients and intercepts.

			14^{th} July to 3^{rd} August						
Soil	**Irrigation**	**Replica**	**Intercept**	**IR850**	**D**	**T**	**RH**	**W**	r^2**(C)**
Loam	40%	1	46.42	-4.44	-0.87	0.04	-0.02		0.99
		2							
	30%	1	33.85	-3.66	-0.87	0.05	-0.02		0.99
		2	31.90	-3.20	-0.83	0.06			0.99
	20%	1	19.16	-2.93	-0.80	0.08			0.99
		2	19.34	-3.74	-0.83	0.07			0.99
Sand	40%	1							
		2	39.99	-5.26	-0.84				0.99
	30%	1	30.10	-4.22	-0.86	-0.02			0.99
		2	30.10	-3.33	-0.56	0.56	-0.02		0.99
	20%	1	18.92	-3.40	-0.86	0.05	-0.02		0.99
		2	18.54	-3.56	-0.85	0.06	-0.02		0.99

Table 5.17: Lucerne NDVI August model coefficients and intercepts.

24^{th} August to 24^{th} August									
Soil	**Irrigation**	**Replica**	**Intercept**	**IR850**	**D**	**T**	**RH**	**W**	r^2**(C)**
Loam	40%	1	47.05	89.95	-1.80			-2.6	0.57
		2							
	30%	1							
		2							
	20%	1							
		2	41.05	63.32	-2.16	-0.42			0.92
Sand	40%	1							
		2							
	30%	1	27.40	7.37	-1.16	0.13			0.98
		2	28.86	5.95	-1.17				0.98
	20%	1							
		2							

Chapter 6

Performance of Estimation Model

The models derived in Chapter 5 were tested for accuracy with modelling and predicting SMC. The accuracy of the modelling phase was tested by calculating the Root Mean Square Error (RMSE) of the calibration data RMSE(C). The accuracy of the SMC prediction was tested by calculating the RMSE of the verification data RMSE(V). Equation 6.1 shows the method of calculating RMSE. The sample size of the July, August and verification data were 11, 21 and 14 observations. The number of observations were affected by the climatic conditions and the time frame to run the experiment. The RMSE uses the average error by dividing by the number of observations, which makes it suitable for comparing blocks of data with a different number of observations.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - y1_i\right)^2}{n}} \tag{6.1}$$

where

y	Actual value
$y1$	Predicted value
n	Number of samples
i	i^{th} sample

Each model was tested for performance by comparing the coefficient of determination (r^2) and the RMSE value between the calibration data and the verification data. The r^2 value provides a general representation of how well the model fits the actual data. The RMSE value is the actual error expected between the predicted and the actual data. The RMSE has the same units as SMC (%). With the range of SMC values of 0 to 50% VWC, an error of 10% would equate to a RMSE value of 5%. A model will be considered successful when the RMSE(V) is less than 5% for both replicates in the sample. The samples are described in the format of plant-spectra-irrigation-soil. For example, chamomile-IR850-40%-loam is describing chamomile response to the IR850 filter with plant sample irrigated to 40% and grown in loam.

6.1 Chamomile Model Performance

July Model

The model performance results for chamomile-IR850 for July are shown in Table 6.1. The coefficient of determination r^2 was greater than 0.96 across all models, indicating the model fits the calibrated and verification data well. The RMSE values for loam samples were between 0.11% and 0.16% for RMSE(C) and 3.58% and 6.65% for RMSE(V). The calibration RMSE values are low which indicates a good match to the data, this can also be attributed to the number of observations being 11 for the July calibration. In terms of meeting the acceptance criteria, the successful models were 40% and 20% irrigation levels. Figure 6.1 shows the actual SMC vs predicted SMC for the chamomile-IR850-40%-loam, and the actual vs predicted SMC for chamomile-IR850–20%-loam is show in Figure E.1.

The RMSE values for the sand sample were generally greater than the Loam samples. The RMSE of between 0.06% and 1.62% was calculated for the calibration data. While RMSE(V) was calculated between 2.49% and 8.57%. The RMSE(V) values had more variance between replicates, each pair of replica had one high and one low value. This indicates the set of models derived for the sand samples were not as successful as the models used in the loam samples.

August Model

Table 6.2 shows the results for the r^2 and RMSE tests on the calibration and verification data. The $r^2(C)$ values for the loam and sand models range from 0.8 to 0.99. The $r^2(V)$ range from 0.28 to 0.99. The RMSE(C) range from 0.12% to 1.77%, indicating the model fits the calibration data well. The RMSE(V) values range from 1.97 to 4.12%, which are an acceptable error for estimating SMC.

Table 6.1: Chamomile-IR850 July model comparison of performance between calibration (C) and verification (V) data sets.

14^{th} July to 3^{rd} August						
Soil	**Irrigation**	**Replica**	r^2**(C)**	r^2**(V)**	**RMSE (C)**	**RMSE (V)**
Loam	40%	1	0.99	0.99	0.15	3.84
		2	0.99	0.99	0.16	3.58
	30%	1	0.99	0.99	0.11	6.65
		2	0.99	0.99	0.15	6.02
	20%	1	0.99	0.99	0.14	3.62
		2	0.99	0.98	0.13	4.84
Sand	40%	1	0.99	0.99	0.13	8.57
		2	0.99	0.99	0.17	2.77
	30%	1	0.99	0.99	0.17	6.37
		2	0.96	0.99	1.62	2.73
	20%	1	0.99	0.99	0.14	8.18
		2	0.99	0.98	0.06	2.49

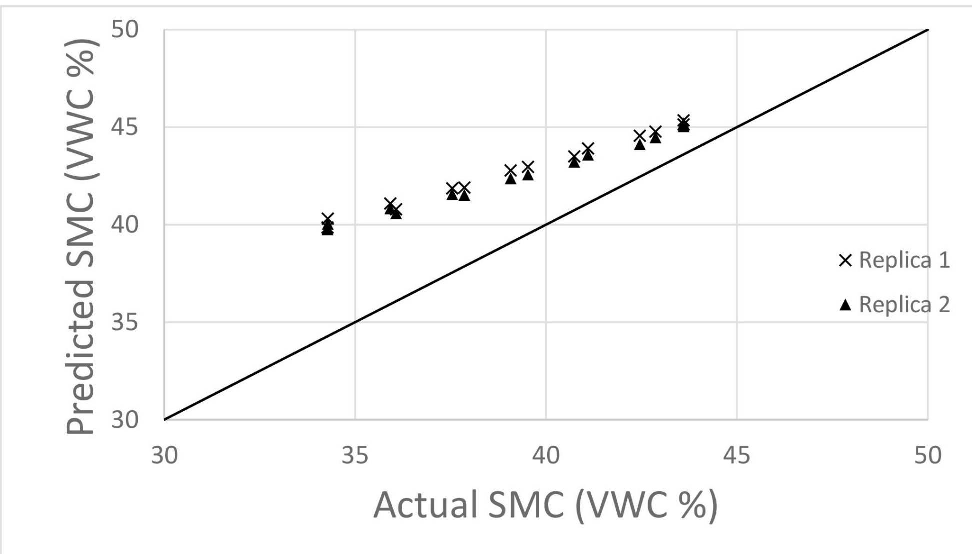

Figure 6.1: Actual vs predicted SMC for chamomile-IR850-40%-loam July model

Table 6.2: Chamomile-IR850 August model comparison of performance between calibration (C) and verification (V) data sets.

			4^{th} August to 24^{th} August			
Soil	**Irrigation**	**Replica**	r^2**(C)**	r^2**(V)**	**RMSE (C)**	**RMSE (V)**
Loam	40%	1	0.97	0.79	0.61	1.73
		2	0.97	0.87	0.56	1.54
	30%	1	0.91	0.32	1.12	2.86
		2	0.96	0.47	0.78	2.60
	20%	1	0.97	0.84	0.82	2.01
		2	0.94	0.79	1.25	2.89
Sand	40%	1	0.80	0.28	0.81	2.39
		2				
	30%	1				
		2	0.99	0.99	0.12	4.12
	20%	1	0.94	0.78	1.77	3.02
		2	0.98	0.72	0.41	1.97

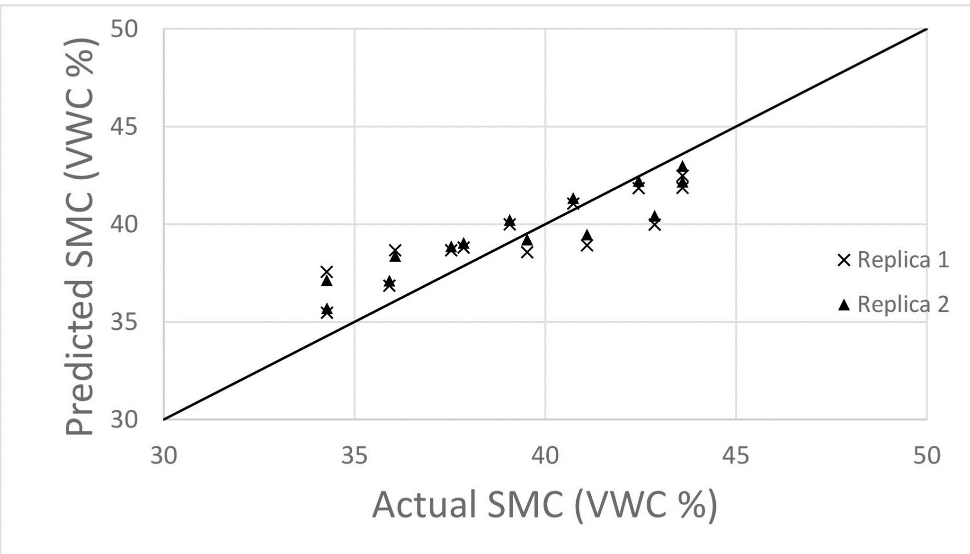

Figure 6.2: Actual vs predicted SMC for chamomile-IR850-40%-loam August model

6.2 Lettuce Model Performance

July Data

Table 6.3 shows the results for the r^2 and RMSE tests on the calibration and verification data. The r^2(C)and r^2(V) values are greater than 0.98, indicating a good fit to the calibration and verification data. The RMSE(C) range between 0.06% and 0.17% and the RMSE(V) for loam and sand range from 1.9% to 20.6% and 2.47% to 14.6% respectively. The loam sample at 20% irrigation had a RMSE(V) of 1.9% and 2.56%, which passes the acceptance criteria. The actual vs predicted SMC for this model is shown in Figure 6.3. The sand at 20% irrigation had RMSE(V) of 2.47% and 5.52% which is marginal in terms of acceptance criteria. All other models had a RMSE larger than 5%, which is not considered acceptable.

Table 6.3: Lettuce-IR850 July model comparison of performance between calibration (C) and verification (V) data sets.

14^{th} July to 3^{rd} August						
Soil	**Irrigation**	**Replica**	r^2**(C)**	r^2**(V)**	**RMSE (C)**	**RMSE (V)**
Loam	40%	1	0.99	0.99	0.06	20.60
		2	0.99	0.99	0.06	13.52
	30%	1	0.99	0.99	0.15	7.73
		2	0.99	0.99	0.14	7.99
	20%	1	0.99	0.99	0.09	2.56
		2	0.99	0.99	0.15	1.9
Sand	40%	1	0.99	0.99	0.14	14.60
		2	0.99	0.99	0.14	4.40
	30%	1				
		2	0.99	0.98	0.04	6.68
	20%	1	0.99	0.98	0.13	2.47
		2	0.99	0.99	0.17	5.52

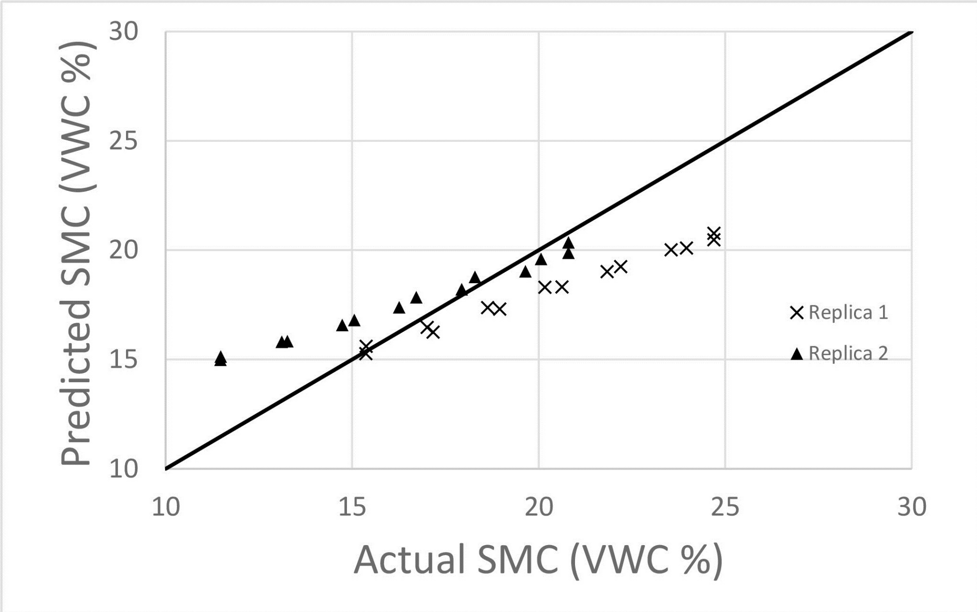

Figure 6.3: Actual Vs predicted SMC for lettuce-IR850-20%-loam July model

August Data

Table 6.4 shows the r^2 and RMSE for calibration and verification data for lettuce models in August. The r^2(C) values range from 0.77 to 0.99 and r^2(V) values 0.21 to 0.99. The RMSE(C) are higher than previous models ranging from 0.02 to 4.12. The RMSE(V) values range from 1.94 to 14.58. The August data shows mixed results in terms of error, the smallest and largest error were produced in the loam samples of 20% and 40% irrigation levels respectively. At least one replica in each irrigation level has no model associated to it or the RMSE(V) is greater than 5%. None of the August models pass the acceptance criteria.

Table 6.4: Lettuce-IR850 August model comparison of performance between calibration (C) and verification (V) data sets.

		4^{th} August to 24^{th} August				
Soil	**Irrigation**	**Replica**	r^2**(C)**	r^2**(V)**	**RMSE (C)**	**RMSE (V)**
Loam	40%	1	0.77	0.09	4.12	14.58
		2				
	30%	1	0.99	0.99	0.02	7.73
		2	0.92	0.21	1.13	2.86
	20%	1	0.93	0.85	1.32	1.94
		2				
Sand	40%	1				
		2				
	30%	1	0.84	0.73	2.86	5.58
		2	0.87	0.66	2.37	3.82
	20%	1	0.99	0.72	0.26	2.39
		2	0.84	0.37	2.27	5.28

6.3 Lucerne Model Performance

6.3.1 Lucerne IR850

July Data

Table 6.5 shows the r^2 and RMSE for calibration and verification data for lucerne models in July. The RMSE(C) values ranged from 0.04 to 0.14, indicating the models are a good fit to the calibration data. The RMSE(V) values ranged from 5.04% to 18.89% for the loam models and 2.04% to 15.40% for the sand models. The replicates associated with the sand samples at 30% irrigation passed the acceptance criteria with RMSE values of 2.7% and 2.04%. Figure 6.4 shows the actual vs predicted SMC for both replicates at 30% irrigation level. The predicted values are overestimated for SMC values under 28% VWC.

Table 6.5: Lucerne-IR850 July model comparison of performance between calibration (C) and verification (V) data sets.

			14^{th} July to 3^{rd} August			
Soil	**Irrigation**	**Replica**	r^2**(C)**	r^2**(V)**	**RMSE (C)**	**RMSE (V)**
Loam	40%	1				
		2	0.99	0.99	0.05	18.89
	30%	1	0.99	0.99	0.11	9.59
		2	0.99	0.99	0.14	4.18
	20%	1	0.99	0.99	0.06	5.04
		2	0.99	0.99	0.05	8.17
Sand	40%	1	0.99	0.98	0.11	6.80
		2	0.99	0.98	0.12	9.80
	30%	1	0.99	0.98	0.13	2.70
		2	0.99	0.99	0.04	2.04
	20%	1	0.99	0.98	0.07	7.85
		2	0.99	0.99	0.11	15.40

August Data

Lucerne models for the IR850 August data were not successful, as only one model was derived for replica 1 of the sand sample at 30% irrigation. The RMSE(V) value for this model was 12.70%. Which is above the acceptance criteria.

6.3.2 Lucerne NDVI

July Data

Table 6.6 shows the r^2 and RMSE for calibration and verification data for lucerne-NDVI models in July. The r^2(C) values are 0.99 for all models and the r^2(V) values range from 1.49% to 12.02%. The sample models for sand at 30% irrigation have RMSE(V) values of 1.49% and 1.59%, which pass the acceptance criteria and is suitable for estimating the SMC. The actual vs predicted SMC for this model are shown in Figure 6.5, this model shows a close representation of the actual SMC.

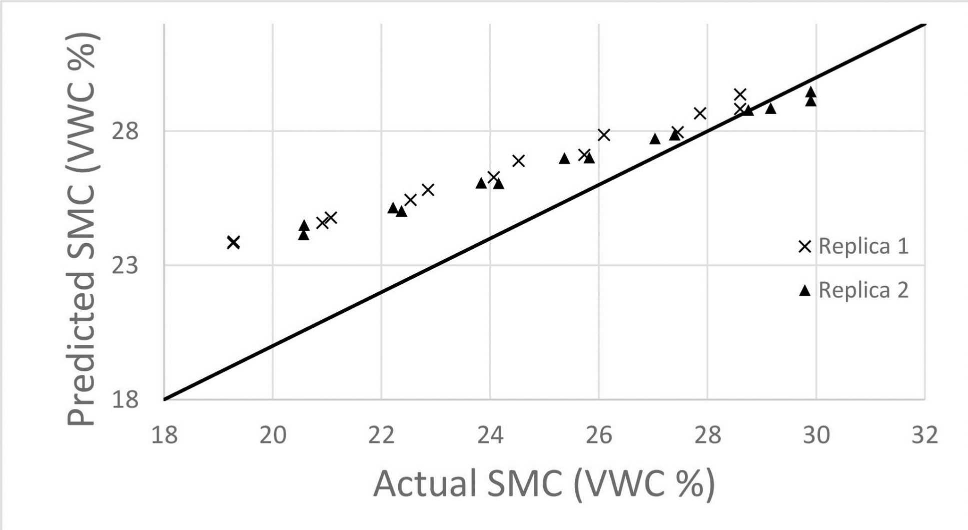

Figure 6.4: Actual Vs predicted SMC for lucerne-IR850-30%-sand July model

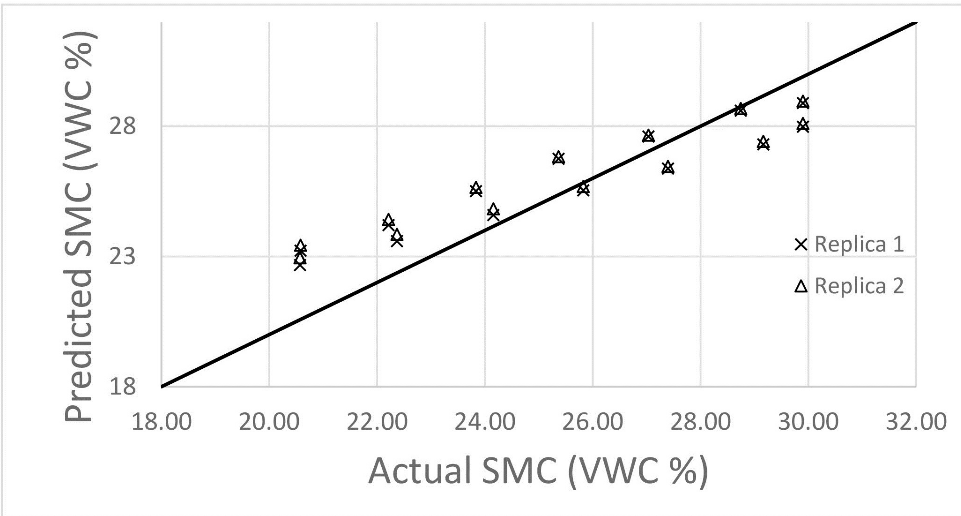

Figure 6.5: Actual Vs predicted SMC for lucerne-NDVI-30%-sand July model

Table 6.6: Lucerne NDVI July model comparison of performance between calibration (C) and verification (V) data sets.

		14^{th} July to 3^{rd} August				
Soil	**Irrigation**	**Replica**	r^2**(C)**	r^2**(V)**	**RMSE (C)**	**RMSE (V)**
Loam	40%	1	0.99	0.89	0.05	12.02
		2				
	30%	1	0.99	0.91	0.04	8.74
		2	0.99	0.92	0.10	3.58
	20%	1	0.99	0.91	0.12	5.99
		2	0.99	0.91	0.10	9.30
Sand	40%	1				
		2	0.99	0.92	0.17	8.3
	30%	1	0.99	0.91	0.05	1.49
		2	0.99	0.91	0.04	1.59
	20%	1	0.99	0.98	0.05	8.68
		2	0.99	0.91	0.06	15.87

August data

Table 6.7 shows the r^2 and RMSE for calibration and verification data for lucerne NDVI models in August. Only 4 out of the 12 samples had models. The loam has models for 40% and 20% irrigation levels. These models have a high RMSE(V) of 26.10% and 16.7% respectively. The sand models for both replicates at 30% irrigation produced a similar RMSE(V) of 1.80% and 1.39%. This error value passes the acceptance criteria. The actual vs predicted values for the 30% model is shown in Figure 6.6.

Table 6.7: Lucerne NDVI August model comparison of performance between calibration (C) and verification (V) data sets.

			24^{th} August to 24^{th} August			
Soil	**Irrigation**	**Replica**	r^2**(C)**	r^2**(V)**	**RMSE (C)**	**RMSE (V)**
Loam	40%	1	0.57	0.05	3.55	26.10
		2				
	30%	1				
		2				
	20%	1				
		2	0.92	0.01	1.91	16.70
Sand	40%	1				
		2				
	30%	1	0.98	0.89	0.43	1.80
		2	0.98	0.89	0.50	1.39
	20%	1				
		2				

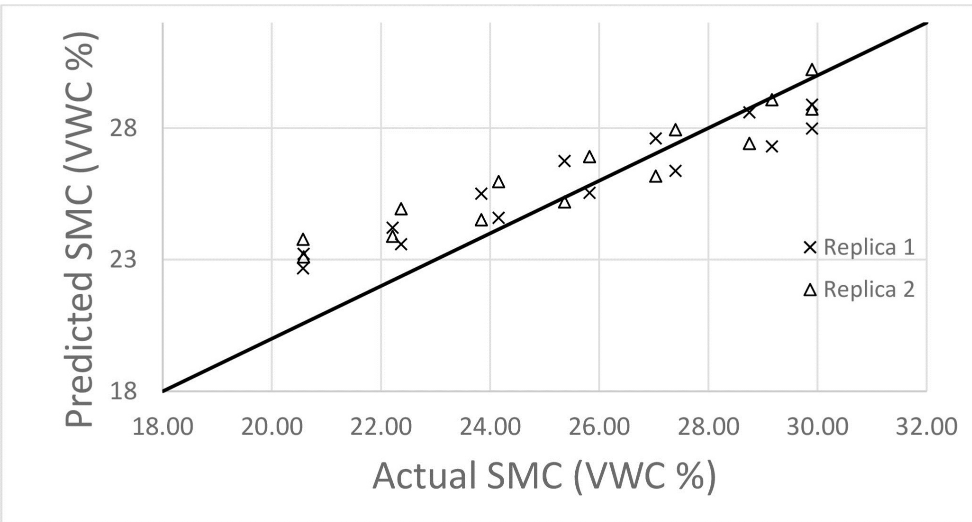

Figure 6.6: Actual Vs predicted SMC for lucerne-NDVI-30%-sand August model

6.4 Estimation Model Summary

The changes in spectral response (IR850) with SMC for chamomile plants was successfully modelled for 4 conditions of the exeriment. The models which were considered successful (refer Chapter 6) are listed in Table 6.8, in order from the smallest to largest Root Mean Squared Error (RMSE). The models were able to consistently predict SMC for loam at all irrigation levels for the month of August. Only one July model was produced for loam at an irrigation level of 20%. There were no estimation models produced for chamomile grown in sand, NDVI or Chl(a/b) ratio.

Table 6.8: Chamomile estimation models

Spectrum	**Irrigation**	**Soil**	**Month**	**RMSE** (Replica 1/2)
IR850	40%	Loam	August	1.73/1.54
IR850	20%	Loam	August	2.01/2.89
IR850	30%	Loam	August	2.86/2.6
IR850	20%	Loam	July	3.62/4.48

The changes in spectral response with SMC for lettuce was successfully modelled for samples grown in loam at irrigation level of 20% in July. This was the only successful model for lettuce. There were 6 models which had an RMSE value less than 5%; however, the replica counterpart did not pass the acceptance criteria.

The changes in spectral response with SMC for lucerne was successfully modelled for IR850 and NDVI plant response. Table 6.9 lists the successful models in order from smallest to largest RMSE. All successful models were irrigated at 30% and grown in sand. The NDVI response produced models for both July and August data and ranked higher than IR850 in terms of RMSE.

Table 6.9: Lucerne estimation models

Spectrum	**Irrigation**	**Soil**	**Month**	**RMSE** (Replica 1/2)
NDVI	30%	Sand	August	1.8/1.39
NDVI	30%	Sand	July	1.59/1.49
IR850	30%	Sand	July	2.7/2.04

Chapter 7

Conclusions and Further Work

7.1 Achievement of Project Objectives

The following objectives have been addressed:

- **Review visual plant and soil responses to soil moisture content.**
  A review of previous research on visual and soil response has been presented in Chapter 2. This also includes a summary of plant physiology which helps explain the plant response to its environment.

- **Review camera/sensor technology and image analysis techniques for capturing and automatically analysing visual plant responses to soil moisture.**
  A summary was presented in Section 2.2, of traditional and new methods of SMC estimation and measurement. Chapter 3 - Proposed Estimation System, describes the equipment including camera and SMC sensors which were used as a result of a thorough review.

- **Design a method of obtaining accurate data of plant response to varying levels of soil moisture content.**
  A fieldwork experiment was designed and implemented to successfully obtain accurate data used to calibrate estimation models. Chapter 4 describes the data collected which included weather, soil moisture and images. A high accuracy was achieved by selecting the most appropriate equipment for the intended purpose.

- **Collect plant image data at varying levels of soil moisture content using candidate camera system/s.**

  Chapter 4. Plant images were taken routinely each day. The SMC content was varied in a controlled way though daily monitoring and controlled irrigation. This provided a periodic cycle of irrigation events and dry days, which would be similar to field conditions.

- **Analyse data to extract plant features that indicate soil water status.**

  Chapter 5 describes the processing and analysis of raw data using MATLAB® and Microsft® Excel. Spectral reflectance information was extracted from the raw plant images, which allowed estimation models to be created.

- **Evaluate algorithm performance on soil moisture content estimation.**

  The estimation models were evaluated as described in Chapter 6, by testing against data reserved for validation. The Root Mean Square Error RMSE of the results were calculated and compared to the selected acceptance criteria of 5% error. There were nine samples out of the 36 which had a RMSE value of less than 5% for both sample replicates.

- **Adapt and refine algorithm to estimate soil moisture for other plant types.**

  The plant samples of chamomile and lettuce were chosen based on findings from the literature review in Chapter 2. The experiment was extended to include lucerne, as it is a commonly irrigated crop at the experiment location in central Victoria. Three lucerne models were created for IR850 and NDVI spectral response, all of the RMSE values were below 2.7%.

7.2 Further Work

This project has identified some conditions were the plant spectral response can be used to estimate the SMC. The fieldwork was designed to control the plant growing conditions in order to focus the research on SMC. The successful models will need further development before they can be applied in a real application. The effect of plant nutrition and disease on the spectral response should be researched, as this may introduce errors into the SMC estimation.

The plant samples used in this project where grown in 100mm pots and the SMC was measured with a capacitive probe each day, by manually inserting the probe and taking readings. Further research should be conducted in the field with in situ moisture sensors logging SMC data continuously. This will provide data based on true field conditions.

Plant chlorophyll (a/b) spectral response did not produce any successful estimation models in this project. Futher research could be done by varying the wavelengths of this ratio for each plant type, which may produce estimation models.

The data obtained during this experiment was categorised into July and August, the July data corresponded to cooler weather and plants at the seedling stage of their life cycle. As a result of dividing the data by two, the number of observations in each category were reduced. It is recommended to include more observations at the seedling stage of the plant life cycle, which would further improve the estimation model and allow for verification data to be reserved within the same category.

References

ABS (2012), '1301.0 - year book australia, 2012', viewed May 4 2014. Online Resource http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/1301.0~2012~Main%20Features~Water~279.

Allen, R. (2003), 'Spreadsheets supporting fao-56 example calculations', Viewed August 23 2014. Online Resource http://extension.uidaho.edu/kimberly/2013/04/spreadsheets-supporting-fao-56-example-calculations/.

Allen, R., Pereira, L., Raes, D. and Smith, M. (1998), 'Crop evapotranspiration - guidelines for computing crop water requirements - fao irrigation and drainage paper 56', Viewd August 23 2014. Online Resource http://www.fao.org/docrep/x0490e/x0490e00.htm#Contents.

Alshikaili, T. Y. (2007), Non-contact measurement of soil moisture content using thermal infrared sensor and weather variables, Master's thesis, University of Saskatchewan. Online Resource http://ecommons.usask.ca/bitstream/handle/10388/etd-03102007-163616/talal.pdf.

Bacci, L., Battista, P., Cardarelli, M., Carmassi, G., Rouphael, Y., Incrocci, L., Malorgio, F., Pardossi, A., Rapi, B. and Colla, G. (2011), 'Modelling evapotranspiration of container crops for irrigation scheduling', Online Resource http://http://cdn.intechopen.com/pdfs-wm/22700.pdf. Viewed August 5 2014.

British Columbia (2001), 'Water conseration fact sheet: Crop coefficients for use in irrigation scheduling', Viewed September 8 2014. Online Resource http://www.agf.gov.bc.ca/resmgmt/publist/500Series/577100-5.pdf.

Carter, G. A., Cibula, W. G. and Miller, R. L. (1996), 'Narrow-band reflectance imagery compared with thermalimagery for early detection of plant stress', *Journal of Plant Physiology* **148**(5), 515–522.

DEPI (n.d.), 'Gypsum blocks for measuring the dryness of soil', Viewed May 20 2014. Online Resource http://www.depi.vic.gov.au/agriculture-and-food/farm-management/soil-and-water/soils/gypsum-blocks-for-measuring-the-dryness-of-soil.

Gibson, P. J. and Power, C. H. (2000), *Introductory Remote Sensing : Digital Image Processing and Applications*, Routledge, London.

Giddings, J. and Williams, D. (2004), 'Neutron probe', *Waterwise on the farm* .

Gilchrist, G. (n.d.), Online Resource http://vixra.org/pdf/1110.0035v1.pdf. Viewed June 4 2014.

IAEA (2008), 'Field estimation of soil water content: A practical guide to methods, instrumentation and sensor technology', viewd April 7 2014. Online Resource http://www-pub.iaea.org/mtcd/publications/pdf/tcs-30_web.pdf.

ICT International (2014), 'Enabling better global research outcomes in soil, plant & environmental monitoring.', viewed May 20 2014. Online Resource http://ict.dev.nucleo.com.au/casestudies/which-soil-moisture-sensor-should-i-choose-2/?from=/casestudies/soils/moisture-portable-capacitance/.

Job Safety Analysis Worksheet (2012), viewed May 10 2014. Online Resource https://www.worksafe.vic.gov.au/__data/assets/pdf_file/0019/3628/jsa_jobsafetyanalysis.pdf.

Kriedemann, P. (1999), 'Plants in action adaptation in nature, performance in cultivation', Online Resource http://plantsinaction.science.uq.edu.au/edition1/?q=content/1-2-2-chlorophyll-absorption-and-photosynthetic-action-spectra. viewed May 24 2014.

Kuenzer, C. and Dech, S., eds (2013), *Thermal Infrared Remote Sensing : Sensors, Methods, Applications*, Vol. 17, Springer Verlag, Dordrecht, Germany.

Lane, P. (n.d.), 'Colourworker digital colour measurement', Onine Resource http://www.chrometrics.com/. Viewed May 20 2014.

min Li, X., lin Liu, A., yu Zhang, S., Wang, Z., Sun, W. and xin Wang, P. (2004), A study on thermal inertia approach for agricultural drought monitoring in shaanxi province, china by using noaa/avhrr data, *in* 'Geoscience and Remote Sensing Symposium, 2004. IGARSS '04. Proceedings. 2004 IEEE International', Vol. 6, pp. 4031–4033.

North Country Radio (2011), 'Low cost ir filter', Viewed on Aug 1 2014. Online Resource http://www.northcountryradio.com/Articles/irfltr.htm.

Peñuelas, J., Pinol, J., Ogaya, R. and Filella, I. (1997), 'Estimation of plant water concentration by the reflectance water index wi (r900/r970)', *International Journal of Remote Sensing* **18**(13), 2869–2875.
http://www.creaf.uab.cat/global-ecology/Pdfs_UEG/penuelasetalIJRS-wi-97.pdf

Pirzad, A., Shakiba, M. R., Zehtab-Salmasi, S., Abolghasem Mohammadi, S., Darvishzadeh, R. and Samadi, A. (2011), 'Effect of water stress on leaf relative water content, chlorophyll, proline and soluble carbohydrates in matricaria chamomilla l.', *Journal of Medicinal Plants Research* **5**, 2483–2488.
http://academicjournals.org/article/article1380714707_Pirzad%20et%20al.pdf

Prichard, T. (n.d), 'Using capacitance sensors to monitor soil moisture interpreting the numbers', Viewed August 24 2014. Online Resource http://cesanjoaquin.ucanr.edu/files/35895.pdf.

Sarker, A. M., Rahman, M. S. and Paul, N. K. (1999), 'Effect of soil moisture on relative leaf water content, chlorophyll, proline and sugar accumulation in wheat', *Journal of Agronomy and Crop Science* **183**(4), 225–229.
http://dx.doi.org/10.1046/j.1439-037x.1999.00339.x

Schnur, M. T., Xie, H. and Wang, X. (2010), 'Estimating root zone soil moisture at distant sites using {MODIS} {NDVI} and {EVI} in a semi-arid region of southwestern {USA}', *Ecological Informatics* **5**(5), 400 – 409. Special Issue on Advances of Ecological Remote Sensing Under Global Change.
http://www.sciencedirect.com/science/article/pii/S1574954110000592

Vegetronix (n.d.), 'Digital soil moisture meter', Online Resource http://www.vegetronix.com/Products/VG-METER-200/. Viewed May 2 2014.

White, B. (n.d), 'Bcg soil test interpretation: Workshop notes', Viewed August 24 2014. Online Resource .

White, S. C. and Raine, S. R. (2008), *A grower guide to plant based sensing for irrigation scheduling*, National Centre for Engineering in Agriculture Publication 1001574/6, USQ, Toowoomba.

Xue, L. and Yang, L. (2009), 'Deriving leaf chlorophyll content of green-leafy vegetables from hyperspectral reflectance', {*ISPRS*} *Journal of Photogrammetry and Remote Sensing* **64**(1), 97 – 106.
`http://www.sciencedirect.com/science/article/pii/S0924271608000610`

Zhang, N., Hong, Y., Qin, Q. and Liu, L. (2013), 'Vsdi: a visible and shortwave infrared drought index for monitoring soil and vegetation moisture based on optical remote sensing', *International Journal of Remote Sensing* **34**(13), 4585–4609.

Appendix A

Project Specification

ENG 4111/2 Research Project

Project Specification

For:	**Paul Watson**
Topic:	Non-contact visual soil moisture content estimation
Supervisors:	Dr Alison McCarthy
Sponsorship:	National Centre for Engineering in Agriculture, Institute for Agriculture and the Environment
Project Aim:	Identify and develop methods to estimate soil moisture content from visual plant response.

Program:

1. Conduct literature review of visual plant and soil responses to soil moisture content.
2. Review camera/sensor technology and image analysis techniques for capturing and automatically analysing visual plant responses to soil moisture.
3. Design a method of obtaining accurate data of plant response to varying levels of soil moisture content.
4. Collect plant image data at varying levels of soil moisture content using candidate camera system/s.
5. Analyse data to extract plant features that indicate soil water status.
6. Develop algorithm which can identify changes in plant reaction and estimate the value of soil moisture content.
7. Evaluate algorithm performance on soil moisture content estimation.

As time and resources permit:

1. Adapt and refine algorithm to estimate soil moisture for other plant types.
2. Develop and evaluate a proof-of-concept non-contact visual soil moisture estimation system.

Agreed:

Student Name: Paul Watson Paul Watson
Date: 8/3/14

Supervisor Name: Dr Alison McCarthy A McCarthy
Date: 10/03/14

Examiner:
Date:

Appendix B

Image Registration Listing

Listing B.1: Image Registration Code.

```
% File Name: ImageReg
% Author:     Paul Watson - Student Number 0050070606
% Date:       October 2014
% Course:     ENG4111 Research Project 2014
%             University of Southern Queensland
%
% Program Description:
% ImageReg takes two separate images (standard visual
% and filtered image)of the 36 plant sample and aligns
% them together. Once the visual has been aligned
% (registered to the filtered image). Each plant sample
% can be selected individually and processed to find the
% average reflectance. The results are stored in a
% file Albedo_IR850.
%
% Program Steps
% 1) Image registration.
% 2) Display overlay of both images to check registration.
% 3) Select reference of ColourChecker and display
%    reference on the image to check placement.
% 4) Select the sample to be processed, then reflectance value is
%    calculated and saved. The last step is repeated 36 times.
%
% Input Parameters:
% Parameter_1:  VIS, JPG visual image of samples, used for image
%               registration.
% Parameter_2:  IR, JPG filtered image of sample, used to
%               calculate reflectance values of samples.
%
% Return Value:
% Returned_Variable: Albedo_IR850.mat, table of results
%                    (type double)
%

%% Clear & close all
clc
clear all
close all

%Add path to image location if required.
```

```
% addpath...
% ('C:\Users\Paul\Documents\USQ\ENG4111_Research\Data\Raw\Images');

%% Read in image pair.
% Import visual and filtered image.
% Select 4 reference points in each image.
% Close window when complete.

IR = imread('20140913_IR850.JPG');
VIS = imread('20140913_VIS.JPG');
VIS = rgb2gray(VIS);
[input_points, base_points] = cpselect(VIS,IR, 'Wait', true);

%% Perform image transformation
%  Show filtered image with registered image overlay.

mytform = cp2tform(input_points, base_points, 'projective');
registered = imtransform(VIS, mytform);

%correct missalighnment
tform = cp2tform(input_points, base_points, 'projective');

registered1 = imtransform(VIS,tform,...
                          'FillValues', 255,...
                          'XData', [1 size(IR,2)],...
                          'YData', [1 size(IR,1)]);
figure;
imshow(registered1)
hold on
h = imshow(IR, gray(256));
set(h, 'AlphaData', -0.5);
clearvars RegVis;
RegVis = registered1;
save RegVis;

%% Select reference area and check alignment
% Steps
% 1) Select reference patch from the colourChecker by
%    click and dragging the curser.
% 2) Right click and select copy position.
% 3) Close Window
% 4) An image is shown with the selected area highlighted.

% Start selection tool to nominate reference patch.
[cropRef] = dim(RegVis);
Known_Ref = imcrop(IR, cropRef);
Known_Ref = rgb2gray(Known_Ref);

% find intensity values at relevent pixels for known reference
ref_refl = mean2(Known_Ref);

% check alignment of selected area
tempIR = IR;
tempIR(cropRef(2) : cropRef(2) + cropRef(4) , cropRef(1) :...
       cropRef(1) + cropRef(3)) = 0;

   imshow(tempIR);

%% select each sample area 1 to 36
% process each sample individually and save the
% reflectance value to file
%
% Steps
% 1) Select sample by click and dragging the cursor.
```

```
% 2) Right Click and select copy position.
% 3) Close window.
% 4) Repeat for 36 samples.
% 5) After 36 samples close the final window.
%
% Returned_Variable: Albedo_IR850.mat, table of results
%                    (type-double)

load Albedo_IR850.mat;
load RegVis.mat;

for sample = 1:36;

    [cropSample] = dim(RegVis);

    A1 = imcrop(RegVis,cropSample);

    A1 = imadjust(A1);

    level = graythresh(A1);
    bw = im2bw(A1,level);

    bw = bwareaopen(bw, 50);

    % find black pixel and work out position in IR image
    [x,y] = find(bw==1);
    x = x + cropSample(1,2);
    y = y + cropSample(1,1);

    IR_gray = rgb2gray(IR);

    %check if pixels align with RegVis
    pixelValue = [];
    for f = 1:size(x,1);
        x1 = x(f);
        y1 = y(f);
        pixelValue(f) = IR_gray(x(f),y(f));
        RegVis(x1,y1) = 0;

    end
    % Update selected samples
    figure; imshow(RegVis);

    % Calculate reference and sample reflectance
    IR_max = max(pixelValue);
    IR_min = min(pixelValue);
    IR_mean = mean2(pixelValue);
    IR_sum = sum(pixelValue);

    % Find mean reference intensity
    Albedo_ref = (IR_mean/ref_refl);

    % Find the absolute intensity
    Albedo_abs = (0.18*Albedo_ref);

    % save results
    Albedo_IR850(53,sample) = Albedo_abs;

end

save Albedo_IR850;
```

Appendix C

Image Analysis Flow Chart

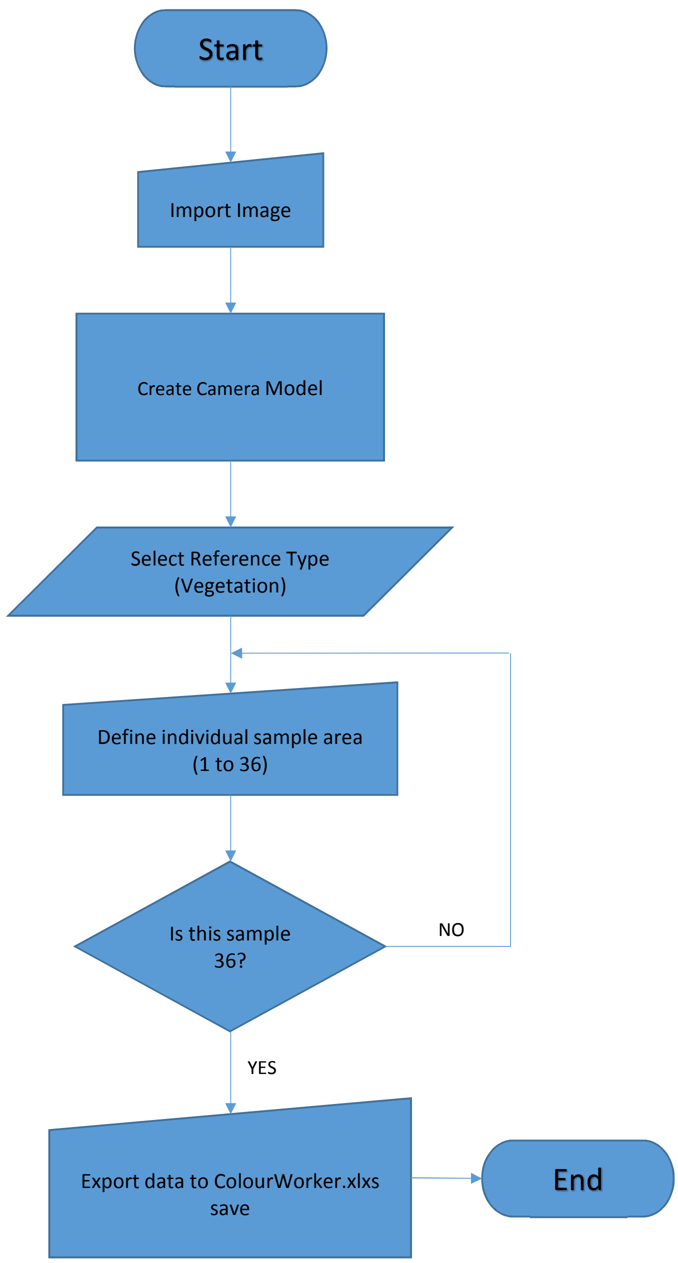

Figure C.1: ColourWorker image processing flow chart

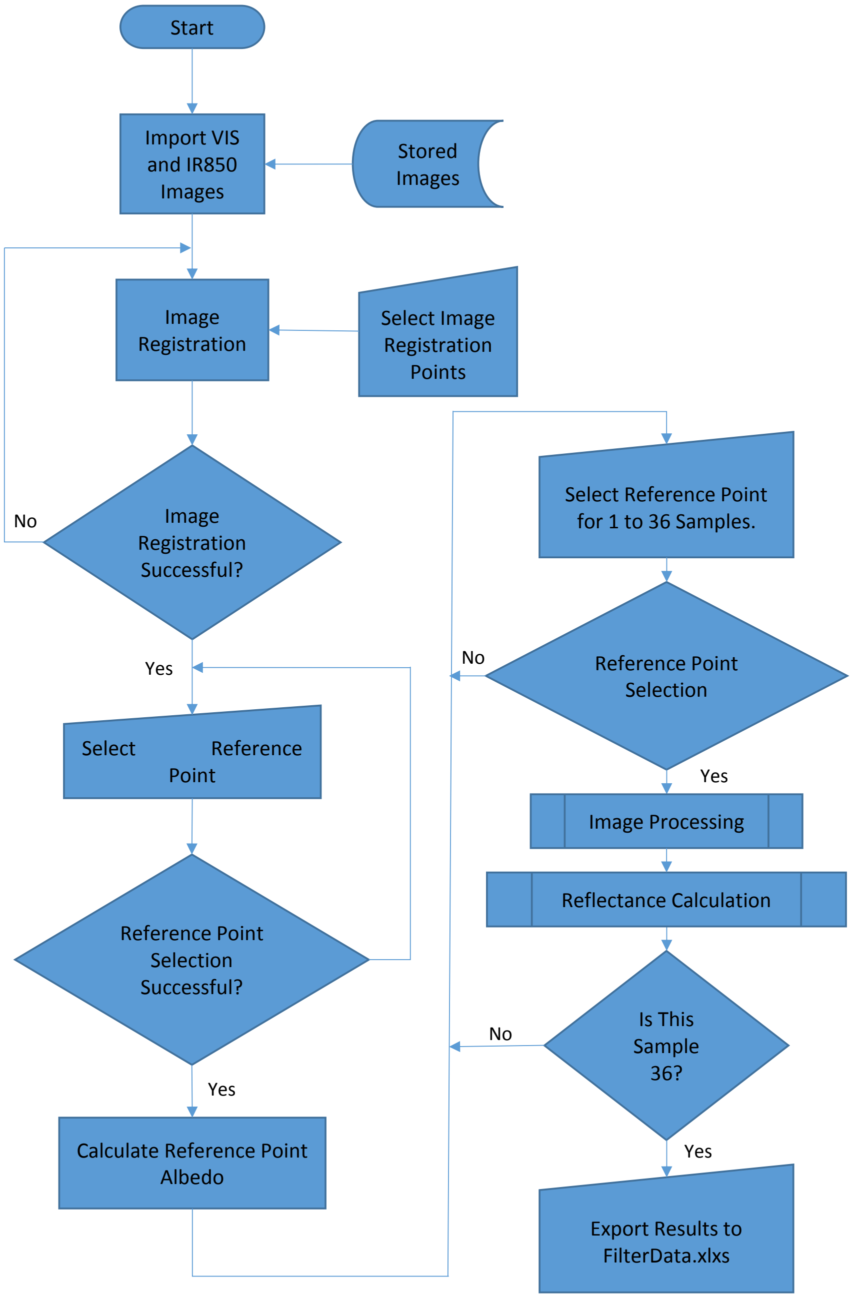

Figure C.2: Image Registration Flow Chart

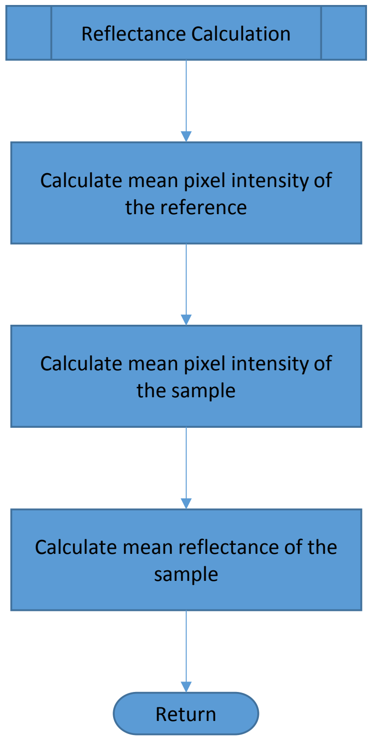

Figure C.3: Image reflectance calculation flow chart

Appendix D

Evapotranspiration Listing

Listing D.1: ETo Calculation Code.

```
function [ EToData ] = ETo( ind )
%
% File Name: ETo.m
%
% Author:     Paul Watson - Student Number 0050070606
% Date:       October 2014
% Course:     ENG4111 Research Project 2014
%             University of Southern Queensland
%
% Program Description:
%
%   This function estimates the evapotranspiration.
%   Takes the ind (index range of weather data
%   for each day to be calculated) and determines the
%   ET values using data from variables weatherData.mat
%   The output is ETo vector which can be inserted into
%   the samples.mat variable.
%
% Input Parameters:
%
% Parameter_1:  ind, a vector containing pre-determined index
%               values to identify weather data for each day.
% Parameter_2:  weatherData, database of local weather parameters.
% Parameter_3:  samples, database containing plant sample data
%
%
% Return Value:
%
% Returned_Variable: EToData, a vector containing the total ETo
%                    for each day.
%

% load data
load 'weatherData.mat';
load 'samples.mat';
m = size(ind,1);

% setup EToData
EToData = zeros(m,1);
```

```
% step through each day to calculate ETo
for days = 1:m ;

% setup variables
Tmax = 0;           %Daily Temp max
Tmin = 0;           %Daily Temp min
RHmax = 0;          %Daily Rel Humidity max
RHmin = 0;          %Daily Rel Humidity min
U = 0;              %Daily Wind speed (km/h)

range = ind(days,1):ind(days,2);
doy = weatherData(range(1))+1 - floor(datenum('1-Jan-2014'));

% Daily Temperature
Tmax = max(weatherData(range,2));
Tmin = min(weatherData(range,2));
Tave = (Tmax + Tmin)/2;

% Daily Rel Humidity
RHmax = max(weatherData(range,3));
RHmin = min(weatherData(range,3));

% Wind Speed
% Convert km/h to m/s
% km/h x 1000/3600
U = mean(weatherData(range,4))*1000/3600;

% Solar Radiation
%Convert Watts/m^2 to MJ/M^2
% W/m^2 x 0.0864
Rs = sum(weatherData(range,5))*1800/1E6;

% Experiment Location Latitude
lat = -36.7;
Lat = (lat*pi)/180;
elev = 208;

% delta
delta = 4098*0.6108*exp((17.27*Tave)/...
        (Tave+237.3))/(Tave+237.3)^2;

% pressure
P = 101.3*((293-0.0065*elev)/293)^5.26;

% Gamma
gamma = (0.00163*P)/2.45;

% variables names refer to ETo (Penman-Monteith)
% spread sheet created by Allen (2003).
E26 = 1+0.34*U;
E27 = delta/(delta+gamma*E26);
E28 = gamma/(delta+gamma*E26);
E29 = 900/(Tave+273)*U;
E30 = 0.6108*exp(17.27*Tmax/(Tmax+237.3));
E31 = 0.6108*exp(17.27*Tmin/(Tmin+237.3));
E32 = (E30+E31)/2;
E15 = (E31*RHmax/100+E30*RHmin/100)/2;
E33 = E32-E15;
E34 = 1+0.033*cos(2*pi/365*doy);
E35 = 0.409*sin(2*pi/365*doy-1.39);
E36 = Lat;

E42 = acos(-tan(E36)*tan(E35));
E43 = 24*60/pi*0.082*E34*(E42*sin(E36)*sin(E35)...
```

```
        +cos(E36)*cos(E35)*sin(E42));
E44 = 24/pi*E42;
E46 = Rs;
E47 = (0.75+0.00002*elev)*E43;
E48 = E46/E47;
E49 = 0.77*E46;
E50 = 0.000000004903*(Tmax+273.16)^4;
E51 = 0.000000004903*(Tmin+273.16)^4;
E52 = (E50+E51)/2;
E53 = 0.34-0.14*sqrt(E15);
E54 = 1.35*E48-0.35;
E55 = E52*E53*E54;
E56 = E49-E55;
E57 = 0;
E58 = E56-E57;
E59 = 0.408*E58;
E60 = 0.408*E58*E27;
E61 = E29*E28*E33;
ETo = E60+E61;

EToData(days,1) = ETo;

ETo = 0;

end

end
```

Appendix E

Actual Vs Predicted Plots Chamomile July & August Models

E.1 July Model

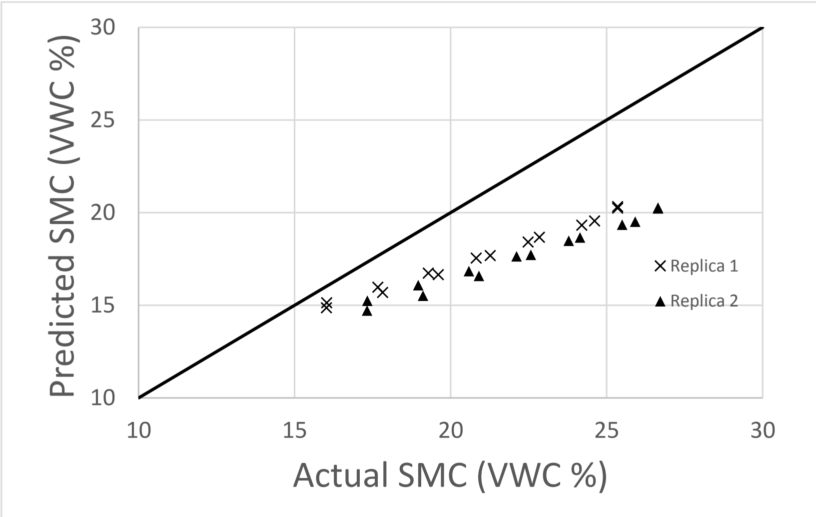

Figure E.1: Actual vs predicted SMC for chamomile-IR850-20%-loam July model

E.2 August Models

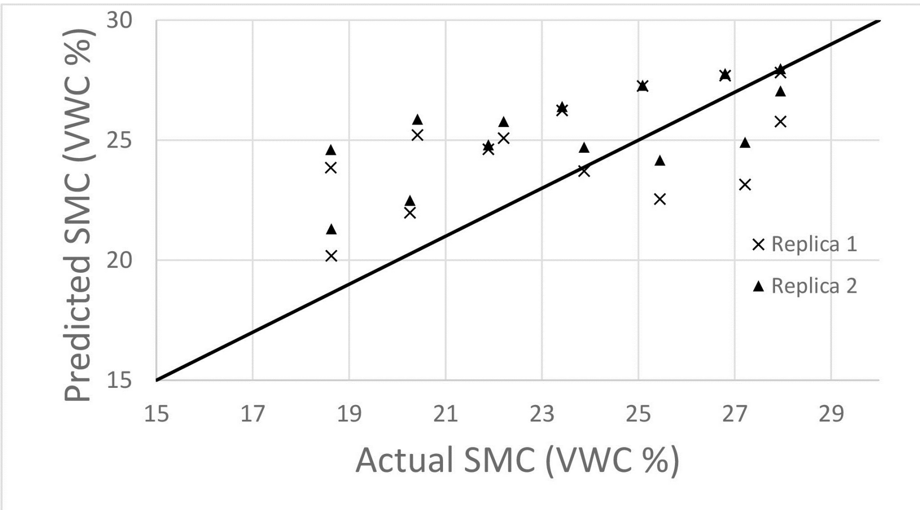

Figure E.2: Actual vs predicted SMC for chamomile-IR850-30%-loam August model

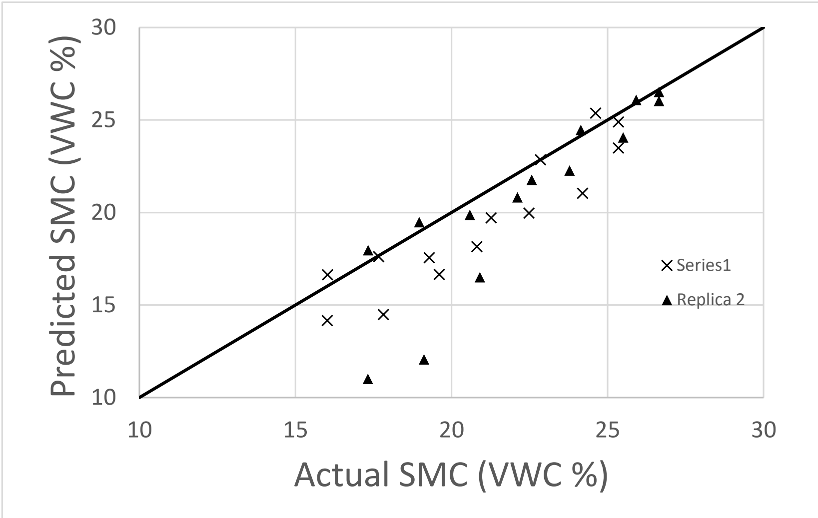

Figure E.3: Actual vs predicted SMC for chamomile-IR850-20%-loam August model

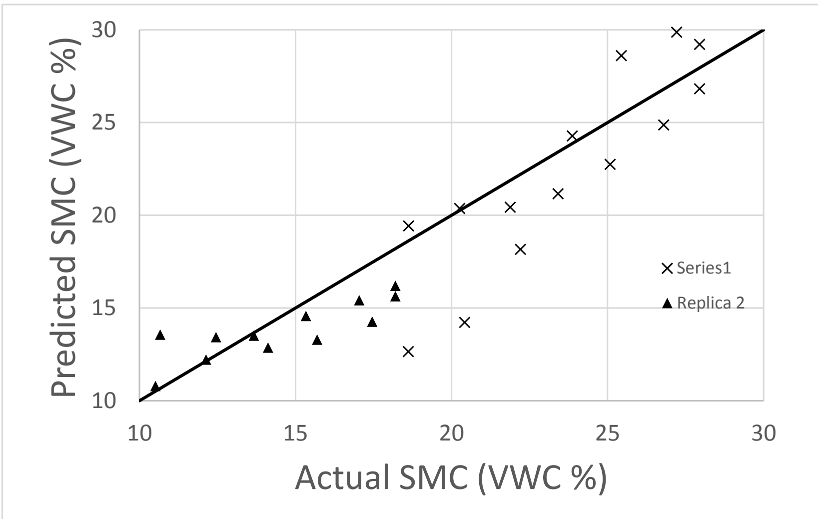

Figure E.4: Actual vs predicted SMC for chamomile-IR850-20%-sand August model