University of Southern Queensland

Faculty of Health, Engineering & Sciences

Validation of Commercial Precision Spraying Technology

A dissertation submitted by

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Abstract

The agricultural industry is a leading contributor to the Australian economy with an approximated revenue of $40 Billion in the 09/10 financial year. Weeds are portrayed as costing the agricultural industry up to $4 Billion per annum in herbicide use and lost production. Research into proposed methods to reduce this cost whilst maximising agricultural produce with sustainable practices will benefit the Australian economy.

Blanket spraying is a procedure utilised by all broadacre farmers to manage and control on-farm weeds. During fallow, paddocks typically have only a 20% coverage of weeds, therefore, a blanket spray could unnecessarily spray as much as 80% of the field. Not only is this an expensive waste of herbicide, it also has negative impacts on the environment and possible accumulation in food products through residue buildup and runoff.

Precision spraying platforms are available in agriculture which detect weeds in real time and activate nozzle solenoids to deliver chemicals to the weed. Precision spraying, therefore, targets only weeds and results in herbicide saving and a decrease in herbicide resistance. In theory this is impressive, however, adoption of this technology has been poor throughout the agricultural industry due to the large capital expenses required to purchase the systems and fear of change with no guarantee of the kill rate. There is no quantitative data that provides proof on the accuracy of any weed detection system commercially available. Therefore, this project aims to develop hardware and associated software to form the basis of a standardised test procedure for evaluating weed detection systems.

Initially an assessment of two commercial weed detection systems were undertaken, the WeedSeeker and WEEDit platforms, to determine interfacing methods to recognise when the systems detect weeds. This assessment led to the development of two separate Weed-Check modules which could interface to the different platforms and capture a signal when

a weed was detected. When this signal is recognised by the WeedCheck module, a camera is triggered which captures an image of the weed, whilst also geotagging the image with GPS position information.

Field trials were designed to test the accuracy of the weed detection platforms. These trials were performed to gather information on three attributes. The first being the accuracy of the weed detection platform. This included determining the hit and miss rates of the technologies through taking images of the weeds detected and post analysing them. The second interest was the spray footprint of the weed detection platforms, which is important to ensure chemical is delivered to the weed. This test clearly showed the WEEDit had a better spray footprint of approximately 500mm whereas the WeedSeeker platform only had 150mm. The third stage of the trial involved using the GPS positions to create weed maps. This, however, proved to be inaccurate as a GPS error of up to 4.3 metres was observed. The images of the weeds were then analysed to match identical weeds captured within and between trials which formed the basis of the weed detection accuracy assessment.

The outcomes of the trials proved a feasible method was developed for determining the accuracy of weed detection platforms. Through matching weeds within the image frame, it allowed an assessment of hit and miss rates of the two technologies. Unfortunately, due to unforeseen GPS error the weed map comparison was deemed unreliable. Further future development of the computer vision algorithm to automatically sort and match weeds within frames would be an excellent method of validation. The final outcome of the project found the WEEDit was better at detecting weeds under different conditions, whereas the WeedSeeker platform regularly missed smaller weeds, however, this comparison was only undertaken with a 0.16ha trial block due to GPS position errors. Further testing would need to be conducted to verify these findings.

These findings and the software developed in this project have industry benefits as the result sets a standard of comparison of new developments in weed detection platforms against current commercial systems. This is of high significance to industry as there is no advantage in developing agricultural robots to change farming systems if the attachments and sensors available have not yet been validated. Robotics in agriculture can only be as effective as the sensors and implements available. To encourage adoption, farmers need to clearly see the benefits of the change and know they are moving forward not backward in weed control, sustainability and profitability.

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Limitations of Use

Certification of Dissertation

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

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

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Chapter 1

Introduction

1.1 Project Aim

This dissertation aims to develop hardware and software which form the basis of a standard procedure for evaluating weed detection systems that can potentially be interfaced to map weeds during precision spraying.

A standardised test procedure for weed detection systems has the benefit of enabling new technological developments for weed detection to be compared against existing weed detection systems. This would ensure future advancements are improving on the currently available technology. Providing farmers with quantitative data on existing weed detection technologies may also aid in their adoption of the technology, benefiting both the environment and their weed control management.

For the trial phase of this project, agricultural robotic platforms will be used to carry out data collection for different weed detection systems.

1.2 Research Objectives

1. Design a trial protocol to determine weed detection accuracy and spray footprint.
2. Develop a universal ground truth method which would enable validation of commercial weed detection technology.
3. Design software capable of interfacing with a range of weed detection technology to

obtain a signal when a weed is detected.

4. Develop software that presents recorded data and allows labelling of correct or incorrect weed detection.

5. Develop software that automatically generates weed maps of the field.

6. Collect data in a field to ground truth the weed detection systems and generate weed maps using the developed software.

Once these steps are complete the protocol should present a hit and miss statistic of the precision spraying technology and a weed map with accuracy within 0.5 metre.

1.3 Background

On a global scale agriculture plays an important role in the economies and health of the world population. Wherever land is put to agricultural use, weeds will grow (Paap 2014). A weed is a plant growing where it is not wanted and in competition with cultivated and naturally growing plants (Natural Resource Management Ministerial Council 2007). Weeds are one of the major problems affecting Australia's natural ecosystems and agricultural vegetation as they compete with agronomic crops for nutrients and water. Weed populations deplete necessary resources required for crop growth and to enable crops to flourish to their maximum potential. This causes a decrease in crop development restricting productivity and yield potential, resulting in less produce. Weeds, along with other invasive species, now arguably pose one of the most significant threats to biodiversity and agricultural production (Natural Resource Management Ministerial Council 2007).

In Australia, the agricultural industry is a leading contributor to our economy. The Australian Bureau of Statistics approximated an agricultural revenue of $40 billion for the 09-10 financial year (Australian Bureau of Statistics 2012). This is produced from approximately 425 million hectares, covering 55% of Australia's land area. The total economic cost of weeds to Australia is close to $4 billion per annum (Natural Resource Management Ministerial Council 2007). It is therefore crucial for the future of agriculture for weeds be assessed and controlled accordingly.

Weed populations are spatially and temporally variable within and between agricultural fields (Peteinatos, Weis, Andujar, Rueda Ayala & Gerhards 2014). To obtain the necessary information about actual weed density and population, weed mapping is necessary (Schuster, Nordmeyer & Rath 2007). The Department of Agriculture, Fisheries and Forestry have published a field manual proposing a standardised, systematic weed assessment procedure that can be applied across all land tenures. The manual suggests decision-makers need comprehensive and objective data on weed distribution and spread to set priorities and measure outcomes of weed research (McNaught, Thackway, Brown & Parsons 2008). This proposal is supported by a publication released by the Department of Environmental Conservation, which discusses the importance of mapping weed species in setting priorities for control work (Brown, Bettink, Paczkowska, Cullity, Region & Shane 2011).

1.3.1 Impacts of Weeds on Agriculture

The problem of weeds is a complex one. In order to reduce their impacts often various methods must be coordinated. The presence of weeds in agriculture not only affects the production and crop quality, they can also be harmful to livestock (Paap 2014). In agronomic crops, weeds compete for resources such as water, light and nutrients. This competition reduces both the quality and quantity of the crop's produce. The yield of harvested crops will be affected and unwanted weeds may cause contamination of the grain sample. Management practices can be invoked to control weeds, however, this causes an increase in the production cost of the crop by investment in machinery, herbicides and labour (Paap 2014).

1.3.2 Weed Management Practices

There are various methods which can be adopted for controlling unwanted pest plants. In Australia, most weed control methods are either through cultivation or the use of herbicides. Traditional farming practices relied heavily upon manual weed control through various cultivation methods, such as ploughing, discing and scarifying. Modern precision farming requires land conservation and soil sustainability practices to be adopted leaving land more susceptible to weed populations. With the adoption of minimum tillage farming, the reliance on herbicides has become crucial. However, often one method is not sufficient to control serious weeds and an integrated approach may be necessary, this is known as Intergrated Weed Managment (IWM). IWM is a "sustainable management system that combines all appropriate weed control options" (Natural Resource Management Ministerial Council 2007). IWM targets all weed species through various means throughout the cropping season, with the aim to reduce weed populations and their impacts on the crop.

The development of new technologies in agriculture can assist IWM by providing site specific weed control and improvements in data collection and management. This is evident through the adoption of Precision Agriculture which has allowed detailed information about variability in soil, crop health and weed density/populations to be collected and used as a resource in farm management practices.

Chemical Application

Chemical control relies on the use of herbicides. Herbicides control weeds by altering the normal growth patterns of the plant, through drying the leaves/stems or by defoliating the plant (dropping leaves) (Department of Agriculture and Fisheries. n.d.). Herbicide application is the most common and sometimes the only viable approach that can be used in broad-acre farming. It involves mixing specific chemical/s (see Figure 1.1) with water, which target specific plant groups, such as broad or narrow leaf. This mixture is then applied to the field with a machine known as a boom spray, as shown in Figure 1.2.

Figure 1.1: Herbicides used to control weeds (Getty Images 2013)

Blanket Spraying

Blanket spraying is a technique commonly utilised by farmers to deliver a range of herbicides for effective weed management. This involves using a large agricultural machine, commonly referred to in industry as a boom spray, to deliver the same quantity of herbicide to the entire field. Blanket spraying is an excellent control measure for weeds. It results in all weeds being targeted and thus none being missed, as the entire paddock is sprayed. However, with weeds becoming increasingly resistant to herbicides, a higher chemical rate is needed for control, which is quickly becoming a costly exercise for farmers. These higher herbicide applications also have negative impacts on the environment and can potentially contaminate food produced for human consumption (Rose, Zwieten, Zhang, Nguyen, Scanlan, Rose, McGrath, Vancov, Cavagnaro, Seymour, Kimber, Jenkins, Claassens & Kennedy 2016).

Figure 1.2: A common spray unit used in broad-acre production systems (AGRONOMO 2015)

Precision Spraying

Precision spray technology has the potential to revolutionise weed management by more effective and efficient control of weeds. Farmers commonly refer to this technology as spot spraying, because that is exactly what it does, sprays individual plants. The sensors used for precision spraying detect plants in fallow (i.e. differentiates green from brown) and sprays them with a predetermined chemical (Silburn, Rojas-Ponce, Fillols, Olsen, McHugh & Baillie 2013). Spot spraying is a much more economical weed control strategy over blanket spraying. Department of Primary Industry research in Northern NSW has shown the average weed cover in fallow paddocks is as low as 20% of the paddock area. This means that often 80% of the herbicide is applied to bare soil and is therefore wasted. This method is inefficient, expensive and environmentally unsustainable (Mcintosh Distrubution 2015). Croplands Australia claim their WEEDit system, shown in Figure 1.3, can save up to 90% chemical usage with an average saving of around 45% (Croplands Australia 2015). The WeedSeeker system claims a similar saving of up to 90% (Mcintosh Distrubution 2015). This method also reduces herbicide resistance and residue build-up in soils from excessive overuse of chemical.

The benefits of this technology are listed below. More detailed impacts on waterways and soils are provided in Section 2.3.

1. Reduced herbicide usage and input cost.
2. More sustainable use of water.
3. Reduced potential for environmental impact.
4. Maximised productivity.
5. Minimised chemical resistance.
6. Reduced residue and run-off into waterways.
7. Reduced chemical drift.
8. Reduced contamination of:
    - (i) Livestock fodder.
    - (ii) Food for human consumption.
    - (iii) Air quality.

Figure 1.3: WEEDit spot spraying technology

Non-Chemical Approach

Herbicide resistance is becoming a significant problem in Australian no-till farming systems. Many weed species have developed resistance to multiple herbicide groups (Brodie 2016). As these weeds develop further resistance to herbicides the need for a more robust weed control method is becoming increasingly necessary. Recent technological developments have trialled two effective, non-chemical approaches to weed control in agriculture.

None of the following alternative non-chemical approaches to weed control, discussed below, are commercially available as yet and are still in early developmental stages.

Microwave Technology

Recently, microwave technology was found to be effective in killing weeds. Cawood (2013) made the discovery that microwave technology ruptures plant cells, causing them to rapidly wilt and die. Microwaves cause water molecules inside the plant cells to rotate and align with the direction of the waves. This movement causes friction and inevitably results in the generation of heat. This heat then produces a build up of steam pressure in the plant cells, eventually causing them to rupture. Weeds are killed within a second of microwave exposure and seeds to a depth of five centimetres are rendered infertile. Cawood (2013) found a percentage of soil microbes were also killed, however, were quickly recolonised. Microwave technology has not yet become commercially available, the latest reports indicate release within the next 2 years (Brodie 2016).

Plucking Technology

Mechanical weed control is once again being taken into consideration for weed control in agriculture. In the past, blanket mechanical weeding was carried out by discs attached to large agricultural machinery which led to soil compaction issues, enormous amounts of time required for workers as well as massive fuel costs and expensive wear and tear on machinery. This, overtime, has been replaced by excessive herbicide use to control weeds, especially with no till practices being adopted. Overuse of herbicides is now coming into question for health safety reasons (Myers, Antoniou, Blumberg, Carroll, Colborn, Everett, Hansen, Landrigan, Lanphear, Mesnage, Vandenberg, vom Saal, Welshons & Benbrook 2016) as well as growing herbicide resistance issues.

New technologies are being developed and researched on a global level to reintroduce mechanical weeding through the possibility of plucking weeds robotically. (Fadlallah & Goher 2015) reviewed many robotic technologies including robots developed by (Blasco, Aleixos, Roger, Rabatel & Molto 2002) and (Gobor, Lammers & Martinov 2013) whose robot's use robotic arms to pluck each weed. It was found the biggest drawback in the robot developed by (Blasco et al. 2002) was issues with safety, accuracy and weed removal efficiency whilst (Gobor et al. 2013)'s robot had not yet been visualised. Further research into this technology, especially to identify weeds and pluck them with robotic arms within crop rows not just between them, would transform weed control significantly.

Naio technologies is currently developing a prototype in France to weed crops mechanically. Supposedly this new technology will enable supervision free weeding which will reduce the impact of herbicides on the environment and due to its lightweight body will reduce soil compaction(Naio Technologies 2016). This robot has yet been seen in action and thus has not been reviewed.

1.3.3 Interaction between Agricultural Chemicals and the Environment

Substantial on-farm benefits can be gained through the use of herbicides for weed control. In most cases the use of herbicides are quicker and less expensive over other methods, such as mechanical weeding (Freedman 2012). In broad-acre farming herbicide use is commonly the only viable option to control unwanted vegetation. However, if herbicides are not used correctly damage to the crop and environment can result.

Incorrect or overuse of herbicides can cause contamination and pollution to the environment, including waterways and soils (U.S Fish and Wildlife Service 2009).

- Waterways are affected by:
  - Chemical spills or leaks
  - Improperly discarded herbicide containers
  - Rinsing equipment near drainage areas
  - Surface run-off
  - Leaching of herbicide into waterways and ground water
  - Spray drift onto un-targeted crops
- Soil properties that may be affected include:
  - Soil chemistry such as pH, CEC and EC
  - Changes to microbial population and activity
  - Fertility and available nutrients
  - Soil composition through a decline in organic matter

The introduction of site specific herbicide application (precision spraying) has reduced the potential risk of environmental pollution as well as production costs for farmers (Schuster et al. 2007). Heap and Trengove (2008) observed "using broad-acre blanket spraying results in the wrong application decision at almost every point in the paddock." This is because weeds tend to grow in clusters and are populated randomly throughout the field. In a fallow field, the use of a blanket sprayer results in non-weed growing areas of the field to also be sprayed, wasting chemical. Site specific herbicide application has the potential to reduce herbicide applications by 10 to 80% with research indicating weed-free crop areas that are not sprayed can yield up to 10% more produce (Heap & Trengove 2008). The potential cost and environmental conservation factors of precision spraying are obvious.

Quality assurance of site specific precision spraying is necessary for farmers to ensure weeds will be controlled effectively using this technique. The aim of this project is to develop a standard procedure to validate the commercially available technology to provide farmers with quantitative measurements for an emotive adoption. Embracing this technology will lead to the reduction of environmental impacts, increased efficiency and profitability for the farmer.

1.4 SwarmBot Platform

This project was sponsored by SwarmFarm Robotics. The SwarmFarm concept is to use a swarm of lightweight autonomous robots to work together achieving better farming systems. Two SwarmBots (see Figure 1.4) will be used in this project, one with an 8 metre WEEDit boom and one with an 8 metre WeedSeeker boom. The benefits of using SwarmBots for this trial, is the ground speed and ground position can be standardised between the two robots. The robots use RTK GPS for localisation, and have a ground repeatability distance of 2cm. Furthermore, this means the two SwarmBots will have position accuracy to within 2cm, which ensure a standardised ground sampling position. The robots travel at a maximum speed of 10 km/hr. The software framework used on the SwarmBot is Robot Operating System (ROS). ROS is an open-source operating system for use in robotics. It provides a link between hardware abstraction, low-level device control, high level systems and also controls messages passing between processes. ROS will be used in this project to interface the proposed module being developed, to both the SwarmBot and the weed detection platforms.

Figure 1.4: SwarmBot with WEEDit Boom

Chapter 2

Technologies to Validate and Ground Truth Precision Spraying

2.1 Introduction

The primary areas researched for this project include; technology already available in agriculture, computer vision techniques relevant to agricultural weed detection, as well as weed mapping techniques and their associated benefits.

2.2 Commercial Weed Spot Spraying Technology

2.2.1 WEEDit

WEEDit units, which are a new technology for use in precision spraying, are attached to the boom sprayer. These WEEDit units illuminate the ground with red light technology, as shown in Figure 2.1. As the vehicle passes over a weed, the natural plant chemical chlorophyll, responds to the red light by absorbing it and emitting Near Infrared (NIR) back into the sensors. The system then reacts, within 1 millisecond, by activating particular sets of spray nozzles to deliver chemical to the targeted weeds identified by the unit (Baillie, Fillols, McCarthy, Rees & Staier 2013). The WEEDit system, unlike some of its competitors, does not require ongoing user calibration. The sensor samples the ground every millimetre enabling it to function irrespective of changes in background conditions or light intensities. Simply, the sensors are not affected by changes in background colour (Romertron 2016). As a result, WEEDit technology can be used in full sunlight or complete darkness. The user can, however, adjust the sensitivity of the sensor (ie the size of plant it picks up) via a control panel in the cab.

Figure 2.1: WEEDit configuration on a common sprayer (Romertron 2016)

WEEDit configuration consists of sensors spaced at 1 metre intervals on the boom, operating at a height of 1100mm from the ground surface. Each individual sensor controls 5 solenoids. When a weed is detected a signal is sent from the sensor to the solenoid, causing an electromagnet to lift a plunger allowing fluid to be discharged through the nozzle. Each nozzle is spaced at 20cm intervals for a more accurate and precise application. Nozzles spraying at an angle of 40 degrees are used to further reduce drift and ensure the smallest footprint possible when spraying the weed (Croplands Australia 2015). The user can change sensitivity and margin (before and after weed) to ensure the weed is hit.

2.2.2 WeedSeeker

WeedSeeker is a commercially available sensor for site specific precision herbicide application. The WeedSeeker is a spectral reflectance sensor which uses red and NIR LEDs for illumination and a photodiode to detect the intensity of light (Paap 2014). The system is designed for discrimination of 'green' vegetation from 'brown' soil background and has been readily adopted to control weeds in fallow (no crop) paddocks. The sensor is able to detect the presence of a weed by assessing the difference between red and NIR reflectance of vegetation and background (Sui, Thomasson, Hanks & Wooten 2008). When the sensor identifies a weed, an electronic signal is sent to a solenoid valve, this signal receival activates a nozzle to deliver chemical to the weed, this is shown in Figure 2.2.

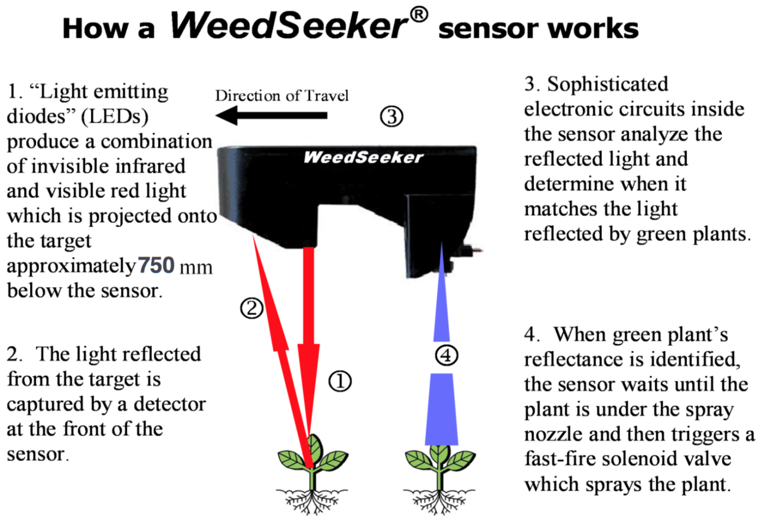

Figure 2.2: How a WeedSeeker works (Crop Optics 2010)

The system allows adjustments for sensitivity and velocity. Unlike WEEDit, before the WeedSeeker can be used the system must be calibrated on a plant-free surface within the paddock and weed size sensitivity must be set. This entails toggling a calibrate switch, which instantaneously sets the background chlorophyll levels for each individual sensor, hence why it is important to calibrate on a plant free surface where chlorophyll levels will be low (Crop Optics Australia 2010). Figure 2.3 shows the WeedSeeker modules mounted on a boom in a fallow field.

Figure 2.3: WeedSeeker Configuration on a common sprayer (Southern Precision2015)

WeedSeeker configuration, for speeds up to 20 km/hr, consists of 1 sensor every 380mm (15 inch), with a 250mm spacing from sensor bracket to spray tip. The operating height of the sensors is recommended between 650-850mm from the ground to the sensor lens.

2.2.3 H-sensor

The H-sensor is a recent technology advancement in weed control for agriculture. This sensor uses computer vision applications to classify weeds, based on their geometric properties. In Australia, the H-sensor is part way through a three year trial which has thus far proved successful performance in lentils, faba beans, chickpeas, lupins, wheat and barley. The technology can distinguish grass weeds in broadleaf crop types and broadleaf weeds in grass crops. This technology therefore acts similar to a selective herbicide (Trengove 2016).

The H-sensor gathers red and near infrared images and separates all crop and weed segments from the background stubble, soil and rock. It then identifies weeds from crop plants based on leaf and plant shape parameters. Once this has been completed, it initiates spray/ management decisions based on weed type and density. Each sensor contains its own light source so can be used both under day and night conditions. The sensor, however, does not perform very well in conditions where leaves overlap and the crop canopy is closed, which greatly reduces the accuracy and applicability of the technology. This technology is only useful in early stages of crop development, however, would still enable weed control for post planting sprays, up until the canopy closes (Trengove 2016).

This sensor was not analysed as part of this project because it was unavailable for testing.

2.3 Weed Detection with Computer Vision in Agriculture

2.3.1 Computer Vision

Computer vision is a tool that deciphers useful information from digital images (Fallis 2013). Technological advances are starting to become more commonplace and are having an enormous impact on modern day agriculture as the industry endeavours to improve on-farm productivity (Chaudhury, Ward, Talasaz, Ivanov, Norman, Grodzinski, Patel & Barron 2015). Computer vision involves the use of a camera and an algorithm to segment, classify, detect, extract and discriminate features within an image frame. By and large, computer vision has many potential applications to revolutionise the agricultural industry not limited to (Zachevsky 2012):

(i) Monitoring product quality

  –Automatic inspection

(ii) Classification and sorting

  –Automation of agricultural production

  –Fruit and Vegetables inspection

(iii) Crop Monitoring

  –Crop disease identification

  –Crop pest identification

  –Crop health status

  –Weed Identification and Mapping

2.3.2 Weed Detection Methods using Computer Vision

Computer vision has the ability to discriminate weeds from soil and has the potential to discriminate weeds from other surrounding plants. This can be achieved through using a range of techniques, algorithms and sensors including:

- Infrared (IR) technology
- NIR technology
- Red light technology
- Low cost cameras

Spectral Reflectance Sensors

The development of narrow band spectral sensors has enabled individual plants to be successfully detected. Current commercially available weed detection systems such as WeedSeeker and WEEDit use Red, IR and NIR light technology to discriminate 'green' from 'brown' for controlling weeds in fallow crops. The naturally occurring plant chemical chlorophyll reacts with these light frequencies by reflecting particular spectral wavelengths. Healthy vegetation absorbs blue and red light energy for use in respiration, photosynthesis and for chlorophyll manufacturing. Green light energy is reflected by pigments in the plant leaf and thus why we perceive plants as green. Chlorophyll reflects NIR light energy and thus a healthy plant flourishing with chlorophyll pigments will reflect much more NIR light energy than that of an unhealthy plant or soil alone (Sui et al. 2008). These sensors use this reflectance data for discrimination between soil and vegetation.

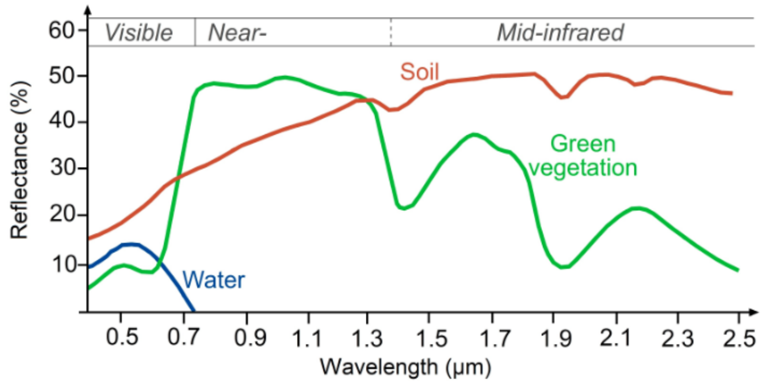

Figure 2.4: Reflectance of vegetation and soil over different wavelengths

Figure 2.4 shows the percentage of light reflected off soil and vegetation over different light wavelengths. Observing the 'green vegetation' line shows a 50% reflectance in the NIR wavelength band. The red line represents 'soil' reflectance. The graph clearly indicates a distinct reflectance difference between soil and vegetation, 10-20%, in this NIR (0.7-1.1 μm) band and 10-30% difference in the mid-infrared band (1.5-2.5 μm). Typically a spectral sensor will use this reflectance intensity as a threshold to discriminate vegetation from soil.

Imaging Sensors and Machine Vision

Research into the use of a low cost imaging sensor using machine vision algorithms/techniques to classify crop and weeds based on leaf properties such as size, shape, colour and texture, seems promising. High spatial resolution is possible with images captured from high-resolution digital cameras. Such technology has the potential to discriminate weeds both in crop and in fallow paddocks and would reduce the cost of herbicides, human labour and environmental impacts. These benefits are maximised since this technology can be used in crops, thus herbicide reduction is possible during the several herbicide applications necessary throughout crop development. Computer vision could assist in improving the IWM strategies in the future (Paap 2014). Machine vision algorithms require high processing power which limits vehicle speed. However, as processing technology develops, this limitation will gradually dissipate.

Steward & Tian (1999) developed a vision-based system which segmented vegetation and estimated weed density in the inter-row region. Utilizing six different image filters they were able to achieve promising discrimination. These trials were conducted under controlled lighting conditions with none of the associated time constraints from real time analysis. Their results indicate, with future work, this system could meet the challenge of site specific weed management and weed variability estimation. Tian (2002) designed a real-time machine vision system to capture images and detect plant density, through the use of a Bayesian classifier (probability of an event, based on information related to an event). This system was limited as it was only applied to inter-row application, of a controlled zone, meaning it was not capable of discriminating weeds from crops when the crop overhangs into the row.

2.4 Existing Technologies for Mapping Weeds

The most beneficial aspect of mapping weeds is the reduction in herbicide use. For this to be effective, reliable information on weed population and distribution is required. Weed mapping is an approach involving the production of a detailed weed map combined with other meta-data for precision agricultural application, mainly variable rate treatment maps. This weed map can be integrated with other available information when making decisions about weed control strategies to increase crop yield and quality (Paap 2014). Mapping can be achieved through either human observation or remote sensing. Human observation is time consuming, inefficient and labour intensive. Thus remote sensing is a more viable option. Remote sensing can produce weed maps where patches of weeds are of sufficient size, however, is limited in spatial resolution and requires considerable time and expense for image acquisition and processing (Swinton 2005).

Proximate sensing is an alternative option to remote sensing. It has the capabilities for real-time detection and spot spraying of weeds. Proximate sensing features high spatial resolution and with the aid of artificial lighting, can illuminate the ground and determine the spectral properties of crop and weeds.

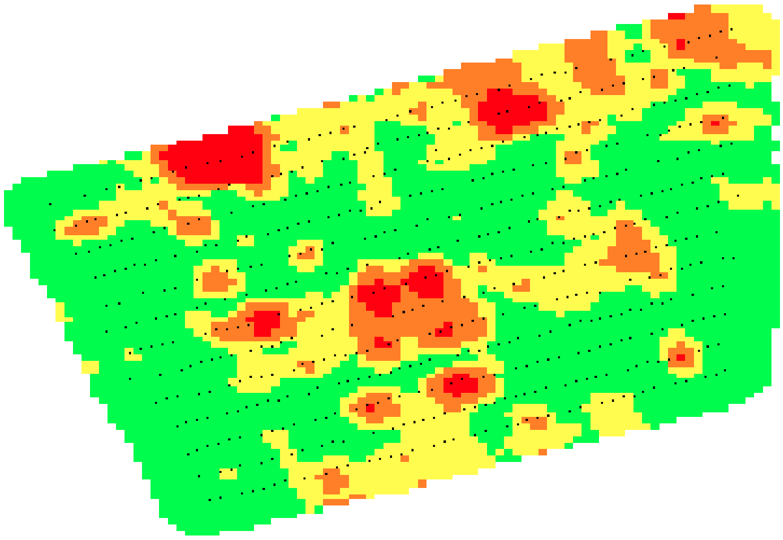

Figure 2.5: Weed map created using vision technology (Tillett and Hague 2014)

A four year study was undertaken by Timmermann, Gerhards & Kuhbach (2003) to determine the effects of site specific weed management in crops. Weed maps were manually created by segmenting the paddock into grids and sampling weed density within. An example of a weed map is shown in Figure 2.5, with higher weed densities being shown in red. The map provided detailed data for site specific weed management and as a result, an average of 54% herbicide was saved over the 4 year period. While this study does not present a viable method for creating weed maps, the outcome shows a significant decrease in herbicide use as a result of using the weed map.

(Sui et al. 2008) developed a weed mapping system based on the spatial properties of the weeds. This system was designed to collect weed-intensity data against spatial information. This system included WeedSeeker PhD600 sensor modules for weed detection, a GPS receiver for measuring location and a data acquisition and processing unit to collect and process weed data and spatial information. The system was field evaluated in a commercial cotton field for 2 years. They found the system performed well in collecting weed data in conjunction with spatial information for creating weed maps of the field.

2.4.1 Weed Mapping using Computer Vision

Computer vision algorithms for use in agricultural weed detection has been an area of interest in recent years. (Schuster et al. 2007) developed an algorithm to detect weeds and map them automatically using computer vision algorithms and a low cost camera. The weed mapping was created by taking images of weeds from a moving tractor (speed 1-2km/hr). Each frame corresponded to 54cm x 40cm on the ground. These images were then transferred to a computer and post-processed using a plant discrimination algorithm that was developed. To validate the algorithm 60 test frames were processed. The research concluded the algorithm generally worked well in discriminating monocotyledonous and dicotyledonous weeds demonstrating the applicability of future automatic weed mapping, using machine vision and image processing. However, development of a real time working application would require higher than available processing power.

2.5 Method to Validate Spot Spraying

The presentation of data by (Gönen 2006) was determined to be an appropriate method to display the data collected during the trial phase of this project. This data will be recorded, analysed and sorted as dichotomous outcomes (positive/negative results). This includes the true positives, true negatives, false positives and false negatives. This data will be sorted into a table similar to that shown in Figure 2.6. This information will be useful in evaluating the behaviour of the sensors after the trial has been completed. From this table, statistical information can be calculated, which include specificity, sensitivity, negative prediction ratio and positive prediction ratios.

Forecast	Observed		
	Positive	Negative	Total
Positive	True Positive (TP)	False Positive (FP)	TP+FP
Negative	False Negative (FN)	True Negative (TN)	FN+TN
Total	TP+FN	FP+TN	TP+FP+FN+TN

Figure 2.6: Standard method of tabulating accuracy of the binary predictor

2.6 Literature Review - Summary and Discussion

Robotics in agriculture have the ability to revolutionise the agricultural industry by changing the way farmers think and as a result change farming practices. SwarmFarm's concept is to replace traditional farming practices with a fleet of small lightweight robots that can move slower and be more accurate in their task. However, robotics in agriculture can only be as effective as the sensors and implements available. There is no advantage in developing agricultural robots to change farming systems if the attachments and sensors have not yet been validated. After reviewing available literature it became obvious there was a need to validate the accuracy of this technology. Precision spraying development needs to be at least as effective as current blanket herbicide use, or it will not be implemented by farmers as an effective method of weed control. Currently there is no quantitative data on the performance and behaviour of commercial weed detection sensors. Therefore, a research idea was identified that could close this gap and provide performance data of these sensors to farmers.

The trial phase of this project will involve the use of commercially available spectral sensors (WeedSeeker and WEEDit) to determine the accuracy and repeatability of the different weed detection platforms through the development of a module to capture images instantaneously when weeds are detected. Computer vision algorithms will then be fused with manual sorting of the images to ground truth the repeatability and accuracy of the sensor's behaviour.

Through the literature review, available weed detection platforms were introduced which have not been validated for accuracy and therefore, this project aims to develop a protocol and associated test hardware that has the ability to close this gap in the industry. These gaps include information on precision agriculture spray foot prints and ground truthing methods to validate commercial weed detection methods. Therefore, software development is necessary in this project to enable the above objectives to be met, including interfacing, recording and generating weed maps.

Chapter 3

Hardware Development of Weed Validation Module

This chapter outlines the steps taken to design and develop the module that would be used to validate the weed detection platforms. The selection of the hardware is also outlined within this chapter. The methods used to interface the module being developed to the weed detection platforms are also outlined and discussed.

The module being developed will be referred to as WeedCheck. The WeedCheck module will interface to both the WeedSeeker and WEEDit systems. When a weed is detected, the WeedCheck module will instantaneously trigger a camera to capture a frame of the ground. These frames will be used to determine if there was actually a weed present when the sensor reacted. The images will also be geo-tagged.

3.1 Idea Initiation

Prior to selecting any hardware it was important to clearly define how the WeedCheck module would function.

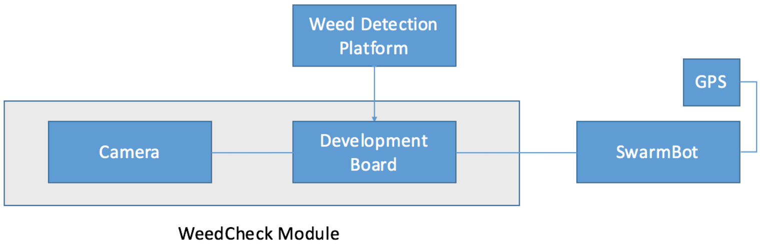

Figure 3.1: Block Diagram of WeedCheck Idea

When a weed is detected by the commercial weed detection systems, WEEDit and WeedSeeker, it is essential this trigger be instantaneously recognised by WeedCheck. The simplest technique which enables this to occur is through the use of a 12V signal that triggers the spray nozzle as a digital input into a development board. The WEEDit system has the potential to interface through serial connection and therefore serial communication should also be viable from the selected board. At the instant a weed is detected the camera must be triggered remotely to capture 2 frames of the ground. This repetition is required to minimise the risk of missing the weed in the image. To enable geo-tagging weeds and photographs, the development board will need to have ROS framework installed to communicate with the GPS on the SwarmBot. A block diagram of the WeedCheck module is provided in Figure 3.1, which showing the types of hardware used in the design.

3.2 Hardware Selection

This stage of the project involved choosing the appropriate hardware for the WeedCheck module. This selection included both an appropriate development board for running the program and a sensor for capturing real time images of weeds when they were detected by the spot spraying technology.

3.2.1 Development Board Requirements

The selection of an appropriate development board was primarily based on integration to the SwarmBot and weed detection platforms (WEEDit and WeedSeeker). It was also important for the selected board to have digital inputs and serial communication. Table 3.1 shows the specific requirements needed for the development board so the WeedCheck module can operate and interface to the weed detection platforms.

Table 3.1: Requirements for Development Board

Operating System	Linux
Digital Communication	I/O Pins
Serial Port	USB or RS232
Software Requirements	ROS
Networking Capabilities	Ethernet or WiFi
Storage	>16GB

Raspberry Pi

After consideration, the Raspberry Pi 3 (RPi) was selected and purchased for a feasibility analysis for this project. RPi is a low cost, credit card sized single board computer, shown in Figure 3.2. RPi is a well known board primarily used for computer vision applications as it is python based, and OpenCV can be installed very easily. The SwarmBot platform used for testing in this project, operate using a framework known as ROS. It is essential the selected board can both support and permit this framework to be installed. The RPi runs an operating system known as Raspbian which does supports ROS installation from source/ binary files.

Figure 3.2: Raspberry Pi 3 (Raspberry Pi 2016)

Further research into installing ROS frameworks onto RPi Raspbian operating system proved this to be a very difficult task. To overcome this, the Raspbian operating system was removed and Linux MATE 16.06 was installed. This enabled full integration to the SwarmBot platform. Not only was ROS installed much easier, but it also enabled access to custom message types from the SwarmBot without being required to write drivers. The benefits of this are numerous, for example with geotagging images. The locomotion package on the SwarmBot uses a NatSavFix message to publish the vehicle's GPS position. The ability to subscribe to this message directly from the RPi is important for geotagging images and the weed mapping portion of this thesis. Another benefit of installing the full framework of ROS, is that the GPS driver being used will communicate with any GPS that outputs an NMEA sentence. This means the module can be interfaced easily to GPS on traditional tractors.

Table 3.2: Hardware Specifications for Raspberry Pi 3

Operating System	Rasbian (configurable to run Linux)
Digital Communication	I/O Pins
	Camera Interface
Serial Port	4 x USB
ROS	Installable
CPU	1.2GHz quad-core ARMv8
Network Capabilities	Ethernet and WiFi
Storage	up to 128GB

Table 3.2 shows the hardware features and specifications of the RPi development board. The Ethernet port allows the RPi to be networked with the SwarmBot's router. Ethernet is needed for ROS to communicate with the ROS Master on the SwarmBots. Other benefits of the Ethernet port is it enables remote access through SSH into the WeedCheck module for testing and software development in the field. The RPi's operating system is installed on its Micro SD card. A 32GB card was used to ensure ample free storage for the data collection phase. As discussed above, GPIOs are required for interfacing to the WeedSeeker and the USB port can be used for communication to the serial port on the WEEDit. The RPi camera interface is a very easy and simple way to integrate a digital image sensor onto the board. The CSI (camera interface) port on the RPi will used for imaging.

3.2.2 Image Sensor Requirements

The image sensor was selected on its capability to interface with the chosen development board, as well as the camera specifications such as frame rate and image quality. The data collection phase of this project will take place outdoors in a sunny environment. It is therefore imperative the camera settings can be adjusted for outdoor use to remove unwanted brightness and white balance errors. The camera shutter speed should be easily altered to remove unwanted motion blur. Table 3.3 shows the requirements of the image sensor for the WeedCheck module.

Table 3.3: Image Sensor Requirements

Frame Rate	2 fps
Megapixel	5
Sensor Adjustment	Manual through program
Balance Adjustment	Outdoor setting
Trigger	Remote

Pi Camera

The Pi Camera is a sensor specifically designed for use with the RPi. It is a small and robust sensor that features a CSI ribbon to connect easily with the CSI port on the RPi for instant interfacing.

The camera sensor is a fundamental component of the WeedCheck module being developed in this project. The camera sensor must be capable of capturing high quality images in an outdoor environment in such a way that the marker dye can be distinctively seen in the images. It is beneficial to use this particular camera module as it was specifically designed for the RPi and can be triggered easily from a python script.

The sensor specifications are showed below in Table 3.4.

Table 3.4: Pi Camera Specifications

Sensor	Sony IMX219 sensor
Frame Rate	up to 30 fps
Megapixel	8
Pixels	3296 (H) x 2512 (V)
Sensor Adjustment	Manual through program
Balance Adjustment	Outdoor setting
Trigger	Remote
Connector	CSI connector

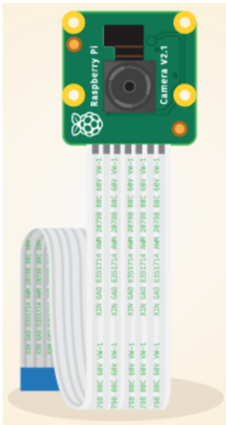

Figure 3.3: PiCamera (Raspberry Pi 2016)

Table 3.4 shows the hardware specifications of the Pi Camera. This camera features the necessary requirements shown above in Table 3.3. The RPi development board and camera module, shown in Figure 3.3, meet the hardware requirements for this project, and were therefore selected for use in developing the WeedCheck module.

3.3 WeedCheck Module Development

The WeedCheck module consists of a simple design comprising of a RPi and a camera module mounted inside a plastic box. The purpose of the WeedCheck module is to validate existing and developing technology, thus it must be able to interface with any weed detection platform and capture images of the weeds as they are detected. It is therefore essential to ensure the module can easily interface to any weed detection platform. For this project two WeedCheck modules were developed, one for the WeedSeeker and one for the WEEDit. It is possible for the WEEDit platform to interface the same way as the WeedSeeker, through using the 12V signal to the solenoid as a digital input. However, for this project it was decided the WEEDit module will be interfaced via serial to demonstrate the simplicity and versatility of the module. Also nozzle activity across the whole boom is of interest later in this project in Chapter 4.6.

Figure 3.4 shows the development of WeedCheck. The RPi was mounted inside a plastic box and a hole was drilled in the lid for the camera lens to fit into as seen in Figure 3.5. The module is powered via 5V USB power source. A hole was also drilled giving access to the Ethernet adaptor on the RPi.

Figure 3.4: WeedCheck module development

Figure 3.5: WeedCheck Module

The WeedSeeker and WEEDit platforms will use different communication protocols when interfacing to the WeedCheck module. The WEEDit console supports serial communication through a fully buffered RS232 port. Therefore, sending a polling serial request to the console, will return a string of nozzle activity. This will be used to determine when the WEEDit detects a weed. However, the WeedSeeker does not support serial communication. Therefore, to interface with the WeedSeeker modules, the 12 volt signal that triggers the nozzle solenoid will be tapped into. This signal will be used as a digital input into the WeedCheck module.

3.3.1 Interfacing to WeedSeeker

The WeedSeeker platform interfaces to the WeedCheck module through a series of digital inputs. When a weed is detected by the WeedSeeker camera module, a 12V signal is sent to the nozzle solenoid to trigger it. The RPi's digital input is 3.3V, meaning the 12V signal needs to be stepped down to 3.3V before it can be used to trigger the RPi digital input to high. To achieve this, a voltage divider module was built for each digital input. Using two series resistors and the 12V input voltage, a 3.3V output was created. This was achieved using equation 3.1 below.

$$Vout = Vin.\frac{R_2}{R_1 + R_2} \tag{3.1}$$

Using a $R_1 = 2.7K$ ohm and $R_2 = 1K$ ohm resistor and an input voltage of $V_in = 12$V a voltage of $V_out = 3.24$ V was obtained.

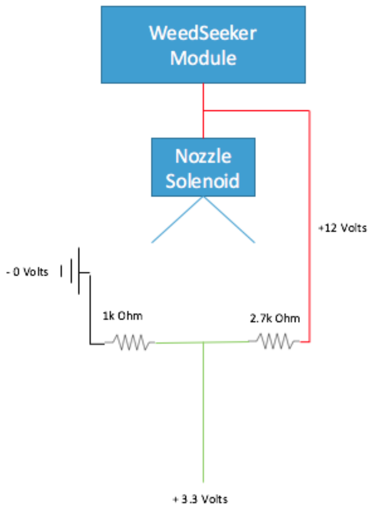

Figure 3.6: Voltage Divider Diagram

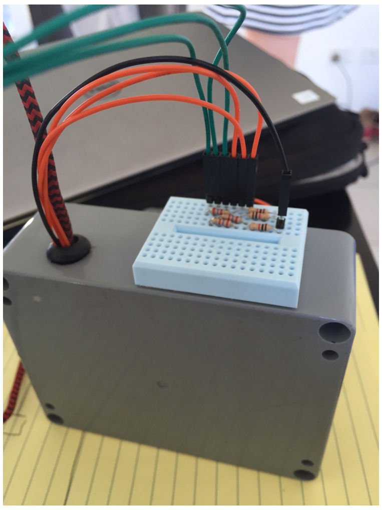

Figure 3.7: Voltage Divider Module

Figure 3.6 shows a schematic diagram of the voltage divider, whereas Figure 3.7 shows the module built to drop three 12V inputs voltages to three 3.3 V digital input.

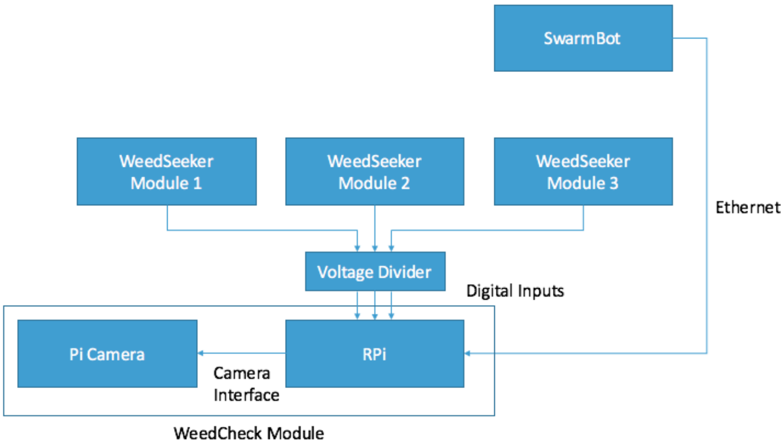

Figure 3.8: WeedSeeker Hardware Diagram

Figure 3.8 shows the design hardware for the WeedCheck module to interface with the WeedSeeker platform. Essentially the WeedCheck module listens for detected weeds via the GPIO pins on the RPi and triggers the camera at every detected weed occurrence.

3.3.2 Interfacing to WEEDit

The WEEDit platform interfaces to the WeedCheck module through a USB to RS232 serial converter. The WEEDit user console has a serial port available for use. Using serial connection enables all communication to be done within the software, and thus minimal hardware is required for these modules to interface.

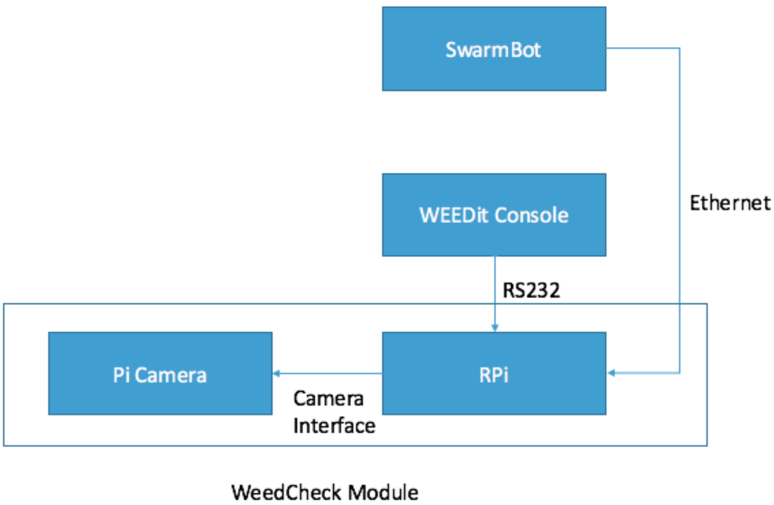

Figure 3.9: WEEDit Hardware Diagram

Figure 3.9 shows the design hardware for the WeedCheck module to interface with the WEEDit platform. The communication protocol and associated software will be discussed in Chapter 4.

3.4 Boom Configuration

For the trial phase of the project two SwarmBots will be used fitted with a RTK GPS. Both SwarmBots will have 8 metre booms attached, however, one will be fitted with WeedSeeker modules and one will be equipped with WEEDit modules. These have slightly different configurations and are discussed below in Sections 3.4.1 and 3.4.2.

3.4.1 WeedSeeker Boom

- 1 WeedSeeker Camera Module per 380mm on the boom, mounted at 700mm high. Mounting starts in the centre of the boom.
- 1 Nozzle is controlled by each Camera Module, and mounted directly behind it.
- Nozzles are spaced 100mm behind the camera module at a height of 700mm from the ground.
- Nozzles are TeeJet 6503E.
- A total of 21 WEEDit Camera Modules and 21 Nozzles are fitted on the boom.

3.4.2 WEEDit Boom

- 1 WEEDit Camera Module per 100mm on the boom, mounted at 1100mm high. Cameras are mounted 500mm either side of the boom centre.
- 5 Nozzles are controlled by each Camera Module, spaced at 20cm.
- Nozzles are spaced 450mm behind the camera module at a height of 700mm from the ground.
- Nozzles are TeeJet 4003E.
- A total of 8 WEEDit Camera Module and 40 Nozzles are fitted on the boom.

3.5 Installation

As stated above in Section 3.4.1 and 3.4.2 the WeedSeeker and WEEDit modules are mounted in a slightly different configuration. However, the nozzle height for both systems are the same at 700mm from the ground. The data collection phase of this project will involve a WeedCheck module mounted on both the WeedSeeker and WEEDit boom. The WeedCheck module was mounted at the height of the nozzles, which gave the same Ground Sample Distance (GSD) of 1 metre, on both booms. One WeedCheck will be used per boom, and thus only a 1 metre section of the boom will be analysed. The WeedCheck module was mounted in the centre of this 1 metre section. It was found that a height of 700mm gave a 1000mm ground sampling distance. The width of this field of view (FOV) is important to ensure the WeedCheck camera has the same FOV as the weed detection modules being assessed, to ensure the weeds detected can be captured by the WeedCheck camera.

WEEDit uses one sensor to detect the 1000mm wide ground spacing which can independently trigger five nozzles spaced 200mm apart. Therefore, 5 nozzles and 1 camera were able to be tested. The WeedSeeker has one camera per nozzle at a spacing of 380mm. Therefore, only 2 nozzles fit within the 1000mm FOV of the WeedCheck camera. This being said the activity of three nozzles were still recorded as it gave a similar ground sample as the WEEDit for overlaying data sets for the weed mapping. Figure 3.10 and Figure 3.11 illustrate the mounting positions of the WeedCheck module for the different boom configurations.

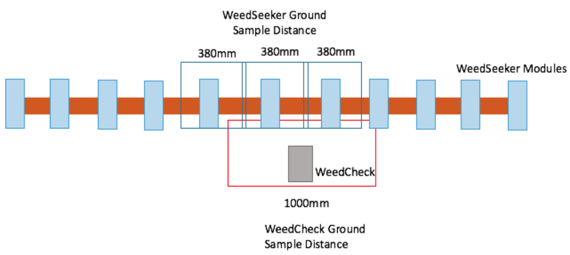

Figure 3.10: WeedCheck installation on WeedSeeker Boom

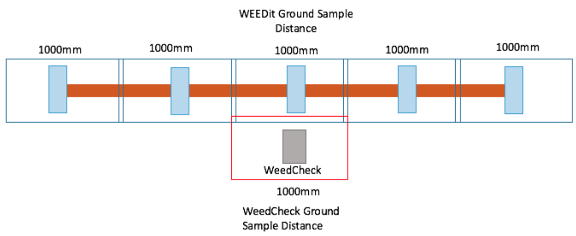

Figure 3.11: WeedCheck installation on WEEDit Boom

Figure 3.12 shows the ground sample width being determined for the WeedCheck module.

Figure 3.12: Determining Ground Sample Width

3.6 Summary

The hardware development chapter introduced the WeedCheck module and its hardware specifications. Two WeedCheck modules were developed for this project, and thus this chapter outlines and discusses the development of each WeedCheck module. The only difference in the two modules being developed was the method of interfacing to the weed detection platforms. The WEEDit will user serial communication to determine when weeds are detected, whereas the WeedSeeker will use the 12V signal from the nozzle solenoid to trigger a digital input on the RPi. The hardware design for both methods of interfacing were shown in this chapter.

Chapter 4

Software Development

This chapter outlines the steps taken to design and produce the software of the WeedCheck module. This includes an outline of the entire software developed for this project. The software designed and implemented in this chapter aims to meet the software requirements of the project objectives.

The software can be broken into seven sections which are shown in Figure 4.1 as a simple block diagram of the WeedCheck system. These sections are; file management, weed detected, SwarmBot messages, trigger camera, record file, weed mapping and finally image analysis.

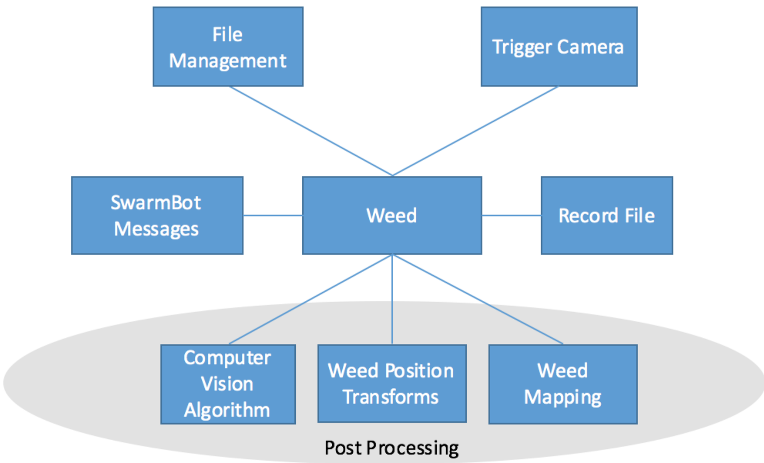

Figure 4.1: Block Diagram of WeedCheck Software

The RPi was developed for use with the Python programming language, which is conveniently compatible with ROS. Rospy is a pure Python library with an API which enables python programs to easily interface with ROS. The software for the WeedCheck module was therefore written using Python and rospy. As stated above in Chapter 3 the WEEDit and WeedSeeker interface differently to the WeedCheck module. Keeping this in mind, the core program of the WeedCheck module was kept the same, which is shown in Figure 4.2.

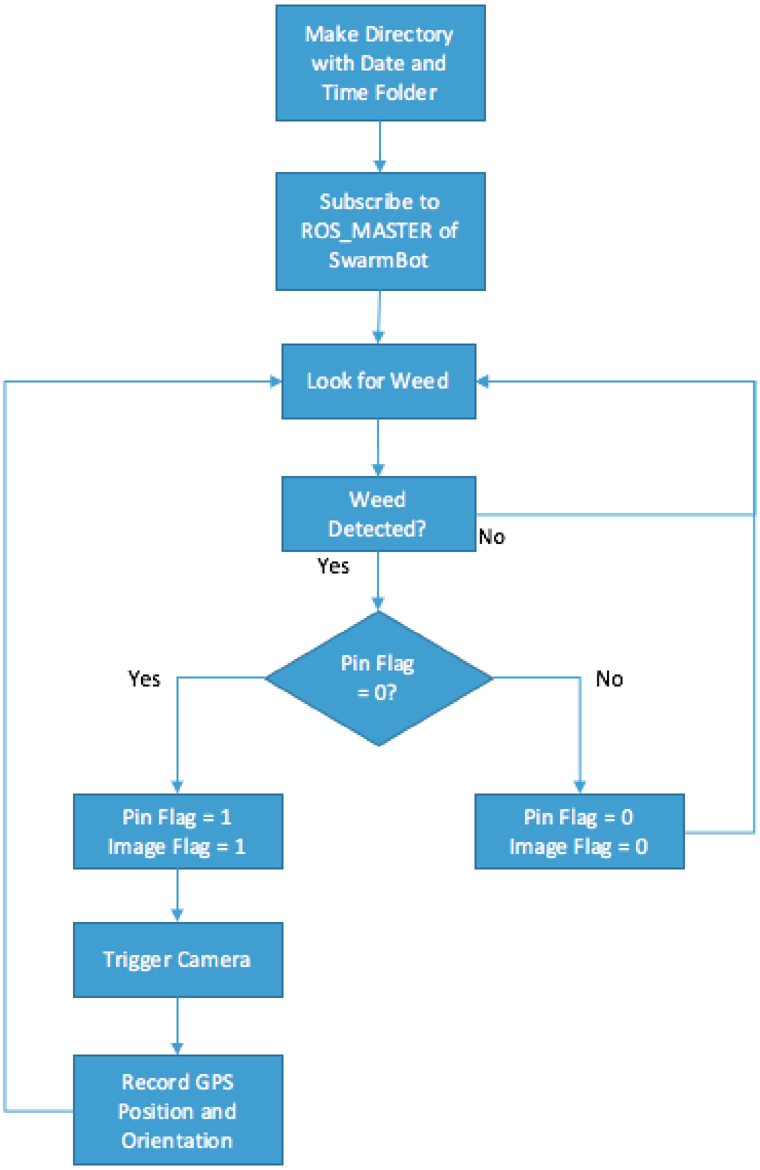

Figure 4.2: WeedCheck Program Flow Chart

On initialisation of the program a directory with the date and time is created which becomes the working directory. The software then looks for GPS messages being published from the SwarmBot. The software will not continue past this point if there is no GPS data. Once subscribed to these messages, the localisation variables are updated five times a second. The software is actively looking for weed triggers, either through the GPIO pins or the serial connection. When a weed is detected, a flag is set which will trigger the camera to instantaneously take two frames to capture the weed. A new line will then be added to the text file with the robots GPS position and orientation. The flag will reset once the signal drops back to low again. The purpose of the flag is to ensure the camera is only triggered once per weed.

After data is collected, the images will then be processed and a weed map will be created. The post processing will take place in MATLAB. The data will be sorted into true positives, true negatives, false positives and false negatives. This analysis will be undertaken using a combination of computer vision and manual hand labelling.

4.1 File Management

The trial phase of this project involves an abundance of images being collected. It was therefore imperative for a robust file management system to be created to ensure both the images and text files were named and stored in correct directories to ensure no data was accidentally overwritten or deleted. The simplest way to do this was to create a time stamped directory inside a date stamped directory. On initialisation of the program, the software checks to see if a date directory exists, then creates one if the test is false, and places a time stamped directory inside that folder. This is performed using a python function called *os.path.join* and *os.path.isdir*, which is shown below in Listing 4.1. Once this directory has been created it becomes the current working directory. This means every time the program is run a different working directory will be created.

```python
dir = os.path.join('/home/pi1/nozzle_activity', date) # Sets Date directory
dir = (os.path.join(dir, '%s') % (time)) # Sets Time Directory
test = os.path.isdir(dir) #Tests if directory exists
if test == False:
  os.makedirs(dir) # If it doesnt, it makes it
```

Listing 4.1: File Managment Program Listing

During initialisation of the program a .txt file is created which is time and date stamped. This file is also initialised with headings, shown in Figure 4.3, for easy importing data into MATLAB for post processing.

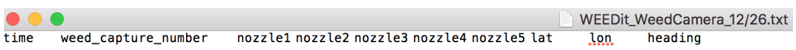

Figure 4.3: Data file headings

4.2 WEEDit Serial Publisher

As stated above the WEEDit interfacing was achieved through serial communication. The serial communication with the WEEDit console is based on polling. When the WEEDit console receives certain messages it responds by sending strings of information back over the serial. For this to be achieved it was necessary to write a serial driver which would send high frequency messages to the console and store the returned string as a published node in ROS. For connection to the external tracking system, only three lines are needed: TX, RX and Ground. The configuration of the RS232 port is as follows: **38400 baud, 8N1, no handshake**.

The poll request was sent over the serial connection at a sample rate of 5 hertz. The poll request has the format shown in Figure 4.4.

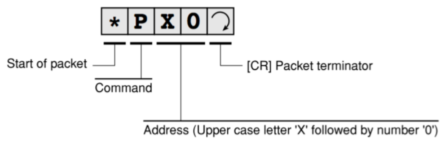

Figure 4.4: WEEDit Poll Request

The WEEDit console will then reply to the Poll request by returning a status string of nozzle activity. The returned string has the following format shown below in Figure 4.5.

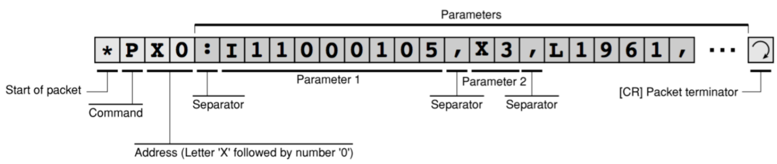

Figure 4.5: WEEDit Nozzle Activity Publisher

The activity of every nozzle in the system is represented in Binary string. Binary 1 indicates the nozzle is on, and thus a weed was detected, and binary 0 represents no weed. Every time the serial returned a nozzle activity string, the nozzle_activity published node in ROS was updated. Figure 4.6 shows the entire nozzle string being printed to a Linux terminal during testing serial communication.

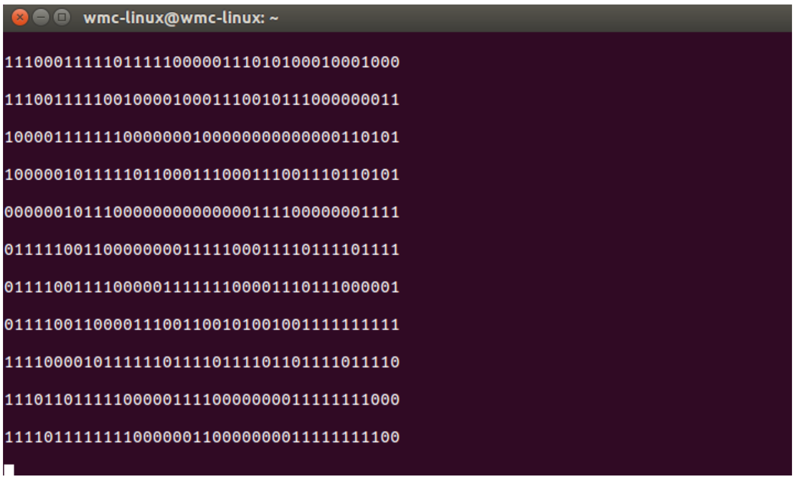

Figure 4.6: WEEDit Nozzle Activity Publisher

4.3 Subscribe to SwarmBot Messages

The Swarmbot's locomotion package publishes position information at a rate of 5 Hertz. This information is available in ROS via a published node labelled robot_pose in the rostopic list on the SwarmBot. The WeedCheck module must subscribe to this robot_pose node to capture the position data for geo-referencing images and the nozzle activity during the trial. Subscribing to this node is remarkably simple using a ROS listener node. Every time the robot_pose node republishes data, the listener node will capture the data. This was incorporated into the main function for the WeedCheck module to update the locomotion variables in the software every time they are published. A snippet of the program is shown below.

```
def listener():

  rospy.init_node('listener', anonymous=True)
  rospy.Subscriber('/SwarmbotLocalisation/robot_pose', PoseStamped, callback
    )
  rospy.Subscriber('/SwarmbotPlatformController/weed_it_nozzle_activity',
    weed_it_nozzle_activity , callback_weedit)
  rospy.spin()

if __name__ == '__main__':
  listener()
```

Listing 4.2: Subscribing to SwarmBot GPS Messages

Line 3, in the Listing 4.2 above, is where the listener function subscribes to the GPS messages from the SwarmBot. These messages are stored in memory, and a function named *callback* is called. The *callback* function is where the software determines if a weed is detected and whether or not to record data based on this finding. Figure 4.7 below shows the localisation parameters being printed to the Linux terminal during testing of the program.

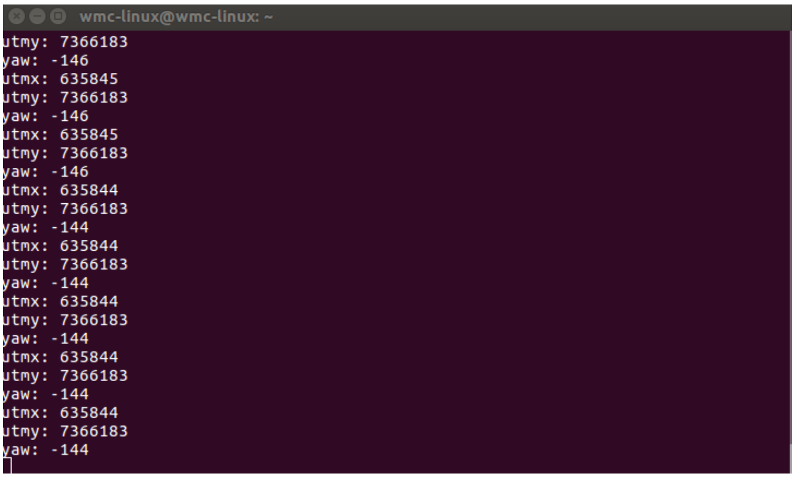

Figure 4.7: Robot Localisation Subscriber Testing

4.4 Determining if a Weed is Detected

For simplicity purposes it was decided individual WeedSeeker and WEEDit launch files for the WeedCheck module would be created. This means the user needs to simply launch the relevant software. Once launched the software constantly checks for any incoming weed activity, through either serial or GPIO pins.

Every time the *callback* function is called, a time stamp is assigned to a global variable in the main program which later stamps the images and text files for easy sorting of data.

The WEEDit launch file subscribes to both the robot_pose and weed_it_nozzle_activity published ROS nodes. This 40 bit binary string contains ones and zeros, where ones indicate the nozzle is active. When the nozzles of interest (located within the 1m section of boom) change from 0 to 1 the camera is triggered and position information is stored.

The WeedSeeker outputs a 12V signal when a weed is detected which triggers the nozzle solenoid. This signal was tapped into to trigger the WeedCheck module. This tapped signal travels through the voltage divider to set a digital pin to high, which indicates to the WeedCheck module a weed has been detected. This high digital pin then triggers the camera to capture an image and stores the position information.

In summary, the WeedCheck software stores an array called nozzle_activity which contains binary information on the nozzle activity. Due to the different spacing of the WeedSeeker and WEEDit modules the nozzle_activity array are different sizes; WeedSeeker is a 3x1 and WEEDit is a 5x1 element array. Figure 4.8 shows the nozzle activity array for the WEEDit region of interest being printed to the Linux terminal during testing.

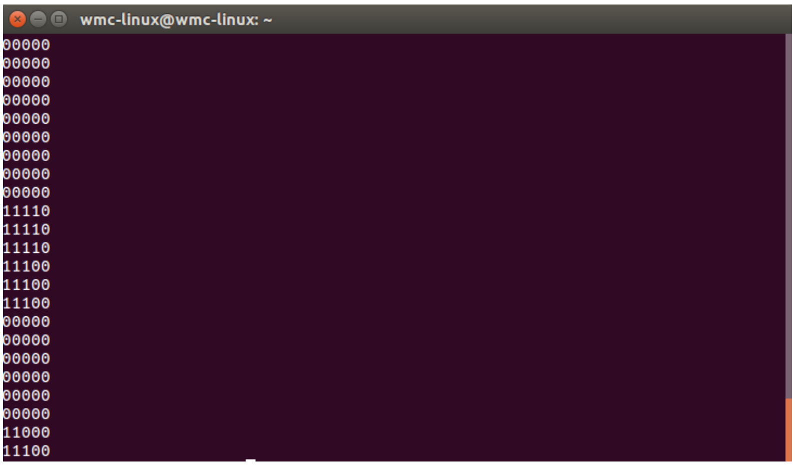

Figure 4.8: WEEDit Region of Interest Nozzle Activity String

When a 1 appears in the Binary string of the nozzle_activity array, it indicates a weed is detected and a weed flag is set, which triggers the camera and the data file is updated with a new line of information. This includes the time stamp, the weed number, nozzle activity string, the latitude, longitude and heading of the robot. The format of this text file is tab delimited so it can be very easily imported and post processed in MATLAB. The program waits for the weed flag to toggle before entering the loop again. This ensures only one location and one set of images are taken per weed. An example of a data file from the field trial has been included, seen in Figure 4.9.

WEEDit_WeedCamera_12/26.txt

time	weed_capture_number	nozzle1	nozzle2	nozzle3	nozzle4	nozzle5	lat	lon	heading
3.290378	1	0	0	0	0	0	636452.651618	7366780.901928	39.205500
3.382787	2	0	1	1	1	1	636454.233425	7366782.110235	39.254000
3.429599	3	0	0	1	1	1	636454.810976	7366782.553725	39.397400
3.507851	4	1	1	1	1	1	636456.278625	7366783.691201	39.643100
3.572437	5	1	1	0	1	1	636457.471772	7366784.620533	39.676900
3.656561	6	1	1	1	1	1	636459.417646	7366786.144311	39.530700
3.705592	7	1	0	0	1	1	636460.017682	7366786.601363	39.412800
3.754422	8	0	0	1	1	1	636460.634464	7366787.065353	39.213800
3.825891	9	0	1	1	1	1	636462.030586	7366788.106720	39.466300
3.899679	10	1	1	1	0	0	636463.612274	7366789.306597	39.721900
3.976371	11	1	1	1	0	0	636465.196801	7366790.525649	40.074200
4.023418	12	1	1	1	1	0	636465.819157	7366791.018489	40.535200
4.07819	13	0	1	0	1	1	636466.768012	7366791.781529	40.124900
4.128485	14	0	0	0	1	0	636467.572328	7366792.419039	39.976800
4.201165	15	1	1	1	1	1	636469.184573	7366793.659087	39.720200
4.255635	16	1	0	0	0	0	636469.978262	7366794.280892	39.618800
4.317064	17	0	0	0	1	1	636471.292074	7366795.321166	39.816200
4.375731	18	0	0	1	1	0	636472.442636	7366796.215415	39.632900
4.447181	19	1	0	1	0	1	636474.116143	7366797.473141	39.150000
4.496034	20	0	0	0	0	1	636474.779330	7366797.986620	39.792900
4.543703	21	0	0	0	0	0	636475.449032	7366798.499145	39.804900
4.613531	22	1	0	0	0	1	636477.131910	7366799.815845	39.997500
4.660412	23	1	0	0	0	1	636477.629913	7366800.218165	39.893000
4.706549	24	1	0	1	0	1	636478.301784	7366800.723906	39.801700
4.753608	25	0	0	1	0	0	636478.991035	7366801.256508	39.693400
4.801258	26	0	0	1	1	0	636479.662100	7366801.769231	39.363900
4.849398	27	0	0	1	1	1	636480.340639	7366802.294849	39.637400
4.897361	28	1	1	0	0	1	636481.021566	7366802.818926	39.822700
4.947058	29	1	1	0	0	0	636481.704914	7366803.356451	39.954200
4.995355	30	0	0	1	1	0	636482.386185	7366803.887766	39.852600
5.044562	31	0	0	0	1	1	636483.075465	7366804.416763	39.910100

Figure 4.9: WeedCheck Data File

4.5 Trigger Camera

As stated in Section 4.4 the nozzle_activity array contains a binary string of the nozzle activity. When there is a binary 1 in this array, it indicates a weed has been detected. The program therefore looks at the nozzle_activity array to determine whether or not to trigger the camera. Listing 4.3 shows an example of the software logic. On line 4 the program tests whether the 15th element of the nozzle_activity string is active. If it is and the pin flag is set to 0, which it is by default, then the pin flag and image flag will be set high. When the image flag is high, line 16 of the program returns true and the data record loop is entered. When the 15th element of the nozzle_activity string is set back to 0 the pin flag will reset. This will ensure the camera is only triggered once per weed detected.

```
1 #Define nozzle activity array
2 nozzle_activity = info.channel_activity
3 # Set image and pin flags
4 if nozzle_activity[15] == 1:
5   if PIN15_FLAG == 0:
6     camera_number = 1
7     PIN15_FLAG = 1
8     IMAGE1_FLAG = 1
9   else:
10    IMAGE1_FLAG = 0
11 else:
12   PIN15_FLAG = 0
```

```
13   IMAGE1_FLAG = 0
14
15 #If Weed is detected and image flag is set to 1, enter data recording loop
16 if IMAGE1_FLAG == 1 or IMAGE2_FLAG == 1 or IMAGE3_FLAG == 1 or IMAGE4_FLAG
     == 1 or IMAGE5_FLAG == 1:
17
18 enter data loop()
19 camera.capture(os.path.join(GPS_dir, '%d_camera_%d_%s_Frame%d.jpg') % (
     weed_capture_number, camera_number, nozzle_time, 1))
20 camera.capture(os.path.join(GPS_dir, '%d_camera_%d_%s_Frame%d.jpg') % (
     weed_capture_number, camera_number, nozzle_time, 2))
21 f = open(GPS_file, 'a' )
22 f.write(('%s\t%d\t%d\t%d\t%d\t%d\t%d\t%f\t%f\t%f\n') % (nozzle_time,
     weed_capture_number, nozzle_activity[0], nozzle_activity[1],
     nozzle_activity[2], nozzle_activity[3], nozzle_activity[4], utmx, utmy,
     yaw))
23 f.close()
```

Listing 4.3: Camera Trigger Code

Line 19 and 20 of Listing 4.3 is where the camera is triggered. Two frames are taken, which will be stitched together later for a larger ground sample distance. Line 22 is where the text file is updated with GPS information.

4.6 Weed Position Transforms

This phase of the project took place after data collection and was completed by post processing the .txt data file. A high GPS precision was obtained through tagging the images with the Real Time Kinematic (RTK) Global Positioning System (GPS) on board the SwarmBot. This GPS data is available from the .txt file that is written every time a weed is detected.

The GPS data being recorded into the .txt file is the front chassis position of the robot. It is therefore imperative for an accurate weed map, to transform the points back to the nozzle position. Figure 4.10 shows this concept quite simply. To achieve this transformation Universal Transverse Mercator (UTM) projection must be used. UTM is similar to GPS coordinates, however, it is a flat representation of the earth surface rather than a spherical representation. UTM uses a 2-dimensional Cartesian coordinate system to give locations and is measured in metres. This means using UTM the x and y difference can be subtracted from the chassis position to obtain the weed location.

The robot_pose node contains the localisation data in a UTM frame and therefore no transform is needed at this point. However, the heading of the robot needs to be taken into consideration to ensure the transform to the nozzle position is correct.

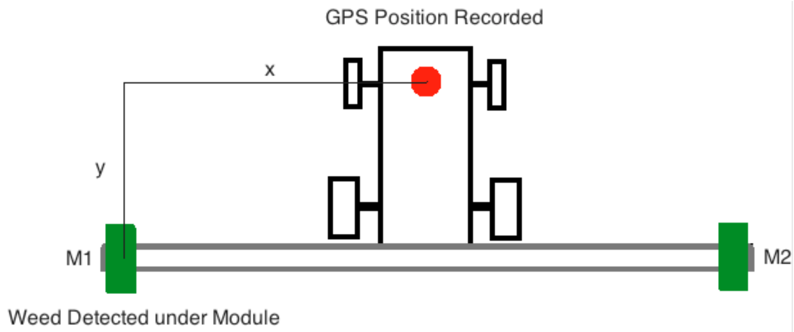

Figure 4.10: Weed position calculation

MATLAB was used to complete the transforms. Firstly a MATLAB program was written to simulate the transform to ensure it was correct. Figure 4.11 shows the output of the software. The green dot in the centre is the robot chassis position, and the blue circles down the bottom are the position of each nozzle on the WEEDit boom. As you can see from the figure, the distance in the y direction is constant for all nozzle positions, however, the x distance changes for each nozzle. Listing 4.4 indicates how each vector was calculated for different x with a constant y value. Line 5 in the listing shows the vector from chassis position to nozzle position, denoted by the red line in Figure 4.11. This vector is rotated through the yaw of the robot, in this case 0 degrees, and then plotted.

```
1 xDistance = -3.9:0.2:3.9;
2 yDistance = -2;
3
4 for i = 1:40
5   V(i) = [-xDistance(i); -yDistance];
6 end
```

Listing 4.4: Transform

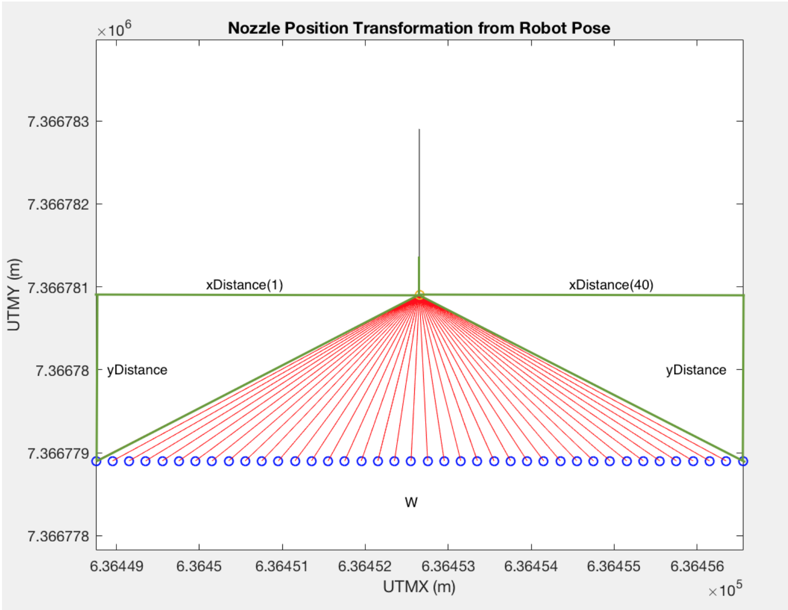

Figure 4.11: Nozzle Positions Transform from SwarmBot Chassis

The simulation transforms were tested and shown to perform correctly for a heading of zero. Adaptations were needed so the transforms would be calculated correctly for different robot headings. This was achieved by altering the script to incorporate a rotation matrix. This would rotate the vector through the robot heading, before undertaking the linear translation. This can be seen below in Listing 4.5. Figure 4.12 shows the transform and rotation of the nozzle positions.

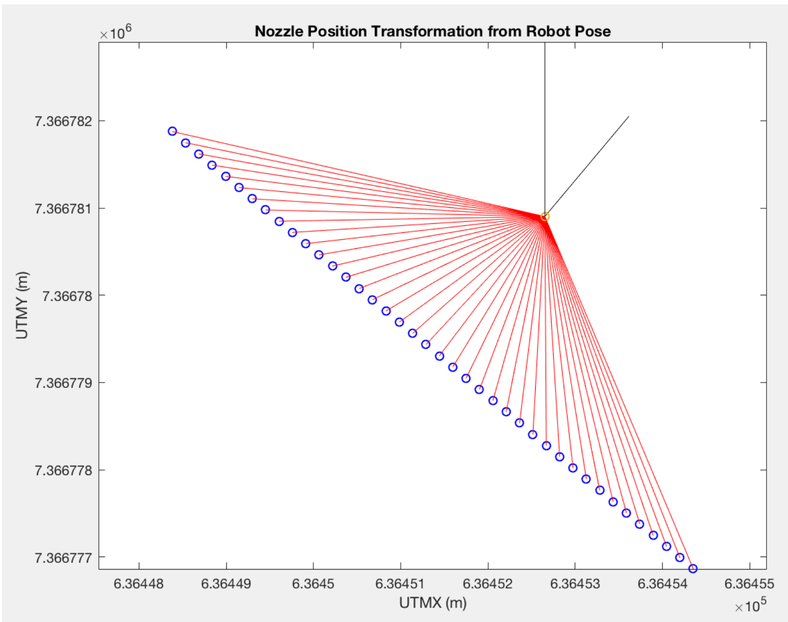

Figure 4.12: Nozzle Positions Transform and Rotation from SwarmBot Chassis

```
xDistance = -3.9:0.2:3.9;
yDistance = -2;
yaw = 40;

for i = 1:40
%Define Vectors for Rotation
V = [-xDistance(i); -yDistance];
Rotater = [cosd(yaw), -sind(yaw) ; sind(yaw), cosd(yaw)];

%Weed Position Matrix
WeedPosition = Rotater * V;
end
```

Listing 4.5: Transform and Rotation

4.7 Weed Mapping

This section of the project also took place after data collection. Mapping the weed positions is useful to determine repeatability of the modules in detecting weeds, this can be achieved by overlaying various weed maps. The aim of this section was to produce code that would enable the weed positions to be mapped on Google Earth. Keyhole Markup Language (KML) is an xml notation for expressing geographic annotation and visualization on two or three-dimensional maps. KML was developed for use with Google Earth and thus was adopted as the format to plot weeds on Google Earth. There are various CSV to KML converters online. For this project Earth Point was used (Bill Clark 2016).

After the nozzle position transformation had been completed, it was necessary to convert the UTM projected points back into latitude and longitude for use with Google Earth. This was done using a function in MATLAB. The data was then written to a text file in a format so it could be uploaded to Earth Point to convert it to KML file. This involved a .txt file with Latitude, Longitude, Icon, IconScale headings and associated data under these headings. Listing 4.6 below shows the sample code that creates the text file for upload to Earth Point. The Icon used here is just a round blob, the colour and size of this icon can be easily set. The images captured can also be used as the icon, which means the weed image can be plotted onto Google Earth at its actual position.

```
Icon = 41
IconScale = 0.5
IconColor = 'DodgerBlue'
% Write KML File for Weed Map
fid = fopen('WEEDitCameraOverlay_fullT2.txt', 'w');
fprintf(fid,'%s\t%s\t%s\t%s\t%s\t%s\n','Latitude','Longitude','Description',
    'Icon', 'IconScale', 'IconColor');

for i = 1:size(lat,1)
fprintf(fid, '%12.12f\t%12.12f\t%f\t%f\t%f\t%s\n', lat(i), lon(i),
   Description(i), Icon, IconScale, IconColor);
end
fclose(fid);
```

Listing 4.6: Text File Ouput for Earth Point KML

As discussed elsewhere the WeedCheck program only looks at a 1 metre section of the boom. However, a secondary launch file was also written which simultaneously captures nozzle activity for the entire WEEDit boom. This enabled a full scale weed map to be produced of the area covered. The nozzle activity will be denoted by green blobs to indicate weed locations on the map. The entire array of nozzle activity can now be recorded using a sample rate of 5 hertz, giving a very fine ground resolution. This will enable the development of a full swath weed map for the WEEDit boom, as seen in Figure 4.13. This process was not carried out for the WeedSeeker platform as it would require 18 additional voltage dividers to drop the 12V signal from the remaining Weed Seeker cameras through the voltage divider.

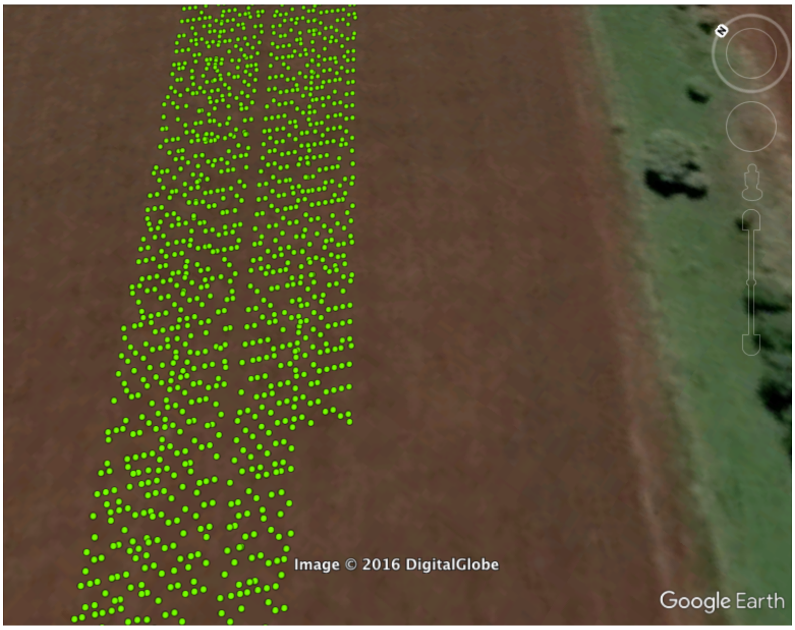

Figure 4.13: Sample Weed Map from Entire Length of WEEDit Boom

4.8 Image Stitching

This section of the software was completed after data was collected. As stated above, two frames are captured for every weed detected, this was to ensure there were no timing errors and the weed can be viewed within the frame. This software step included stitching the two frames together to generate one image. This was completed using open source code written with OpenCV by PyImageSearch's Adrian Rosebrock (Adrian Rosebrock 2016). Using the open sourced code was very simple. A script was written which loops through all the images in the working directory and calls the image stitcher to stitch the two frames together. The resulting image was then labelled and stored in a separate directory.

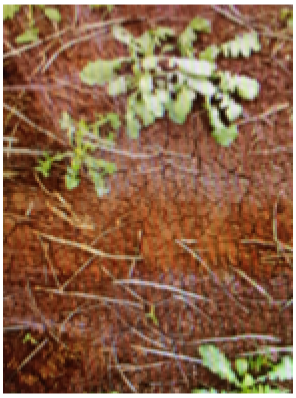

Figure 4.14: Frame 1

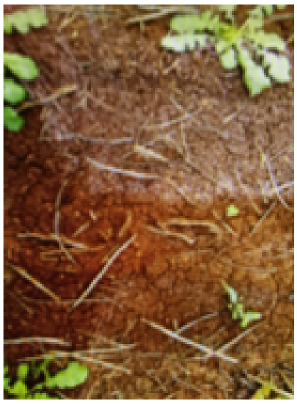

Figure 4.15: Frame 2

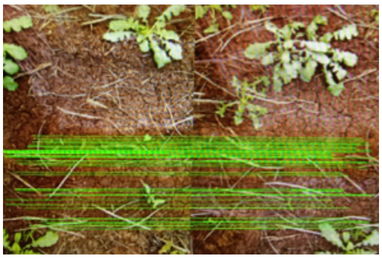

Figure 4.16: Stitching

Figure 4.17: Stitched Frame

Figure 4.14 - 4.17 shows the process of stitching the frames together. Figure 4.14 and Figure 4.15 are the two frames taken during data collection. Figure 4.16 shows the common points found between the two frames, and finally Figure 4.17 shows the resulting image after the stitching process is complete.

Comp

4.9 Computer Vision Algorithm Development

The development of the computer vision algorithm took place after the data collection phase of this project. This section refers to the techniques used to construct the computer vision algorithm used in image classification and sorting. It is important to know whether a weed is present in the captured frame and therefore a computer vision algorithm was implemented to automatically detect weeds within the frame. The computer vision algorithm was implemented using the computer vision toolbox in MATLAB.

Figure 4.18: Frame used to determine computer vision thresholds

Thresholding pixel values in different colour channels and colour spaces proved to be a robust method for detecting whether weeds were present within the frames. The first step in this process was to find which colour spaces and associated channels were suitable for use. This was completed using MATLAB computer vision code from (Byles 2016). An image was selected from the collected data, and the RGB and HSV colour spaces were plotted using a surf plot in MATLAB. Figure 4.18 was the image used for the thresholding analysis.

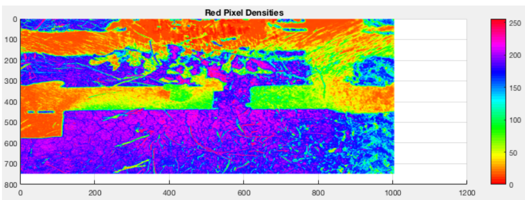

Figure 4.19: RGB Red Pixel

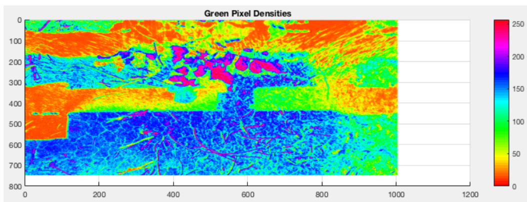

Figure 4.20: RGB Green Pixel

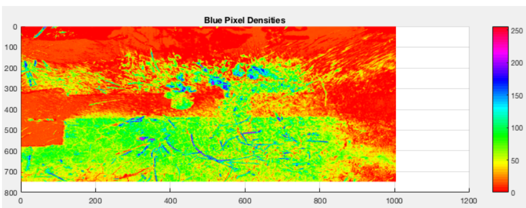

Figure 4.21: RGB Blue Pixel

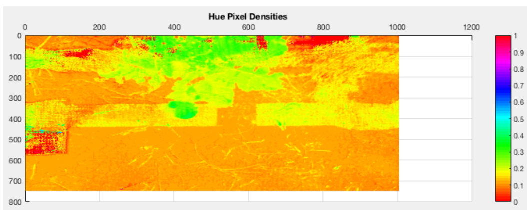

Figure 4.22: HSV Hue Pixel

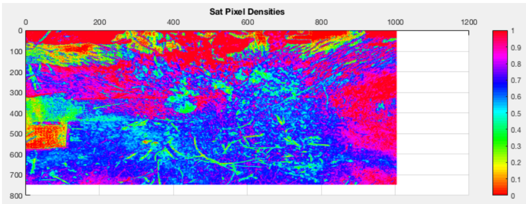

Figure 4.23: HSV Saturation Pixel

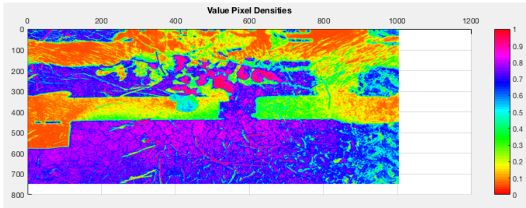

Figure 4.24: HSV Value Pixel

Figure 4.19 - 4.24 show the surf models generated from MATLAB. Observing these Figures it is obvious the shadow from the boom has a negative effect on most of the colour channels. The Hue colour channel, shown in Figure 4.22, shows the weed quite prominently in the top of the frame. This indicates that Hue may be a good channel for colour thresholding. Figure 4.20 shows some very high pixel values in the region where the plant is in the frame. This is logical because the weed is green, and the soil is brown and thus the weed would have a higher green intensity.

Using MATLAB skeleton code from (Byles 2016), a pixel threshold algorithm was created. This was achieved by using the surf plots to find appropriate thresholding values. The pixels range from 0 which is black to 255 which is white. Listing 4.7 shows sample code of the thresholding.

Various computer vision techniques were used when performing the thresholding on the test image. The steps were:

- Sets Hue channel pixel to 0 if the Hue value is below 0.15 or above 0.25. This can be seen in Figure 4.25 below.
- Converts the Hue array to a binary image, seen in Figure 4.26.
- Remove the small objects from the binary image, using *bwareaopen* function in MATLAB. This can be seen in Figure 4.27.
- Sets the Hue channel pixel to 0 if the Blue channel has a value higher than 150 and the pixel in the Hue array is a 1.
- Sets Hue channel pixel to 0 if the Red, Green or Blue channels are all below 100.
- Sets the Hue channel pixel to 0 if the Green channel value is below 150. The result of this thresholding can be seen in Figure 4.28.

- The image dilated to make blobs larger, using *imdialate* function in MATLAB. This can be seen in Figure 4.29 below.
- Places a box around the biggest blob detected in the frame, using *regionprops* in MATLAB. The final image can be seen in Figure 4.30.

```

for i = 1:size(Hue,1);
  for j = 1:size(Hue,2);
        if (Hue(i,j) < 0.15 || Hue(i,j) > 0.25);
      Hue(i,j) = 0;
    end
  end
end

Hue = imbinarize(Hue);
Hue = bwareaopen(Hue,5000);

for i = 1:size(Hue,1);
for j = 1:size(Hue,2);
    if (Hue(i,j) == 1) && Blue(i,j) >150;
      Hue(i,j) = 0;
    end

    if Red(i,j) < 100 && Green(i,j)<100 && Blue(i,j)<100
      Hue(i,j) = 0;
    end
    if Green(i,j)<150
      Hue(i,j) = 0;
    end
  end
end

Hue = imdilate(Hue,se);
```

Listing 4.7: Thresholding Code

Figure 4.25: First threshold

Figure 4.26: Create binary array

Figure 4.27: Removed small blobs

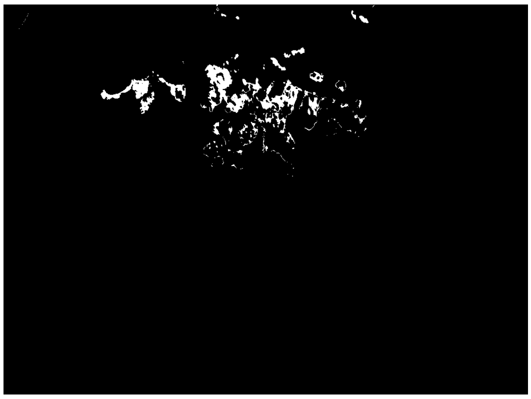

Figure 4.28: Apply second threshold filter

Figure 4.29: Dilate the image

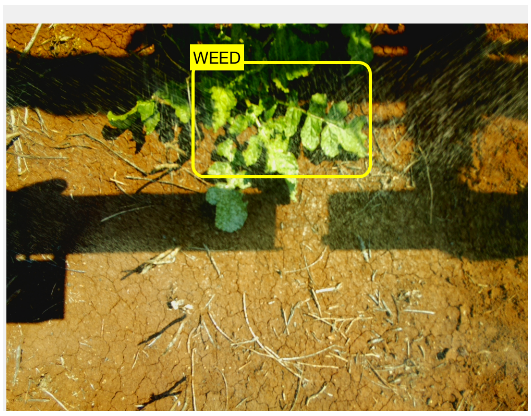

Figure 4.30: Put a box over the weed

4.10 Summary

The software design stage of this project was important, the bulk development within this project transpired within the software. This chapter summarised the various software developed for real time data collection as well as software for post processing the data.

The software developed within this chapter meets the requirements of the project's software objectives. Section 4.4 outlines the software designed to interface with the WeedSeeker and WEEDit platforms to obtain a signal when a weed is detected. Section 4.9 refers to the computer vision software designed to present recorded data and the automatic labelling of whether a weed was detected within the frame. Section 4.7 and Section 4.6 above discuss how the weed position was determined from the robot chassis position and then explains the software development of the weed mapping program. This proves these proposed outcomes of this project were met.

Chapter 5

Results and Evaluation

The hardware and software developed in the above sections were used to construct the WeedCheck module. The following chapter discusses the development and implementation of a field trial, designed to collect data for validating the accuracy of commercial weed detection platforms. The experimental design procedures implemented throughout the trial are introduced in this chapter, plus the results of the trial as well as the different sources of error introduced throughout the data collection phase.

5.1 Experimental Tests

The data required for this project was obtained through a fieldwork programme designed to test various features of commercial weed detection systems. The aim of the experiment was to design a trial protocol for comparing two weed detection platforms. The objectives of the experiment were to determine: (i) the weed detection accuracy, (ii) the spray footprint and (iii) the repeatability of the commercial weed detection systems. To achieve this the protocol development was broken into three stages these being accuracy, spray footprint and weed mapping.

5.1.1 Weed Detection Accuracy

The aim of the first stage of the protocol was to give quantitative information on the true positives, false positives, true negatives and false negatives of both the WeedSeeker and WEEDit systems. Table 5.1 below shows how each of the binary classifications are tested in the protocol.

Table 5.1: Protocol stage 1

Binary Classification Test	**How was it tested?**
True positive	When a weed is detected the WeedCheck module will photograph the ground. The image is a true positive if a weed is present in the frame
False positive	When a weed is detected the WeedCheck module will photograph the ground. The image is a false positive if NO weed is present in the frame
True negative	Every 60 seconds throughout the trial, if there was no nozzle activity, the camera would be triggered. This image is stored in a separate directory. If there is NOT a weed in the frame it is a true negative.
False negative	Every 60 seconds throughout the trial, if there was no nozzle activity, the camera would be triggered. This image is stored in a separate directory. If there is a weed in the frame it is a false negative.

5.1.2 Spray Footprint

The spray footprint refers to the spray length of the liquid applied to the ground, as denoted in Figure 5.1 and Figure 5.2. When a weed is detected the nozzle solenoid is opened to deliver chemical to the weed. The length of time the nozzle solenoid is open will affect the spray footprint and the platform's ability to deliver chemical to the entire plant. Figure 5.1 below shows a small footprint with part of the plant being missed, whereas Figure 5.2 shows a scenario with a larger spray footprint with chemical being delivered to the entire weed.

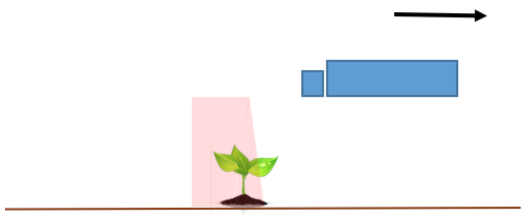

Figure 5.1: Small spray footprint

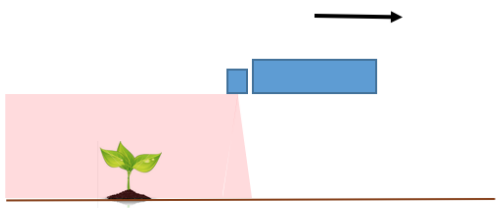

Figure 5.2: Large spray footprint

In this stage of the protocol, the aim is to determine the difference in spray footprint between the two commercial weed detection systems to test whether the chemical was delivered to the entire weed. WEEDit system has an adjustable margin to spray before and after the weed. Its default value is 200mm either side of the weed. WeedSeeker has no such calibration parameter, the nozzle is activated when on top of the weed.

Dye was added to the spray tank on both SwarmBots so the spray footprint could be easily assessed. White pigment was added to the WEEDit tank whilst blue pigment was added to the WeedSeeker boom. The dye was added to the tank so the footprint of each system was visible on the images acquired by the WeedCheck module. With each repetition, the dye marker on the weeds was still easily visible and became brighter due to overlap.

The spray footprint measurements were both observed during the trial and were physically measured using marker paper after the trial had been completed. This included placing marker paper encircling weeds in the paddock then running the platform over the weed. The marker dye was then visible on the paper and thus a measurement was able to be recorded. This test was repeated three times with various sized weeds and the average values were calculated and used for further analysis.

5.1.3 Weed Mapping

The final section of the protocol was to overlay various weed maps on top of each other. These overlays were used to determine the repeatability between different passes over the same block and to assess whether the maps line up from the different weed detection platforms. The maps were analysed using both Google Earth and MATLAB figures.

The first test in this section was to overlay the weed maps from multiple passes of the same system. As the field trial was carried out on the same ground three times under different environmental conditions, it is of interest to see if the sensors behaved differently. For example, the weed positions from the three passes of the WEEDit were overlaid on the same plot. This information can then be analysed to determine the repeatability of the sensors.

The second proposed test in this section was to overlay the WeedSeeker and WEEDit weed maps to assess the discrepancy between the systems. If GPS proves to be a valid method to compare the systems a correction on the WeedSeeker data samples is first required. Figure 5.3 below shows the FOV of both the WEEDit and WeedSeeker units. The green blobs in the diagram represent weeds. The position of any weed detected within the FOV will be taken from the centroid of that platform's FOV. For example, in the case of weed 1, the weed position would be recorded differently between the WEEDit and WeedSeeker modules. The WEEDit platform would record the weed's position as the centroid of WEEDit sensor 1's FOV (shown in Figure 5.3, denoted by the blue dot. However, the same weed when recognised with the WeedSeeker would have a slightly different position. The position would be taken as the centre of the WeedSeeker Sensor 1's FOV, denoted by the red dot in the figure. To correct this discrepancy in the recorded data, the WEEDit and WeedSeeker data were compared and if there was a data point in the WeedSeeker array within 0.19m of the WEEDit array the points were adjusted and matched.

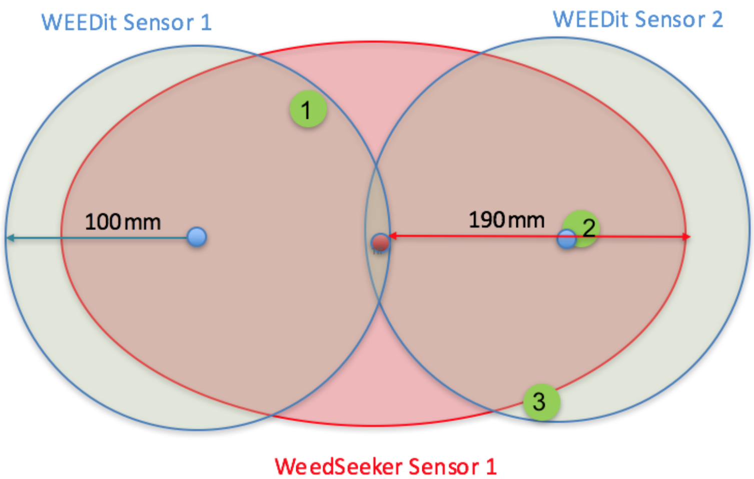

Figure 5.3: GPS Correction for weed map

5.1.4 Experimental Design

This section outlines techniques employed to ensure the field trial results were sound, reliable and valid. These procedures ensure the experiment is measuring precisely what it is intended to measure.

Accuracy

To maximise accuracy within the experimental design various procedures were undertaken. This included conducting the experiments with spray application of dye for easy visibility, which were assessed by visual inspection and through a computer vision algorithm. GPS position data collection and hand matching weed images between and within trials as well as visual observations of the platform behaviours were conducted throughout the experiment. These three processes provided a fail safe and robust method for ensuring the collected data could be reliably analysed to meet the project's objectives.

GPS was used in the experiment to geotag weed locations to produce a weed map of the detected weeds. The GPS data from each trial can be overlaid to observe the behaviour of the weed detection sensors both for repeatability of the individual sensor and to compare the different systems.

Due to the large number of images taken throughout the trials it was extremely difficult to individually match the weed image manually between repetitions and between sensors. Therefore, a small random sample of a cross section of images were chosen and matched through visual inspection to validate the findings. The hand matched images were used to determine if there were any GPS inaccuracies or discrepancies between the weed positions as well as compare hit and misses of particular weeds.

Repeatability

To ensure repeatability, the field trial for this project was conducted three times, with results being visually matched and GPS locations converted to a map. Three repetitions allowed more confidence and stability in the results obtained from this experiment, as repetition removes bias and error from experimental data. Repetition is re-running the exact same experiment with the same method on the same or similar system and obtaining the same or very similar results (Vitek & Kalibera 2011). With this in mind, the exact same procedure was implemented for each experiment and each repeated trial. The aim of repeating the trial was not only to minimise errors in the experimental procedure, it also gave an understanding of the ability of commercial weed sensors to reproduce similar performance over the same area. It is expected commercial sensors would have minimal variances in hit and miss rates between the repeated trials.

Standardisation

Standardised procedures were established throughout the experiment to reduce the chances of bias occurring in the results and ensuring reliability. The two SwarmBots used in the trials were identical including all software and hardware, apart from the booms and modules being tested.

The GPS modules on each robot were exactly the same, both with correction signals being sent from the same RTK base station to give a theoretical position accuracy of 2cm. The same area was used for every repetition and test throughout the course of the trial phase. The two SwarmBots were given the same waypoint file, meaning the exact same path would be travelled by both robots (assuming no GPS inaccuracies).

To standardise the environmental conditions the SwarmBots travelled concurrently, with one behind the other as seen in Figure 5.4. The weed detection systems were tested concurrently to ensure sunlight levels and weather conditions remained constant between the tests. This reduced the possibility of lighting and wind differences between experiments, which may have affected the behaviour of the sensors. The WeedCheck module was also mounted in the same location on the WeedSeeker and WEEDit boom, to ensure the same ground sample field of view. Standardising the ground sample field of view was important in matching weed images between tests and trials.

Throughout each repeated trial the speed remained constant for both robots with 2.5 m/s on repeated tests 1 and 2 and 1m/s on repeated test 3. The speeds were exactly the same for both platforms being concurrently tested. The core software design of the WeedCheck module was also standardised between the two modules developed. The only difference between the WeedCheck modules were the way they interfaced to the commercial weed detection platforms, which is explained in Section 3.3.1 and Section 3.3.2 above.

Standardising these variables ensured the independent variable, that is the weed detection platform, is the only reason for the difference in the results, that being the number of weeds detected. This ensures validity in data collected.

Randomisation

Randomisation is also essential as it minimises the chances of a biased result. Randomisation reduced bias by equalising other factors that have not been explicitly accounted for in the experimental design. Randomisation procedures were established throughout the field trials through randomly assigning which platform would lead the experiment. This reduces the external variation such as weather conditions and marker dye which may have impacted results.

During the analysis phase, selection of images and tests to be hand matched was random. Due to the large volume of images detected only 5% of the images will be sorted and manually matched. Similarly, the sample of weeds for visual observation in the paddock during the trial phase was also randomly selected. This also included the selection of weeds used to assess spray footprints.

5.1.5 Field Trials

The experiment was conducted on a private broad acre property in Gindie, QLD. The trial area for data collection was selected to be a 3.2 ha block of a fallow paddock. This involved two 8 metre swaths, 1 down and 1 up, on the edge of a large field. The test was repeated three times, over three days with different weather conditions to determine the effect of the environment on the systems. The weather conditions recorded during the tests, can be seen below in Table 5.2.

Sections 5.1.1 - 5.1.3 above outline the purpose of the field trial as well as the types of data to be collected and observed throughout each trial. During the data collection the SwarmBots followed one another so the tests of both systems occurred concurrently, this can be seen in Figure 5.4. During the first two tests the ground speed was set to 2.5 m/s (9km /hr) and the third test was carried out at 1 m/s (3.6km/hr). This was to see the effect of speed on the sensors.

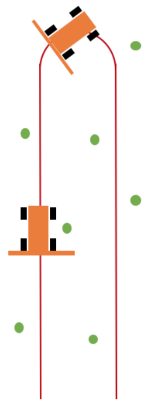

Figure 5.4: Schematic of Field Trial

Table 5.2: Data collection weather conditions

Day	**Weather**	**Time**	**Wind Speed (km/hr)**
1	Sunny	1 pm	7.0
2	Sunny/ Cloudy	10 am	16.4
3	Overcast	5 pm	9.1

5.2 Results

The data presented in this section is derived from the field trials discussed above. These results were both generated from collected data and through visual observations throughout the trials.

5.2.1 Weed Detection Accuracy

By Visual Inspection

During the data collection phase the SwarmBots were personally followed, to visually monitor the accuracy and spray footprint of the different weed detection systems. These observations were recorded and presented below in Table 5.3. These inspections revealed the WEEDit sensor had an extremely high hit rate when compared to the WeedSeeker sensors. It was also noted the WEEDit system detected smaller weeds more consistently than the WeedSeeker sensors, which failed to detect a larger percentage of these smaller weeds.

The spray footprint of the two systems is also shown in Table 5.3. The WEEDit system had a footprint of approximately 500mm from nozzle on to nozzle off, whereas the WeedSeeker platform had a smaller footprint of 150mm.

A larger spray footprint is important when using precision spraying as chemical drift, due to wind, greatly effects the accuracy and ability to hit the target. A larger spray footprint gives a smaller margin of error to ensure the chemical is delivered to the plant guaranteeing a higher kill rate.

Table 5.3: Visual inspection of hit rates

	WeedSeeker	**WEEDit**
Small Weeds	80%	100%
Large Weeds	95%	100%
Footprint	150mm	500mm

By Computer Vision

After the data collection was completed, the next step was to sort the image data to determine the hit and miss rates of each weed detection technology. This was completed using a combination of computer vision and manual hand labelling. The computer vision algorithm developed in 4.9 was not sufficient enough to be 100% reliable. Therefore, after the computer vision algorithm had analysed and classified the images it was necessary to undertake a manual hand correction to accurately sort the data. Even though the computer vision algorithm was not 100% reliable, it proves the possibility of future development in automatically sorting images.

Table 5.4 show the results of the computer vision program. It is obvious from these results, the computer vision software was built to be very sensitive. The vision software yielded no false positives, however, there is a large percentage of false negatives. The data shows 45.5% of the WeedSeeker data and 39.9% WEEDit data were sorted incorrectly. It was found the colour of the marker dye used in the trial had a significant effect on the ability to use colour thresholding to detect and classify weeds within the image frame.

Table 5.4: Results of computer vision sorting

	WeedSeeker	WEEDit
True Positives	392	635
True Negatives	21	5
False Positives	0	0
False Negatives	346	425

By Hand Validation

After the computer vision program had sorted the images there was still some hand labelling corrections that needed to be undertaken due to the high number of false negatives. This was completed by manually viewing the negative labelled images from the computer vision software and correctly sorting them. The images from each trial repetition were sorted and the average value from these tests were used for the analysis below. Table 5.5 and Table 5.6 present the results of the hit and miss rates from the repeated trials. The numbers represent images captured with the WeedCheck module.

Table 5.5 presents a discrepancy between the number of weeds captured over the duration of each three repetitions. After the trial, an intermittent timing error in the WeedCheck module was discovered. This was caused by a hardware limitation in the RPi camera simply due to the fact the frame rate was not high enough. Because of the large density of the weeds in the paddock some weeds were not able to be captured because the camera was already busy when the trigger command was issued. This did not affect the position data from being written to the data file.

Table 5.5: WeedSeeker results

	WeedSeeker Test 1	WeedSeeker Test 2	WeedSeeker Test 3	Average
True Positives	675	732	800	736
True Negatives	21	19	21	20
False Positives	1	2	4	2
False Negatives	26	16	29	24

Table 5.6 similarly shows the results from the WEEDit repeated test trials. It can be seen that test 1 and 2 have very similar values, whereas test 3 has only three quarters of the true positive result. This was caused by a GPS drop out for some of the trial. This can be seen in the weed map in Figure 5.6 below.

Table 5.6: WEEDit results

	WEEDit Test 1	**WEEDit Test 2**	**WEEDit Test 3**	**Average**
True Positives	1205	1198	913	1105
True Negatives	3	3	6	4
False Positives	38(14)	31(21)	27 (20)	32(18)
False Negatives	0	0	0	0

Table 5.6 shows a high number of false positives for the WEEDit system. However, for a large majority of images sorted into this category a dark shadow was cast over most of the frame. Therefore, a weed may have been present under the shadow, but was not visible within the frame. An example of these images can be seen in Figure 5.5 below. To overcome this problem, images with excessive shadow in the frames were disregarded and the corrected values are shown in the brackets in Table 5.6. These values were used for the analysis.

Figure 5.5: Shadow effect on sorting image

Table 5.7 and Table 5.8 show the average hit and miss rates from the field trial. This data was used to perform a sensitivity and specificity analysis. The results from this analysis are shown in Table 5.9.

Table 5.7: WeedSeeker Results

Forecast	**Observed**		
	Positive (P)	**Negative (N)**	**Total**
Positive (P)	736	2	738
Negative (N)	24	20	48
Total	760	22	1568

Table 5.8: WEEDit Results

Forecast	**Observed**		
	Positive (P)	**Negative (N)**	**Total**
Positive (P)	1105	18	1123
Negative (N)	0	4	4
Total	1105	36	2268

Sensitivity is the probability the test result will be positive when a weed is present (true positive rate, expressed as a percentage). Whereas, specificity is the probability the test result will be negative when a weed is not present (true negative rate, expressed as a percentage). The positive predictive value is the probability the weed is present when the test is positive (expressed as a percentage). The negative predictive value is the probability the weed is not present when the test is negative (expressed as a percentage). These statistics are mathematically represented below in Equation 5.1 - 5.4.

$$\text{Sensitivity} = \frac{PP}{PP + PN} \tag{5.1}$$

$$\text{Sensitivity} = \frac{PP}{PP + PN} \tag{5.2}$$

$$\text{Positive Predictive Value} = \frac{PP}{PP + NP} \tag{5.3}$$

$$\text{Negative Predictive Value} = \frac{NN}{PN + NN} \tag{5.4}$$

Table 5.9: Data Statistic

	WeedSeeker	**WEEDit**
Sensitivity	0.97	1
Specificity	0.91	0.11
Positive Predictive Value	0.997	0.984
Negative Predictive Value	0.417	1

Table 5.9 presents the statistical analysis on the accuracy of weed detection systems. It can be seen the sensitivity of the WeedSeeker and the WEEDit systems are quite similar. This variable refers to the probability of the modules to positively detect a weed when one is present. The WEEDit system had zero false negatives which indicates its ability to detect a weed is excellent. The WeedSeeker sensitivity result is 97% which is still a very high percentage accuracy. However, the table depicts quite a large difference in specificity between the weed detection systems. This statistic refers to the probability a weed will not be detected when there is not one present. The results indicate the WeedSeeker system has a better ability to prevent false firing over the WEEDit system. However, this result was not observed through visual inspection during the trial. Various errors could have been introduced affecting this result, such as during the manual sorting of the WEEDit images. As stated above, the effect of shadow in the images posed as a problem when sorting. Also it was quite difficult to detect small weeds within the frame and therefore some may have been sorted incorrectly.

The Positive predictive value of the WeedSeeker and WEEDit were very similar, with only a 0.013% difference. This statistic refers to the probability a weed is present when the system detects a weed. There is a large variance in the negative predictive value between the two systems. This statistic refers to the probability the system successfully did not detect a weed. This statistic shows the WEEDit system has a better ability to correctly detect when there is not a weed present, whereas the WeedSeeker has only a 0.417 negative predictive value. This indicates the system struggles in detecting some weeds, which as confirmed through observation, were mainly smaller weeds.

Therefore, the results from this test indicate the WEEDit sensors are more sensitive in detecting weeds than the WeedSeeker system. Even though there were minimal false positives with the WEEDit sensors, it is more advantageous to have a few false fires rather than multiple missed weeds which was shown to occur with the WeedSeeker sensors.

5.2.2 Repeatability

This section presents results of the proposed methods used to show the repeatability of two commercial weed detection platforms. Two proposed methods were employed to test the behaviour of the sensors over the same section of ground during their repeated trials. This included generating weed maps from the GPS data as well as manual hand matching of weeds within image frames. An independent comparison of the WEEDit and the WeedSeeker systems was undertaken between their repeated trials. Section 5.3 below will compare the WEEDit and WeedSeeker platforms against one another.

The repeatability of WEEDit and WeedSeeker systems were separately analysed, this involved referring individually to the data from each system's repeated trials, to determine the sensor's behaviour between trials. This was achieved by generating a weed map to overlay the weed positions from the three repeated trials. The use of RTK GPS was expected to give highly accurate weed positions and it was speculated the data from the different trials would overlay quite well. However, the generated maps seen below in Figure 5.6 and Figure 5.7 proved this expectation to be incorrect. The different sized markers and colours in the figure represent data from the repeated trials.

As discussed above in Section 5.2.1 there was a GPS drop out for some of the data in test three of the WEEDit trials, which is apparent in Figure 5.6 as some of the black marker dots are missing. It was found at this stage, trial 2 of the WeedSeeker repeated run failed to record the GPS positions. This is apparent in Figure 5.7, where only the weed positions of test 1 and test 3 are displayed. Comparing Figure 5.6 and Figure 5.7 it appears the WeedSeeker system has a better repeatability as the weed positions are much closer together when compared to the WEEDit map, however, this is still a poor result. Therefore, these weed maps indicate either the sensor's repeatability is poor, or there is a GPS position error. The ground speed of the trial did not seem to have an effect on the sensors ability to detect weeds.

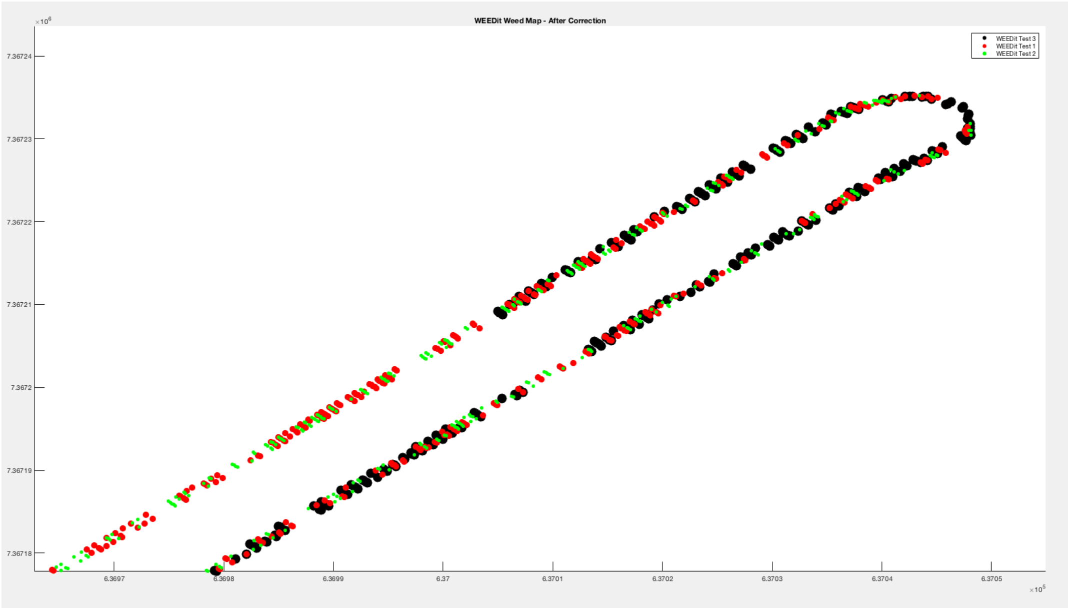

Figure 5.6: WEEDit weed map of the repeated trials

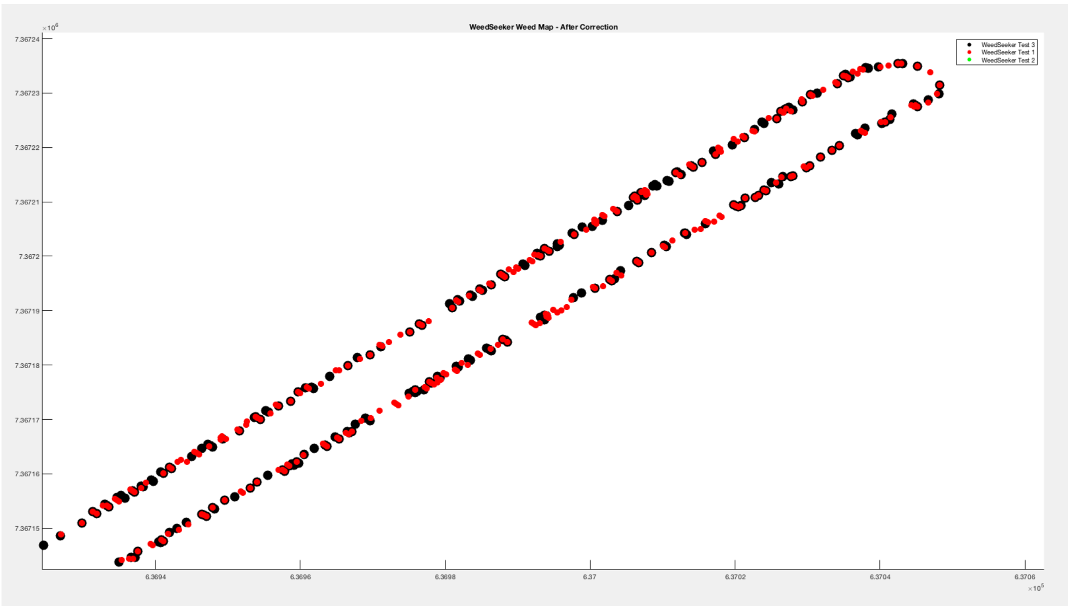

Figure 5.7: WeedSeeker weed map of the repeated trials

Figure 5.8 shows an example of GPS positions recorded throughout the repeated trials. This figure is a zoomed in snippet of Figure 5.6. This dataset is after the 0.19m GPS correction had been applied. The image shows two weeds which were detected throughout the three trials have very similar GPS positions and are thus very close to one another, signified by the three coloured dots on top of each other. Whereas in one case, depicted by the top left side marker, the weed was only detected in trial 1 and 3. The standalone green dots represent the weeds only detected in trial 2.

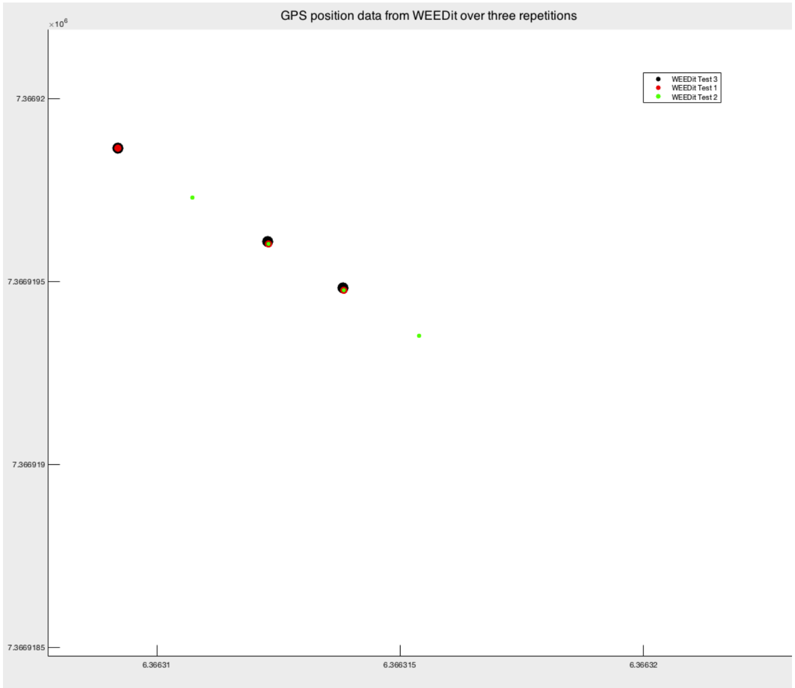

Figure 5.8: Example of WEEDit matched GPS points

To determine if the GPS was the source of error, a random sample of weed images were manually sorted and matched. This involved visual inspection of various frames to match up identical weeds in exact locations. Two tests were randomly selected for this analysis which were test 1 and 3. Matching weeds within frames was quite a tedious task and therefore only a small 5% sample of the images were matched. An image in test 1 was randomly selected, then the GPS coordinates of that weed were then searched and matched with GPS coordinates from test 3. Images from around this GPS position in test 3 were then visually searched to find the identical images from test 1 around that specific location. These images were sorted through and then visually matched and recorded when paired, with their GPS position noted. This method proved to work well and the results from this manual sorting can be seen in Table 5.6.

Through visual inspection and observation of the trial, it was surmised there was a GPS position error in the weed map. The WEEDit sensors have no visual discrepancies between the repeated trials. Therefore, the next step was to compare the geo-tagged position of the hand matched images to determine the GPS error. This was achieved with a simple MATLAB script which calculated the distance between the recorded positions. The results from this can also be seen in Appendix B, Table B.1 and Table B.2. The GPS offsets calculated are summarised in Table 5.10 and Table 5.11.

This method ground truthed there was a GPS position error during data collection. Table 5.10 and Table 5.11 presents the minimum, maximum, average and standard deviation of the GPS error. It can be seen the WEEDit has a smaller mean position error of 0.415m and the WeedSeeker has a larger mean position error of 0.618m. However, the standard deviation of the WeedSeeker error is quite large and thus represents a large spread from the mean which is caused by three outliers of above 3m position inaccuracy. With these excluded the average error would be much less, which is reflected in the weed map presented in Figure 5.6.

Table 5.10: WEEDit GPS Position Error

Minimum error (m)	0.0196
Maximum error (m)	1.265
Average error (m)	0.415
Standard Deviation	0.309

Table 5.11: WeedSeeker GPS Position Error

Minimum error (m)	0.018
Maximum error (m)	3.848
Average error (m)	0.618
Standard Deviation	0.868

After analysing the GPS error in this project, it has proved the weed mapping concept is not feasible for comparing and validating the repeatability of the weed detection sensors. This is due to a range of errors such as GPS drop out and excessive position variation. After this conclusion, an analysis on the manually matched weeds was carried out. After manually hand matching a random sample of weed images collected throughout the trial an analysis could be carried out to determine the hit and miss rates between repeated trials, these results are discussed in the sections below.

WEEDit

This section focuses on using the hand matched images to generate repeatability statistics of the WEEDit system. A random weed image was selected from the WEEDit data collected and approximately 10-15 images were analysed around this to determine whether the same weeds are present over each trial repetition. Then another random place in the image director was selected and further images analysed. This process was repeated until approximately 5% of the data had been analysed, equating to an area of 0.16ha.

Figure 5.9 and Figure 5.10 below show two weed frames matched during the repeated trials for the WEEDit. In the figure on the right, the marker dye being sprayed onto the weed is clearly visible. In the figure on the left it is harder to see, however, upon close inspection the dye is visible. Table 5.12 shows the percentage of matched weeds between trial 1 and trial 3. The results indicate test 1 detected 98.4% of the weeds identified in test 3, and similarly test 3 detected 91.8% of the weeds identified in test 1.

Table 5.12: WEEDit repeatability percentage

WEEDit	
Test 1	**Test 3**
98.4%	91.8%

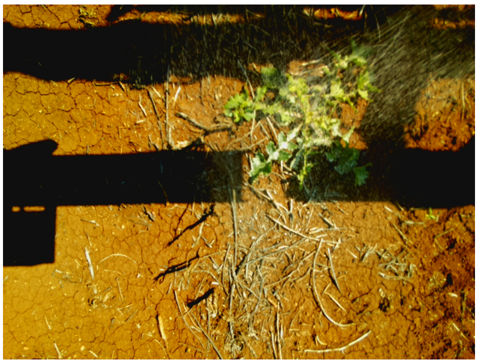

Figure 5.9: Image from Test 1

Figure 5.10: Image from Test 3

After analysing the weeds not detected in test 3, there was an apparent trend that the small weeds were the ones missed in the third test. This may have been a result of the cloudy weather in test 3 affecting the weed reflectance. Figure 5.11 below shows a weed detected in test 1 and was not identified in test 3. This weed is quite small, with a diameter of around 30mm.

Figure 5.11: Example of missed weed from WEEDit test 3

WeedSeeker

An identical approach was taken with analysing the WeedSeeker images to match up weeds between repeated trials. WeedSeeker required user calibration every time the system is powered on, which sets the background chlorophyll levels. This calibration is greatly affected by background lighting and therefore many calibrations may be needed throughout the day. However, because each trial run took 20 minutes only one calibration was undertaken on the system immediately prior to running the test.

Table 5.13 shows the repeatability results of the WeedSeeker modules between test 1 and test 3 repeated trials. The results indicate test 1 detected 95% of weeds identified in test 3. Similarly test 3 detected 82% of the weeds identified in test 1. These results show there is a large percentage of weeds missed in test 3 of the trial. It is interesting that test 3 for both the WEEDit and WeedSeeker repeated trials had larger error percentages. It is possible the cloudy environment affected the performance of both systems, which is of interest for further research as would be information important to industry. If cloud covers affects accuracy and thus kill rate, this is of very high significance for field commercial use. To conclude this result, further testing would need to be undertaken under differing environmental conditions, however, this was outside the scope of this project.

Table 5.13: WeedSeeker repeatability percentage

WeedSeeker	
Test 1	**Test 3**
95%	82%

Figure 5.12: WeedSeeker image from test 1

Figure 5.13: WeedSeeker image from test 3

An analysis of Test 3 was undertaken on the types of weeds not detected by the WeedSeeker. The behaviour of this system's results were similar to the WEEDit Test 3 results; with many of the small weeds not being detected. However, unlike the WEEDit system there were also some large weeds not detected. Figure 5.14 below shows a weed detected in test 1 that was not identified in test 3 by the WeedSeeker platform. This weed is quite small with a diameter around 40mm. The size of weeds missed by the WeedSeeker range from 10mm - 200mm. These results can be further verified by the visual observation data collected during the trials, shown in Table 5.3. It was observed the WeedSeeker's weakest point was the ability to recognise and hit smaller weeds.

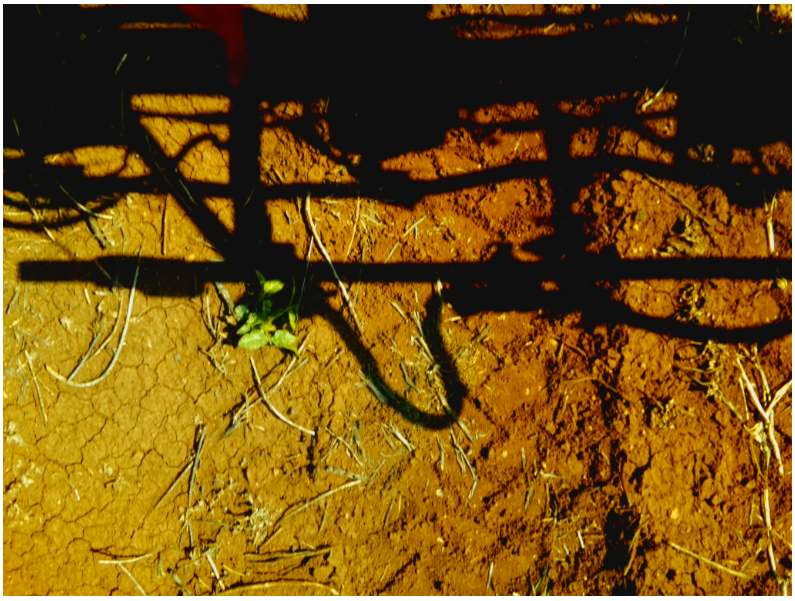

Figure 5.14: Example of missed weed from WeedSeeker test 3

5.3 Comparison of WeedSeeker and WEEDit

This section compares the behaviour of the WeedSeeker and WEEDit systems against one another. Even though in the above sections the weed map was disproved to be a valid method of comparison due to GPS position errors, a weed map was still produced to overlay the recorded positions of the WeedSeeker and the WEEDit trials. The weed maps were originally generated because it was expected that when overlaying the WeedSeeker and WEEDit trial data, the maps would visually show the locations of weeds either detected or missed between the two systems. It was surmised the same weed would be detected by both systems and the GPS position would be within 2.5cm, therefore allowing an easy analysis and observation of the weed map as an accurate comparison of the two systems.

It was thought the GPS error may have been introduced between the repeated trials due to satellite movement, thus by creating a weed map between the WEEDit and WeedSeeker tests carried out concurrently, the GPS error may have been much less. Therefore, the weed map was still produced. These maps can be seen below in Figure 5.15 and Figure 5.16. The data from trials 1 and 3 from the different weed detection technologies were overlaid. Figure 5.16 again shows there was a GPS drop out for part of the WEEDit trial 3. Ignoring this section of the figure, it is still apparent the weed positions are not similar, otherwise the green and blue markers would be laying on top of each other. Both these maps further reinforce GPS is not a valid method for comparison.

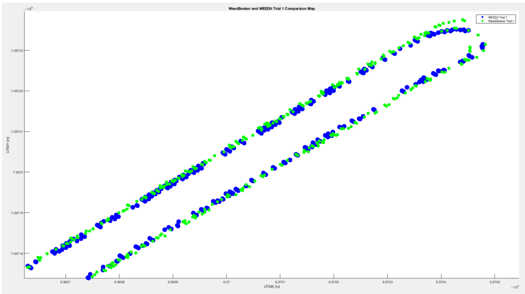

Figure 5.15: WeedSeeker and WEEDit test 1 overlay

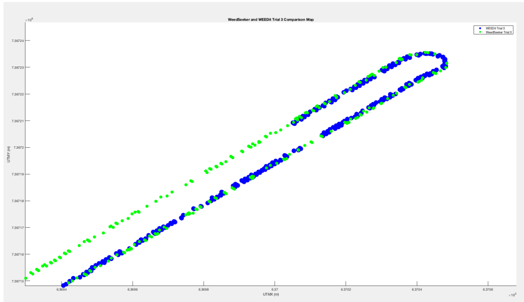

Figure 5.16: WeedSeeker and WEEDit test 3 overlay

After disproving the validity of the GPS positions to compare the WEEDit and WeedSeeker platform, the weed images collected during the trial were once again analysed visually by hand. The same image numbers used in the repeatability analysis were compared, however, this time to compare the weed detection platforms. Manual matching of images between the WeedSeeker and WEEDit trials was carried out. The results from this analysis can be seen in Appendix B, Table B.3. The images were used to ground truth weed recorded positions, from this a calculation to determine the GPS position error between the WEEDit and WeedSeeker systems could be performed. These results are shown in Table 5.14. The table shows the minimum GPS error is only 7cm, which would be an acceptable error. However, the maximum error is 4.3m with the average error being 1.9m. These results cements the fact that the GPS position data recorded in this experiment cannot be used to validate the weed detection platforms.

Table 5.14: Weed GPS position error between platforms

Minimum error (m)	0.07
Maximum error (m)	4.3
Average error (m)	1.901

After the image matching and comparison between the WeedSeeker and WEEDit platforms Table 5.15 was produced to show the hit and miss rates of the systems. A random selection of 47 images, equating to 0.16ha, were matched and labelled accordingly. Due to time constraints only 4% of the collected data was analysed in this section. This comparison did, however, yield some expected results. Table 5.15 show that of the 47 images analysed the WEEDit platform missed only 1 weed detected by the WeedSeeker platform. Whereas the WeedSeeker missed 9 weeds detected by the WEEDit platform. These missed weeds range from approximately 10mm to 200mm, confirmed by visual observation throughout the trials.

Table 5.15: Comparison of WEEDit and WeedSeeker performance

	WEEDit	**WeedSeeker**
Hit	46	38
Missed	1	9

Table 5.16 below shows the percentage of weeds detected between the systems. These results show the WeedSeeker system detected only 80.85% of the weeds the WEEDit system detected. Similarly the WEEDit detected 97.88% of the weeds the WeedSeeker detected. A statistical significance calculation can be undertaken on the collected data to determine whether the sample size of the experiment accurately represents the data. With a population size of 1200 images and a sample size of 47 images being analysed, with a 90% confidence level that the results actually portray behaviour of the population, a 12% margin of error was statistically calculated. A P-value of 0.007 was obtained. Essentially this P-value represents the probability that the WEEDit and WeedSeeker sensors operate identically. Therefore a low P-value means that from the results of this experiment the platforms do not act identically.

Table 5.16: Percentage of weeds detected by the different platforms

Comparison percentage	
WeedSeeker	**WEEDit**
80.85%	97.88%

5.4 Weed Mapping

The entire WEEDit nozzle activity (8m section) was also recorded in trial 1. The objectives of this section was to produce a full boom weed map, to prove the possibility of geo-tagging every weed detected over the length of the boom. Geotagging every weed sprayed within the paddock provides the ability to produce an entire field map. With the use of multiple WeedCheck modules to cover the entire ground view of the boom, the entire system could be evaluated. This method proves with a more accurate GPS there is the possibility to record every single spray application within a field. The benefits of this would have a large impact on the agricultural industry, especially if the application was also tagged with weather conditions. This would mean quantitative data on every spray would be available and may limit legal issues with spray drift.

Other benefits of geotagging weed locations with weather information include the possible use of herbicides that have been taken off the shelf due to user misuse and off label use. Imagine if every weed sprayed was logged into a database with weather conditions and chemical application rate data, it would allow governmental bodies to track the use and application of chemicals. This is especially important for restricted chemicals proven as outstanding knockdowns in controlling weeds, however, due to misuse and residual build up the products have been banned. This means farmers could insure themselves against spray drift and minimise legal ramifications because quantitative data would be stored and analysed if a problem was to occur. This would be very possible in agricultural robotics especially with chemical application constraints being applied to the robotic software, the robot could stop and start depending upon various conditions such as wind and delta-t. This would mean chemicals could not be misused and therefore may see the return of unique herbicides that have been banned. This would be advantageous to industry as with a wider array of chemicals for use, it would help the fight against resistance.

Recording weed position, application rate and weather information would allow for residual chemical calculations on soil and waterways, which would pose as a huge environmental benefit. In the future, with this technology, it may be possible to spray 24D up to the fence of a cotton crop providing the weather conditions were optimal and recorded. The farmer would then have the data to prove the wind direction was away from the neighbouring farm if litigation arises.

Even though the GPS data in this project proved to have inconsistent positions and large variances between trials the production of a full scale weed map would still be possible with a more precise GPS. Regardless of this, a weed map was produced over the full length of the WEEDit boom, which proves the ability to geo-tag every weed within the field, even though the positions acquired in this experiment may be inaccurate. These weed positions were overlaid on Google Earth, so the weed can be seen on a satellite map. Figure 5.17 and Figure 5.18 show the same data set once they were uploaded into Google Earth. The figure on the left hand side shows the full run throughout the trial, whereas the right hand image shows a closer view of the data.

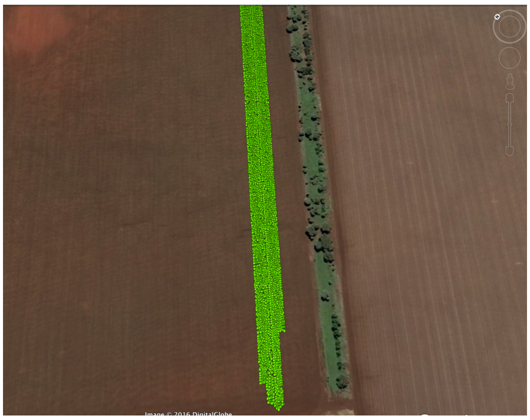

Figure 5.17: WEEDit full nozzle map

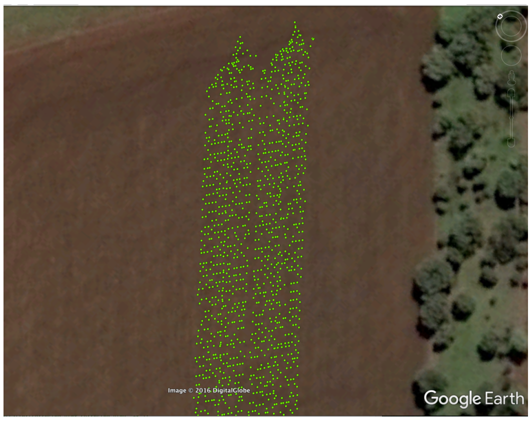

Figure 5.18: WEEDit zoomed nozzle map

The images collected by the WeedCheck module during the trial can be plotted on Google Earth by using the recorded geo-tagged data. This application would be useful for farmers and agronomists to remotely and virtually walk through the field to identify specific weed species and weed distribution patterns for future spray applications. The GPS inaccuracy was deemed acceptable in this section, as the maximum weed position error found in the experiment is 4.3m, shown in Table 5.14. This error would not affect the ability to determine trends and patterns of weed species within different areas of the field, for a more direct and targeted spray application. The Google Earth weed image map can be seen below in Figure 5.19.

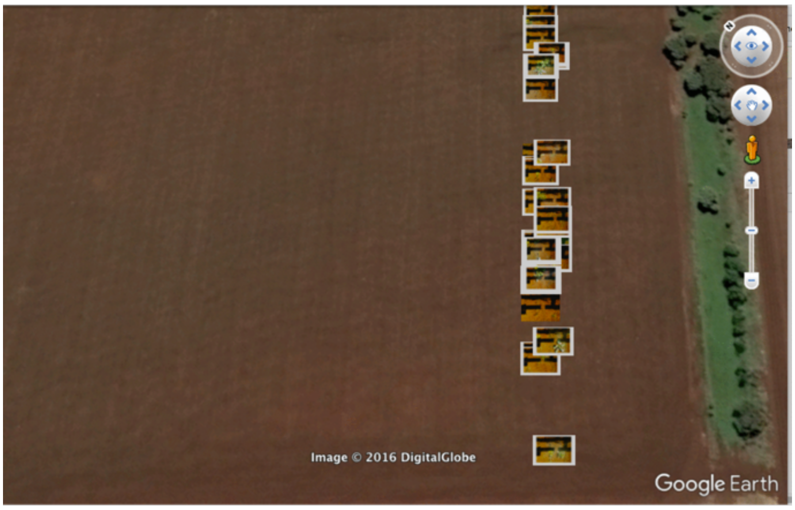

Figure 5.19: Images overlaid on Google Earth

5.5 Sources of error

Throughout this project many sources of errors were introduced, these are discussed in the following sections.

5.5.1 GPS error

As mentioned above there is a large GPS position error which was unexpected. This error could be minimised with further software development and implementation of a more precise GPS system. A variety of methods were used to overcome the errors in results from the GPS variance. Manual hand matching of images within repetitions and between trials proved to be a robust method for analysing the data. This method enabled calculations of repeatability and the generation of comparison statistics of the sensors. Therefore, a comparison on the reliability of WeedSeeker and WEEDit platforms was still able to be completed.

A further GPS error became evident when assessing data. The test 3 results of the WeedSeeker trial was missing data in sections and test 2 of the WeedSeeker trial was also missing a large amount of GPS data. This affected the ability to produce weed maps that overlay the data from the trials. This GPS error did not affect the results of the project, as it was deemed using GPS to create weed maps was not a valid method for validating the commercial weed detection technology.

5.5.2 WeedCheck interfacing methods

A small error was introduced through the used of the serial communication with the WEEDit platform. Essentially the nozzle activity string was updated at a constant rate of 5 hertz. When the robot was travelling at 2.5m/s this only gives a ground resolution of 0.5 metres. This error is not present with the WeedSeeker interfacing method because the 12V signal is essentially a hardware trigger.

The WEEDit WeedCheck module is actively looking for changes in the nozzle activity string five times a second, whereas the WeedSeeker WeedCheck module is triggered any time a weed is detected. This resulted in a separate error being present in the WeedSeeker module, because the RPi camera frame rate was not quick enough. This resulted in random errors throughout the trial, where the camera would be busy and the weed would not be captured. This error did not affect the analysis of the weed detection accuracy because the missed images could be identified by the frame numbers and therefore the images around the skipped frames were matched and the missing images were disregarded in all datasets.

5.5.3 Computer vision algorithm

The computer vision algorithm developed to sort and analyse the images from the trial proved to have a large false negative sample. This error was introduced because the marker dye used throughout the trial caused issues when running colour thresholding algorithms.

The shadow cast from the sun also affected the ability to sort weeds through computer vision techniques, such as colour thresholding. Computer vision techniques are very sensitive to lighting. The shadow caused a large dark region over part of the images, which affected the colour thresholding algorithm's ability to positively detect weeds. Therefore, manual sorting was needed after the computer vision analysis was completed so results were not affected.

5.5.4 Image Capture

Unfortunately due to the timing of the repetitions, during trial 3, a shadow was cast over some of the images captured. This was due to the position of the sun when the robot turned at the end of the first swath. This affected the quality of images recorded because some of the frames were too dark to identify whether a weed was present. This affected the ability to sort the images both with computer vision algorithms and through manual hand labelling. It was quite difficult to detect small weeds within the frame and therefore some may have been sorted incorrectly. To overcome this error, images were adjusted to try make weeds more visible, if this was not possible then the images with shadows cast were disregarded during analysis and thus did not affect results.

5.5.5 Human error

Human error could have been introduced into various parts of this project. This includes the calibration of the WeedSeeker unit, which would have affected the results from those trials. However, this calibration was carried out exactly as per the user handbook to ensure the error remained minimal. The weed sensitivity size is also a parameter that can be changed on both the WeedSeeker and WEEDit platforms. To minimise the impact of weed size sensitivity the modules were set to have the same sensitivity.

Human error may also be present in the hand matching of images between trials and within them. This error could also affect the validity of the results. To minimise this error, the images sorted were double checked twice by two separate individuals.

Another possible human error could be introduced in the mounting of the WeedCheck module. If the module was not mounted to have the exact same ground sample distance and field of view, the ability to match weeds would have been compromised. To minimise the effect of this error a ground sample calibration was undertaken to ensure the WeedCheck modules had identical field of views.

5.5.6 Experimental Errors

Even though all steps were taken to ensure standardisation, some unforeseen errors occurred through the use of a different robot for each platform being tested as this proved to introduce a higher level of GPS variance between positioning data for the different platforms being tested. To confirm and overcome this error, a sample of images with weeds detected were hand matched and compared. This enabled confirmation of a position error in the GPS. The matched weed images were then used to analyse the commercial weed detection systems.

The tests were undertaken concurrently so each platform being tested occurred during the exact same weather conditions, including sun position, wind and reflectance. However, the three repetitions were undertaken over separate days and times of the day when weather conditions were obviously not identical. This is of interest to observe the effect weather conditions had on the results collected. After analysing the results, it is possible that during trial 3 when the weather conditions were cloudy, this cloudiness could have led to a reduced weed reflectance making detection of smaller weeds less likely to be identified. Therefore, this could have caused a higher percentage error in repeatability. The WEEDit system claims the sensors are not affected by background lighting and environmental conditions, however, the results of this project show that cloud cover could have had an effect. Further research into this area would yield more accurate results.

Due to the inaccuracy of the GPS position it was determined the accepted method to validate weed detection accuracy was through labelling and matching weed images that were collected from the WeedCheck module. However, due to the large sample of images that were obtained during the trial, only 5% of the data was able to be analysed. This is only a small portion of the data set and therefore may introduce an error in the reliability of the results. To reduce this error more images could be analysed.

5.6 Summary

The project presents the successful development of the WeedCheck module which has the ability to photograph weeds at the instant they are detected by commercial weed detection sensors. By classifying these images using both computer vision and manual sorting, identical weeds were able to be successfully matched across platforms and repetitions. Although this method is quite labour intensive results from this project prove a robust method to validate and compare the accuracy of different weed detection platforms. Through advancement and further computer vision algorithms this matching may be possible automatically.

The benefit of this outcome of this project are directly beneficial to the agricultural industry. If farmers have quantitative data available comparing weed detection platform performance under a variety of conditions, which can be tested using the WeedCheck module and analysed through matching weed frames, it may influence the chances of adoption of this technology on farm. Imagine the positive environmental impacts if every farmer adopted precision spraying technology. Residual chemical in soils would be reduced, the chances of chemical leaching minimised and weed resistance to herbicides would also be decreased.

In the literature review of this project it was found the total economic cost of weeds to agriculture is $4 Billion per year with the average chemical saving from using precision spraying technology being around 45%. If the outcome of the WeedCheck module assisted farmer adoption of precision spraying technology, the saving to the industry could be up to $1.8 Billion dollars annually, plus environmental and human/animal health benefits which are invaluable.

Section 5.1 in this chapter presents the design of the trial protocol developed for testing, to determine the weed detection platform's accuracy and spray footprint. Within this chapter, Section 5.2.1 outlines the development of a universal ground truth method which both enable validation of commercial weed detection technology and enables calculation of GPS inaccuracy and offsets. Section 5.2 of this chapter presents the results from the field trials collected and the associated weed maps generated, yet disproved. This proves these proposed outcomes of this project were met.

Chapter 6

Conclusions and Further Work

6.1 Achievement of Project Objectives

The following objectives have been assessed:

- **Design a trial protocol to determine weed detection accuracy and spray footprint.**

  A fieldwork experiment was designed to implement and successfully obtain data on the accuracy of different weed detection platforms. Section 5.1 describes the experimental methods used for the trial phase of the project. The results from the trial can be seen in Chapter 6 - Results and Evaluation. Accuracy and footprint which correspond to kill-rate are important for commercial applications of precision spraying technology.

- **Develop a universal ground truth method which would enable validation of commercial weed detection technology.**

  The trial phase of the experiment yielded both expected and unexpected results. Section 5.2.2 discusses and introduces different methods used for ground truth and validation of the commercial weed detection technology. Through trial and error it has been determined which methods are valid for comparing the accuracy of weed detection platforms. This project has proved GPS cannot be relied upon as a usable platform for validating the accuracy of each weed detection platform. In theory the method is highly plausible, however, unforeseen variance in GPS location skewed the results so map overlays do not easily portray the accuracy of the platforms.

To overcome the GPS error, Section 5.2.2 explains the use of a random selection of images which were matched originally by their GPS coordinates, then double checked for accuracy by visual confirmation of images to ensure the exact same location of ground area was captured in each matched image. This enabled an accurate comparison of GPS coordinate precision at each weed location tested as well as being able to assess whether weeds were detected or failed to be detected, by each platform tested. Due to the time consuming nature of this task, a small cross-section of images (5%) were randomly chosen to validate the GPS coordinates recorded. These showed an average error of 1.9m with an error range of 0.7-4.3m even though the RTK was updated every 200 ms. Hand matching of images visually proved to be a valid method of comparison, however, too time consuming for commercial use. Hence future research into the development of a computer vision algorithm to sort images captured would be beneficial. The concept of using a low cost camera and dye to capture the weed detection platform accuracy is very workable, however, alternative methods to collect and/or sort this data need to be addressed in future research.

- **Design software capable of interfacing with a range of weed detection technology to obtain a signal when a weed is detected.**

  The software development and design for the WeedCheck module can be found in Chapter 5 - Software Development. Two methods were used to interface with the different weed detection platforms, which are discussed in Section 4.4. These methods both proved to be effective methods in obtaining a signal from the weed detection platform when a weed was detected. The software developed has an application within the agricultural industry to validate new developments in weed detection systems. This would enable a quantitative comparison between technologies to determine whether new developments were actually better than available technology.

- **Develop software that presents recorded data and allows labelling of correct or incorrect weed detection.**

  Chapter 5 describes the software used to record and sort the images based on whether a weed was present within the image frame. The computer vision algorithm used for detecting and sorting weeds within frames is described in Section 4.9. This algorithm proved the ability for computer vision to correctly identify weeds and sort the images based on this finding. The algorithm implemented was very sensitive and thus a large portion of the images were incorrectly labelled as negatives. Further development of this algorithm to automatically match and sort images would prove highly significant to ensure accurate comparisons for industry. The computer vision program sorted and presented the images in clearly labelled directories which allowed manual correction of the images by sorting them into their correct directories. The software successfully enabled accurate recording of usable data with frame and positioning information attached which is beneficial to industry for comparing weed detection technology.

- **Develop software that automatically generates weed maps of the field.**

  Software was developed to automatically generate weed maps of the field from the collected data obtained in the field trials. An explanation of the software development can be viewed in Section 4.7. The weed maps produced to validate the repeatability and compare the different modules were disregarded as an effective method. This was a result of inaccurate GPS data being obtained.

  However, the software developed within the project successfully proves the feasibility of creating weed maps if the GPS positions recorded had a higher accuracy. This objective aims to develop software to automatically generate weed maps from the data collected in the field. Section 4.7 discusses the successful implementation of the weed mapping software. Therefore, this objective has been met, however, the maps were not useful for analysis in this instance because of the position variance in GPS.

  The benefits of generating weed maps throughout the growing season would enable the identification of growth patterns and species distribution throughout the field. This information would be useful for site selective weed management systems for a more targeted approach to weed control.

- **Collect data in a field to ground truth the weed detection systems and generate weed maps using the developed software.**

  Chapter 6 describes the experimental design procedures undertaken during the trial when data collection occurred. Section 5.2.2 presents the weed maps automatically generated to overlay the data from the repeated trials for the WEEDit and WeedSeeker systems. A comparison of the WEEDit and WeedSeeker was undertaken in Section5.3. This analysis included using the images collected in the trial to ground truth and validate the accuracy of the two systems. The analysis also ground truthed the GPS position accuracy between trials. Section 5.4 presents a weed map produced from the entire WEEDit boom. Also this section provides information on how images can be overlaid on Google Earth. This could be beneficial to industry as would enable virtual walk through or flyovers to remotely inspect weed species, densities and distribution within a field. This objective has therefore been met throughout various sections of the project.

In conclusion, this project disproves GPS as an accurate method of validation for testing the accuracy of weed detection platforms. Visual inspection and hand matching of images captured proved to be a robust method of validation, however, inapplicable to industry due to the time consuming nature of the task. The project did, however, prove the successful development of software and hardware in the form of a WeedCheck module to enable instantaneous image capture when these weed detection platforms identified a weed. This module enabled comparison of weed detection platforms both within trials for repeatability and between trials for comparison. The WeedCheck module had the added benefit of being versatile in its connectability to different platforms. This module proved to work successfully and enabled all outcomes of this project to be met. With further modification to this project, namely in the use of dye colours used for assessment in conjunction with further development of the computer vision software to analyse the data more efficiently, a more accurate automatic sorting and thus comparison would be possible for commercial use. This would enable farmers to have access to important comparison and repeatability data they can use to access whether to implement precision spraying practices commercially.

The results of this project cannot definitively portray which weed detection platform is better than the other due to the small percentage of frames that had to be hand analysed and matched after the GPS proved unsuccessful. However, what has been proved is that over an area of 0.16ha, the WEEDit proved to be better. What was also proven throughout this project is a method for validation and comparison of weed detection accuracy, just not through GPS. The development of a computer vision algorithm that would take the manual sorting out of matching weeds across frames would be an excellent procedure for validation.

6.2 Further Work

This project identified a large variance in GPS positions between and within the repeated trials. This error could be eliminated with further software and hardware development.

To further standardise the trials the WeedCheck module could be interfaced to the different sensors identically. This would determine if there is a timing error in either method of interfacing, which may have affected the weed maps.

The WeedSeeker WeedCheck module had an intermittent error where the camera would be busy when the trigger was sent, resulting in some weeds not being captured. This was due to a slow frame rate on the RPi camera. In future testing, the camera on the WeedCheck module should be replaced with a sensor with a higher frame rate. This will provide more accurate weed images and eliminate errors in triggering the camera.

Future testing with repeated trials under different weather conditions could validate whether the sensor's performance is affected by cloudy and overcast weather. The ground speed could also be adjusted and repeated to determine the effect of this on commercial weed detection platform behaviour.

This research proved the ability to use computer vision algorithms to automatically detect weeds within an image. Further development of this algorithm could prove to have increased success. Shadow from the sun was present in most weed images, which affected the ability of the computer vision program. Therefore, to create the optimal environment for computer vision, a sun shield and own light source could be used. This would eliminate the error seen in the images due to the shadow from the sun and would make identification of weeds much easier, both for computer vision and manual sorting. The project proved matching weeds within and between trials was the most robust method for validating the commercial sensors. Further development of computer vision which compares plant and stubble geometry could enable automatic matching and classification of weed frames.

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Appendix A

Project Specifications

For: William McCarthy

Title: Standardised test procedure to evaluate the efficacy of automated weed spot spraying

Major: Agricultural Engineering

Supervisors: Dr Cheryl McCarthy

Enrolment: ENG4111 EXT S1, 2016 ENG4112 EXT S2, 2016

Aim: To develop a standard procedure for evaluating efficacy of existing weed detection systems that can potentially be used by agronomists.

1. Review automated weed spot spraying technologies and their performance for different industries, e.g. existing industry reports that describe hit and miss rate, ground conditions, day and night operation.

2. Design a trial protocol to determine weed detection accuracy and spray footprint.

3. Identify up to 3 existing weed spot spraying technologies to evaluate on a ground platform.

4. Develop a method and / or electronic module that potentially interfaces with a range of existing weed spot spraying technologies and records additional metadata (e.g. a camera image and GPS location) whenever a weed is detected, and at periodic intervals so that the metadata can be reviewed for missed weeds.

5. Perform trials of weed detection accuracy and spray footprint.

6. Develop software that (a) presents recorded metadata and allows manual labeling of correct and incorrect weed detection; and (b) automatically generates maps of weed detection performance from the recorded metadata and labels.

   If time and resources permits

7. Extend the software to produce an interface overlaid on Google Earth.

8. Using the developed software, evaluate the performance of a weed detection technology after multiple passes over the same field locations.

Appendix B

Results

Table B.1: WeedSeeker Repeatability Test - Hand Validated

Weed Image Number Test1	**Weed Image Number Test3**	**GPS Position Error (m)**
31	38	0.06
31	38	0.06
32	39	0.02
32	39	0.02
34	40	0.09
34	40	0.09
35	41	0.09
35	41	0.09
36	Failed To Detect Weed	-
36	42	0.10
39	42	3.85
40	44	1.01
40	44	1.01
41	46	0.48
42	46	0.48
201	185	0.99
201	185	0.99
Failed To Detect Weed	186	-
204	Failed To Detect Weed	-
204	186	0.54

205	187	0.28
205	187	0.28
206	Failed To Detect Weed	-
207	189	0.23
207	189	0.23
208	190	1.69
208	Failed To Detect Weed	
209	191	0.06
209	191	0.06
480	430	0.02
480	430	0.02
484	Failed To Detect Weed	-
484	Failed To Detect Weed	-
485	432	0.09
486	433	0.04
313	283	0.53
314	284	0.05
314	Failed To Detect Weed	-
640	560	0.76
641	561	0.09
641	561	0.09
642	562	0.12
643	563	1.75
643	563	1.75
644	564	0.05
644	564	0.05
645	Failed To Detect Weed	-
645	Failed To Detect Weed	-
646	565	1.33
646	565	1.33
647	566	1.43
901	798	0.15
901	798	0.15

902	799	1.10
902	799	1.10
903	799	2.67
903	Failed To Detect Weed	-
Failed To Detect Weed	800	
1100	904	3.33
Failed To Detect Weed	904	
1102	905	0.02
1102	905	0.02
1103	Failed To Detect Weed	-
1105	Failed To Detect Weed	-
1106	908	0.04
	Average error (m)	0.617529
	Minimum error (m)	0.018192
	Maximum error (m)	3.848142
	Range (m)	3.82995

Table B.2: WEEDit Repeatability Test - Hand Validated

Weed Image Number Test1	**Weed Image Number Test3**	**GPS Position Error (m)**
81	72	0.28
82	73	0.39
83	74	0.32
84	75	1.20
87	77	0.02
86	76	0.04
85	75	0.17
87	78	1.26
89	79	0.66
90	79	0.54
332	290	0.17
333	291	0.21

333	291	0.21
334	292	0.27
335	293	1.14
336	294	0.31
337	294	0.58
336	294	0.31
337	295	0.19
338	295	0.69
338	296	0.35
339	296	0.51
340	297	0.15
341	Failed To Detect Weed	-
342	298	0.28
343	298	0.58
922	689	0.59
922	690	0.68
923	Failed To Detect Weed	-
924	691	0.34
924	691	0.34
925	Failed To Detect Weed	-
925	692	0.65
926	692	0.32
926	693	0.96
927	693	0.02
928	694	0.18
929	695	0.13
930	695	0.83
930	696	0.44
1200	920	0.51
1201	921	0.02
1201	921	0.02
1202	922	0.42
1203	922	0.44

1203	923	0.84
1204	924	0.81
1206	Failed To Detect Weed	-
1206	925	0.30
1207	926	0.11
1207	926	0.11
1208	926	0.54
Failed To Detect Weed	927	-
1208	927	0.73
1209	928	0.25
1209	928	0.25
1210	928	0.64
1210	929	0.66
1211	929	0.02
1211	929	0.02
1212	930	0.38
	Average error (m)	0.415319
	Minimum error (m)	0.01955
	Maximum error (m)	1.264973
	Range (m)	1.245423

Table B.3: WeedSeeker and WEEDit Comparison - Hand Validated

WeedSeeker Weed Number	**WEEDit Weed Number**	**GPS Position Error (m)**
32	40	1.65
32	40	1.65
34	42	1.77
34	42	1.77
Failed To Detect Weed	43	-
35	43	2.43
35	44	3.31
36	44	2.99

36	45	4.31
Failed To Detect Weed	45	-
39	46	2.14
40	46	2.14
40	47	2.81
Failed To Detect Weed	47	-
Failed To Detect Weed	48	-
41	48	0.75
41	49	1.86
Failed To Detect Weed	49	-
46	50	1.50
201	202	2.64
201	202	2.64
204	204	2.19
205	204	0.70
Failed To Detect Weed	205	-
Failed To Detect Weed	206	-
206	206	0.99
Failed To Detect Weed	207	-
206	207	1.84
207	208	1.27
207	208	1.27
208	209	1.62
208	209	1.62
Failed To Detect Weed	210	-
209	211	1.56
209	Failed To Detect Weed	-
481	525	1.18
481	526	2.05
483	526	0.87
485	527	1.36
485	527	1.36
1105	1188	1.31

1105	1189	2.40
1105	1188	1.31
1103	1187	2.18
1102	1185	1.14
1100	1184	2.93
1100	1184	2.93
	Average error (m)	1.90
	Minimum error (m)	0.70
	Maximum error (m)	4.31
	Range (m)	3.61