Analysing the influence of TNT on Southern African trees, grass and shrubs using *in-situ* hyperspectral data

by

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DECLARATION

I, Niëll du Plooy, declare that this thesis, submitted for the qualification Master of Science, specialising in Geoinformatics, is my work, and has not been previously presented for acceptance at the University of Pretoria, or any other tertiary institution**.**

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An application was submitted to the Faculty of Natural and Agricultural Sciences' Ethics Committee for the use of potentially biohazardous material, and to cover the environmental aspect of this project.

ABSTRACT/OPSOMMING

Landmines pose a significant risk to the health and livelihood of millions of people in war-torn countries. From a humanitarian point of view, these hidden dangers must be detected and removed. Several detection methods exist, including ground-penetrating radar, sniffer dogs and rats. It is a tedious process and can take months to clear only a single minefield. This study investigates whether TNT from leaking landmines can be detected using hyperspectral remote sensing of plant foliage, with the aim of being an area reduction aid. Increasing concentrations of TNT was administered to a study sample of five species of trees, five species of grasses and four species of shrubs, and leaf-clip readings were taken at regular intervals with a field spectrometer. Statistical correlation testing of seven plant health indices (red-edge position, first derivative reflectance, normalised difference water index, moisture stress index, water band index, photochemical reflectance index and nitrogen index) was done on the results of the readings. TNT has a mixed effect on the health of the tested plants, with some species displaying adverse effects of TNT on their health, while others proved to be healthier or more resilient against the effects. Results also varied in magnitude. Even in a single species, differing concentrations TNT lead to varying results. The various indices delivered varying results, with some indices delivering inconclusive results. Positive results were yielded from the REP analysis, indicating this as a possible index to use in landmine detection.

Keywords: hyperspectral remote sensing; landmine detection; vegetation indices; humanitarian demining

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Landmyne is ‘n noemenswaardige risiko vir die gesondheid en lewensbestaan van miljoene mense in oorloggeteisterde lande. Vanuit ‘n humanitêre oogpunt is dit belangrik dat hierdie versteekte gevare opgepoor en verwyder word. Verskeie opspoormetodes is beskikbaar, insluitende gronddringende radar, snuffelhonde en rotte. Dit is ‘n langdradige proses, en dit kan maande neem om ‘n enkele mynveld skoon te maak. Hierdie studie ondersoek die moontlikheid dat die effekte van TNT wat lek uit landmyne deur middel van hiperspektrale afstandswaarneming waargeneem kan word, met die doel dat dit toegepas kan word as ‘n gebiedsverminderingmiddel. A steekproef van vyf boomspesies, vyf grasspesies en vier struikspesies was besmet met toenemende konsentrasies TNT, en lesings is met ‘n hiperspektrale spektrometer op blaarvlak op gereëlde tye geneem. Statistiese korrelasie toetse van sewe plantgroei indekse (rooirand posisie, eerste afgeleide uitstraling, genormaliseerde onderskeidelike waterindeks, plantvog stresindeks, waterbandindeks, fotochemiese uitstralingsindeks en stikstofindeks) is uitgewerk vanaf die resultate van die lesings. Dit is gevind dat TNT ‘n gemengde uitwerking op die gesondheid van die plante gehad het. Verskeie plante het negatiewe effekte gehad as gevolg van TNT terwyl ander verbeterde gesondheid getoon het. Die indekse het ook verskillende vlakke van bruikbaarheid getoon, met sommige indekse wat nutteloos was. Die rooirand posisie het belowende resuktate gelewer, en blyk dat dit ‘n nuttige indeks kan wees om mynvelde op te spoor.

Sleutelwoorde: hiperspektrale afstandswaarneming; landmyn opsporing; plantgroei indekse; humanitêre landmynopruiming

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EQUATIONS

ABBREVIATIONS/ACRONYMS

AP - Anti-personnel
AT - Anti-tank
CSIR - Council for Scientific and Industrial Research
DPSS - Defence, Peace, Safety and Security
ERW - Explosive remnant of war
ESRI - Environmental Systems Research Institute
GICHD - Geneva International Centre for Humanitarian Demining
GIS - Geographical information systems
HMX - 1,3,5,7-Tetranitro-1,3,5,7-tetrazocane/Octogen ($C_4H_8N_8O_8$)
HS - Hyperspectral
IED - Improvised explosive device
IR - Infrared
MOOC - Massive open online course
MS - Multispectral
NCBI - National Centre for Biotechnology Information
NDVI - Normalised difference vegetation index
NDWI - Normalised difference water index
NIR - Near infrared
PRI - Photochemical reflectance index
RDX - 1,3,5-Trinitro-1,3,5-triazinane/Cyclonite (O_2NNCH_2)
REP - Red-edge position
RPAS - Remotely piloted aircraft system
RS - Remote sensing
SANBI - South African National Biodiversity Institute
SWIR - Shortwave Infrared
TNT - 2,4,6-Trinitrotoluene ($C_6H_2(NO_2)_3CH_3$)
UAV - Unmanned aerial vehicle
UN - - United Nations
UPLC QToF - Ultra performance liquid chromatography quadrupole time of flight
UXO - Unexploded ordnance

Chapter 1. INTRODUCTION

1.1 Landmines

Landmines are explosive weapons used in conflict situations. They are intentionally hidden and are used as "booby-traps", with the aim of damaging, disabling or killing what or whoever triggered it, slowing down the progress of troops and vehicles (Keely: 2003). The two common types of landmines are anti-personnel (AP) and anti-tank mines (AT). The key components of both versions are the same: a casing, a firing mechanism or trigger, and an explosive charge, often TNT.

Unfortunately, after the resolution of the conflict, any landmines laid are usually not recovered. These abandoned minefields not only pose a serious threat to people who come into immediate contact with them, but they could also prohibit access to critical resources, such as water or medical services (Oppong & Kalipeni: 2005). If an individual triggers a landmine, the consequences can be severe. Damage to the muscular or skeletal system of the individual can render him/her disabled, and may even lead to death.

In an article by Walsh & Walsh (2003), they state that as many as 110 million landmines were planted during various conflicts. Africa, Angola specifically, is probably most threatened by mines and explosive remnants of war. Although the estimation differs between sources, it is reckoned that there are at least 10 million unrecovered landmines in Angola alone. Mozambique and Zimbabwe also have significant amounts of landmines still to be recovered, with an estimated 3 million and 2 million landmines respectively.

Because of the threat landmines pose to civilian society, efforts to find and safely remove landmines are often made by organisations such as the United Nations and the Geneva International Centre for Humanitarian Demining (GICHD). It is a tedious process, with many risks, and extremely high costs.

1.2 Hyperspectral remote sensing

Hyperspectral remote sensing refers to a system of sensors which are used to detect the spectral reflectance of target objects. These objects can include anything that reflects light. The reflectance of certain bands of the electromagnetic spectrum and the absorption of others gives an object a spectral signature. This signature can be used for object identification, and in objects such as plants, it can be used to identify plant health. Figure 1 represents a range of spectral signatures typical of a Wild Olive tree employed in the study, which had 30mg TNT per 1kg soil. The erratic values between 350µm and 450µm are due to a sensor fault in that range but do not influence the indices used in this study.

Sensors are available that can detect thousands of wavelengths. The ASD Field Spectrometer used in this study can detect wavelength reflection between 350µm and 2500µm, in 1µm increments.

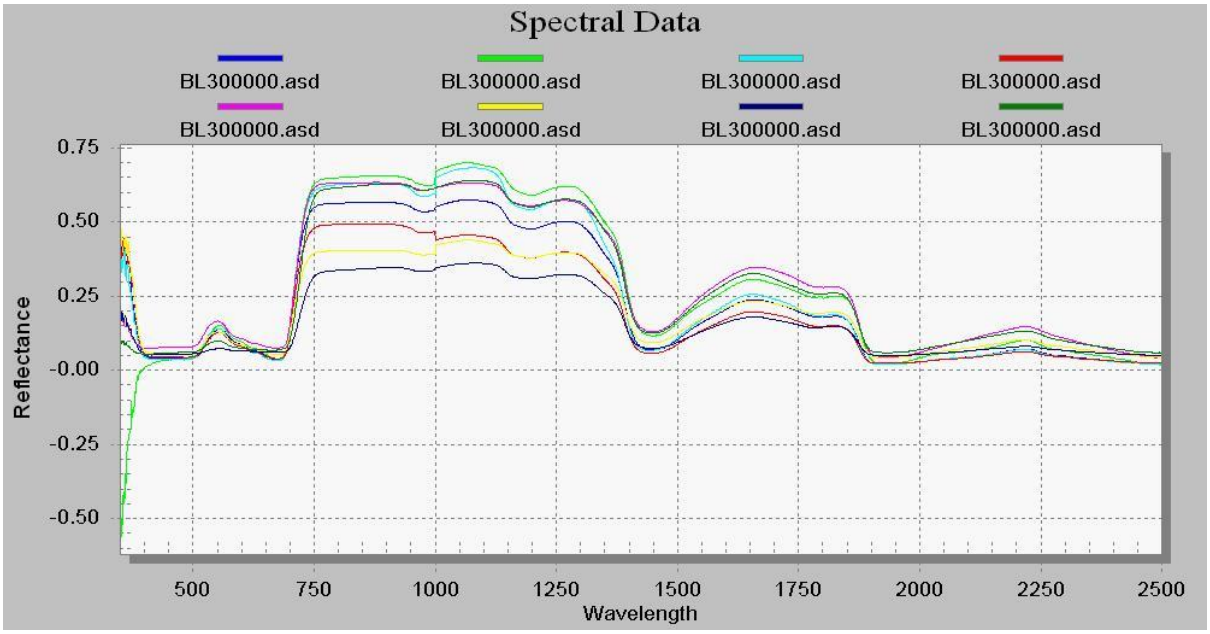

Figure 1 - Spectral reflectance signature of a Wild Olive tree contaminated with 30mg/kg TNT

1.3 Project background

Dr Antony Cooper of the CSIR asked the original question:

"*What is the physiological and spectral reflectance response to the leaching of 2,4,6-Trinitrotoluene (TNT) into the soil of South African indigenous trees?"* (Smit: 2013)

Because of the use of hyperspectral remote sensing to determine changes in vegetation, as well as using it to monitor changes in plant health, it was observed that the influence of TNT on the health of plants might be observable using an HS remote sensing platform. It was also noted that if it was indeed possible, this technology might apply to the fields of military mine clearance and humanitarian demining.

For her honours research project, Rene Smit (2013) tried to answer this question by analysing spectral reflectance data captured from seven species of indigenous Southern African trees. Seven examples of each species were used for the data analysis, five of which were exposed to different concentrations of TNT. Two specimens of each species were left uncontaminated and served as control plants.

Although the findings of her research were inconclusive, the potential for a long-term study was seen, whereby continued readings would be taken from the tree samples, with the addition of other plants, to simulate TNT contamination in different plant biomes.

The project, **Mapping and analysing the influence of TNT on Southern African trees, grass and shrubs using *in-situ* Hyperspectral data**, serves as a continuation of Smit, 2013, with the addition of endemic species of grass and shrubs.

1.4 Research questions

The original question, asked by Dr Cooper will remain the basis for the research, albeit with two questions added:

1. What is the physiological and spectral response to the leaching of TNT into the soil of South African indigenous trees?
2. Will different types of indigenous/cosmopolitan plants react differently to the leaching of TNT into their soil?
3. Do specific spectral bands tend to be better indicators of TNT contamination than others?

1.5 Objectives of research

The following research objectives have been devised to answer the research questions as completely as possible:

1. Capture as much spectral reflectance data as possible from the available plant species, as is possible in the projected timeframe, using *in-situ* hyperspectral remote sensing
2. Consult further literature and improve literature review to determine theoretical soundness of methodology
3. Test the collected data using the different vegetation indices to determine whether exposure to TNT creates differences in spectral reflectance
4. Identify possible spectral bands which show correlation to the concentration TNT in the soil
5. Determine whether a correlation exists between the plants' spectral reflectance and weather occurrences around the time of measurement
6. Compare canopy readings to leaf clip readings to determine whether the methodologies developed can be practically used in actual fieldwork

Chapter 2. LITERATURE REVIEW

2.1 Threat of landmines

According to the UN, hidden landmines kill between 15,000 and 20,000 individuals, with a large number being women, children and the elderly. Oppong (2005) has the number of landmines buried worldwide at 120 million, with more than 37 million scattered in more than nineteen countries.

Although the estimations widely vary between sources, it is estimated that there are more than 10 million landmines in Angola alone (Walsh: 2003), and if one adds Zimbabwe and Mozambique, it puts the Southern African landmine tally at more than 14 million.

The immediate threat of landmines is bodily harm or death from the explosion. Bendinelli (2009) found that in research done in Cambodia, that at least a quarter of landmine victims were children, and while most cases had severe trauma, children were more likely to get maimed or killed. Some landmines have trigger weights of as little as 6kg, according to the UN, meaning even toddlers can trigger an antipersonnel mine. Makris et al. (2006) studied the blast effects of mines to the heads of deminers, and even with head protection, the effects are often fatal.

Not only do landmines threaten the lives of people that live in their vicinity, but they also contain explosives, such as TNT. TNT's toxicity and carcinogenic properties have been known as early as 1917 (Roberts: 1947). Won (1976) states that TNT is highly toxic to marine forms, which can indirectly influence the health of the humans who rely on the contaminated marine life, such as fish, for sustenance. Leaching of TNT from abandoned landmines into soil and groundwater also influence the communities exposed to it. These communities often also do not have immediate access to medical treatment. The Human Rights Watch estimate that more than half of landmine casualties in Mozambique die before they can reach medical care.

TNT has cytotoxic properties (Banerjeea et al.: 1999). It was determined that TNT exposure could be detected in urine samples and haemoglobin adducts of workers in explosives factories after exposure to TNT aerosols, and due to physical contact with the substance (Woollen et al.: 1986; Sabbioni et al.: 2005).

The indirect threat of landmines stretch as far as inhibited economic growth (Robledo: 2007), and subpar rates of development. Andersson, da Sousa and Paredes (1995), studied the social cost of landmines in Afghanistan, Bosnia, Cambodia and Mozambique. Elliot and Harris (2001) also did a cost-benefit analysis of mine clearance in Mozambique. The study parameters ranged from economic factors such as food security, physical factors such as the extent of landmine-related injuries, to psychological effects. They concluded that, in some cases, as many as 80% of families were influenced by landmines.

The also stated that the presence of landmines threatens food security, and adds to the economic burden of these areas.

Andersson et al. (1995) added that agricultural production could significantly increase if landmines were not present. The estimated increase in production ranged from 3% to 6% in Mozambique, to 88% and 200% in Afghanistan. Livestock loss to landmines was conservatively estimated to be greater than $6,5 million, or about $200 per studied household.

This threat is not only limited to mines, with unexploded ordnance and explosive remnants of war causing similar issues (MacDonald: 2001). After clean-up of war zones and military bases, explosive munitions often remain. Finding and disposing of such munitions often entail similar processes to demining.

2.2 Types of demining

Demining usually happens at two distinct levels (Tiwari et al.: 2008). Military mine clearance and humanitarian demining. Kasban et al. (2010) mention some fundamental differences between the two types (Table 1).

Table 1 - Comparison between military mine clearance and humanitarian demining (Adapted from Kasban et al. (2010))

Type	**Military**	**Humanitarian**
Cost	Low (millions of dollars)	High (billions of dollars)
Clearance rate	Rapid	Long-term (years or decades)
Training of personnel	High	Little to no formal education
Clearing area	Detect and avoid mine areas	Need to clear entire area
Target clearance rate	Up to 80%	100%

According to Kasban et al. (2010), military mine clearance involves the rapid removal of landmines to ensure the safe passage of troops or convoys. The target clearance rate is usually limited to landmines directly threatening this movement of personnel or equipment. Thus, if a path is cleared, anything less than 100% is acceptable. For humanitarian demining, the aim is to ensure a safe environment for all the inhabitants of an area affected by landmines, which means a clearance rate of 100% is required. Smith (2016) states that the target result for military demining is not to eliminate risk, but to reduce risk, whereas, with humanitarian demining, the idea is to eradicate the danger of landmines.

Although there are some similarities in the methods of mine detection and removal, there is also a big fundamental difference. It is preferred that mines be removed as a unit, and disarmed safely in the

context of humanitarian demining. Military mine clearance disregards this and aims to remove landmines as quickly and efficiently as possible. In many cases, this can involve simply driving over a minefield with a mine-resistant vehicle, which detonates any landmines which it crosses. In other cases, devices such as flails attached to tanks, or even bulldozers are used. (Gonzales-de-Santos et al.: 2007). These devices are effective against AP mines, which lack the power to damage the device severely. In the case of AT mines, soldiers using metal detectors are often used, as they lack the weight to trigger a mine.

Because of the threat to civilians, often innocent bystanders of war, organisations such as the United Nations (UN), GCIHD and the International Campaign to Ban Landmines have started humanitarian efforts to stop the use of landmines and to safely remove as many as possible, if not all, of the hidden landmines, still left. In 1997, 133 signatories signed the Ottawa Treaty, a treaty that aims to eliminate the use of landmines, prohibit their manufacture and seek their destruction (Anderson: 2000; Barlow: 2004).

Humanitarian demining is usually a tedious and primitive process (Biddle et al.: 2007), with a person only being able to clear a couple of metres a day. Several tools are used to aid in this process, including prodders, metal detectors and ground-penetrating radar (Brushini and Gros: 2012). These tools are often problematic, as they may produce false alarms (between 100 and 1000 for each real mine found), and may not be able to detect the small metal parts in landmines. Landmines are commonly made of materials other than metal, meaning that metal detectors may not always be effective. Gourlay (2000) urges cooperation between military and humanitarian demining entities for effective demining.

Table 2 compares the relative complexity, cost, speed of operation, safety, environmental effects and false alarm rates of common mine detection techniques and technologies. From this, it is evident that techniques requiring personnel to operate near landmines are more dangerous than remote detection systems, sometimes with high false alarm rates.

For effective humanitarian demining, it is felt that a comprehensive database of soil properties is needed (Das et al.: 2003). Magnetic susceptibility and electrical conductivity of soils influence the effectiveness of some sensors, and may even render them unusable.

Minefield delineation remains a problem, as the random distribution of landmines often mean that the exact boundaries of minefields are hard to detect. Mine detection also often involves physical proximity between deminers and mines. Dilibal et al. (2004) describe the development of a robotic hand, actuated by shape memory, to aid in the removal of landmines.

Table 2 - Comparison of mine detection techniques (Adapted from Kasban et al. (2014))

Technique	Sensor	Complexity	Cost	Speed	Safety	Environmental effect	False Alarm
Biological	Dogs	Low	Medium	Medium	Medium	Medium	Medium
	Rats	Low	Low	Low	High	High	High
	Bees	Low	Medium	Low	High	High	High
	Plants	Medium	Medium	Low	High	High	High
	Bacteria	Medium	Medium	High	Low	High	Low
Electromagnetic	MD	Low	Low	Low	High	Low	High
	GPR	Medium	High	Medium	High	Medium	Low
	MWR	Medium	Medium	Low	High	Medium	Medium
	MMWR	High	Medium	Low	High	Medium	Medium
	EIT	Low	Low	Medium	High	High	Medium
	IR	Medium	High	Medium	Medium	High	Medium
Optical	Light	Low	Low	Medium	High	High	High
	LiDAR	High	High	Medium	High	Low	Medium
Nuclear	NQR	High	Medium	Medium	Medium	High	Low
	Neutron	High	High	High	Low	Low	Medium
Acoustic	A/S	Medium	High	Medium	High	Low	Low
	US	Medium	Medium	Low	Low	Medium	High
Mechanical	Prodders	Low	Low	Medium	Low	Low	High
	Machines	Medium	Low	High	Low	Low	High

2.3 Effects of explosives on plant health

It has been found that TNT influences plant health. Ali (2006) found that plants exposed to an increased concentration of TNT in their soils produced less biomass than uncontaminated plants. Fluorescence studies of chlorophyll transients also showed reduced yield with an increase in TNT. In Ali's (2006) study, the effect of TNT on *Lactuca Sativa*, lettuce, was investigated.

Krishnan et al. (2000) found that warm-season grasses were more sensitive than cold-season grasses to TNT contamination. They found that germination of grasses decreased with an increase of TNT contamination. Similarly, root area, biomass and plant height also reduced with an increase in TNT concentration.

Conversely, some plants may absorb TNT from contaminated soil without significant toxic effect. Makris et al. (2006) studied the ability of Vetiver grass to absorb TNT in aqueous media. A hydroponic study was done, and it was concluded that Vetiver could absorb TNT from aqueous media with no visible toxic effect.

Giles (2004) mentions the need for environmentally friendly explosives and munitions. In this article, it is said that the use of compounds containing lead should be reduced to reduce the environmental impact. It also states that studies have been done investigating explosive compounds that have little or no lasting effects on the environment.

In a study where seven forage and conservation crop species were evaluated for the phytoremediation of organic contaminants (Checkol et al.: 2002) it was found that soils with high organic matter, factors such as covalent bonding were responsible for the removal of TNT and pyrene, and the plant itself had a minimal role in TNT removal. In soils with the less organic matter, the removal of organic contaminants was mostly done by the plant. Another finding was that interactions between the plants, soil and contaminants were particular to plants.

2.4 General characteristics of TNT

TNT is a pale to yellow solid, or pale to yellow crystalline solid, and has no odour. According to the National Centre for Biotechnology Information (NCBI: 2004), it does not form naturally. It is a stable explosive and may explode when exposed to intense heat. It is relatively soluble in methyl acetate and benzene and extremely soluble in acetone (109g of TNT in 100g of acetone). Hundal et al. (1997) studied the effectiveness of removing TNT and RDX from soil and water using iron.

Apart from the immediate health threat due to the explosion, the NCBI also states that when TNT decomposes, it emits toxic fumes of nitrogen oxides. It is also toxic when swallowed, and is a known irritant. It is a human carcinogenic and can be inhaled, absorbed through the skin or ingested.

It has been found that TNT, like other common explosives, is slightly soluble in water. It has a solubility rate of less than 200mg of TNT per litre of water (Ro et al.: 1996; Alnemrat et al.: 2014; National Centre for Biotechnology Information: 2004, Taylor et al.: 2009). Lynch et al. (2002) determined that the dissolution rates of common explosives increase with an increase in surface area, temperature and mixing rates and that TNT had the highest dissolution rate of the tested explosives, which included TNT, HMX and RDX. In a previous study (Lynch et al.: 2001), it was found that the dissolution rates of these explosives were not significantly affected by pH level.

Remediation of TNT contaminated soil has been found to be possible through composting, with acetone added to the ground (Block: 2000; Radtke et al.: 2000; 2007).

2.5 Methods of mine detection

Several different methods of mine detection exist. These include knives and blast-resistant gear to physically search for mines (mechanical mine clearance (Habib: 2002), using animals such as dogs (Brushini and Gros: 2012), rats (Poling: 2011), bees (Bromenshenk: 2003) or bacteria (biological mine clearance (Habib: 2007). Table 3 lists various methods of landmine detection, as well as the relative availability of the method, and the relative costs of implementation and operation.

Pohling (2011) refers to the use of giant African rats (Figure 2) to detect the smell of landmines and emit a reaction, such as pawing or biting the ground. An American Forces Press article, on the other hand, states that research is being done on the use of honey bees to find landmines. While using rats might be expensive due to high training costs, they are small and light enough not to trigger any mine detonators.

Bromenshenk et al. (2003) mention the usefulness of using bees as a detection method, as thousands of bees can be trained in less than an hour to search for explosives. They can detect odours at far lower concentrations detectable by most sensors. They also mention that their sense of smell is like that of dogs. They can be trained to detect single explosives or several various types. A trial study proved that bees could successfully assist in area reduction of potential minefields, but using bees is reported to be impractical as of yet, due to field conditions differing from laboratory conditions.

Brushini and Gros (2012) states that dogs can effectively detect tiny amounts of explosives, but that they are unable to pinpoint exact mine locations. Due to environmental effects, mines are often as far

as 10m from where the dog first detected the odour. Goth et al. (2003) support the usage of dogs in the field of demining.

Settles and Kester (2001) studied aerodynamic sampling to detect landmines using "electronic noses" under laboratory conditions. They concluded that several technical issues need to be resolved if such sensors are to be used in real-world conditions. Beetner et al. (2004) refer to the usage of high-pressure water jets as a method of mine detection.

Yagur-Kroll et al. (2014) mention the potential to detect TNT, as well as common impurities found with TNT, namely 2,4-dinitrotoluene (DNT) and 1,3-dinitrobenzene (DNB), using E.Coli. It was found the TNT and DNT were metabolised by E.Coli. The E.Coli was genetically engineered with bioluminescent genes to fluoresce after exposure.

Table 3 - Landmine detection methods, maturities and costs (Adapted from Brushini and Gros: 2012)

Detection method	**Maturity**	**Cost/Complexity**
Passive IR	Near	Medium
Active IR	Near	Medium
Polarised IR	Near	Medium
Passive electro-optical	Near	Medium
Multi/Hyperspectral	Far	High
Passive mm-wave	Far	High
mm-Wave radar	Near	High
GPR	Near	Medium
Ultra-wideband radar	Far	High
Active acoustic	Mid	Medium
Active seismic	Mid	Medium
Magnetic field sensing	Near	Medium
Metal detection	Available	Low
Neutron activation analysis	Near	High
Charged particle detection	Far	High
Nuclear quadrupole resonance	Far	High
Chemical sensing	Mid	High
Biosensors	Far	High
Dogs	Available	Medium
Prodding	Available	Low

Figure 2 - Giant African pouched rat used for landmine detection in Angola (Source: APOPO, Wikimedia Commons: 2016)

Robledo (2007) lists ground-penetrating radar, electromagnetic induction and nuclear quadrupole resonance as non-invasive means of detecting landmines. Also mentioned is nuclear analysis as a possible mine detection technology by Rosengard et al. (2001). Phelan (2002) refers to trace chemical detection as a means of sensing buried landmines. Anderson et al. (2006) studied the potential of multiplexed liquid array displacement immunoassays and found that it is a rapid, user-friendly and sensitive method for TNT detection. Brooks et al. (2004) mention the use of neutrons and gamma-rays and Lunardon et al. (2004) investigated using neutron-tagged beams for mine detection. Viesti (1999) mentions nuclear mine detection techniques and Williams et al. (2001) quantum magnetics using quadrupole resonance.

Ground-penetrating radar has proved to be a popular mine detection tool and is the basis of several research projects (Eide and Hjelmstad: 2004; Ishikawa et al.: 2005; Torrione et a.l: 2006). It provides a three-dimensional view of the subsurface layer of soil, within which landmines are often buried. They can be mounted on vehicles or aerial platforms, minimising contact with the ground. At the bi-annual conference of the 2014 Genevan International Centre for Humanitarian Demining (GICHD), in Lyttleton, the use of vehicle-mounted GPR was discussed in detail, with projects such as TIRAMISU showing promise.

Brushini and Gros (2012) list some drawbacks of using GPR. These include the fact that high frequencies are needed to detect little landmines, reducing penetration, and increasing static clutter.

Other issues include the high costs of obtaining and using GPR, which often exceeds the budget of many demining operations.

From the 2014 GICHD conference, it was noted that in future, the most efficient way to detect landmines might be in combined sensors. This notion is echoed by Mine Action Coordination Centre of Afghanistan. This concept is supported by researchers (Cremer et al.: 2001; Scott et al.: 2008; Van Dam: 2005), who tested EMI, GPR and seismic sensors, and found that false alarms in mine detection were significantly reduced. The addition of chemical detectors such as used by Phelan (2002), and hyperspectral sensors (Winter: 2004) may further increase the hit-rate of such multi-sensor platforms.

Hyperspectral remote sensing has been used for some years to monitor the apparent health of plants (Penuelas: 1998; Chaerle: 2000; Ivashov et al.: 2003; Jensen: 2007). Vegetation indices, such as the NDVI, NDWI, water band index, nitrogen index (Cho: 2010) and red-edge position are all dimensionless indicators of plant stress, health, water uptake, chlorophyll levels and nitrogen intake. Ali (2006) tested photosynthetic parameters as indicators of TNT and found that there was a correlation between chlorophyll levels and TNT concentrations, which leads to the conclusion that hyperspectral remote sensing may be a viable tool to detect landmines.

The promise of support vector machines, which can perform independent analysis, sometimes with minimal learning has been studied (Mountrakis et al.: 2010). These machines can generalise data well but are prone to parameter assigned issues which may significantly influence results. This means that they require careful parameterisation to function properly. If such machines can be refined, they can be of value in the detection of landmines.

The use of robots as mine detection tools has also been researched in the past (Nicoud: 1997; Trevelyan: 1997), especially as a tool for humanitarian demining, as they provide a means of accessing minefields, without putting lives immediately at risk. They tend to be expensive, but with a combined sensor system may prove invaluable.

Data recorded from sensors were subject to statistical algorithm testing (Torrione: 2002), and it was found that with the correct application, the number of false alarms picked up by EMI sensors can significantly be reduced.

Mather (2000) investigated the role of GIS in the field of humanitarian demining. He found, that up to recently, the use of GIS in humanitarian demining has not been widely accepted. Technology regarding humanitarian demining has been the subject of much debate, and the use of GIS can be seen as more of an obstacle than a tool. Should issues surrounding training and technical aspects of GIS be overcome, the application of GIS might be more viable.

The advantages of GIS are that remote sensing data which is spatially referenced can be overlaid and analysed (Jensen: 2007). Thus, data from a multi-sensor mine detection platform can be combined, together with statistical algorithms to generate hot spot maps, which indicate areas of high likelihood for landmines.

Multi-sensor remote sensing systems combining LiDAR, multi and hyperspectral sensors have proven beneficial in the search for exposed, and sub-surface remains in archaeological applications (Rowlands and Sarris: 2007). These systems provide a means to search for anomalies, based on the belief that hidden objects or archaeological remains may alter the immediate environment physically or chemically.

The project on which this proposal is based, namely Smit (2013), found that there seems to be a correlation between the concentrations of TNT with the health of the plants, with some plants showing an improvement with an increase in TNT concentrations, while others had declining health. Also, she found that the vegetation indices used showed to some correlation to TNT, calling for further research to be done, which is the aim of this study. Similarly, Rubis (2011) found that plant health was influenced by exposure to varying concentrations of TNT. Low TNT concentrations provided a nitrogen boost to plants, which caused an improvement in health. Higher concentrations of TNT led to stressed plants. She identified PRI and, importantly for this study, chlorophyll fluorescence as markers in identifying TNT contaminated plants as opposed to naturally stressed plants.

2.6 Hyper and multispectral remote sensing

The terms hyper and multispectral refer to the ability of an imaging device or sensor to be able to measure light reflectance beyond the normal electromagnetic spectrum visible to humans (Jensen: 2007).

The difference between *multispectral* and *hyperspectral* lies in that a multispectral sensor can sense reflectance in the ordinary range of electromagnetic radiation (blue, green and red), and certain other relevant bands (NIR, and IR; Campbell and Wynne: 2011), whereas a hyperspectral sensor can measure reflectance over hundreds of bands, in some cases from ultraviolet to far infrared (Borengasser, Hungate and Watkins: 2007).

In the context of this project, hyper and multispectral remote sensing is referred to in the sense of earth observation. This includes aerial and satellite imagery (Jensen: 2007), as well as data collected using a handheld spectrometer.

2.7 Applications of hyper and multispectral imagery

The applications of hyper and multispectral imagery range from earth observation (GIS, agriculture (Ustuner et al.: 2014)), to applied sciences, medicine and food sciences. Satellite imagery has proven useful in the field of mineral exploration (Azizi et al.: 2010, Ninomiya: 2004), where the use of shortwave infrared (SWIR) imagery has been used to detect minerals including lunite and pyrophyllite.

Lobitz et al. (1999) found that by studying remotely-sensed data, including sea surface temperature and height, a correlation between *Vibrio cholerae (Asiatic cholera)* outbreaks and climate change could be found.

Imaging techniques at different levels can be used to detect plant stress caused by various sources, even before the plant appears visibly unhealthy (Hunt, and Rock: 1989; Chaerle and Van der Straeten: 2000; Zarco-Tejada et al: 2002; Liew et al.: 2008; Govender et al.: 2009; Main et al.: 2011; Ramoelo et al.: 2015). These techniques can be applied at levels ranging from microscopic to spaceborne and may include thermography (IR radiation), near-infrared reflectance, fluorescence and reflectance imaging of visible light and UV-induced fluorescence. Applications include the detection of water based stress, heavy metals, infection by virus, pathogen or fungus.

Chen et al. (2005) and Herold et al. (2002) studied the use of remote sensing, especially image based analysis to determine quantitative relationships between the urban heat island and land use and cover changes. Images from Landsat Thematic Mapper and Enhanced Thematic Mapper were used. Similarly, LANDSAT imagery was used with supervised classification to determine land cover and land use changes in the north-western coastal zone of Egypt (Shalaby and Tateishi: 2007). Similarly, land use change in the Zhuijang delta in China was studied by Weng (2002). Severe land cover changes due to agricultural and tourist development were assessed, and it was found that these changes lead to degradation of vegetation and waterlogging of some areas.

Using the PROSPECT+SAIL model, simulations were used, comparing the effectiveness of vegetation indices to estimate green leaf area index and chlorophyll density (Broge and Leblanc: 2000). It was found that the second soil adjusted vegetation index (SAVI2) is the best greenness measure, but that different indices had vastly different reactions to external factors. They mention that the choice of the index should be influenced by prior knowledge of external factors.

Panda et al. (2010) determined the perpendicular vegetation index (PVI), to be the most accurate index to predict crop yields when using neural network technologies. PVI outperformed NDVI, GVI and SAVI when predicting crop yields for three years.

Figure 3 - Real colour Sentinel-2 multispectral image, Roodeplaat area (By author)

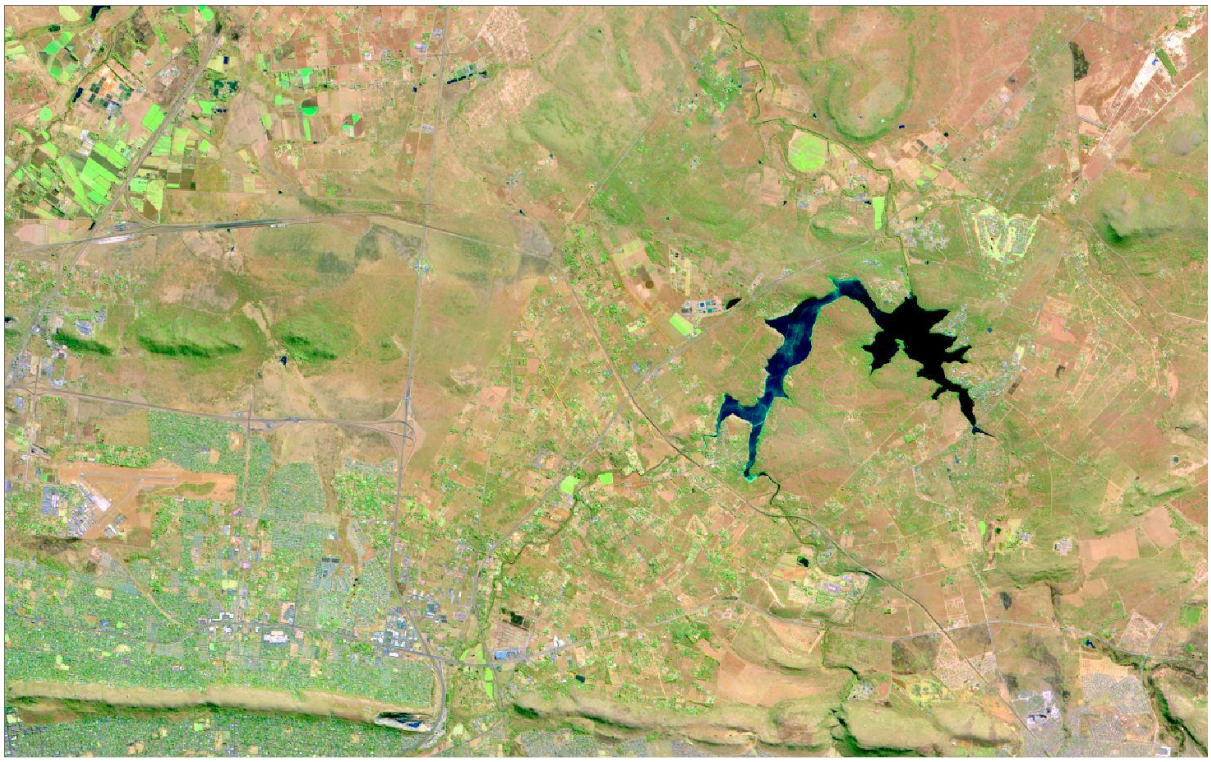

Figure 4 - Shortwave infrared false colour Sentinel-2 multispectral image, Roodeplaat area (By author)

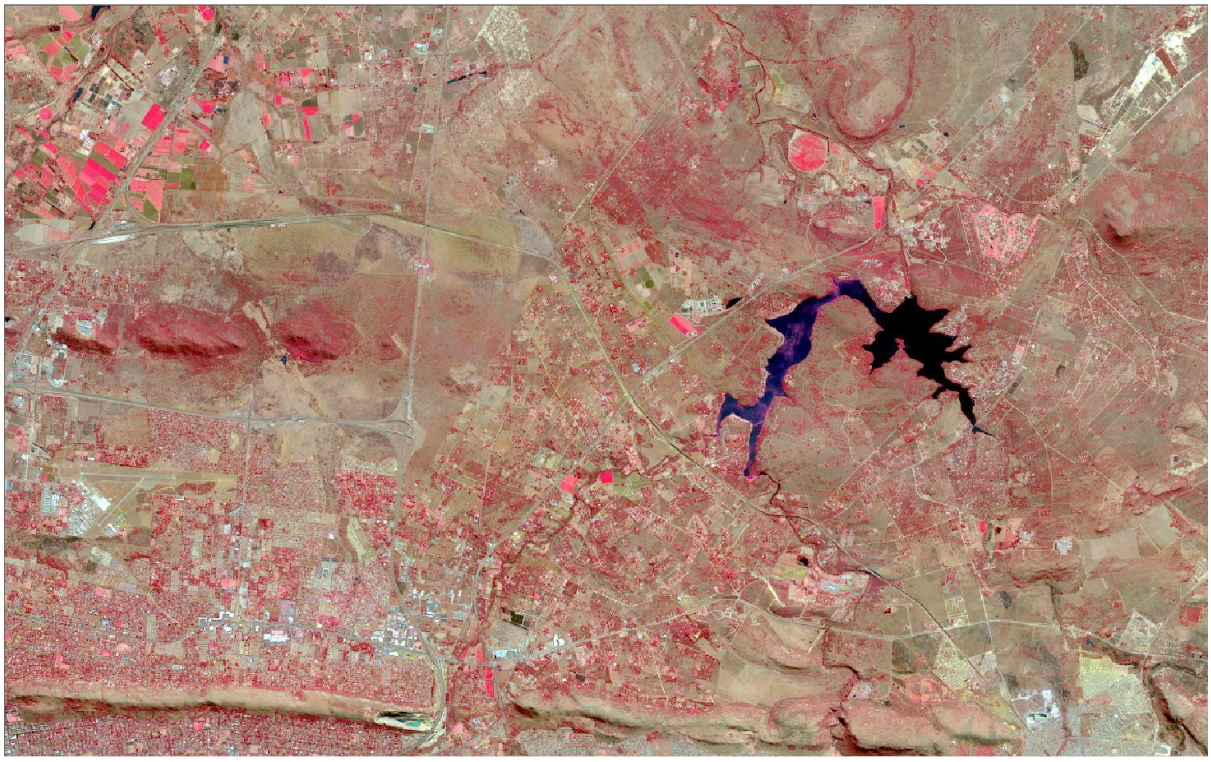

Figure 5 - Infrared false colour Sentinel-2 multispectral image, Roodeplaat area (By author)

Figures 3, 4 and 5 represent respectively true colour, SWIR false colour and IR false colour images of the Roodeplaat area, extracted from Sentinel-2 satellite data. For SWIR images, the red, green and blue bands are replaced with SWIR, NIR and green respectively, and are commonly used to detect areas of flooding or newly burned land. Plants will appear bright green, due to the strong reflectance of NIR by plants, and developed areas grey or purple (NASA: n.d.).

Similarly, for the IR false colour image, RGB bands are replaced by NIR, green and red respectively. Barren land will be pale or greyish, while vegetation would be in hues of red. Healthier vegetation would appear as bright hues of red, due to the strong reflectance of NIR by green vegetation (NASA). Thus, irrigated fields would appear as bright red and patchy pivot irrigated fields may indicate issues with fertilisation, sickness or plant-specific problems in that field

In an ESRI MOOC (2017), it was stated that because of the availability, temporal resolution and the relative ease with which multispectral imagery can be accessed; it is becoming a vital tool for the determination of vegetation health, using vegetation indices such as NDVI or REP.

Reflectance spectra as a tool to monitor plant health and to detect chlorophyll in vegetation using remote sensing platforms such as MODIS has been discussed by Gitelson et al. (1996; 1998).

Tests done to determine the operational readiness of a fixed wing mini-UAV (unmanned aerial vehicle; ATMOS-3), fitted with a colour infrared camera (VEGCAM-1) states that the system can be used in

applications (Lobo: 2009). Continuous development and testing of this scheme in conservation applications, and landmine detection scenarios proved successful.

Mutanga et al. (2003) studied the potential application of remote sensing for estimating and mapping pasture quality. In their study, they concluded that there is a significant difference in reflectance between control, low and high nitrogen specimens of tropical grass, which signals a shift of the usefulness of spectra from the mid-infrared wavelengths to the visible spectra. Mutanga et al. (2007) also investigated the relationship between the red-edge and biochemical content in grass.

Smith et al. (2004) used derivatives ratios in the red-edge region to detect plant stress in response to gas leaks. The study concluded with the results that spectral reflectance increased in the visible spectrum, but decreased in the near-infrared region, indicating plant stress caused by soil oxygen being replaced with gas. It was seen that long-term effects were observable in grasses, wheat and bean, but short-term effects were only observable for grasses. Nooman (2007) used the red-edge position (REP) to detect stress induced by gas leaks on seedlings.

2.8 Vegetation indices

The usage of vegetation indices has proved to be effective in monitoring changes in plant health, land cover, land use, soil moisture, to name a few (Bannari et al.: 1996). Vegetation indices have been developed as early as the 1970s, according to Bannari, and he cites Pearson and Miller (1972) as pioneers. They developed indices to determine land cover, namely the Ration Vegetation Index and Vegetation Index Number.

Spectral vegetation indices provide a non-invasive means of determining crop yield (Aparicio et al.: 2000). This study compared the effectiveness of various vegetation indices, including the normalised difference vegetation index (NDVI), photochemical reflectance index (PRI), leaf area index (LAI) and green area index (GAI), to determine durum wheat crop yield.

Similarly, vegetation indices offer the potential for land cover and crop identification (Mroz and Sobieraj: 2004). It is found that even though there are slight differences, the effectiveness of different vegetation indices to discern between the various land cover types or crops are similar, and no one index is superior for the task.

Due to regular flooding of rivers in Europe, heavy-metal contamination of soils is a major environmental concern (Cleavers et al.: 2004). A strong negative correlation was found between REP and heavy metal concentrations, and multiple peaks were observed using the first derivative method. In his doctoral thesis, Cho (2007) mentions using linear extraction of REP to minimise uncertainty.

Cammarano et al. (2014) studied several vegetation indices to determine their robustness to estimate nitrogen content in wheat in Mediterranean environments. A comparative study was done at both leaf level, as well as canopy level. It was found that the perpendicular vegetation index best-predicted plant nitrogen levels and that canopy nitrogen content related the best to the canopy chlorophyll index. Simple ration or normalised vegetation indices were influenced by geographical location. Indices using red-edge wavelengths were more robust and were more accurate when estimating canopy parameters. Remote sensing as a tool to detect nitrogen content was also studied by Ramoelo et al. (2011; 2015)

Gao (1996) suggested the usage of the NDWI to determine plant liquid water content from space. This index monitors the reflectance values around 860nm and 1240nm, values representing high plateau vegetation reflectance, which is also less sensitive to airborne aerosols. It has been found that the NDWI does not fully eliminate background soil values. The index has been compared to the NDVI, but it is to be used as a complementary index for the NDVI, and not a replacement. A modified NDWI was used by Xu (2006) to enhance open water features.

Rokni et al. (2014) similarly found that the NDWI was superior to the NDVI, NDMI (normalised difference moisture index), WRI (water ration index), modified NDWI and AWEI (automated water extraction index) for the application of water feature extraction and change detection.

In a study to monitor live fuel moisture (Dennison et al.: 2005), NDVI and NDWI were compared. Both indices correlated positively with live fuel moisture, but indices such as NDWI proved more efficient for monitoring live fuel moisture than NDVI, which monitors chlorophyll absorption.

Limitations in vegetation indices do exist, especially due to topographic, atmospheric and background effects from soil (Moreira et al.: 2016). Four vegetation indices were evaluated for the influence of topography, namely NDVI, RVI, EVI and SAVI. It was found that, when compared to the near-infrared band which was not topographically corrected, vegetation indices were less influenced by topography, and they were only independent of topography after correction.

2.9 Successes in humanitarian demining

During the period of this study, the Halo Trust declared Mozambique mine free, with an estimated 171 000 mines being removed over 20 years. The Halo Trust is a charity organisation dedicated to humanitarian demining. Other African countries that have recently been declared landmine-free include Burundi, Republic of Congo, Gambia, Guinea-Bissau and Uganda.

Chapter 3. ETHICAL CONSIDERATIONS

This project necessitates the use of explosives, which are deadly if not employed in a controlled environment. TNT will again be used for this project, as was the case with Smit, 2013. TNT is a stable explosive and can be dissolved in acetone to break down the crystal structure and render it inert, which means that the TNT cannot be used as explosives after the acetone has evaporated.

The plants are kept at CSIR Paardefontein, which is a facility where explosives are tested, to the north of Pretoria. The facility has strict access control, and no member of the public has access to the facility without the proper consent and clearance of one of the facility's supervisory staff. Handling and mixing of explosives were overseen by trained and licensed explosives technicians.

Usage of electronic devices such as cell phones and cameras at the facility is restricted and only permitted devices are allowed. Usage of the ASD spectrometer and cameras was approved by the supervisor at the farm. Also, no materials are allowed to be removed from the farm, and rules and regulations on the farm are strictly enforced by the staff on the farm, as well as third-party security.

As there are regular explosives testing events at the farm, the soil and surrounding vegetation are already contaminated with TNT and other explosives, and the project will not add significant additional TNT contamination to the area.

When choosing plant species, care was taken not to select any species that are on an endangered or protected species list. Criteria for plant selection also included that the plant should be indigenous to Southern Africa, or have a cosmopolitan distribution. Care has also been taken to ensure that no 'pest plant' or invasive has been used, to ensure that the environmental damage caused by such plants are eliminated.

Chapter 4. METHODOLOGY

4.1 Overview

As with Smit (2013), the plants are located at one of the CSIR's explosive research facilities, namely Paardefontein, which is situated to the North of Pretoria. There the plants were exposed to semi-natural conditions, in the sense that weeds interfering with the research were manually removed, and that the plants were manually watered in the absence of rain. They were also exposed to natural rainfall and frost. Due to the location of Paardefontein, as well as the site where the plants were housed, frost was not a common occurrence. Furthermore, the plants were housed between three major revetments, each about 2 meters in height.

Except for *Ilex Mitis* (Cape Holly), which died out during Rene Smit's study, all remaining tree species were monitored and served as a long-term study. The partial reasoning to the long-term study is to determine whether there is a "window of opportunity" within which the effects of non-continuous exposure to TNT is evident.

Additionally, five species of grasses were added, as well as four species of shrub. All of the additional plant species are either indigenous to Southern Africa or have a cosmopolitan distribution. As with the trees, the grasses and shrubs were arranged in columns by species type and in rows by TNT concentration. A brief description of the plant species used is given later in this chapter.

The TNT concentrations of the tree samples were unchanged. The concentrations (mg TNT per kilogram soil mass) thus remain at 30mg/kg, 300mg/kg, 600mg/kg, 1200mg/kg and 5000mg/kg. The newly added grasses and shrubs were weighed, and the same concentrations of TNT were administered. For the amount of TNT needed for each plant, it was weighed. Due to the plants being watered relatively close to the time of weighing, a "dry" mass for each plant was calculated. This means that an estimation of water in the soil was made, and it was believed that between 10% and 35% of the soil weight could be attributed to the plant and water mass. Unfortunately, no material may be removed from the farm, the actual moisture and organic content of the soil could not be determined. It was agreed that the TNT requirement would be calculated assuming a 22.5% moisture content.

4.2 TNT calculation and administration

Thus, for example, if a specimen had a gross weight of 7.2kg, and it was estimated that 22.5% of this weight was due to moisture in the soil, the net weight would be 5.58kg. If that plant were to be subjected to 30mg TNT per kg of soil, 167mg TNT would be required to simulate a leaking mine in the vicinity of the plant. Any further reference made to these concentrations later in this report is used in the format

milligrammes of TNT to a kilogram of soil. For example, 30mg/kg refers to 30mg TNT per 1kg of soil Tables 4 and 5 respectively represent the TNT calculations for grasses and shrubs.

For the new additions to the study, namely the grasses and shrubs, it was calculated that 342g of TNT would be required in total. TNT flakes were supplied by the staff at Paardefontein. Each dosage of TNT was weighed using a powder measure at one of the packing facilities at Paardefontein, and stored in a labelled Ziploc bag for transfer to each plant. At the site where the plants were kept, a small amount of acetone was added to each bag to ensure that all the TNT flakes in the bag could be completely dissolved, and the mixture was added to the plant for which it was intended.

Ali (2006) uses a similar technique, whereby TNT is dissolved in acetone. In that study, TNT was mixed with 200ml acetone, homogenised with soil with low nitrogen content, and kept in a dark environment to avoid photodegradation of the TNT. Due to the plants at Paardefontein being exposed to semi-natural conditions, they were not kept in the dark after TNT administration. Also, the amount of acetone was not measured and was estimated on the spot. Another fundamental difference to Ali (2006) is that control plants were not exposed to acetone. Similar methods were used in studies by Nauman et al. (2010), Rubis (2011), and Zinnert et al. (2012)

Care was taken not to administer the TNT/acetone solution directly to the plant, but rather to the soil surrounding the plant, ensuring that any uptake of TNT would happen at the root level of the plants. A small-scale test was also done on soil using only acetone, and it was found that the acetone evaporated quickly enough not to influence plant health.

Table 4 - TNT calculation for Grass species

Grass	Mass (kg) - Watered previous day	Mass (kg) - Correction for water (10-35% of mass = water; taken at 10%)	Mass (kg) - Correction for water (10-35% of mass = water; taken at 22,5%)	Mass (kg) - Correction for water (10-35% of mass = water; taken at 35%)	Concentration	TNT Needed (Wet)	TNT Needed (Dry@10% Field Capacity)	TNT Needed (Dry@22.5% Field Capacity)	TNT Needed (Dry@35% Field Capacity)
A1	7.40	6.66	5.74	4.81	0	0.00	0.00	0.00	0.00
A2	7.40	6.66	5.74	4.81	0	0.00	0.00	0.00	0.00
A3	6.10	5.49	4.73	3.97	30	183.00	164.70	141.83	118.95
A4	5.50	4.95	4.26	3.58	300	1650.00	1485.00	1278.75	1072.50
A5	5.00	4.50	3.88	3.25	600	3000.00	2700.00	2325.00	1950.00
A6	6.10	5.49	4.73	3.97	1200	7320.00	6588.00	5673.00	4758.00
A7	6.10	5.49	4.73	3.97	5000	30500.00	27450.00	23637.50	19825.00
C1	12.60	11.34	9.77	8.19	0	0.00	0.00	0.00	0.00
C2	6.80	6.12	5.27	4.42	0	0.00	0.00	0.00	0.00
C3	12.00	10.80	9.30	7.80	30	360.00	324.00	279.00	234.00
C4	12.80	11.52	9.92	8.32	300	3840.00	3456.00	2976.00	2496.00
C5	14.20	12.78	11.01	9.23	600	8520.00	7668.00	6603.00	5538.00
C6	13.40	12.06	10.39	8.71	1200	16080.00	14472.00	12462.00	10452.00
C7	12.30	11.07	9.53	8.00	5000	61500.00	55350.00	47662.50	39975.00
D1	12.30	11.07	9.53	8.00	0	0.00	0.00	0.00	0.00
D2	12.30	11.07	9.53	8.00	0	0.00	0.00	0.00	0.00
D3	12.30	11.07	9.53	8.00	30	369.00	332.10	285.98	239.85
D4	12.90	11.61	10.00	8.39	300	3870.00	3483.00	2999.25	2515.50
D5	10.40	9.36	8.06	6.76	600	6240.00	5616.00	4836.00	4056.00
D6	13.00	11.70	10.08	8.45	1200	15600.00	14040.00	12090.00	10140.00
D7	10.60	9.54	8.22	6.89	5000	53000.00	47700.00	41075.00	34450.00
E1	11.40	10.26	8.84	7.41	0	0.00	0.00	0.00	0.00
E2	11.40	10.26	8.84	7.41	0	0.00	0.00	0.00	0.00
E3	12.40	11.16	9.61	8.06	30	372.00	334.80	288.30	241.80
E4	13.30	11.97	10.31	8.65	300	3990.00	3591.00	3092.25	2593.50
E5	11.30	10.17	8.76	7.35	600	6780.00	6102.00	5254.50	4407.00
E6	12.00	10.80	9.30	7.80	1200	14400.00	12960.00	11160.00	9360.00
E7	11.30	10.17	8.76	7.35	5000	56500.00	50850.00	43787.50	36725.00
					TNT Needed (mg)	294074.00	264666.60	227907.35	191148.10
					TNT Needed (g)	294.07	264.67	227.91	191.15

Table 5 - TNT calculation for Shrubs

Shrub	Mass (kg) - Watered previous day	Mass (kg) - Correction for water (10-35% of mass = water; taken at 10%)	Mass (kg) - Correction for water (10-35% of mass = water; taken at 22,5%)	Mass (kg) - Correction for water (10-35% of mass = water; taken at 35%)	Concentration	TNT Needed (Wet)	TNT Needed (Dry@10% Field Capacity)	TNT Needed (Dry@22.5% Field Capacity)	TNT Needed (Dry@35% Field Capacity)
A1	8.00	7.20	6.20	5.20	0	0.00	0.00	0.00	0.00
A2	6.80	6.12	5.27	4.42	0	0.00	0.00	0.00	0.00
A3	7.20	6.48	5.58	4.68	30	216.00	194.40	167.40	140.40
A4	6.30	5.67	4.88	4.10	300	1890.00	1701.00	1464.75	1228.50
A5	6.80	6.12	5.27	4.42	600	4080.00	3672.00	3162.00	2652.00
A6	6.40	5.76	4.96	4.16	1200	7680.00	6912.00	5952.00	4992.00
A7	6.80	6.12	5.27	4.42	5000	34000.00	30600.00	26350.00	22100.00
B1	3.10	2.79	2.40	2.02	0	0.00	0.00	0.00	0.00
B2	3.10	2.79	2.40	2.02	0	0.00	0.00	0.00	0.00
B3	3.10	2.79	2.40	2.02	30	93.00	83.70	72.08	60.45
B4	3.10	2.79	2.40	2.02	300	930.00	837.00	720.75	604.50
B5	3.10	2.79	2.40	2.02	600	1860.00	1674.00	1441.50	1209.00
B6	3.10	2.79	2.40	2.02	1200	3720.00	3348.00	2883.00	2418.00
B7	3.10	2.79	2.40	2.02	5000	15500.00	13950.00	12012.50	10075.00
C1	6.80	6.12	5.27	4.42	0	0.00	0.00	0.00	0.00
C2	5.90	5.31	4.57	3.84	0	0.00	0.00	0.00	0.00
C3	5.90	5.31	4.57	3.84	30	177.00	159.30	137.18	115.05
C4	5.00	4.50	3.88	3.25	300	1500.00	1350.00	1162.50	975.00
C5	5.70	5.13	4.42	3.71	600	3420.00	3078.00	2650.50	2223.00
C6	4.80	4.32	3.72	3.12	1200	5760.00	5184.00	4464.00	3744.00
C7	4.80	4.32	3.72	3.12	5000	24000.00	21600.00	18600.00	15600.00
D1	6.60	5.94	5.12	4.29	0	0.00	0.00	0.00	0.00
D2	6.60	5.94	5.12	4.29	0	0.00	0.00	0.00	0.00
D3	7.00	6.30	5.43	4.55	30	210.00	189.00	162.75	136.50
D4	6.20	5.58	4.81	4.03	300	1860.00	1674.00	1441.50	1209.00
D5	6.80	6.12	5.27	4.42	600	4080.00	3672.00	3162.00	2652.00
D6	6.80	6.12	5.27	4.42	1200	8160.00	7344.00	6324.00	5304.00
D7	5.60	5.04	4.34	3.64	5000	28000.00	25200.00	21700.00	18200.00
					TNT Needed (mg)	147136.00	132422.40	114030.40	95638.40
					TNT Needed (g)	147.14	132.42	114.03	95.64

4.3 Readings

Baseline readings were taken for the plants before the addition of TNT to the soil. This was to allow for the plants to settle at the new location. The baseline readings were used as control readings.

Figure 6 - Taking spectral reflectance readings (P Ramaloko: 2016)

Spectral reflectance readings were taken on a bi-weekly basis (Figure 6), using one of the CSIR's ASD field spectrometers. Due to time limitations, two leaf clip readings (Figure 7) were taken for each plant, where possible. Originally five readings per plant were planned, but due to an issue with the spectrometer lead to this number being reduced. In some cases, where plants had insufficient foliage to take proper readings, one reading was taken. If a plant should have no foliage, no readings were taken. The spectral signature of a specific plant for a day is represented by the average of the readings for the plant for the day. The readings that were used from Smit (2013) were initially five readings per plant per session.

Leaf clip readings were taken to ensure that all readings happened under controlled circumstances and that external factors such as light and cloud cover did not influence the outcome. Initially, canopy readings under natural light were also planned, but time constraints prevented this.

Figure 7 - Leaf clip readings with ASD field spectrometer (P Ramaloko: 2016)

Please note that photographs depicting readings being taken are used for reference purposes. The supervisor of this project was always present when readings were taken, and provided assistance where necessary

4.4 Indices

Data from spectral readings are stored in a proprietary format and was converted for use using ASD ViewSpec Pro. The resultant text files were imported into MS Excel, where averaging of readings and statistical analysis was done. Excel was used to calculate the relevant vegetation indices, and the built-in statistical analysis tools were used to determine whether a noteworthy variance exists between the contaminated and control plants. Relevant bands for the vegetation indices were extracted using Pivot Tables. Box plots were made using R.

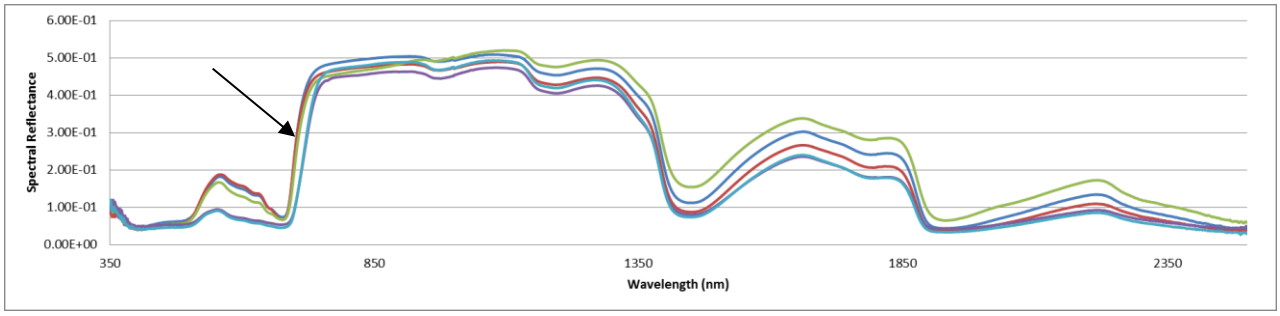

Figure 8 - Typical spectral reflectance of Soap Dogwood (Control), five readings

Figure 8 displays a typical reflectance signature of a Soap Dogwood tree, with leaf clip readings taken of 5 green leaves. Care was taken to include as much green foliage as possible, as browning foliage

have different spectral profiles. The area marked by the arrow indicates the red-edge position of the spectral reflectance.

For the results of this study to be compared to that of Smit (2013), the same vegetation indices were examined, namely:

1. Red-edge position
2. First derivative reflectance
3. Normalised difference water index
4. Moisture stress index
5. Water-band index
6. Photochemical reflectance index
7. Nitrogen index

$$REP = 700 + 40\left[\frac{\rho_{RE} - \rho_{700nm}}{\rho_{740nm} - \rho_{700nm}}\right] \; where \; p_{RE} = \frac{\rho_{760nm} + \rho_{780nm}}{2}$$

Equation 1 - Red-edge position (Cho and Skidmore: 2006)

$$FDR = \frac{(R_{\lambda(j+1)} - R_j)}{\Delta\lambda}$$

Equation 2 - First derivative reflectance (Cho and Skidmore: 2006)

$$NDWI = \frac{(860nm - 1240nm)}{(860nm + 1240nm)}$$

Equation 3 - Normalised difference water index (Gao: 1996)

$$MSI = \frac{1600nm}{817nm}$$

Equation 4 - Moisture stress index (Hunt and Rock: 1989)

$$WBI = \frac{970nm}{900nm}$$

Equation 5 – Water-band index (Penuelas et al.: 1995)

$$PRI = \frac{(531nm - 570nm)}{(531nm + 570nm)}$$

Equation 6 - Photochemical reflectance index (Gamon et al.: 1992)

$$NI = \frac{(2150nm - 2250nm)}{(2150nm + 2250nm)}$$

Equation 7 - Nitrogen index (Cho, n.d.)

The red-edge position is related to the chlorophyll content of the plant's foliage and represents the change in reflectance due to chlorophyll absorption in the red wavelength spectrum, and the reflectance

in the near-infrared spectrum (Cho and Skidmore: 2006). Higher chlorophyll content means that the REP will shift toward the infrared spectrum, indicating a healthier plant.

The maximum of the first derivative reflectance represents the red-edge position (Cho and Skidmore: 2005). As explained by Dr Cho during a personal meeting, when examining the first derivative reflectance, one should look for flat, broad peaks. Sharp peaks in the red spectrum indicate unhealthy vegetation.

The normalised difference water index is used as an indicator of vegetation water content (Jackson et al.: 2003) and can be used to delineate water features (Ji et al.: 2009). Gao (1996) formulated the NDWI, and selected two narrow reflectance channels to compare, one sensitive to moisture change, and one largely unaffected by moisture, to give a ratio of plant water content.

The moisture stress index was developed by Hunt and Rock (1989), as a tool to detect plant stress during drought. Similarly, the water band index (Penuelas et al.: 1995) may be used to detect moisture stress in vegetation.

The photochemical reflectance index (Gamon et al.: 1997) is an indicator of the optical relationship between plant-based chemicals and light energy. It can be used to determine light use efficiency in plants.

The nitrogen index is an indicator of plant nitrogen content (Delgado et al.: 2008) and was developed to determine nitrogen losses to environmental factors. A loss of nitrogen is detrimental to plant health, and an increase in environmental nitrogen can lead to a boost in plant health.

4.5 Statistical analysis

Along with these indices, each of the recorded bands was subject to statistical analysis, to determine the variance of the post-contamination values with that of the original baseline readings. Significant variances were tested for using Microsoft Excel's built-in statistics tools.

Mrs Renée Koen, a statistician at the CSIR, suggested that the "F-test of two-sample equality of variances" and "T-test: two sample assuming unequal variances" tools in MS Excel's be used to test whether there may be a difference in the values of the indices for each of the contaminated plants when compared to the control plants. An F-test is used to determine whether two statistical populations have equal variances. This is the null hypothesis. Thus, in the case of this study, we assume that the populations should differ, and therefore not be equal. This means that, for each tested index to be successful, the null hypothesis should be rejected, and the hypothesis that the sample variances differ should be accepted. In this study, a α-level of 0.05 was always used.

For the F-test, the marker to look out for is the difference in value between F and F-critical. If F is greater in value than F-critical, we reject the null hypothesis, indicating that there is a difference in variance.

Similarly, when using the T-test, we perform a two-tailed test (which assumes inequality in variances). The marker values to consider are t-stat and t-critical. Should t-stat be smaller than the negative of t-critical, or greater than the positive of t-critical, we reject the null hypothesis.

For the statistical analysis of the readings, it is always considered that the only variable is the concentration TNT to which each plant has been subjected. Due to the plants being in the same immediate area, it is accepted that they have been submitted to the same environmental factors, such as rainfall and temperature. The limitations chapter of this report discusses the environmental factors in more detail.

The physical condition of the plants was noted, but spectral readings were mainly used to derive any conclusions.

Toward the very end of the project, a study was done by Dr Xolani Peter of Defence, Peace, Safety and Security (DPSS) at the CSIR. This study is ongoing, and the initial results are used with permission. The study consists of using ultra-performance liquid chromatography combined with hybrid quadrupole orthogonal time of flight spectrometry to determine chemical compositions of compounds. In his study, Dr Peter examined three species of plants used for this study, namely *Portulacaria Afra* (Spekboom), *Celtis Africana* (White Stinkwood) and *Olea Europaea subsp. Africana* (Wild Olive). The results of Dr Peter's study were compared with the results of this study, at very high level.

4.6 Plant species

The tree species, as per Smit (2013), are:

A. *Ilex Mitis* (Cape Holly)
B. *Olea Europaea subsp. Africana* (Wild Olive)
C. *Combretum Erythrophyllum* (River Bushwillow)
D. *Noltea Africana* (Soap Dogwood)
E. *Acacia Karroo* (Sweet Thorn)
F. *Celtis Africana* (White Stinkwood)

With the assistance of Flip Breytenbach of the Agricultural Research Council's Grasslands Institute at Roodeplaat, the following grass species have been identified and acquired for the project:

A. *Themeda Triandra* (Red Grass)
B. *Heteropogon Contortus* (Speargrass)
C. *Eragrostis Curvula* (Lovegrass)
D. *Setaria Sphacelata* (African Bristlegrass)
E. *Hyparrhenia Hirta* (Common Thatching Grass)

In a one to one meeting with Dr Marinda Koekemoer of the South African National Biodiversity Institute, she suggested that different types of shrubs be used to determine whether one type will be a better indicator than others. It was decided that the following species of shrubs be used:

A. *Freylinia Tropica* (Transvaal Honey-bell Bush)
B. *Portulacaria Afra* (Spekboom)
C. *Carissa Macrocarpa* (Natal Plum)
D. *Dovyalis Caffra* (Kei Apple)

Ilex Mitis (Cape Holly; Figure 9) is an evergreen tree, growing between 10m and 25m in height. It has a wide distribution across Africa and is the only species of holly endemic to South Africa. It is preferential to areas close to rivers and moist areas in forests (SANBI: 2004).

Figure 9 - Cape Holly (Smit (2013))

Combretum Erythrophyllum (River Bushwillow; Figure 10) is a deciduous tree that is medium to large and fast-growing. It can grow to 6m within three years. It has a distribution that stretches from Zimbabwe to the Eastern Cape, occurring where there are rivers or sufficient groundwater to sustain the plant. (SANBI: 2003)

Figure 10 - River Bushwillow (Smit (2013))

Acacia Karroo (Sweet Thorn; Figure 11) is a widespread tree in Southern Africa, varying greatly in shape and size. It is characterised by small leaves and prominent thorns. It can be found as far south as the Western Cape, northwards to Zambia and Angola. Where water is plentiful, specimens can reach 12m in height. It is semi-deciduous. (Foden and Potter: 2005)

Figure 11 - Sweet Thorn (Smit (2013))

Celtis Africana (White Stinkwood; Figure 12) is a large deciduous tree, reaching up to 25m in the wild. It is widespread in Southern Africa and is found in varying habitats as far north as Ethiopia. (Foden and Potter: 2005)

Figure 12 - White Stinkwood (Smit (2013))

Noltea Africana (Soap Dogwood; Figure 13) is a small tree, growing up to 6m in height under suitable conditions. It has a natural distribution from KwaZulu-Natal, to the Western Cape. It is an evergreen tree and is characterised by leaves that lather when rubbed between the hands under water. (SANBI: 2016)

Figure 13 - Soap Dogwood (Smit (2013))

Olea Europaea subsp. Africana (Wild Olive; Figure 14) is an evergreen tree, being medium in size. It can reach up to 12m. It is widely found across Africa, as well as being found in the Middle East, India and China. It can grow in a variety of habitats, but preferably near water. (SANBI: 2002)

Figure 14 - Wild Olive (Smit (2013))

Themeda Triandra (Red Grass; Figure 15) is a perennial species of grass, which is widely distributed around South Africa. It also occurs in Australia, Asia and the Pacific. (SANBI: 2004)

Figure 15 - Seed tuft on Red Grass (Wikimedia Commons (User: Peripitus: 2007))

Heteropogon Contortus (Speargrass; Figure 16) is a grass with a cosmopolitan distribution. It is common in Southern Africa, ranging from savannah habitats to Karoo and fynbos. (SANBI: 2016)

Figure 16 - Speargrass (Wikimedia Commons (User: Eugene van der Pijll: 2006))

Eragrostis Curvula (Lovegrass; Figure 17) is a cosmopolitan grass, being found in Southern Africa, northwards to East Africa. It is also found in the Americas and Australia. It is a drought tolerant grass and is commonly used as pasture or animal feed. (United Nations Food and Agriculture Organisation: n.d.)

Figure 17 - Weeping Lovegrass (Wikimedia Commons (Forest and Starr: 2005))

Setaria Sphacelata (African Bristlegrass; Figure 18) is native to subtropical Africa. It is endemic to Africa but has been introduced to other regions. It is commonly used as pasture. It prefers habitats with rainfall of more than 900mm. (United Nations Food and Agriculture Organisation: n.d.)

Figure 18 - African Bristlegrass (United Nations Food and Agriculture Organisation, S Reynolds: n.d.)

Hyparrhenia Hirta (Common Thatching Grass; Figure 19) is a grass species that ranges from the Mediterranean, Iran, Iraq and the northeast of India, toward the tropical east of Africa and Southern Africa. It is tolerant of many soil types and is drought-resistant. (United Nations Food and Agriculture Organisation: n.d.)

Figure 19 - Thatching Grass (United Nations Food and Agriculture Organisation, JE Victor: n.d.)

Freylinia Tropica (Transvaal Honey-bell Bush; Figure 20) is an evergreen herbaceous shrub that is found in Zimbabwe and Northern South Africa, usually at high altitude. It can also be found as far south as the Cape Peninsula. It can grow to about 2m in height and is characterised by flowers ranging from light to bright blue. (SANBI: 2016)

Figure 20 - Freylinia Tropica (Wikimedia Commons: 2007)

Portulacaria Afra (Spekboom; Figure 21) is a succulent shrub, found in semi-arid regions. It is distributed from the Karoo to KwaZulu-Natal, Mpumalanga, Limpopo, Swaziland and Mozambique. It can reach up to 5m under suitable conditions and is a hardy plant. (SANBI: 2009)

Figure 21 - Spekboom (SANBI: 2009)

Carissa Macrocarpa (Natal Plum; Figure 22) is an evergreen shrub characterised by Y-shaped thorns. It can reach heights of up to 4m. Although it is mainly an ornamental shrub, it naturally occurs from the south-west coast of South Africa, northwards to Mozambique through KwaZulu-Natal. (SANBI: 2004)

Figure 22 - Natal Plum (Wikimedia Commons (User: Unknown: 2012))

Dovyalis Caffra (Kei Apple; Figure 23) is an evergreen shrub. It is a woody shrub, and can occasionally grow to about 8m. It prefers drier areas, such as bushveld, and is found from the Eastern Cape, northwards to Swaziland, Limpopo and Zimbabwe. (SANBI: 2003)

Figure 23 - Kei Apple (Wikimedia Commons (User: Kenraiz: 2010))

The grasses used in the study were all sourced from ARC Roodeplaat and were transferred to plant bags, with soil, under the supervision of trained workers. The trees, as per Smit (2013), as well as the shrubs, were sourced from a nursery. Special care was taken not to include species listed on the SANBI Red List. Figures 24 and 25 show the grasses and shrubs, respectively, at Paardefontein.

Figure 24 - Grasses at Paardefontein (P Ramaloko: 2016)

Figure 25 - Shrubs at Paardefontein (P Ramaloko: 2016)

Box plots for the various indices in this document were prepared using R. A workspace was created containing CSV files with the relevant vegetation indices. Appendix B contains a sample of the code used to generate the box plots.

4.7 Summary

To summarise the basic methodology:

- Six species of trees, five species of grasses, and four species of shrubs were selected for the study and placed at Paardefontein
- Baseline readings were taken with a hyperspectral ASD Field Spectrometer
- The plants were weighed, and the subsequent amount of TNT needed to represent concentrations of 30, 300, 600, 1200 and 5000mg/kg TNT in the soil
- Readings at regular intervals were taken with a hyperspectral ASD Field Spectrometer
- The readings were processed in ASD Viewspec Pro to be compatible with Microsoft Excel and R
- The readings were further processed to determine values for the following indices over the duration of the project: REP, 1st derivative reflectance index, NDWI, MSI, WBI, PRI and NI
- The subsequent statistics were subjected to F and T-tests and the results plotted as box plots, and compared
- The findings were compiled in a final report, and recommendations into further research were made

Chapter 5. RESULTS

5.1 What was expected?

During the study, different expectations of the outcome were developed. As the research questions stated, the purpose of the project is to determine whether the presence of TNT in their soil will influence the spectral response of plants. If there was a difference in the spectral response, it was expected that it might manifest as an improvement in plant health (fertiliser effect), or as a deterioration in plant health (poison effect). Figure 26 shows the comparison between fertilised (left) and unfertilised (right) tomato plants. The plants on the left look healthy, while the plants on the left look unhealthy, with smaller leaves and less dense foliage.

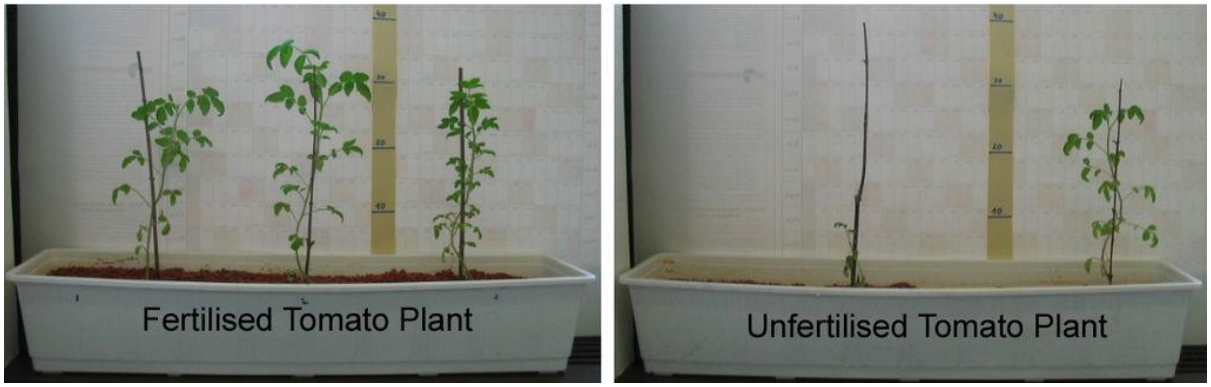

Figure 26 - Comparison of fertilised and unfertilised tomato plants (Source: Wikimedia Commons (User: Fæ: 2014))

5.2 Grasses

The grasses used for the study were obtained from the nearby Agricultural Research Commission facility at Roodeplaat. They were removed from the veld at the facility, but unfortunately during a timeframe where the area had had high volumes of rainfall, meaning all the specimens were subject to high moisture conditions. The grass specimens were noted to be under stress for the entire duration of the study, and several specimens started dying within a couple of weeks of being at Paardefontein.

By the time the TNT was administered to the plants, several species did not have the full representation of 2 control plants and five specimens to represent five concentrations of TNT. Specimens continued dying off after the administration of TNT, to such an extent that we were unable to take note-worthy readings with the ASD spectrometer.

The possible reasons for the grass species dying out are speculative. Possible factors were discussed with botanists and earth observation science professionals at the CSIR and ARC. One reason may be in the stress of the move from ARC Roodeplaat to Paardefontein. The grasses were free-growing and unrestricted up to the point where they were transferred to the bags and moved to Paardefontein. As

stated previously, the bags were also drenched, meaning the specimens may have had severe moisture stress throughout the move. Also, due to the specimens being wild species, removed from the veld, their age was not specified. In some cases, grasses may live to two years. If the grasses used for the study were close to their age of maturity, they might have died naturally.

Thus, the experiment on the grasses was considered a failure with regards to the expected study outcomes. Taking this into consideration, the influence of some external factors was more prominent in the grass specimens than in that of the trees or the shrubs. What was prominent within two weeks after the administration of the TNT dissolved in acetone, were what was believed to be chemical burns on the plants. Figure 27 illustrates this. Note the dark area toward the bottom of the plant.

Figure 27 - Possible chemical burn marks on grass specimen (P Ramaloko: 2016)

Care was taken when the acetone/TNT mixture was added to the soil so that the contact between plant matter and the mixture was minimised. The purpose was to administer the mixture to the soil, as would be the case with a leaking landmine, rather than directly to the plants.

Within the first couple of weeks, after the grasses were moved from Roodeplaat to Paardefontein, it was obvious that the plants were not isolated from animals, as grasses were regularly eaten by what was guessed to be rabbits or small antelope, such as duiker. After the administration of the TNT, it was noted that whatever animal was eating the grass, preferred control plants to contaminated plants. Although this is not relevant to the outcome of the project, it was interesting to note.

The grass species also attracted other fauna, as snakes were noticed to have been present in some of the bags used to house the grasses. Bees were also noted to be more frequently present in the area after TNT was administered to the grass and shrub specimens. The increased presence of bees in the area is consistent with research mentioned in Bromshenk (2003), where bees proved useful in the detection of explosives, as well as minefield area reduction.

Although the outcome of the experiment regarding the grasses was considered a failure, the promise of a simulated minefield in the presence of grasses is still seen. The experiment will have to be redesigned to feature plants that can either adapt to restrictive growing environments or feature plants in their natural environment. In the chapter for future research, this is discussed further.

5.3 Trees

Smit (2013) found little correlation between TNT concentrations and vegetation indices. Initial statistical analysis of the vegetation indices in the current study supports this result. When using F- and T-tests to determine whether there is a clear correlation between the vegetation indices and the increasing TNT concentration for each plant species, all the indices indicated no statistical difference. In a meeting with Dr Moses Cho of the CSIR, it was discussed that although the REP also showed little statistically significant differences correlating with an increase in TNT concentration, it was worthwhile doing a complete analysis of REP values for the plants over the study period.

5.4 Shrubs

During the study, all the shrub species, in general, appeared resilient, coping well with environmental factors. After the administration of the TNT to the plants the shrub species Transvaal Honey-bell Bush, Natal Plum and Kei Apple, had discolouration in some leaves (Figure 28), but throughout the study, all the plants had green foliage.

All the plants in the study have been manually watered, including the succulent shrub, Spekboom. Under normal conditions, succulents would require infrequent watering under horticultural conditions, whereas in the wild, any environmental moisture would be sufficient. The frequency of manual watering meant that the species would have been exposed to over watering. Considering the entire range of sample plants from this species were subjected to the same watering regime, any stress induced due to this was assumed to be constant. It was also noted that the plants were physically resilient.

Figure 28 - Brown and green foliage on Carissa Macrocarpa (Natal Plum; P Ramaloko: 2016)

5.5 Vegetation indices

F-tests and T-tests were run in Microsoft Excel to determine whether there were any differences between the spectral indices for control plants and contaminated samples. In the following section, the results of these tests are discussed. Box plots were also generated to give a graphical representation of reading distributions.

Statistical testing was not done for first derivative reflectance, the graphs of which serve as a visual indicator for plant health.

In this section, the plants are referred to by the code given to them when taking readings. A prefix is not assigned to trees, while grasses and shrubs are identified by the prefixes *G* and *S* respectively. The suffix *L* indicates leaf-clip readings. Canopy readings were not used for this study.

A list of the plants is provided in Chapter 4 – Methodology.

5.5.1 Red-edge position

Under the advice of Dr Cho, all values of the red-edge position (REP) for trees and shrubs were analysed, and box plots were created to view any trends which may have formed. The box plots used in this study have four features of note. First is the box itself, of which the bottom and top represents the first and third quartiles of the reading distribution respectively, the whiskers, which represent the extremes of the normal distribution, markers beyond the whiskers, representing outliers and a line within each box, representing the median value. Furthermore, box plots were also generated for each of the other tested indices.

The red-edge position is an indication of the relative greenness of a plant. A red edge position that propagates below the 700nm region indicates a plant with brown of yellow leaves, i.e. an unhealthy plant. A red-edge beyond 700nm reflects electromagnetic energy in the infrared region, which means that they appear greener, and thus healthier.

Tables 6 and 7 respectively show the results for F-test (two sample for variance) and T-test (two sample assuming unequal variances) for the REP for trees. Tables 8 and 9 shows the same tests for shrub species.

F-test (two sample for variance) for trees lead to mixed results for the REP. If F is greater than F-critical the null hypothesis, meaning there is a difference between contaminated plants and control plants. No clear pattern has emerged from this test, with contaminated plants having both significant and insignificant variances, even in the same species. It is worthwhile noting that except for DL3, all other 30mg/kg plants had significant differences when using this testing method. This is important because it is believed the average leaking AP mine causes soil TNT concentrations of around 30mg/kg.

Except for BL5 and BL7, the null hypothesis for the study can be rejected when using the T-test (two sample assuming unequal variances). If t-stat is smaller than the negative of t-critical, or greater than the positive of t-critical, we reject the null hypothesis.

For the shrubs, using the same tests, mixed results were again generated using the F-test, and when using the T-test, the null hypothesis is rejected outright.

Table 6 - F-test (two sample for variance) results, REP for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	716.1826923	717.5408163	712.9285714	715.8854167	717.9183673	717.1363636
	Variance	20.88433668	15.59110036	45.03608247	12.46041667	7.457184936	8.980519481
	Observations	208	98	98	96	98	22
	df	207	97	97	95	97	21
	F		1.339503704	0.463724541	1.67605444	2.800565744	2.325515436
	P(F<=f) one-tail		0.052148829	2.22797E-06	0.002426377	2.43859E-08	0.012798479
	F Critical one-tail		1.344489802	0.756752215	1.347744645	1.344489802	1.84346916
CL	Mean	709.6258065	709.1976744	709.5125	710.3703704	710.1625	710.7157895
	Variance	42.88504399	97.36046512	35.06313291	27.53611111	33.25174051	35.48219485
	Observations	155	86	80	81	80	95
	df	154	85	79	80	79	94
	F		0.440476984	1.223080781	1.55741106	1.289708248	1.208635604
	P(F<=f) one-tail		5.07887E-06	0.160143128	0.014329543	0.104365809	0.159090335
	F Critical one-tail		0.735320764	1.395509287	1.393268015	1.395509287	1.366591725
DL	Mean	713.8596491	716.4691358	713.7625	715.5061728	714.9775281	714.3253012
	Variance	110.9801858	6.052160494	10.43655063	18.17808642	7.158580184	29.68557155
	Observations	171	81	80	81	89	83
	df	170	80	79	80	88	82
	F		18.33728399	10.63379939	6.105163283	15.50310018	3.738522789
	P(F<=f) one-tail		5.98289E-33	3.52688E-24	1.9904E-16	7.62625E-33	2.029E-10
	F Critical one-tail		1.387319372	1.389581897	1.387319372	1.370945552	1.382948261
EL	Mean	715.7848101	713.6025641	715.4512195	715.5357143	713.9324324	714.4166667
	Variance	9.58397162	13.46336996	7.386479976	13.02280551	21.43372825	30.4469697
	Observations	158	78	82	84	74	12
	df	157	77	81	83	73	11
	F		0.711855326	1.297501875	0.735937553	0.447144403	0.314775878
	P(F<=f) one-tail		0.037860981	0.096352085	0.050884231	1.43042E-05	0.000649323
	F Critical one-tail		0.729931034	1.389873523	0.734764572	0.726378467	0.540515214
FL	Mean	711.443299	707.9166667	711.6231884	714.5151515	712.1348315	714.8219178
	Variance	44.35352234	118.2183099	52.73827792	14.69507576	59.00434116	23.70395738
	Observations	97	72	69	33	89	73
	df	96	71	68	32	88	72
	F		0.375183188	0.841011957	3.018257481	0.751699307	1.871144198
	P(F<=f) one-tail		4.34957E-06	0.215878387	0.000347027	0.085757182	0.00288847
	F Critical one-tail		0.697349794	0.694776417	1.67159077	0.709221019	1.4481645

Table 7 - T-test (two sample assuming unequal variances), REP for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	716.1826923	717.5408163	712.9285714	715.8854167	717.9183673	717.1363636
	Variance	20.88433668	15.59110036	45.03608247	12.46041667	7.457184936	8.980519481
	Observations	208	98	98	96	98	22
	Hypothesized Mean Difference		0	0	0	0	0
	df		217	141	234	287	32
	t Stat		-2.666073695	4.34866763	0.619591251	-4.131398251	-1.337229338
	P(T<=t) one-tail		0.004125971	1.30428E-05	0.268064874	2.36739E-05	0.095288096
	t Critical one-tail		1.651905861	1.655732287	1.651391475	1.650180211	1.693888748
	P(T<=t) two-tail		0.008251941	2.60856E-05	0.536129747	4.73478E-05	0.190576193
	t Critical two-tail		1.970956301	1.976931489	1.970153643	1.968264113	2.036933343
CL	Mean	709.6258065	709.1976744	709.5125	710.3703704	710.1625	710.7157895
	Variance	42.88504399	97.36046512	35.06313291	27.53611111	33.25174051	35.48219485
	Observations	155	86	80	81	80	95
	Hypothesized Mean Difference		0	0	0	0	0
	df		127	175	196	179	213
	t Stat		0.360708794	0.134002124	-0.948177772	-0.645017558	-1.35177612
	P(T<=t) one-tail		0.35945821	0.446777438	0.172103274	0.259870825	0.088940336
	t Critical one-tail		1.656940344	1.653607437	1.652665059	1.6534108	1.652038878
	P(T<=t) two-tail		0.71891642	0.893554876	0.344206549	0.51974165	0.177880672
	t Critical two-tail		1.978819535	1.973612462	1.972141222	1.973305434	1.971163885
DL	Mean	713.8596491	716.4691358	713.7625	715.5061728	714.9775281	716.4691358
	Variance	110.9801858	6.052160494	10.43655063	18.17808642	7.158580184	6.052160494
	Observations	171	81	80	81	89	81
	Hypothesized Mean Difference		0	0	0	0	0
	df		206	226	246	209	206
	t Stat		-3.067385126	0.110037548	-1.761791445	-1.308880124	-3.067385126
	P(T<=t) one-tail		0.001224649	0.456238623	0.039673317	0.096006145	0.001224649
	t Critical one-tail		1.652284144	1.651623859	1.651071345	1.652177009	1.652284144
	P(T<=t) two-tail		0.002449299	0.912477246	0.079346634	0.192012291	0.002449299
	t Critical two-tail		1.971546669	1.970516243	1.969654176	1.971379462	1.971546669
EL	Mean	715.7848101	713.6025641	715.4512195	715.5357143	713.9324324	714.4166667
	Variance	9.58397162	13.46336996	7.386479976	13.02280551	21.43372825	30.4469697
	Observations	158	78	82	84	74	12
	Hypothesized Mean Difference		0	0	0	0	0
	df		133	184	149	105	12
	t Stat		4.51833669	0.859218828	0.536352135	3.129735234	0.848828518
	P(T<=t) one-tail		6.80875E-06	0.195668899	0.296257532	0.001132859	0.206294897
	t Critical one-tail		1.656391244	1.653177088	1.655144534	1.659495383	1.782287556
	P(T<=t) two-tail		1.36175E-05	0.391337799	0.592515063	0.002265719	0.412589795
	t Critical two-tail		1.977961264	1.972940542	1.976013178	1.982815274	2.17881283
FL	Mean	711.443299	707.9166667	711.6231884	714.5151515	712.1348315	714.8219178
	Variance	44.35352234	118.2183099	52.73827792	14.69507576	59.00434116	23.70395738
	Observations	97	72	69	33	89	73
	Hypothesized Mean Difference		0	0	0	0	0
	df		110	139	97	175	168
	t Stat		2.434086372	-0.162759173	-3.233424859	-0.653371762	-3.820723998
	P(T<=t) one-tail		0.008269386	0.435472218	0.000836126	0.257187081	9.35251E-05
	t Critical one-tail		1.658824187	1.655889868	1.66071461	1.653607437	1.653974208
	P(T<=t) two-tail		0.016538772	0.870944436	0.001672253	0.514374162	0.00018705
	t Critical two-tail		1.981765282	1.977177724	1.984723186	1.973612462	1.974185191

Table 8 - F-test (two sample for variance) results, REP for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	0.043477706	0.03174739	0.038084843	0.034563351	0.051846208	0.03115854
	Variance	0.001215997	0.001243545	0.001526692	0.000854423	0.001959391	0.000841491
	Observations	67	34	34	34	26	34
	Hypothesized Mean Difference		0	0	0	0	0
	df		66	60	78	38	78
	t Stat		1.585698148	0.679157022	1.355032934	-0.86540171	1.880866409
	P(T<=t) one-tail		0.058793923	0.249824994	0.089659255	0.196124599	0.031861104
	t Critical one-tail		1.668270514	1.670648865	1.664624645	1.68595446	1.664624645
	P(T<=t) two-tail		0.117587845	0.499649988	0.17931851	0.392249199	0.063722209
	t Critical two-tail		1.996564419	2.000297822	1.990847069	2.024394164	1.990847069
SBL	Mean	0.25449143	0.238788561	0.23640054	0.252788875	0.255829026	0.200302469
	Variance	0.002123207	0.004663216	0.008011977	0.002336512	0.003846383	0.005778848
	Observations	66	31	34	32	31	28
	Hypothesized Mean Difference		0	0	0	0	0
	df		43	42	59	46	36
	t Stat		1.162072606	1.105456154	0.166005616	-0.107008814	3.508443829
	P(T<=t) one-tail		0.12580776	0.137627178	0.434360047	0.457623667	0.000614817
	t Critical one-tail		1.681070703	1.681952357	1.671093032	1.678660414	1.688297714
	P(T<=t) two-tail		0.25161552	0.275254355	0.868720094	0.915247335	0.001229635
	t Critical two-tail		2.016692199	2.018081703	2.000995378	2.012895599	2.028094001
SCL	Mean	0.050962633	0.051702948	0.060160023	0.050297432	0.039189178	0.066682461
	Variance	0.001123783	0.000667394	0.000887524	0.0006651	0.001397485	0.000683834
	Observations	56	31	24	24	24	20
	Hypothesized Mean Difference		0	0	0	0	0
	df		76	49	56	40	43
	t Stat		-0.114786019	-1.217714724	0.096234111	1.330558282	-2.134081213
	P(T<=t) one-tail		0.454458727	0.114582009	0.461839105	0.095435161	0.01928979
	t Critical one-tail		1.665151353	1.676550893	1.672522303	1.683851013	1.681070703
	P(T<=t) two-tail		0.908917455	0.229164018	0.92367821	0.190870323	0.038579581
	t Critical two-tail		1.99167261	2.009575237	2.003240719	2.02107539	2.016692199
SDL	Mean	0.029718059	0.031127356	0.036745647	0.04696116	0.018339708	0.027076356
	Variance	0.00136213	0.000794738	0.004066401	0.002129028	0.001380363	0.001008737
	Observations	65	32	24	31	20	24
	Hypothesized Mean Difference		0	0	0	0	0
	df		78	29	49	31	47
	t Stat		-0.208262254	-0.509313478	-1.821288007	1.199556708	0.332858801
	P(T<=t) one-tail		0.417783531	0.307193186	0.037335546	0.119699903	0.370360547
	t Critical one-tail		1.664624645	1.699127027	1.676550893	1.695518783	1.677926722
	P(T<=t) two-tail		0.835567062	0.614386371	0.074671091	0.239399806	0.740721093
	t Critical two-tail		1.990847069	2.045229642	2.009575237	2.039513446	2.011740514

Table 9 - T-test (two sample assuming unequal variances), REP for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	706.641791	702.9117647	704.2352941	704.8235294	703.1538462	699.6764706
	Variance	46.29398462	59.23440285	47.51871658	43.36185383	58.61538462	352.1648841
	Observations	67	34	34	34	26	34
	df	66	33	33	33	25	33
	F		0.781538808	0.974226325	1.067620052	0.789792389	0.131455425
	P(F<=f) one-tail		0.195697344	0.452291517	0.428005003	0.221154935	1.88749E-12
	F Critical one-tail		0.62026433	0.62026433	1.69223579	0.597599661	0.62026433
SBL	Mean	689.2272727	672.2580645	690.7941176	676.53125	686.8709677	683.25
	Variance	242.1783217	1334.864516	390.5926916	1949.289315	303.3827957	318.9351852
	Observations	66	31	34	32	31	28
	df	65	30	33	31	30	27
	F		0.181425395	0.620027786	0.124239291	0.798259905	0.759333974
	P(F<=f) one-tail		4.56634E-09	0.050454948	1.1211E-12	0.221951869	0.182706144
	F Critical one-tail		0.611791438	0.619231816	0.614387171	0.611791438	0.60319704
SCL	Mean	715.5	716.1290323	713.4166667	715.0416667	711.2083333	717.1
	Variance	16.69090909	19.91612903	31.47101449	12.5634058	20.60688406	4.726315789
	Observations	56	31	24	24	24	20
	df	55	30	23	23	23	19
	F		0.838059899	0.530358152	1.328533788	0.809967632	3.531484106
	P(F<=f) one-tail		0.279931709	0.028175058	0.230013609	0.257061914	0.001841075
	F Critical one-tail		0.600093146	0.578887635	1.873976147	0.578887635	1.988234971
SDL	Mean	707.4615385	701.46875	699.375	709.65625	708.45	702.7916667
	Variance	39.65865385	72.96673387	66.85326087	41.97479839	42.05	98.7807971
	Observations	65	32	24	32	20	24
	df	64	31	23	31	19	23
	F		0.543516912	0.593219438	0.944820592	0.943130888	0.401481411
	P(F<=f) one-tail		0.020095209	0.052619743	0.413349666	0.410898211	0.002188852
	F Critical one-tail		0.613351431	0.588471294	0.613351431	0.570978698	0.588471294

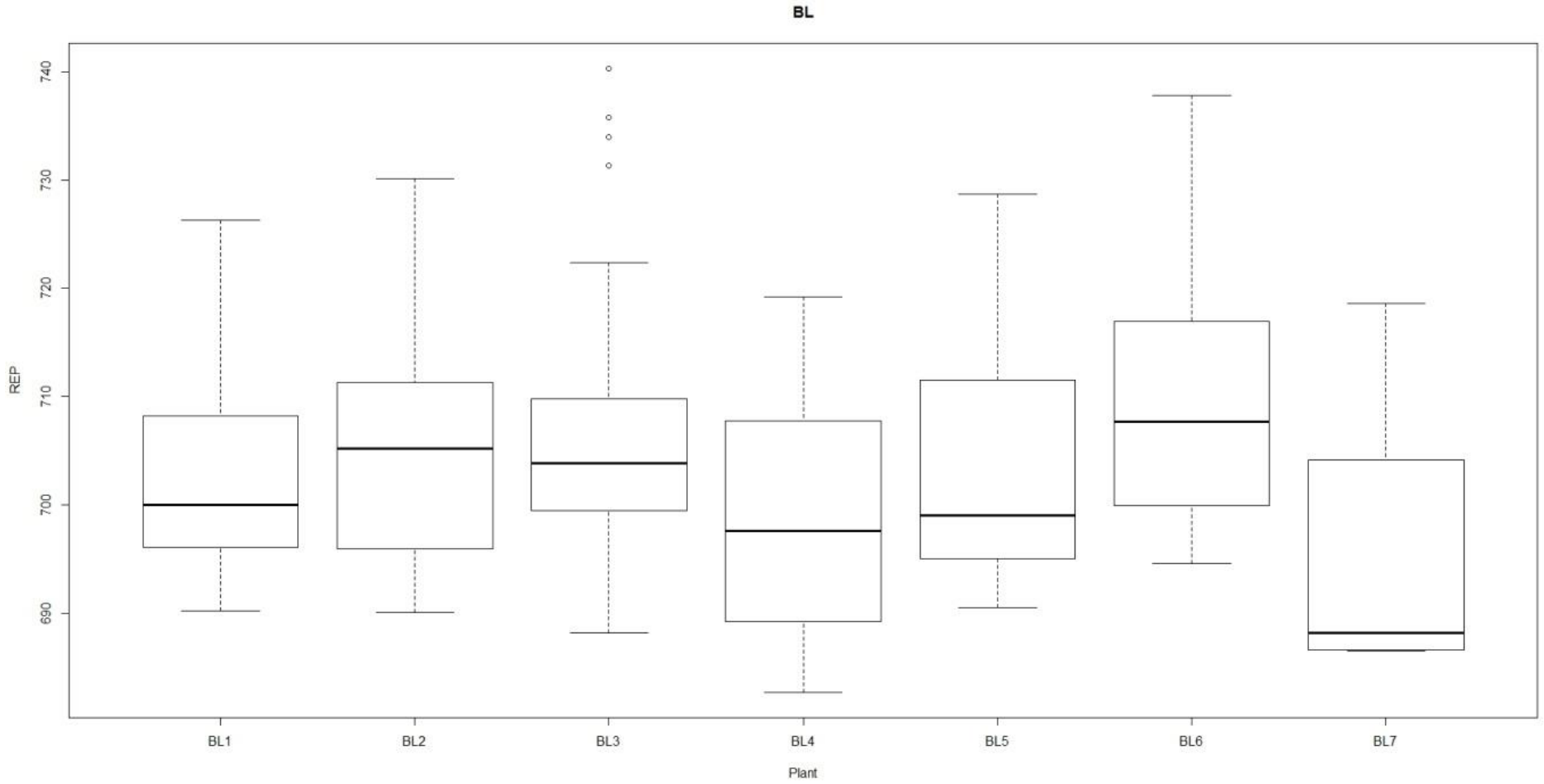

Figure 29 - Box plot for REP, from leaf clip readings for Wild Olive

From Figure 29, it is evident that there is a mix between the expected fertiliser effect and poison effect from the trend seen in the REP for Wild Olive. The plant with the 30mg/kg concentration (BL3) shows a REP between the two control plants, meaning that it is possible that plants exposed to that concentration of TNT leakage may not be easily detectable using a hyperspectral detection system. What is evident are the outliers for BL3, which are higher than the maximum values of both the control plants. This means that when long term readings are available for a suspected minefield, such outliers may be indicative of the presence of AP mines.

For higher concentrations of TNT, namely 300mg/kg and 600mg/kg (BL4 and BL5), the median values of the REP are visibly lower than that of BL3, as well as the control plant BL2. The mean REP of these plants is slightly lower but similar to the control plant BL1. This may be due to the poison effect as explained earlier in this chapter. This may serve as an indication of the presence of a severely deteriorated AP mine or a concentration of AP mines in the area.

For the plant subjected to 1200mg/kg (BL6), the opposite is true. The mean REP is similar to that of the control plant BL2 and BL3, and significantly higher than that of the control plant BL1. What is prominent, though, is that the lower and upper 25^{th} percentile limits of the box are higher than that of the control plants. This indicates that this plant was healthier than the control plants. Although it is opposite to how the plants subjected to lower concentrations of TNT reacted, this gives a vital insight into how the application of hyperspectral detection systems may work.

Note that BL7, which was subjected to 5000mg/kg, showed REP values that look drastically different to those of the other plants when referring to the box plots in Figure 29. This is evidence of the failing health of the plant. Readings of this plant were only possible for four days before the plant died entirely. The plant showed signs of ill health after the TNT was administered, before dying.

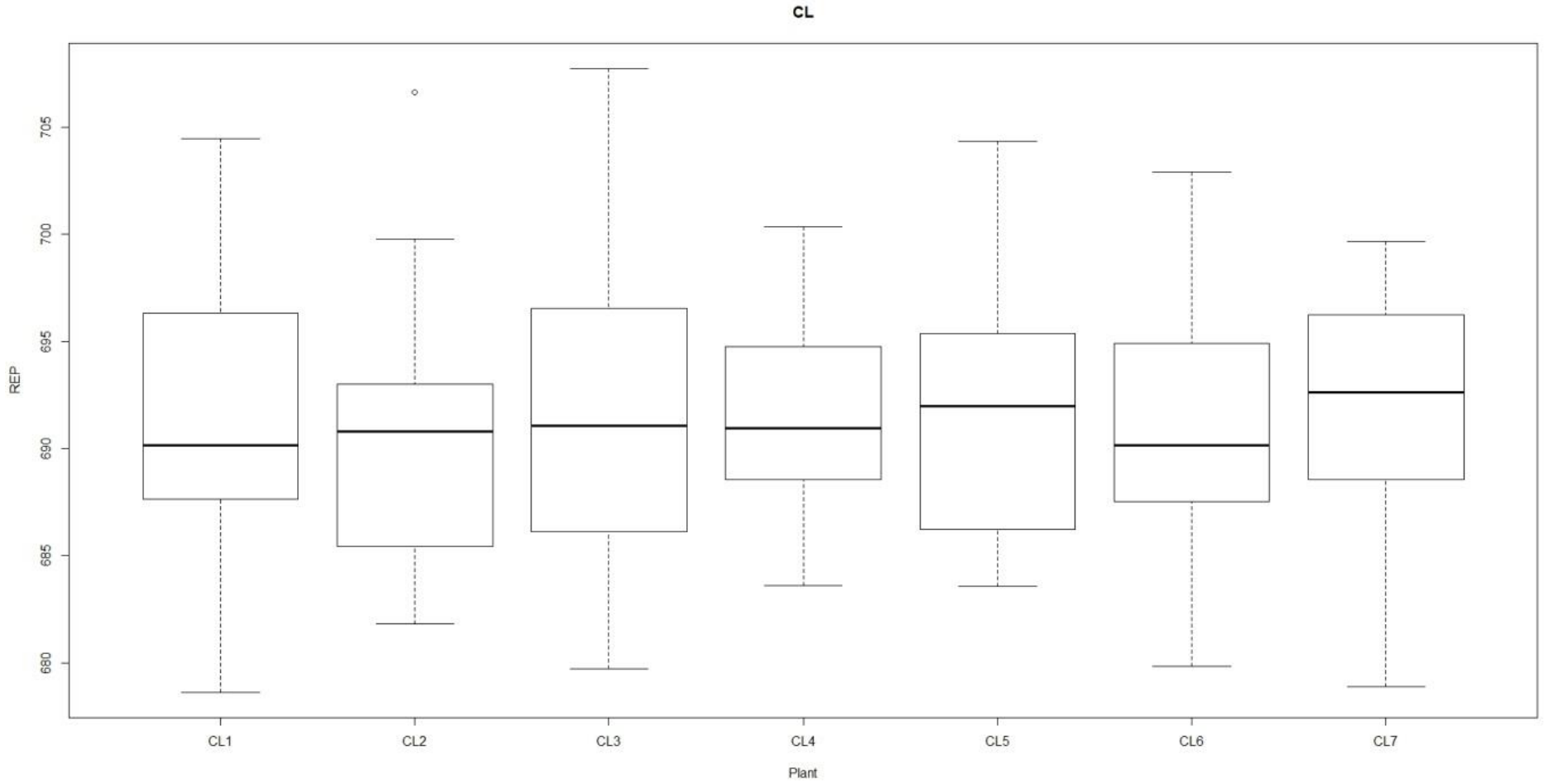

Figure 30 - Box plot for REP, from leaf clip readings for River Bushwillow

Figure 30 is a box plot representing REP for leaf clip readings for River Bushwillow. Firstly, it is evident that the mean REP for all plants is roughly similar, between 690nm and 695nm. Some of the plants, namely CL3 and CL5 show greater variances in REP values than other plants. CL4, on the other hand, shows a smaller range of REP than the other plants, especially the control plants CL1 and CL2. The change in variance magnitudes may indicate that contaminated plants may react differently to changes in the environment. The differences in this specific species may mean that it would not be an ideal plant to use as an indicator species.

When looking at CL7, which was subjected to a 5000mg/kg TNT concentration, one can see that the mean REP is higher than that of all other species, but the upper limits of the REP never exceed the 700nm mark, which is lower than any of the other plants. It also has a relatively smaller variance between the upper and bottom 25^{th} percentile limits than most of the other plants. This may indicate that this plant is more resilient than the other plants, but may not be as healthy, because it never reaches REP values as high as other plants. What is also visible is that the lower limit of the REP for this plant is the lowest, second only to the control plant, CL1.

As was the case with Wild Olive, a trend emerges that a positive or negative difference respectively may not be an indication of the presence of TNT in the soil, but any difference may be an indication. In other words, if several plants of the same species exist in an area that is a suspected minefield, and they react differently to environmental changes, this may be an indication of the presence of TNT. If long term hyperspectral readings are possible, and some plants have values that consistently differ from others, or plants that are known to be not exposed to TNT, this may be an indicator of TNT presence.

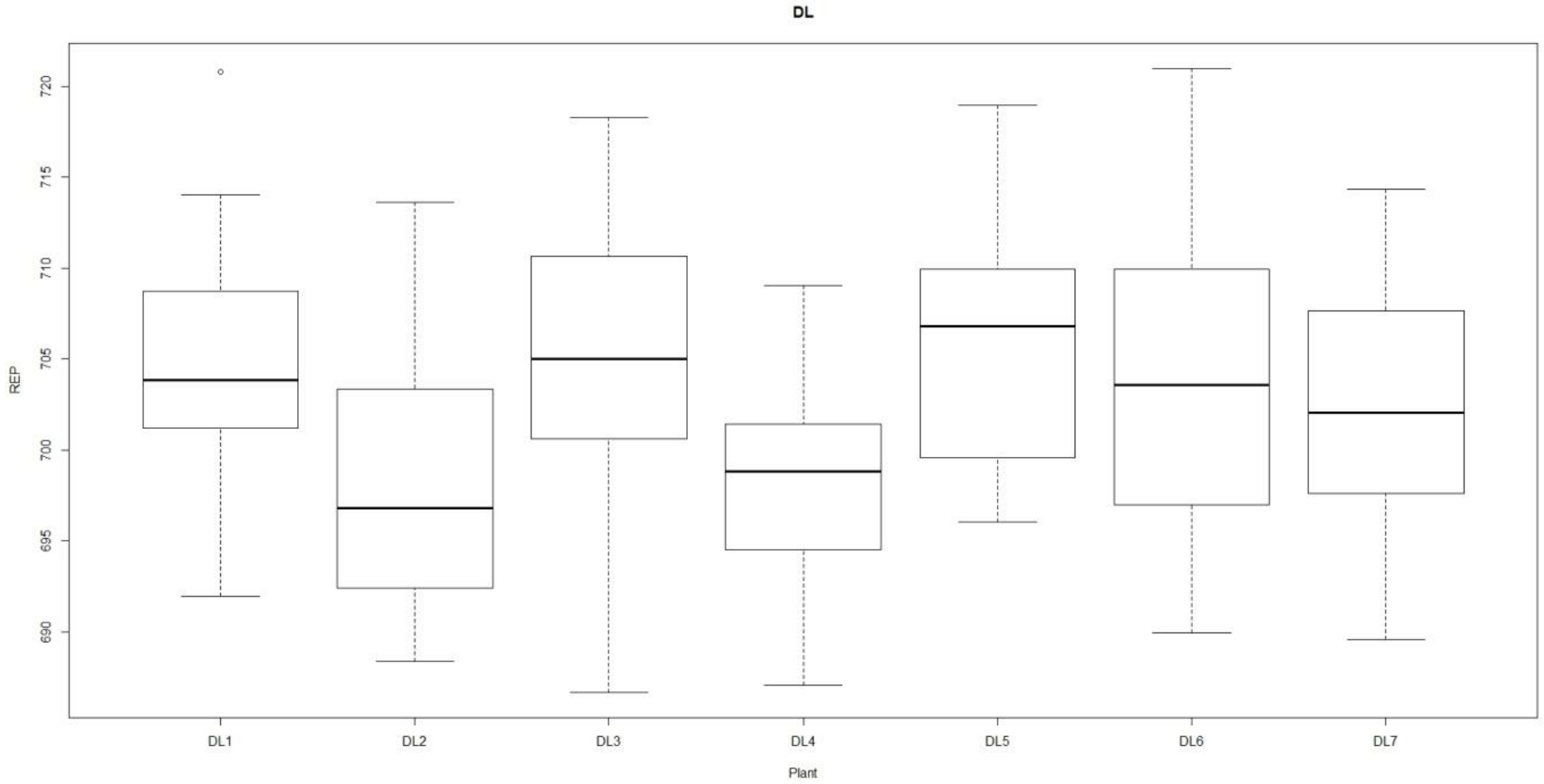

Figure 31 - Box plot for REP, from leaf clip readings for Soap Dogwood

When looking at the box plot for the tree species Soap Dogwood (Figure 31), wide variability in the REP of the plants are visible. Even in the control plants, DL1 and DL2 show significant variance between the two, but it is important to note that DL2 had deteriorating health, and died before the study was finished. Thus, DL1 will be representing the control plants.

The indication from the box plot of DL3, which was exposed to 30mg/kg TNT, is that the plant was greener than the control plant. The mean REP is higher than that of the control plant, but the variances in REP is also greater. Both the minimum and maximum values of the REP for DL3 exceed that of the control plant DL1 and the lowest value of DL3 is the lowest of all the readings for this species.

From the plot of DL4 (300mg/kg), the mean REP and maximum REP are significantly lower than that of the other plants, except for the control plant DL2. This may indicate failing plant health as well. For all plants in this species' range, a reduced number of readings were taken, except for the control plant, DL1, and the 1200mg/kg plant, DL6, which had continuous readings throughout the study. The reduced readings are due to a loss of foliage due to reasons including the heatwave during the latter part of the study. Growth returned to a normal rate after a sufficient supply of water resumed. It is important to note that the heatwave and corresponding drought had a significant effect on all the plants.

DL5 (600mg/kg), has a mean REP that lies higher than any of the other plants. This indicates that the plant was greener than the other plants in this species. It is also noteworthy that it has the highest minimum REP and second largest maximum REP value of all the plants for this species. This was seen in the physical health of the plant as well, as it seemed more hardy and resilient in than the other Soap Dogwood trees.

The plants with the shock doses of TNT, DL6 and DL7 had similar mean REP to the control plant, DL1, but with greater variances in the REP.

Considering all the variability between samples of Soap Dogwood, this species may be unsuitable to use as an indicator species to determine the presence of TNT in the soil surrounding the plants. There is some evidence of a fertiliser effect, with plants exposed to lower concentrations of TNT having higher mean REP, but also a poison effect, where high levels are present. The fact that DL4 had a noticeable poison effect may indicate adverse environmental factors, which lead to the ill health of the plant.

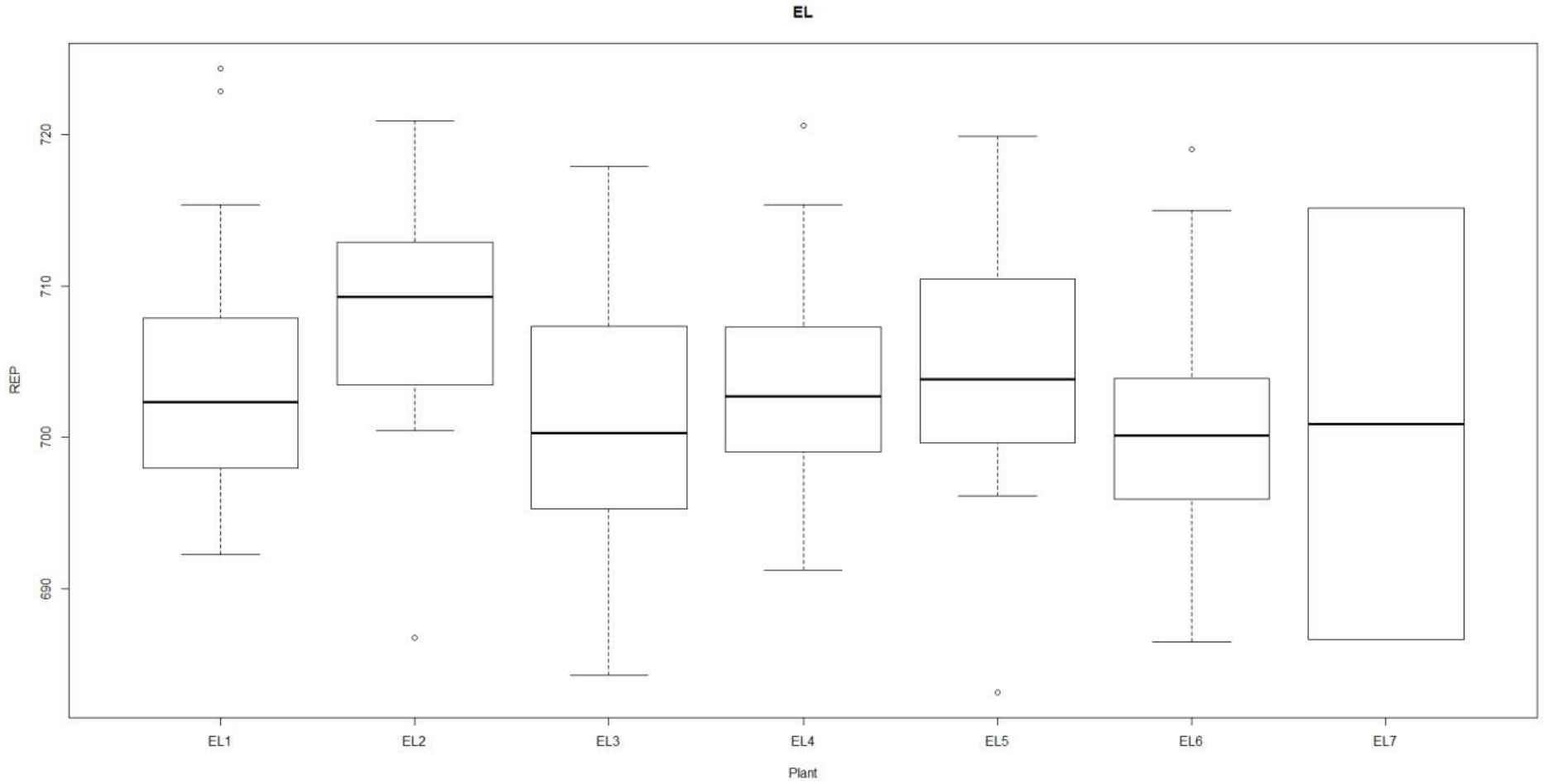

Figure 32 - Box plot for REP, from leaf clip readings for Sweet Thorn

It is important to note that, when viewing Figure 32, EL7, the tree exposed to 5000mg/kg TNT died shortly after the administration of TNT. Three sets of readings were taken of this plant, and the highest value was the initial reading, the mean REP was after the TNT administration, and the lowest reading was before the plant died.

As with the other plants, variances between the control plants are visible, indicating possible differences in specific plant health, or potential environmental issues. Also, when taking readings of the Sweet Thorn trees, physical effects of environmental changes were noticed. Whenever an adverse environmental influence happened, such as a cold front passing, or an extended dry period, it was noticed that the Sweet Thorn trees had significant browning and leaf loss. In the case of the Sweet Thorn trees, this was more prominent relative to the other trees. What was also prominent was that new leaves were quickly formed following such an event and that the trees seemed extremely resilient, apart from EL7, which died completely shortly after the administration of TNT to its soil. Where specimens appear to have died out, new sprouts were formed low on the main stem of the tree, giving it a shrub-like appearance, and new leaves and thorns appeared on these sprouts.

EL3, which was exposed to 30mg/kg TNT showed a trend of having a lower mean REP than either of the control plants. This plant also had a higher variance in REP, with both the majority of the readings, as well as the maximum and minimum readings varying more greatly from the mean than either of the control plants. This slight difference in the mean, as well as the considerable variability of the readings, mean that the plant may have undergone more stress relating to TNT exposure than the control plants.

Contrasting, EL4 (300mg/kg), has a similar mean REP to EL1, as well as a similar level of variability. This indicates that the exposure to TNT may have had little effect on the plant. A similar effect is seen when comparing EL5 (600mg/kg), but what is of interest here is that the plant has a significantly higher minimum REP value than either of the preceding plants, except for EL2. It also had a slightly higher maximum value, as well as a slightly higher mean value. This may even indicate that TNT may have had a fertiliser effect on this plant.

It was noted that when physically comparing plants when readings were taken, plants exposed to 600mg/kg TNT seemed healthier. They would tend to have more green foliage, and also seemed to handle environmental changes better.

EL6, which was exposed to 1200mg/kg showed the lowest mean REP value of the species. Although the majority of readings were relatively close to the average value, it is noteworthy that the plant had high variability in the readings, greater than either control plant, and similar to EL3. This may indicate that the high concentration of TNT had a profound impact on the health of the plant, as well as its reaction to environmental changes.

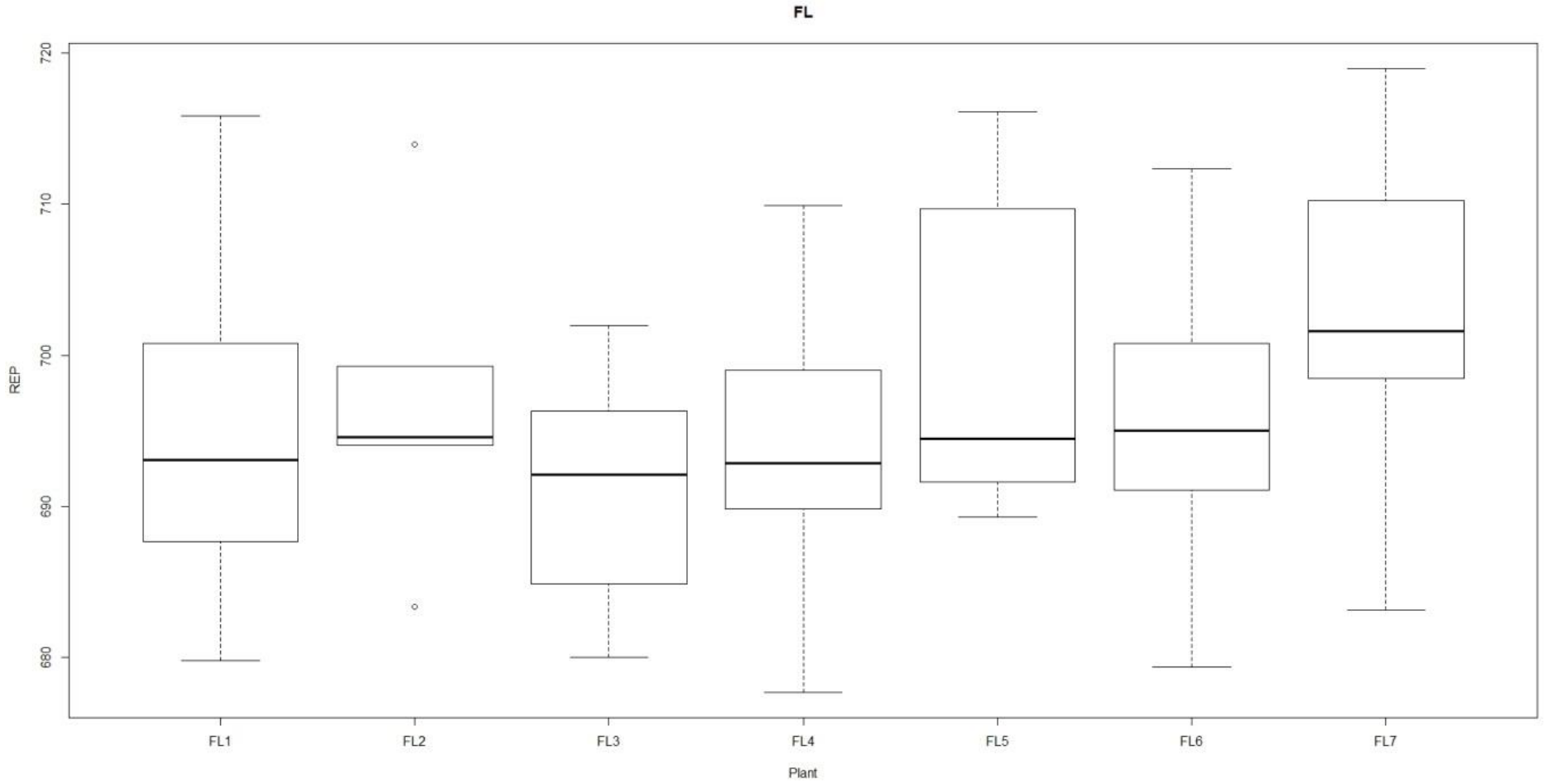

Figure 33 - Box plot for REP, from leaf clip readings for White Stinkwood

From Figure 33, it can be seen that FL2, the second control plant, has readings dissimilar to the rest of the species. This plant died early in the study, and thus, FL1 is representative of the control species. As White Stinkwood is a deciduous plant, significant differences between maximum and minimum REP values are expected, as the leaves vary between brown and yellow in the autumn and light green to green in spring and summer.

Immediately it can be seen the FL3 (30mg/kg) tended to have lower REP values than the control plants, having a slightly lower mean value, and a prominently lower maximum value. This means that the plant was not as healthy as the control plants, but the lower variability indicates that it changed less with environmental changes.

Similarly, FL4 has a similar mean to that of the control plant, and a slightly smaller variance, again showing that the plant did not change as much with environmental changes as the control species.

When looking at the plants with higher concentrations TNT, a positive trend in the mean REP emerges. FL5 has a higher mean REP than any of the plants subjected to lower concentrations TNT and also has a much higher minimum REP value than any of the other plants. Again, as discussed with the Sweet Thorn, plants subjected to 600mg/kg TNT seemed to be healthier than other plants.

This trend continues with FL6 and FL7, where the mean REP is slightly higher, and significantly higher respectively, indicating a definite fertiliser effect with higher TNT concentrations. A total variance in values for the plants subjected to higher concentrations of TNT in similar to that of the control plant.

This gives the impression that White Stinkwood may be a sufficient indicator plant for the presence of TNT in the soil, with plants of lower than normal health being indicative of AP mines, and trees with better health being indicators of possible AT mines.

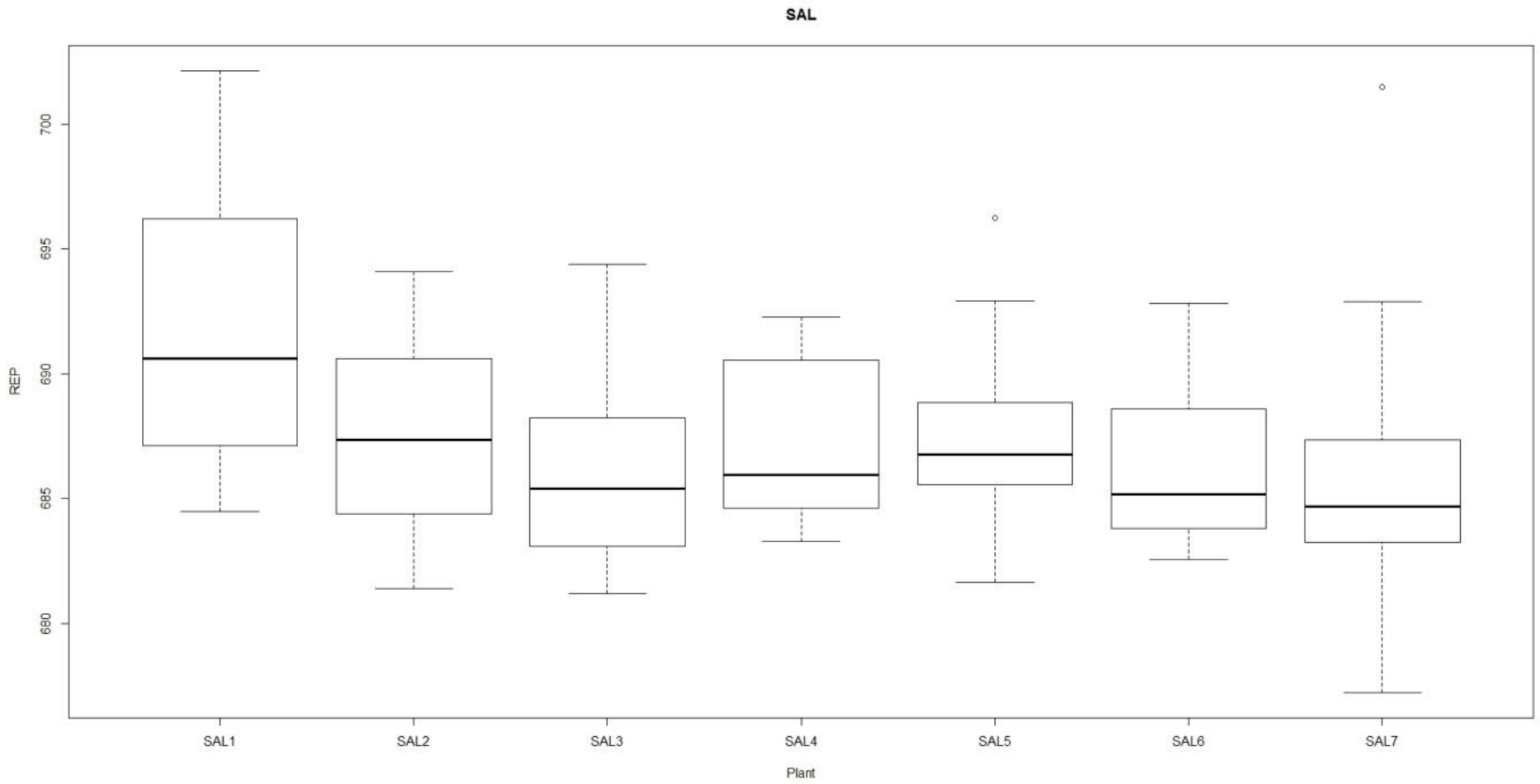

Figure 34 - Box plot for REP, from leaf clip readings for Freylinia Tropica (Transvaal Honey-bell Bush)

Figure 34 represents the box plot results for the REP for Transvaal Honey-bell Bush. It is important to note the variance between the control species, with the plant SAL1 being the plant with the highest maximum, mean and minimum REP values. In comparison, all of the contaminated plants, starting at SAL3, had lower mean REP values than either of the control plants. This indicates that for this species, a general poison effect is evident.

For SAL3 (30mg/kg), the plant had similar maximum and minimum values than the control plant SAL2, and these values were significantly lower than those of SAL1. The mean value of the REP was also lower than either of the control species. This means that in a possible minefield situation, plants with lower REP values may indicate leaking AP mines in the vicinity of the plants.

This difference becomes less prominent when comparing SAL4 (300mg/km) and SAL5 (600mg/kg) to the control plants. While SAL4 has a lower mean REP value than that of SAL3, the bulk of the readings are in a similar range to that of SAL2. The similar size of the box to that of SAL2 means that most of the REP values for this plant are in a similar range to SAL2, albeit tending to be slightly lower. This may be due to the poison effect, but it can be argued that the poison effect be less prominent than in the case of SAL3.

The REP values for Spekboom (Figure 35) show mixed results. SBL3, SBL5 and SBL7 (30mg/kg, 600mg/kg and 5000mg/kg respectively) have lower median values, while SBL4 and SBL6 (300mg/kg and 1200mg/kg respectively) show similar median values to the control plants. Note that the variance for SBL4 differs significantly from any of the other values.

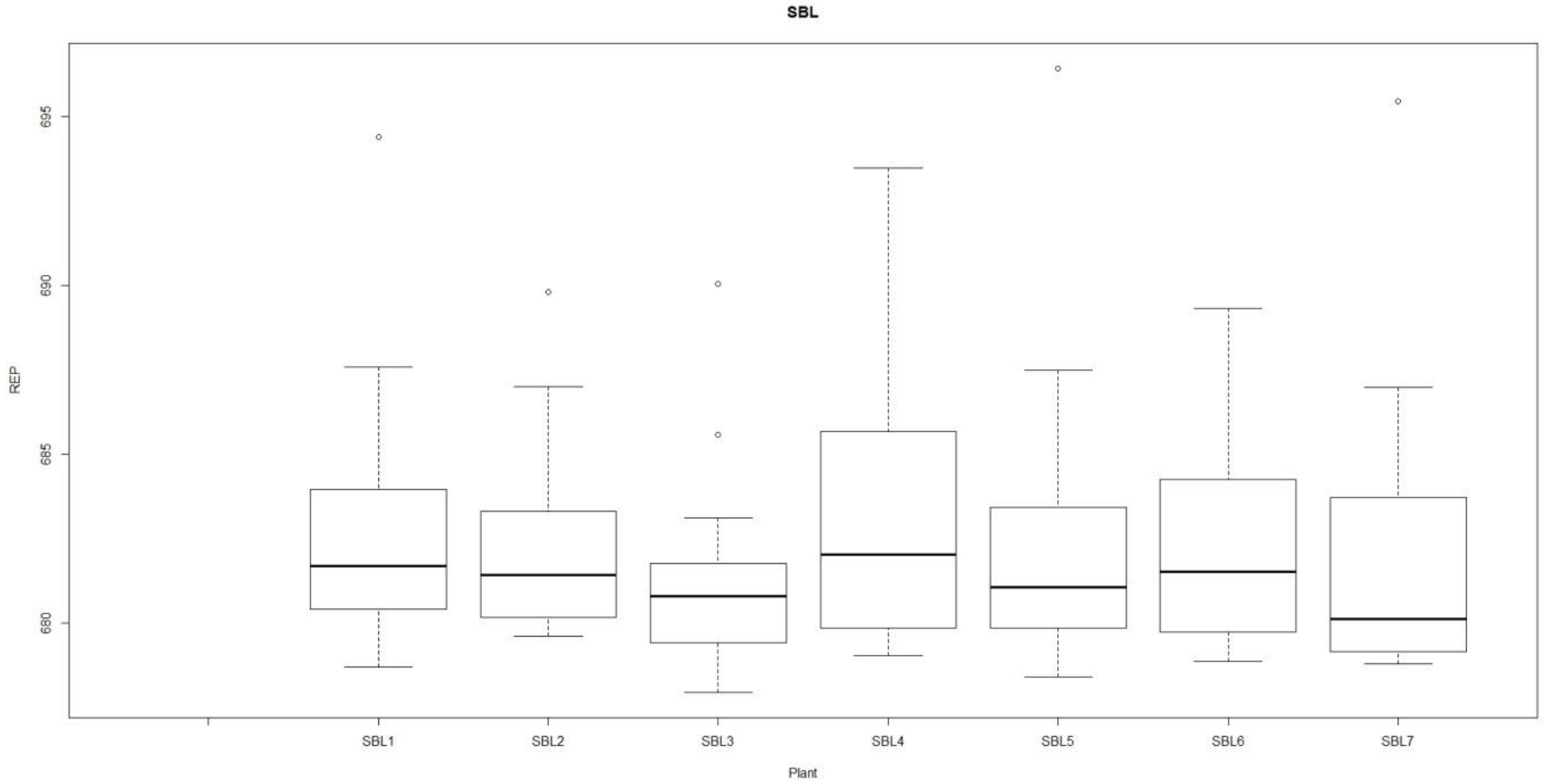

Figure 35 - Box plot for REP, from leaf clip readings for Portulacaria Afra (Spekboom)

When looking at Figure 36, a trend can be seen where contaminated plants tended to show a negative trend with an increase in TNT concentration. When comparing the control plants, it can be seen that SCL2 showed better REP values than SCL1, despite having a lower minimum value. It has a larger variance, but the median value is higher than that of SCL1, and most readings were greater than this median and greater than the majority of values taken from SCL1.

SCL3 (30mg/kg) had a somewhat lower median value, but also a smaller variability than the control plants. It had the second highest maximum value of all the samples. This trend is continued when in SCL4, which has significantly lower REP values than any of the preceding plants. It also has the second lowest minimum value, but it has a relatively smaller variability than SCL3 and the control plants. This indicates that, although the plant was not as healthy, it was also influenced less by environmental factors.

With SCL5 (600mg/kg), it would seem as if the plant was healthier than SCL4. Most the readings tended to be higher than the median value, despite the high variability of the REP values for this plant. It also had a relatively high maximum value, and a similar minimum than SCL 3. The plant would have shown similar health to SCL3, albeit with a higher influence of external factors.

SCL6 (1200mg/kg) was the least healthy plant for this species. It had low REP values throughout the study period and had the lowest median and minimum values. This is reflected in the narrow distribution of REP readings, all of which propagate below 700nm.

Conversely, with SCL7 (5000mg/kg), TNT seemed to have a fertilising effect on the plant. Only a few of the REP readings were below 700nm, indicating the plant was mostly relatively green, more so than any of the other plants of the same species.

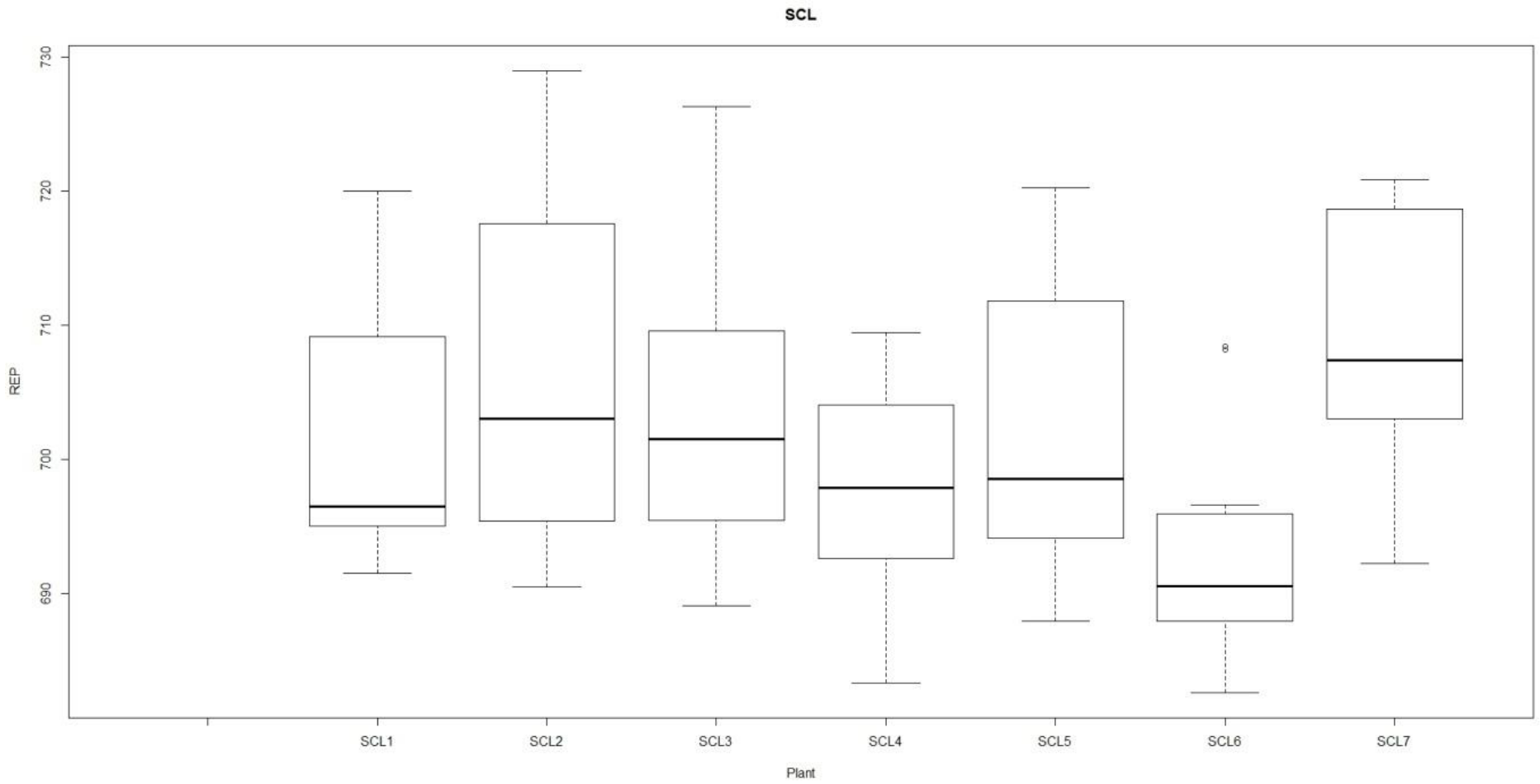

Figure 36 - Box plot for REP, from leaf clip readings for Carissa Macrocarpa (Natal Plum)

The box plots for Kei Apple (Figure 37) a difference is visible between the control plants, SDL1 and SLD2, with SDL2 having a wider range of REP values. The control plants, and the lower concentration plants (SDL3 and SDL4) all had REP values below 700nm, except for an outlier of SDL2.

SDL3 (30mg/kg) had lower REP values than either of the control species throughout the study, indicating that low concentrations of TNT may hurt the health of the species. 300mg/kg TNT may have had a greater harmful effect, as SDL4 has the lowest maximum, median and minimum value of all plants of this species. It was significantly less healthy than either of the control plants or the higher concentration plants.

SDL5 (600mg/kg) seemed to be considerably healthier than any of the other plants, but it had a wider distribution of values than any other plants of the species, indicating the TNT exposure may have caused the plant to be more sensitive to change. This broad distribution is also seen ion SDL6 (1200mg/kg) and SDL7 (5000mg/kg). SDL7 had lower median values than any of the other plants except for SDL4, but also had a large distribution of values, meaning that the shock dose of TNT had a mixed result.

It is noteworthy that all the plants had REP values lower than 700nm. This means that the plants seldom had green foliage or proper health.

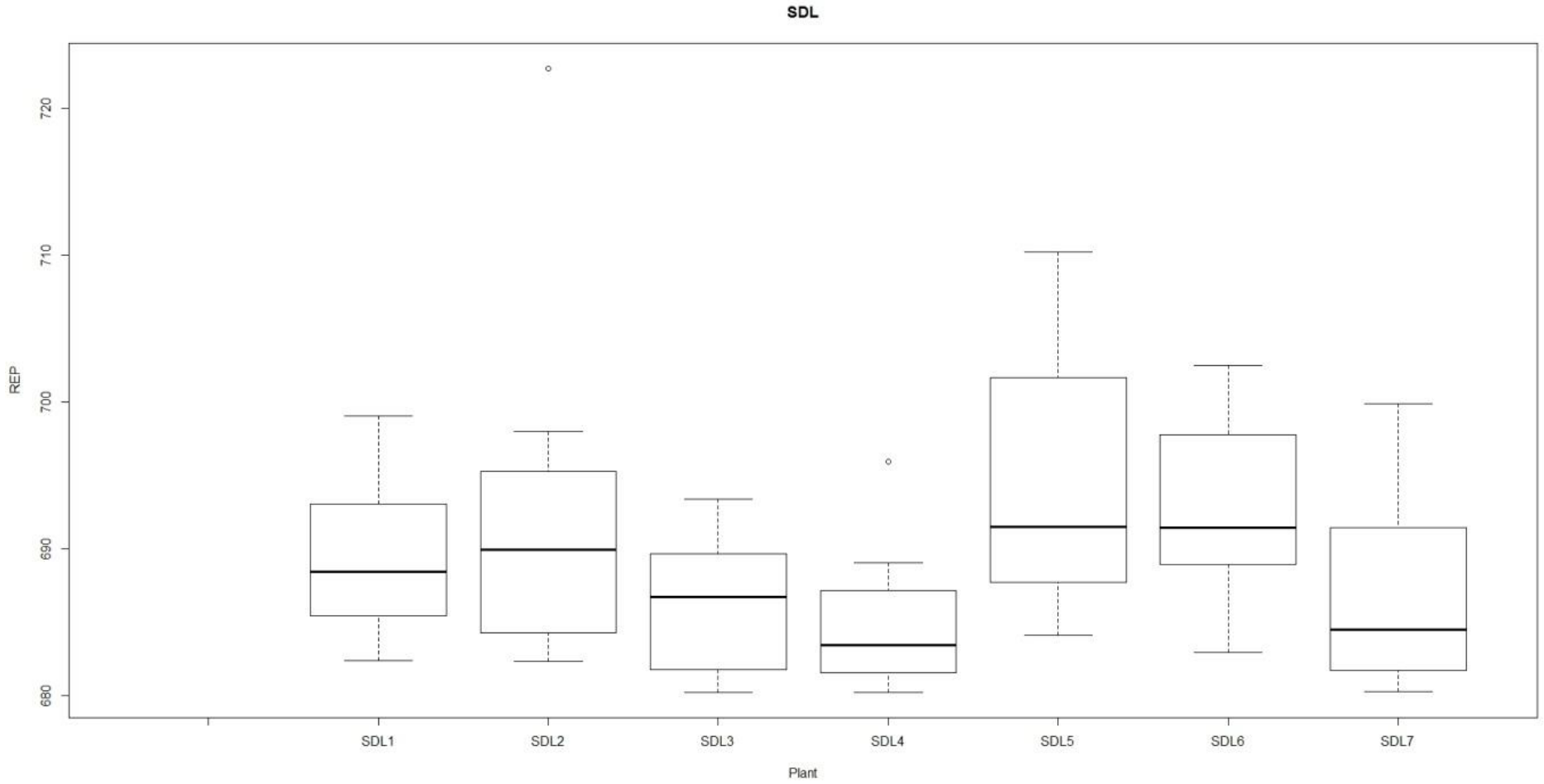

Figure 37 - Box plot for REP, from leaf clip readings for Dovyalis Caffra (Kei Apple)

5.5.2 First derivative reflectance

When examining the first derivative reflectance, which is a representation of the red-edge position, one needs to look for broad, flat profiles for healthy vegetation, or sharp peaks below 700nm for unhealthy vegetation. In Figure 38, the red arrow indicates the "unhealthy" region, while the green arrow indicates the "healthy" region.

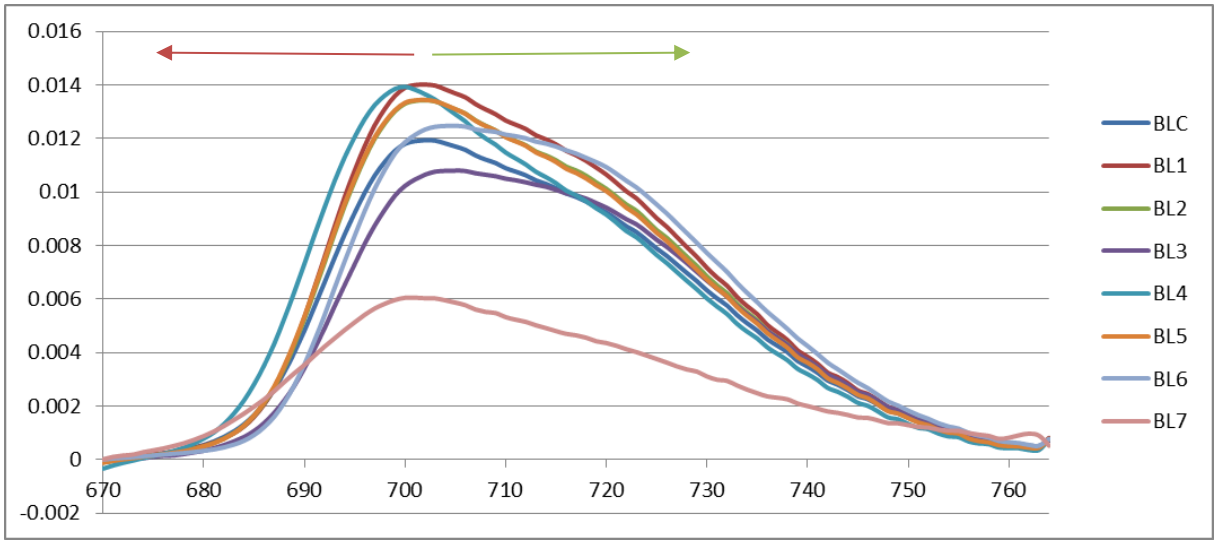

Figure 38 - First derivative reflectance, Wild Olive

The first derivative reflectance of Wild Olive (Figure 38), shows that one control plant (BL1), BL4 (300mg/kg) and BL5 (600mg/kg) showed peaks toward the red, indicating that the plants were less healthy than the other plants. BL7, which has a significantly different profile compared to the other plants. This is because the plant died relatively early in the study. BL3 (30mg/kg) and BL6 (1200mg/kg) had similar profiles to the average control curve. A peak at around 700nm and a relatively broad profile toward the infrared spectrum indicates that these plants were healthier than the others throughout the study.

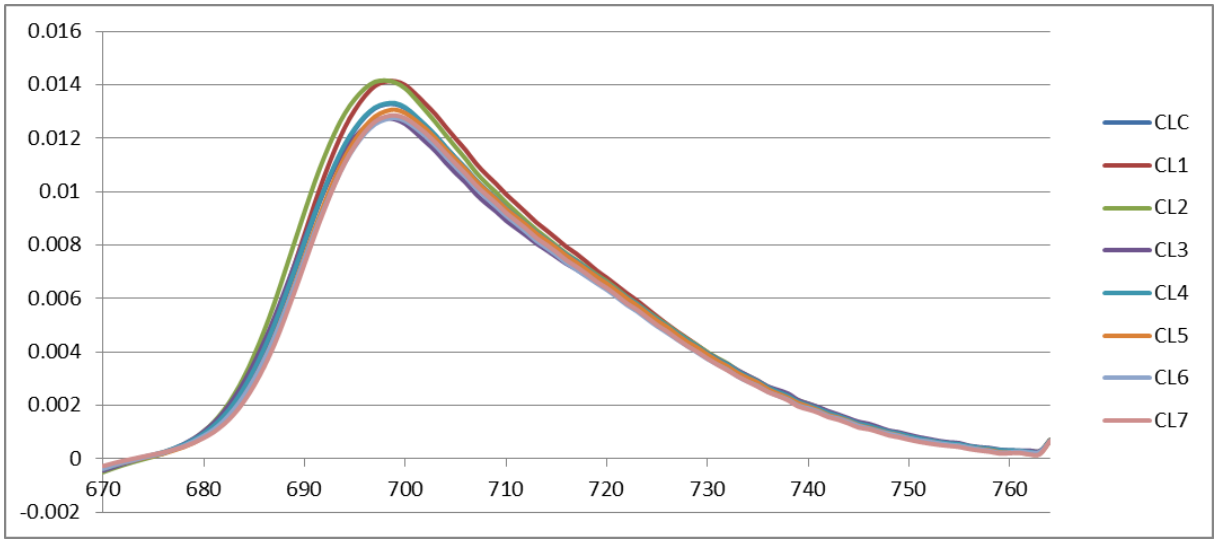

Figure 39 - First derivative reflectance, River Bushwillow

The first derivative reflectance profiles of all River Bushwillow samples (Figure 39) look similar. Sharp peaks below 700nm indicate that the entire sample set of the species was unhealthy. This includes the control species. This correlates with the F-test results, which indicates that this might not be a suitable species to use in the detection of TNT. It is important to note that River Bushwillow requires a significant amount of water in its natural environment, so plant stress in the case of this study may also have been due to the species' water requirements not being met.

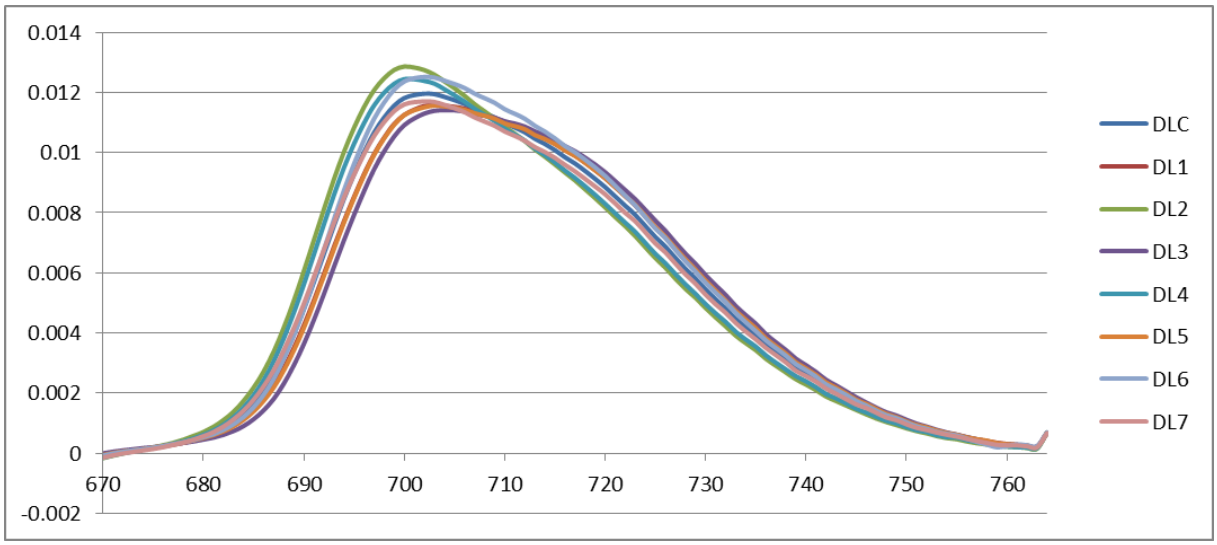

Figure 40 - First derivative reflectance, Soap Dogwood

Mixed profiles are also seen for Soap Dogwood (Figure 40). None of the plants was healthy, and even the control plants have different profiles. What is interesting to note is that the DL3 and DL5 (300mg/kg and 600mg/kg respectively), have profiles indicating healthier plants than DL2, which is a control plant. Again, this may indicate a fertiliser effect.

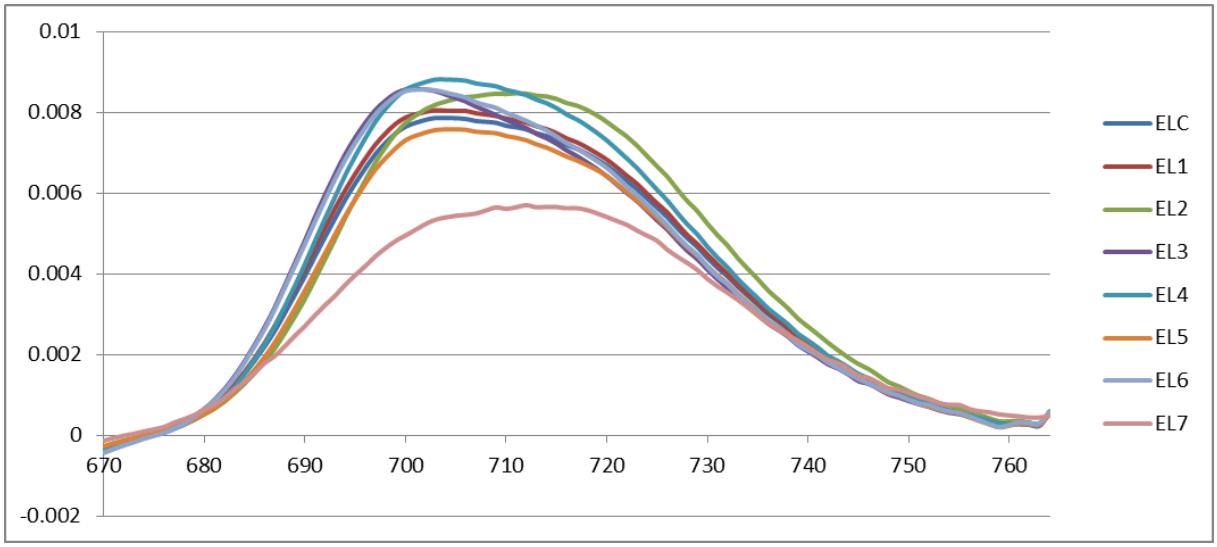

Figure 41 - First derivative reflectance, Sweet Thorn

Figure 41 represents the first derivative reflectance of Sweet Thorn. As with Wild Olive, EL7 (500mg/kg) died out early in the study, causing the unique profile. Two plants have profiles with peaks below 700nm, namely EL3 and EL6 (30mg/kg and 600mg/kg respectively). The other plants showed profiles indicating good health, similar in shape to the general control profile (ELC). This may suggest that the TNT had little effect on the species below concentrations of 5000mg/kg. This was reciprocated in the general behaviour of the plants as well. All plants tended to lose foliage at similar times, but all plants, apart from EL7, were resilient.

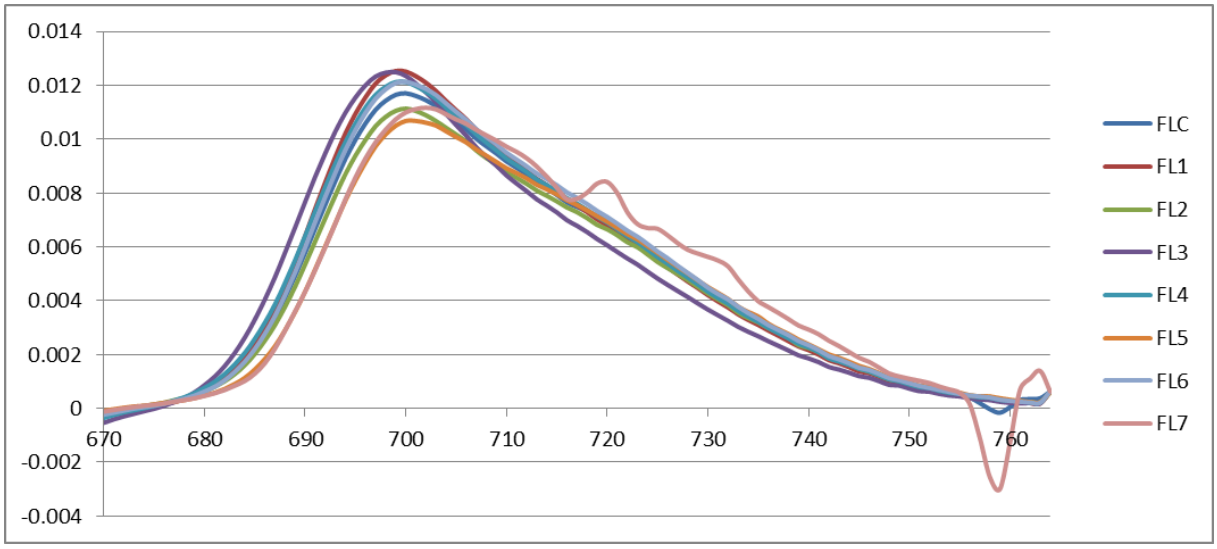

Figure 42 - First derivative reflectance, White Stinkwood

As with the profiles for Soap Dogwood, those for White Stinkwood (Figure 42) show that all of the plants were unhealthy. All profiles have peaks toward the red part of the spectrum (below 700nm). FL7 (5000mg/kg) shows an anomalous profile beyond 720nm but has a profile similar to the other plants before that.

First derivative reflectance profiles for the shrubs show that most of the plants show sharp peaks toward the red part of the spectrum, including the control plants. Figures 43, 44 and 45 have no profiles with the flat, broad peak beyond 700nm, while Figure 46, representing Natal Plum, has two plants SCL5 and SCL6 (600mg/kg and 1200mg/kg) have sharp peaks in the red spectrum. The rest of the plants for that sample species showed healthy profiles. This may indicate that the TNT had a positive effect on the health of the plants, or may be circumstantial.

Apart from Natal Plum (Figure 46), all the shrub species show profiles indicating unhealthy plants. Figures 43, 44 and 46 all show profiles with sharp peaks between 690 and 700nm. This indicates a unhealthy trend for all plants.

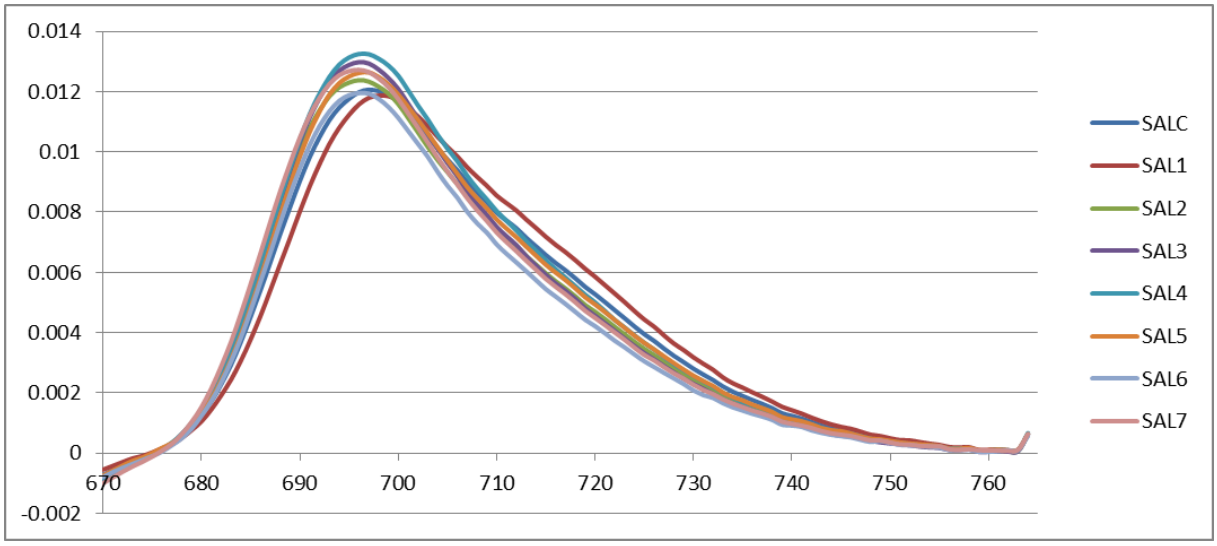

Figure 43 - First derivative reflectance, Transvaal Honey-bell Bush

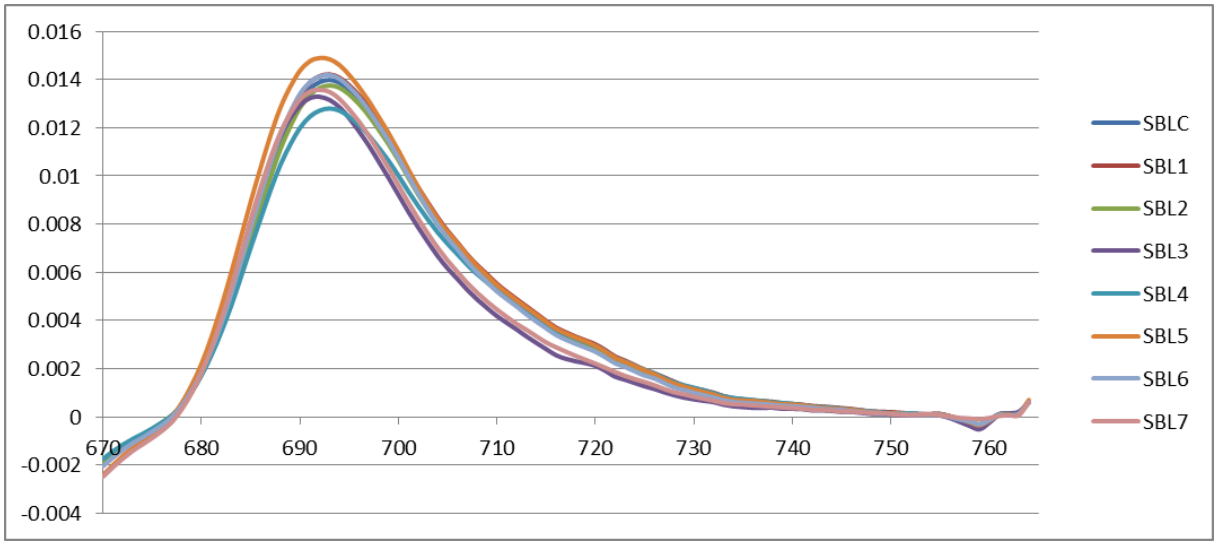

Figure 44 - First derivative reflectance, Spekboom

All of the profiles for the first derivative reflectance of Spekboom (Figure 44) are similar, with sharp peaks in the red spectrum. This indicates that the plants were all relatively unhealthy.

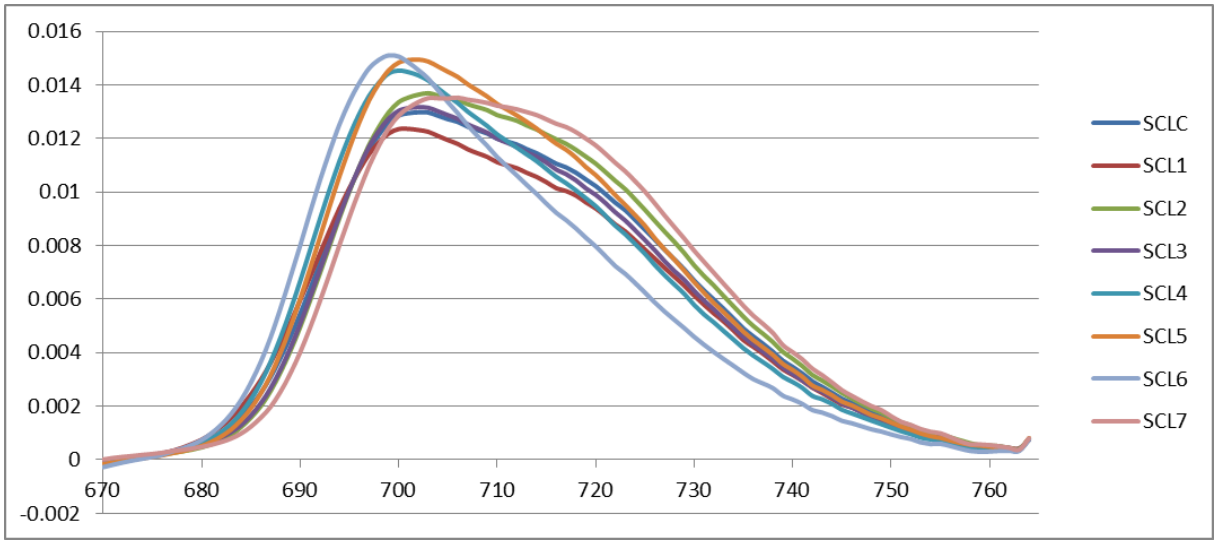

Figure 45 - First derivative reflectance, Natal Plum

From Figure 45, it is seen that plants SCL4, SCL5 and SCL6 (300mg/kg, 600mg/kg and 1200mg/kg respectively) have peaks within the red part of the spectrum, indicating that higher concentrations of TNT have a detrimental effect on the species. Conversely, SCL3 and SCL 7 (30mg/kg and 5000mg/kg), have profiles similar to the control plants, meaning that TNT has little effect on the plants at these concentrations.

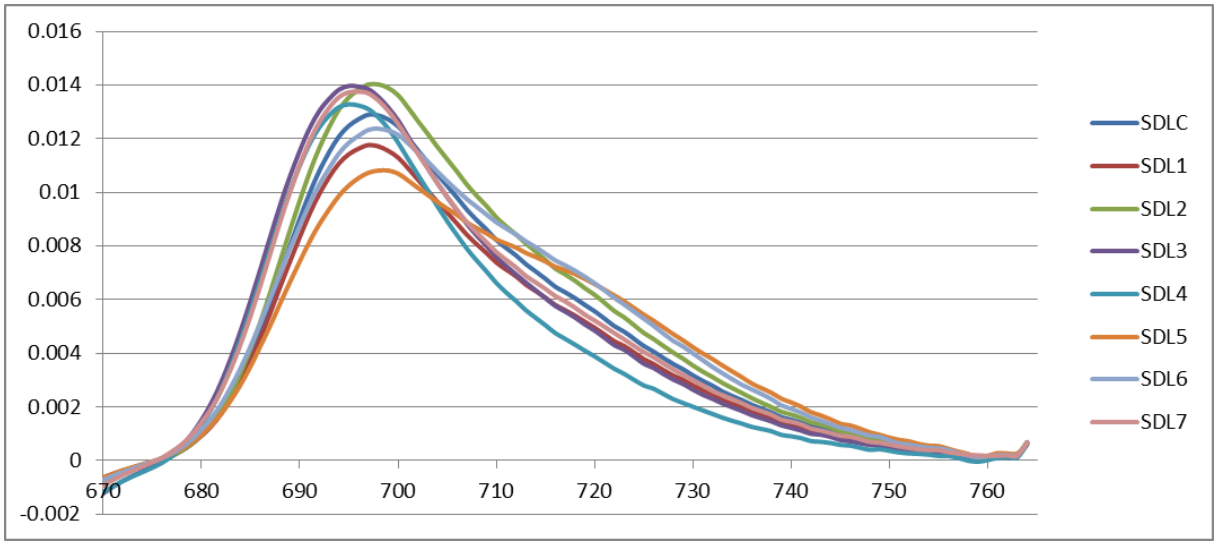

Figure 46 - First derivative reflectance, Kei Apple

Kei Apple (Figure 46) have peaks below 700nm, indicating unhealthy plants, but from the first derivative profiles, it seems as if SDL5 has a profile which is broader than the other plants, suggesting that it might have been healthier.

Because the shrubs were not studied over an extended period, the general trend of the unhealthy plants may indicate that the effect of the TNT contamination is more prevalent closer to its release into the

environment. This supports the idea of a window of opportunity to detect landmines by remote sensing of plants.

Please note that the box plots for sections 5.5.3 to 5.5.7 are included in Appendix A

5.5.3 Normalised difference water index

The normalised difference water index is an indicator of water in plants, as well as a water detection tool. It is a ration between a water sensitive band and a band not sensitive to moisture in plant foliage. Values of between -1 and +1 are expected, with -1 indicating no moisture content and +1 indicating plant foliage moisture.

As per the REP, F and T-tests were performed with the NDWI for trees and shrubs. Tables 10 and 11 respectively represent the results for the F and T-tests for trees, while Tables 12 and 13 show the same for the shrubs.

Again, when considering the F-test for trees, it is found that plants contaminated with 30mg/kg TNT had different values when compared to the control plants. However, the results were mixed, and no clear pattern can be seen. Except for the plants in the range BL, and two plants in the range CL, the null hypothesis is rejected when the T-tests are considered.

Mixed results are also found for the shrubs, with the null hypothesis being both accepted and rejected even for differing concentrations of TNT in the same species. The null hypothesis is rejected outright again considering the T-test.

Table 10 - F-test (two sample for variance) results, NDWI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	0.047269397	0.04706189	0.044119596	0.046706867	0.046640635	-0.048182361
	Variance	0.000625261	0.00108437	0.0004154	0.0007365	0.000286318	0.005548046
	Observations	208	98	98	96	98	22
	df	207	97	97	95	97	21
	F		0.576611776	1.505199894	0.848962437	2.183794623	0.112699262
	P(F<=f) one-tail		0.000540491	0.011847959	0.167675205	1.23243E-05	0
	F Critical one-tail		0.756752215	1.344489802	0.755443298	1.344489802	0.622199166
CL	Mean	0.047269397	0.04706189	0.044119596	0.046706867	0.046640635	-0.048182361
	Variance	0.000625261	0.00108437	0.0004154	0.0007365	0.000286318	0.005548046
	Observations	208	98	98	96	98	22
	df	207	97	97	95	97	21
	F		0.576611776	1.505199894	0.848962437	2.183794623	0.112699262
	P(F<=f) one-tail		0.000540491	0.011847959	0.167675205	1.23243E-05	0
	F Critical one-tail		0.756752215	1.344489802	0.755443298	1.344489802	0.622199166
DL	Mean	0.051028222	0.047326545	0.050645134	0.051228899	0.051835429	0.056284347
	Variance	0.000263344	0.000434395	0.000280828	0.000229439	0.000222141	0.000468639
	Observations	171	81	80	81	89	83
	df	170	80	79	80	88	82
	F		0.606231384	0.937742778	1.147775726	1.185481027	0.56193322
	P(F<=f) one-tail		0.003517115	0.360222307	0.245686728	0.187820503	0.000869879
	F Critical one-tail		0.736053041	0.735223294	1.387319372	1.370945552	0.73766633
EL	Mean	0.041614199	0.042084986	0.050472357	0.045238311	0.053263247	-0.004156258
	Variance	0.001386722	0.00136453	0.000765018	0.001231094	0.001342056	0.003486112
	Observations	158	78	82	84	74	12
	df	157	77	81	83	73	11
	F		1.016263796	1.812665462	1.126414888	1.033282061	0.397784801
	P(F<=f) one-tail		0.476364161	0.00166626	0.275848696	0.445004276	0.006088854
	F Critical one-tail		1.398966676	1.389873523	1.385633902	1.408985738	0.540515214
FL	Mean	0.024401371	0.024520641	0.033324912	0.02580039	0.033474319	0.067273684
	Variance	0.001083963	0.000820228	0.00017008	0.000311943	0.000271206	0.015458389
	Observations	97	72	69	33	89	73
	df	96	71	68	32	88	72
	F		1.321537571	6.373244476	3.474871481	3.996821048	0.070121318
	P(F<=f) one-tail		0.108603832	6.34518E-14	7.91989E-05	1.2951E-10	0
	F Critical one-tail		1.450768168	1.459017356	1.67159077	1.414231175	0.698169939

Table 11 - T-test (two sample assuming unequal variances), NDWI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	0.047269397	0.04706189	0.044119596	0.046706867	0.046640635	-0.048182361
	Variance	0.000625261	0.00108437	0.0004154	0.0007365	0.000286318	0.005548046
	Observations	208	98	98	96	98	22
	Hypothesized Mean Difference		0	0	0	0	0
	df		152	229	172	267	22
	t Stat		0.055318557	1.170223466	0.172148308	0.258252487	5.975195861
	P(T<=t) one-tail		0.477978662	0.121563731	0.43176166	0.398205504	2.58179E-06
	t Critical one-tail		1.654940175	1.651534805	1.653760949	1.650580601	1.717144374
	P(T<=t) two-tail		0.955957324	0.243127461	0.86352332	0.796411008	5.16358E-06
	t Critical two-tail		1.975693928	1.970377283	1.973852169	1.968888622	2.073873068
CL	Mean	0.037298369	0.031915691	0.034158705	0.036880181	0.032858942	0.034259919
	Variance	0.000388372	0.000670533	0.000228152	0.000526325	0.000227908	0.00077662
	Observations	155	86	80	81	80	95
	Hypothesized Mean Difference		0	0	0	0	0
	df		140	200	143	200	152
	t Stat		1.676975253	1.356441535	0.139368881	1.918528931	0.929725509
	P(T<=t) one-tail		0.047889378	0.088243979	0.444677377	0.028233971	0.176993699
	t Critical one-tail		1.655810511	1.652508101	1.655579143	1.652508101	1.654940175
	P(T<=t) two-tail		0.095778757	0.176487958	0.889354753	0.056467941	0.353987398
	t Critical two-tail		1.97705372	1.971896224	1.976692198	1.971896224	1.975693928
DL	Mean	0.051028222	0.047326545	0.050645134	0.051228899	0.051835429	0.056284347
	Variance	0.000263344	0.000434395	0.000280828	0.000229439	0.000222141	0.000468639
	Observations	171	81	80	81	89	83
	Hypothesized Mean Difference		0	0	0	0	0
	df		128	150	167	192	128
	t Stat		1.408905349	0.170465713	-0.095968369	-0.401799654	-1.960710744
	P(T<=t) one-tail		0.0806439	0.432436804	0.46183038	0.344139186	0.026042212
	t Critical one-tail		1.656845226	1.6550755	1.654029128	1.652828589	1.656845226
	P(T<=t) two-tail		0.161287799	0.864873609	0.92366076	0.688278371	0.052084424
	t Critical two-tail		1.97867085	1.975905331	1.974270957	1.972396491	1.97867085
EL	Mean	0.041614199	0.042084986	0.050472357	0.045238311	0.053263247	-0.004156258
	Variance	0.001386722	0.00136453	0.000765018	0.001231094	0.001342056	0.003486112
	Observations	158	78	82	84	74	12
	Hypothesized Mean Difference		0	0	0	0	0
	df		155	209	178	145	12
	t Stat		-0.091852056	-2.081754905	-0.748671724	-2.245497213	2.645708713
	P(T<=t) one-tail		0.463467094	0.019291289	0.227521613	0.013124397	0.010673775
	t Critical one-tail		1.654743774	1.652177009	1.653459126	1.655430251	1.782287556
	P(T<=t) two-tail		0.926934188	0.038582578	0.455043226	0.026248793	0.02134755
	t Critical two-tail		1.975387131	1.971379462	1.973380889	1.976459563	2.17881283
FL	Mean	0.024401371	0.024520641	0.033324912	0.02580039	0.033474319	0.067273684
	Variance	0.001083963	0.000820228	0.00017008	0.000311943	0.000271206	0.015458389
	Observations	97	72	69	33	89	73
	Hypothesized Mean Difference		0	0	0	0	0
	df		163	134	104	144	80
	t Stat		-0.025106938	-2.416201643	-0.308033553	-2.405836227	-2.871369756
	P(T<=t) one-tail		0.490000188	0.008515256	0.379336443	0.008702121	0.002614438
	t Critical one-tail		1.654255585	1.656304542	1.659637437	1.655504177	1.664124579
	P(T<=t) two-tail		0.980000377	0.017030511	0.758672887	0.017404242	0.005228877
	t Critical two-tail		1.974624621	1.977825758	1.983037526	1.976575066	1.990063421

Table 12 - F-test (two sample for variance) results, NDWI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	0.043477706	0.03174739	0.038084843	0.034563351	0.051846208	0.03115854
	Variance	0.001215997	0.001243545	0.001526692	0.000854423	0.001959391	0.000841491
	Observations	67	34	34	34	26	34
	df	66	33	33	33	25	33
	F		0.977847382	0.796491575	1.423180335	0.620599638	1.445050406
	P(F<=f) one-tail		0.45715565	0.213859896	0.134408282	0.063681708	0.124285464
	F Critical one-tail		0.62026433	0.62026433	1.69223579	0.597599661	1.69223579
SBL	Mean	0.25449143	0.238788561	0.23640054	0.252788875	0.255829026	0.200302469
	Variance	0.002123207	0.004663216	0.008011977	0.002336512	0.003846383	0.005778848
	Observations	66	31	34	32	31	28
	df	65	30	33	31	30	27
	F		0.455309527	0.265004071	0.908707645	0.552000826	0.367409977
	P(F<=f) one-tail		0.004153007	2.42887E-06	0.36441711	0.023329522	0.000518984
	F Critical one-tail		0.611791438	0.619231816	0.614387171	0.611791438	0.60319704
SCL	Mean	0.050962633	0.051702948	0.060160023	0.050297432	0.039189178	0.066682461
	Variance	0.001123783	0.000667394	0.000887524	0.0006651	0.001397485	0.000683834
	Observations	56	31	24	24	24	20
	df	55	30	23	23	23	19
	F		1.683835667	1.266200149	1.689644463	0.804146515	1.643356018
	P(F<=f) one-tail		0.062469423	0.271582614	0.084136656	0.250351432	0.116301449
	F Critical one-tail		1.749331453	1.873976147	1.873976147	0.578887635	1.988234971
SDL	Mean	0.029718059	0.031127356	0.036745647	0.04598988	0.018339708	0.027076356
	Variance	0.00136213	0.000794738	0.004066401	0.002090538	0.001380363	0.001008737
	Observations	65	32	24	32	20	24
	df	64	31	23	31	19	23
	F		1.713935911	0.334971768	0.651569014	0.986790624	1.350331771
	P(F<=f) one-tail		0.051008342	0.000301057	0.074592516	0.459044315	0.213992814
	F Critical one-tail		1.719525158	0.588471294	0.613351431	0.570978698	1.858509008

Table 13 - T-test (two sample assuming unequal variances), NDWI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	706.641791	702.9117647	704.2352941	704.8235294	703.1538462	699.6764706
	Variance	46.29398462	59.23440285	47.51871658	43.36185383	58.61538462	352.1648841
	Observations	67	34	34	34	26	34
	Hypothesized Mean Difference		0	0	0	0	0
	df		60	66	68	41	37
	t Stat		2.391266907	1.665180766	1.296674839	2.032347649	2.095485273
	P(T<=t) one-tail		0.009971582	0.050308572	0.099563019	0.024315205	0.021514379
	t Critical one-tail		1.670648865	1.668270514	1.667572281	1.682878002	1.68709362
	P(T<=t) two-tail		0.019943164	0.100617143	0.199126038	0.04863041	0.043028758
	t Critical two-tail		2.000297822	1.996564419	1.995468931	2.01954097	2.026192463
SBL	Mean	689.2272727	672.2580645	690.7941176	676.53125	686.8709677	683.25
	Variance	242.1783217	1334.864516	390.5926916	1949.289315	303.3827957	318.9351852
	Observations	66	31	34	32	31	28
	Hypothesized Mean Difference		0	0	0	0	0
	df		35	55	35	53	45
	t Stat		2.48236675	-0.402451748	1.579803253	0.64235478	1.54025232
	P(T<=t) one-tail		0.008997786	0.344455763	0.061574122	0.261705934	0.065251023
	t Critical one-tail		1.689572458	1.673033965	1.689572458	1.674116237	1.679427393
	P(T<=t) two-tail		0.017995572	0.688911527	0.123148243	0.523411869	0.130502046
	t Critical two-tail		2.030107928	2.004044783	2.030107928	2.005745995	2.014103389
SCL	Mean	715.5	716.1290323	713.4166667	715.0416667	711.2083333	717.1
	Variance	16.69090909	19.91612903	31.47101449	12.5634058	20.60688406	4.726315789
	Observations	56	31	24	24	24	20
	Hypothesized Mean Difference		0	0	0	0	0
	df		58	34	50	40	63
	t Stat		-0.648622089	1.642231169	0.505673823	3.990440593	-2.188768691
	P(T<=t) one-tail		0.259571319	0.054880385	0.307653885	0.000136839	0.016163971
	t Critical one-tail		1.671552762	1.690924255	1.675905025	1.683851013	1.669402222
	P(T<=t) two-tail		0.519142638	0.10976077	0.615307771	0.000273677	0.032327942
	t Critical two-tail		2.001717484	2.032244509	2.008559112	2.02107539	1.998340543
SDL	Mean	707.4615385	701.46875	699.375	709.4516129	708.45	702.7916667
	Variance	39.65865385	72.96673387	66.85326087	41.98924731	42.05	98.7807971
	Observations	65	32	24	31	20	24
	Hypothesized Mean Difference		0	0	0	0	0
	df		48	34	58	31	30
	t Stat		3.524960162	4.388326328	-1.419807581	-0.600156127	2.148117898
	P(T<=t) one-tail		0.000471142	5.25154E-05	0.080508275	0.276382268	0.019950343
	t Critical one-tail		1.677224196	1.690924255	1.671552762	1.695518783	1.697260887
	P(T<=t) two-tail		0.000942284	0.000105031	0.16101655	0.552764536	0.039900686
	t Critical two-tail		2.010634758	2.032244509	2.001717484	2.039513446	2.042272456

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The normalised difference water index (NDWI) values for Wild Olive (Figure A-1) show that the differences between plants are much less obvious compared to the REP. There is only a marginal difference in values between readings, considering the NDWI has a range between -1 and 1. All plants have a median value of around 0.05, but what is interesting to note is that BL3 (30mg/kg) has a much broader distribution of values than any of the other samples. Also, outliers are present in readings for all Wild Olive samples.

The same is seen in Figure A-2, representing the NDWI values for River Bushwillow. Outliers are present for all plants, and all plants have similar distribution profiles of values. CL3, CL5 and CL7 (30mg/kg, 600mg/kg and 5000mg/kg respectively) have wider distributions than the other plants. The magnitude of the distributions is small enough to mean the differences are insignificant.

Similar lack of trend is visible for Soap Dogwood (Figure A-3), Sweet Thorn (Figure A-4) and White Stinkwood (Figure A-5). All values are between -0.25 and 0.25, which may indicate plants were watered regularly, but also had adverse health effects due to the drought and subsequent water shortages.

This lack of significant value differences for the NDWI in the tree samples means that TNT does likely not have a major influence on the water uptake of the trees used for the study.

The box plots for the shrubs show mixed results when compared to one another. As with the trees, it is noted that the magnitude of the distribution is small, and may be unsuitable for a landmine detection tool in shrubs.

The other indices for Transvaal Honey-bell Bush have largely mixed results or marginal differences in values. Figure A-6, the NDWI box plot for Transvaal Honey-bell Bush, show that the contaminated plants have median values lower than that of the control plants, as well as lower maximum values.

The NDWI values for Spekboom (Figure A-7) have a decreasing trend for the minimum values with an increase in TNT concentration. Also, the median value increases with an increase in TNT concentration, except for SDL7 (500mg/kg), where the all values tend to be significantly lower than for the other plants. Most of the contaminated plants have broader NDWI value distributions than the uncontaminated samples, indicating that the TNT may make the water uptake capability of a plant more varied.

Figure A-8, which represents the NDWI for Natal Plum shows the familiar pattern, with small distributions and outliers. SCL6 (1200mg/kg) has a profile, unlike the other plants, with a wide value distribution. Whether TNT caused this is doubtful, because SCL7, which had a dose of 5000mg/kg TNT showed a small distribution of values, and a higher median compared to the other plants. A different

profile exists even between the control specimens, but all plants, have medians values between 0.04 and 0.07, meaning the difference is very small.

Kei Apple (Figure A-9) follows suit, with a small range of values, and outliers. Most notable of the profiles are SDL4 and SDL6, 300mg/kg and 600mg/kg TNT respectively. They have a larger distribution range than the other plants. Due to the relatively major difference in profiles of the control plants, the influence of TNT causing the differences in the pattern is, again, doubtful.

5.5.4 Moisture stress index

The moisture stress index is used to detect stress in plants induced by lack of moisture, or drought. It is an alternative to the water-band index.

Table 14 and 15 represents the F-test and T-test values, respectively, for trees, while tables 16 and 17 represent that of the shrubs.

Again, a high variability in the outcome of the tests cast doubt whether the tests can measure the differences in readings accurately. As in the case of the NDWI, it is also noteworthy that the drought and water shortage may have induced moisture stress in the plants.

Table 14 - F-test (two sample for variance) results, MSI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	0.504289538	0.477540291	0.539176126	0.509075816	0.504847388	0.860841229
	Variance	0.008708944	0.016995357	0.002136569	0.009692916	0.003121288	0.071960731
	Observations	208	98	98	96	98	22
	df	207	97	97	95	97	21
	F		0.512430791	4.076136273	0.898485458	2.790176569	0.121023568
	P(F<=f) one-tail		3.41532E-05	2.67048E-13	0.262606754	2.6993E-08	0
	F Critical one-tail		0.756752215	1.344489802	0.755443298	1.344489802	0.622199166
CL	Mean	0.631772777	0.647219687	0.636401523	0.645209789	0.651456618	0.656409074
	Variance	0.008281428	0.015768945	0.002191704	0.008620645	0.004446416	0.007967766
	Observations	155	86	80	81	80	95
	df	154	85	79	80	79	94
	F		0.525173273	3.778533249	0.960650625	1.862495287	1.039366374
	P(F<=f) one-tail		0.0002706	3.96568E-10	0.410401157	0.001233063	0.423524672
	F Critical one-tail		0.735320764	1.395509287	0.731499402	1.395509287	1.366591725
DL	Mean	0.520568502	0.534191618	0.524773902	0.509264	0.519430482	0.521331644
	Variance	0.002197001	0.005552531	0.003305473	0.001540107	0.002664357	0.006220468
	Observations	171	81	80	81	89	83
	df	170	80	79	80	88	82
	F		0.395675544	0.664655471	1.426524452	0.824589406	0.353188952
	P(F<=f) one-tail		2.2889E-07	0.014361759	0.037268113	0.143205686	5.74656E-09
	F Critical one-tail		0.736053041	0.735223294	1.387319372	0.742167055	0.73766633
EL	Mean	0.575164475	0.5702455	0.542895877	0.580145635	0.541115483	0.727699062
	Variance	0.005498701	0.006638576	0.004342396	0.007452313	0.006563804	0.047020924
	Observations	158	78	82	84	74	12
	df	157	77	81	83	73	11
	F		0.828295179	1.266282642	0.73785155	0.837730761	0.116941571
	P(F<=f) one-tail		0.161709034	0.11886757	0.052350426	0.180031772	9.85334E-12
	F Critical one-tail		0.729931034	1.389873523	0.734764572	0.726378467	0.540515214
FL	Mean	0.665790664	0.67178308	0.637773515	0.660356287	0.642226213	0.620651306
	Variance	0.004857079	0.003160849	0.001369756	0.001693807	0.00110256	0.016751685
	Observations	97	72	69	33	89	73
	df	96	71	68	32	88	72
	F		1.536637768	3.545945329	2.867551982	4.405273224	0.289945721
	P(F<=f) one-tail		0.028956107	6.66733E-08	0.000579376	8.51972E-12	1.07627E-08
	F Critical one-tail		1.450768168	1.459017356	1.67159077	1.414231175	0.698169939

Table 15 - T-test (two sample assuming unequal variances), MSI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	0.504289538	0.477540291	0.539176126	0.509075816	0.504847388	0.860841229
	Variance	0.008708944	0.016995357	0.002136569	0.009692916	0.003121288	0.071960731
	Observations	208	98	98	96	98	22
	Hypothesized Mean Difference		0	0	0	0	0
	df		146	303	176	287	22
	t Stat		1.8230462	-4.372053426	-0.400475869	-0.064971896	-6.19475437
	P(T<=t) one-tail		0.035171022	8.46973E-06	0.344645875	0.474120805	1.55071E-06
	t Critical one-tail		1.655357345	1.649898073	1.653557435	1.650180211	1.717144374
	P(T<=t) two-tail		0.070342044	1.69395E-05	0.68929175	0.948241609	3.10142E-06
	t Critical two-tail		1.976345655	1.967824098	1.973534388	1.968264113	2.073873068
CL	Mean	0.631772777	0.647219687	0.636401523	0.645209789	0.651456618	0.656409074
	Variance	0.008281428	0.015768945	0.002191704	0.008620645	0.004446416	0.007967766
	Observations	155	86	80	81	80	95
	Hypothesized Mean Difference		0	0	0	0	0
	df		135	233	160	206	202
	t Stat		-1.003832849	-0.514861908	-1.062766402	-1.885294153	-2.102521719
	P(T<=t) one-tail		0.158627538	0.303568793	0.144744656	0.030398873	0.018373163
	t Critical one-tail		1.656219133	1.651419647	1.654432901	1.652284144	1.652431964
	P(T<=t) two-tail		0.317255076	0.607137586	0.289489311	0.060797747	0.036746326
	t Critical two-tail		1.977692277	1.970197599	1.97490156	1.971546669	1.971777385
DL	Mean	0.520568502	0.534191618	0.524773902	0.509264	0.519430482	0.521331644
	Variance	0.002197001	0.005552531	0.003305473	0.001540107	0.002664357	0.006220468
	Observations	171	81	80	81	89	83
	Hypothesized Mean Difference		0	0	0	0	0
	df		111	130	185	164	111
	t Stat		-1.509977069	-0.571402869	2.0027072	0.173982914	-0.081446915
	P(T<=t) one-tail		0.066945358	0.284356581	0.023334444	0.431046733	0.467616609
	t Critical one-tail		1.658697265	1.656659413	1.653131869	1.654197929	1.658697265
	P(T<=t) two-tail		0.133890716	0.568713162	0.046668888	0.862093466	0.935233218
	t Critical two-tail		1.981566757	1.978380405	1.972869946	1.974534576	1.981566757
EL	Mean	0.575164475	0.5702455	0.542895877	0.580145635	0.541115483	0.727699062
	Variance	0.005498701	0.006638576	0.004342396	0.007452313	0.006563804	0.047020924
	Observations	158	78	82	84	74	12
	Hypothesized Mean Difference		0	0	0	0	0
	df		141	182	149	132	11
	t Stat		0.449203899	3.444584515	-0.448189868	3.063848795	-2.426013785
	P(T<=t) one-tail		0.326987134	0.000354967	0.327333602	0.001324785	0.016823257
	t Critical one-tail		1.655732287	1.653269024	1.655144534	1.65647927	1.795884819
	P(T<=t) two-tail		0.653974267	0.000709934	0.654667203	0.002649571	0.033646514
	t Critical two-tail		1.976931489	1.973084077	1.976013178	1.978098842	2.20098516
FL	Mean	0.665790664	0.67178308	0.637773515	0.660356287	0.642226213	0.620651306
	Variance	0.004857079	0.003160849	0.001369756	0.001693807	0.00110256	0.016751685
	Observations	97	72	69	33	89	73
	Hypothesized Mean Difference		0	0	0	0	0
	df		166	153	95	140	103
	t Stat		-0.618157207	3.350496642	0.539671786	2.981616669	2.69977198
	P(T<=t) one-tail		0.268659455	0.00050806	0.295343067	0.001691355	0.004056132
	t Critical one-tail		1.654084713	1.654873847	1.661051817	1.655810511	1.659782273
	P(T<=t) two-tail		0.53731891	0.001016119	0.590686133	0.00338271	0.008112264
	t Critical two-tail		1.974357764	1.975590315	1.985251004	1.97705372	1.983264145

Table 16 - F-test (two sample for variance) results, MSI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	0.584033106	0.613310067	0.609833583	0.604930912	0.590183654	0.617883858
	Variance	0.005657417	0.007868787	0.009495092	0.008240813	0.006893074	0.00665544
	Observations	67	34	34	34	26	34
	df	66	33	33	33	25	33
	F		0.71896948	0.595825435	0.686512009	0.820739337	0.850044054
	P(F<=f) one-tail		0.127138734	0.037288932	0.097244192	0.257931187	0.282919817
	F Critical one-tail		0.62026433	0.62026433	0.62026433	0.597599661	0.62026433
SBL	Mean	0.214347276	0.232186189	0.264293955	0.211713965	0.218988795	0.250296122
	Variance	0.00161217	0.005741976	0.052353513	0.002513577	0.003411493	0.008308574
	Observations	66	31	34	32	31	28
	df	65	30	33	31	30	27
	F		0.280769211	0.030793923	0.64138491	0.472570223	0.194036903
	P(F<=f) one-tail		9.29587E-06	0	0.066777496	0.005978866	3.26365E-08
	F Critical one-tail		0.611791438	0.619231816	0.614387171	0.611791438	0.60319704
SCL	Mean	0.487951518	0.479423312	0.435238692	0.473058157	0.495890153	0.427662919
	Variance	0.014803349	0.013300926	0.010050459	0.008244837	0.009151626	0.012774569
	Observations	56	31	24	24	24	20
	df	55	30	23	23	23	19
	F		1.112956303	1.472902776	1.795468974	1.617564893	1.158814007
	P(F<=f) one-tail		0.382852299	0.154787763	0.06238386	0.103142159	0.373475532
	F Critical one-tail		1.749331453	1.873976147	1.873976147	1.873976147	1.988234971
SDL	Mean	0.649053898	0.628503678	0.653881856	0.60377009	0.675044156	0.64977564
	Variance	0.009189365	0.004490039	0.007267275	0.004905343	0.005624959	0.00881127
	Observations	65	32	24	32	20	24
	df	64	31	23	31	19	23
	F		2.046611173	1.264485651	1.873337937	1.63367684	1.042910371
	P(F<=f) one-tail		0.015537818	0.270558902	0.028832241	0.116582924	0.473372515
	F Critical one-tail		1.719525158	1.858509008	1.719525158	1.973522215	1.858509008

Table 17 - T-test (two sample assuming unequal variances), MSI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	0.584033106	0.613310067	0.609833583	0.604930912	0.590183654	0.617883858
	Variance	0.005657417	0.007868787	0.009495092	0.008240813	0.006893074	0.00665544
	Observations	67	34	34	34	26	34
	Hypothesized Mean Difference		0	0	0	0	0
	df		58	54	57	42	62
	t Stat		-1.647286266	-1.352858003	-1.155976728	-0.328968764	-2.022293096
	P(T<=t) one-tail		0.052453575	0.090869204	0.12625652	0.371907054	0.023732893
	t Critical one-tail		1.671552762	1.673564906	1.672028888	1.681952357	1.669804163
	P(T<=t) two-tail		0.104907151	0.181738409	0.252513041	0.743814108	0.047465786
	t Critical two-tail		2.001717484	2.004879288	2.002465459	2.018081703	1.998971517
SBL	Mean	0.214347276	0.232186189	0.264293955	0.211713965	0.218988795	0.250296122
	Variance	0.00161217	0.005741976	0.052353513	0.002513577	0.003411493	0.008308574
	Observations	66	31	34	32	31	28
	Hypothesized Mean Difference		0	0	0	0	0
	df		38	34	51	44	32
	t Stat		-1.232023646	-1.262860763	0.259497961	-0.400257431	-2.005963984
	P(T<=t) one-tail		0.112754801	0.107615869	0.398147862	0.345451835	0.026687842
	t Critical one-tail		1.68595446	1.690924255	1.67528495	1.680229977	1.693888748
	P(T<=t) two-tail		0.225509602	0.215231739	0.796295723	0.690903671	0.053375683
	t Critical two-tail		2.024394164	2.032244509	2.00758377	2.015367574	2.036933343
SCL	Mean	0.487951518	0.479423312	0.435238692	0.473058157	0.495890153	0.427662919
	Variance	0.014803349	0.013300926	0.010050459	0.008244837	0.009151626	0.012774569
	Observations	56	31	24	24	24	20
	Hypothesized Mean Difference		0	0	0	0	0
	df		65	52	58	55	36
	t Stat		0.323864528	2.016830943	0.604064958	-0.312422825	2.00619679
	P(T<=t) one-tail		0.3735402	0.02444514	0.274078024	0.377950342	0.02619666
	t Critical one-tail		1.668635976	1.674689154	1.671552762	1.673033965	1.688297714
	P(T<=t) two-tail		0.747080401	0.04889028	0.548156048	0.755900683	0.052393321
	t Critical two-tail		1.997137908	2.006646805	2.001717484	2.004044783	2.028094001
SDL	Mean	0.649053898	0.628503678	0.653881856	0.60455392	0.675044156	0.64977564
	Variance	0.009189365	0.004490039	0.007267275	0.005048538	0.005624959	0.00881127
	Observations	65	32	24	31	20	24
	Hypothesized Mean Difference		0	0	0	0	0
	df		84	46	77	40	42
	t Stat		1.224424096	-0.229078855	2.55127995	-1.264253399	-0.032006006
	P(T<=t) one-tail		0.112107585	0.409911547	0.006357521	0.106728287	0.48730944
	t Critical one-tail		1.663196679	1.678660414	1.664884537	1.683851013	1.681952357
	P(T<=t) two-tail		0.22421517	0.819823095	0.012715042	0.213456573	0.974618879
	t Critical two-tail		1.988609667	2.012895599	1.991254395	2.02107539	2.018081703

When comparing plots for the moisture stress index (MSI) for Wild Olive (Figure A-10), varying patterns are seen. There is a difference in distribution even for the control plants. BL3 (30mg/kg) has a lower first and third quartile distribution than any of the other plants, as well as a lower median, but it has a similar maximum to the control plant, BL2. This indicates that exposure to a small dosage of TNT may reduce water stress found in these plants.

Conversely, BL4 (300mg/k) shows a jump in the MSI values, as it has the highest first and third quartile distribution, as well as the highest median of the surviving plants. It also has a similar difference between maximum and minimum values to BL1, a control plant. BL5 and BL6 (600mg/kg and 1200mg/kg) show similar patterns to the control plants, possibly indicating that the TNT has little effect on plant moisture stress at these concentrations.

BL7 showed extremely high MSI values before dying out, which may shed light on the reason for the plant dying.

A moisture stress index of between 0.4 and 1.2 is expected for healthy vegetation, and from the profiles for Wild Olive, it is seen that most these readings fall within this range.

For River Bushwillow (Figure A-11), a small distribution magnitude is perceived for all plants, with a higher variation in distribution between CL1 and CL2, the control plants. Although there are some outliers, especially with CL3, most MSI readings for this species fall within the normal range, and thus it seems unlikely that the TNT influenced the water uptake of the species.

The pattern continues with Soap Dogwood (Figure A-12), where the distribution of MSI values for all TNT concentrations have a similar range and a similar median value. All plants, even with outliers are in the lower normal range.

Sweet Thorn (Figure A-13) and White Stinkwood (Figure A-14) show MSI readings for all plants in the normal range. FL7 (5000mg/kg) has several outliers beyond the lower extreme of the normal range, but these may have been due to a plant-specific reason rather than due to the TNT. EL7 also has a wide distribution of values, but this may be due to a reduced number of readings.

The MSI for the Transvaal Honey-bell Bush (Figure A-15) showed higher medium and third quartile values for all contaminated plants in comparison to the control plants. Furthermore, there was a large difference between the distributions of values for control plants. There is also a decreasing trend in maximum values from SAL3 (30mg/kg) toward SAL7 (5000mg/kg). None of the plants have MSI values beyond the normal thresholds.

MSI values for Spekboom (Figure A-16) show an increasing trend for maximums of contaminated plants, which is more prominent than the differences in values for the control plants. The magnitude of differences is small, with the median values for all plants ranging around 0.2. This indicates that the plants may have been under moisture stress during the study. As stated previously, Spekboom is a succulent, and the plants were watered on a regular basis, meaning the species may have received more water than it would have under natural conditions.

Natal Plum (Figure A-17) had values with small ranges, but SCL4 (300mg/kg) has a dip in values, there is a slight positive increase in general profiles at SCL5 and SCL6 (600mg/kg and 1200mg/kg) respectively. SCL7 has the lowest median values, as well as a small profile. Most values for this species is within the normal threshold.

Figure A-18, representing Kei Apple, shows a lower median MSI value for SDL3 (30mg/kg) and SDL5 (600mg/kg). Conversely, SDL4 (300mg/kg), SDL6 (1200mg/kg) have higher median values, but not significantly different from the control species. All plants have values within the normal range, even the outliers.

5.5.5 Water-band index

The water-band index can be used to detect plant stress caused by drought or lack of watering, similar to the moisture stress index.

Tables 18 and 19 displays the F and T-tests respectively for trees and tables 20 and 21 show the same tests for shrubs.

For the water-band index, values of between 0.8 and 1.2 are expected for typical vegetation, where values below 0.8 indicate a low plant moisture, and values of higher than 1.2 indicate extreme plant moisture.

From the tables below, it can be seen that all trees and all shrubs have values within the normal threshold, except for the Spekboom control plants. The control plants fall close enough to the normal range that when rounded, it would be normal.

Table 18 - F-test (two sample for variance) results, WBI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	0.964813579	0.960261932	0.966674823	0.965787454	0.963508153	1.034814647
	Variance	0.000141809	0.000238047	6.58704E-05	0.000115502	5.43787E-05	0.002298405
	Observations	208	98	98	96	98	22
	df	207	97	97	95	97	21
	F		0.595719616	2.152856907	1.227766436	2.607813977	0.061699068
	P(F<=f) one-tail		0.001062371	1.69697E-05	0.128898368	1.639E-07	0
	F Critical one-tail		0.756752215	1.344489802	1.347744645	1.344489802	0.622199166
CL	Mean	0.975570954	0.978889285	0.977402193	0.977013467	0.978497354	0.977878569
	Variance	0.000120174	0.000226472	6.1275E-05	0.000114795	8.37728E-05	0.00017546
	Observations	155	86	80	81	80	95
	df	154	85	79	80	79	94
	F		0.530636191	1.961222337	1.0468538	1.434522841	0.684909223
	P(F<=f) one-tail		0.000332767	0.000540795	0.415561288	0.037580483	0.018720736
	F Critical one-tail		0.735320764	1.395509287	1.393268015	1.395509287	0.741393569
DL	Mean	0.96228492	0.964389387	0.9633327	0.962249491	0.963542663	0.96295581
	Variance	3.76048E-05	7.60803E-05	8.31842E-05	3.19598E-05	6.38135E-05	0.000135344
	Observations	171	81	80	81	89	83
	df	170	80	79	80	88	82
	F		0.494277903	0.452066573	1.176628147	0.589291702	0.277845899
	P(F<=f) one-tail		6.83138E-05	8.85653E-06	0.207569304	0.001711683	9.74554E-13
	F Critical one-tail		0.736053041	0.735223294	1.387319372	0.742167055	0.73766633
EL	Mean	0.970524469	0.969709973	0.966211665	0.971956124	0.96649521	0.995174952
	Variance	7.13102E-05	0.000100227	7.74449E-05	0.000114952	0.000101797	0.000773163
	Observations	158	78	82	84	74	12
	df	157	77	81	83	73	11
	F		0.711487311	0.920786142	0.62034765	0.700513248	0.092231815
	P(F<=f) one-tail		0.037638324	0.327051711	0.005340223	0.033487388	9.99201E-15
	F Critical one-tail		0.729931034	0.73321421	0.734764572	0.726378467	0.540515214
FL	Mean	0.979713975	0.979978841	0.978312715	0.979346012	0.978658365	0.968953917
	Variance	0.000117534	2.86919E-05	4.58856E-05	8.8341E-06	1.20439E-05	0.001722666
	Observations	97	72	69	33	89	73
	df	96	71	68	32	88	72
	F		4.096423311	2.561456533	13.30457747	9.75881615	0.068227928
	P(F<=f) one-tail		1.61208E-09	3.20827E-05	1.995E-12	3.92684E-23	0
	F Critical one-tail		1.450768168	1.459017356	1.67159077	1.414231175	0.698169939

Table 19 - T-test (two sample assuming unequal variances), WBI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	0.964813579	0.960261932	0.966674823	0.965787454	0.963508153	1.034814647
	Variance	0.000141809	0.000238047	6.58704E-05	0.000115502	5.43787E-05	0.002298405
	Observations	208	98	98	96	98	22
	Hypothesized Mean Difference		0	0	0	0	0
	df		153	266	203	282	21
	t Stat		2.580657741	-1.599581768	-0.709343761	1.173888662	-6.826377015
	P(T<=t) one-tail		0.005400614	0.055439219	0.239462544	0.12071503	4.74411E-07
	t Critical one-tail		1.654873847	1.650602207	1.65239446	1.650274966	1.720742903
	P(T<=t) two-tail		0.010801227	0.110878437	0.478925088	0.24143006	9.48822E-07
	t Critical two-tail		1.975590315	1.968922324	1.971718848	1.968411901	2.079613845
CL	Mean	0.975570954	0.978889285	0.977402193	0.977013467	0.978497354	0.977878569
	Variance	0.000120174	0.000226472	6.1275E-05	0.000114795	8.37728E-05	0.00017546
	Observations	155	86	80	81	80	95
	Hypothesized Mean Difference		0	0	0	0	0
	df		136	210	166	187	171
	t Stat		-1.797318348	-1.47505455	-0.974194613	-2.167718288	-1.425034676
	P(T<=t) one-tail		0.037252009	0.070847773	0.165688694	0.015721902	0.077984902
	t Critical one-tail		1.656134988	1.652141981	1.654084713	1.653042889	1.653813324
	P(T<=t) two-tail		0.074504017	0.141695545	0.331377388	0.031443804	0.155969804
	t Critical two-tail		1.977560777	1.971324793	1.974357764	1.972731033	1.973933954
DL	Mean	0.96228492	0.964389387	0.9633327	0.962249491	0.963542663	0.96295581
	Variance	3.76048E-05	7.60803E-05	8.31842E-05	3.19598E-05	6.38135E-05	0.000135344
	Observations	171	81	80	81	89	83
	Hypothesized Mean Difference		0	0	0	0	0
	df		119	114	169	143	105
	t Stat		-1.954645525	-0.93354295	0.045196055	-1.299395695	-0.49317341
	P(T<=t) one-tail		0.026485049	0.176256396	0.482002199	0.097949566	0.311459967
	t Critical one-tail		1.657759285	1.658329969	1.653919942	1.655579143	1.659495383
	P(T<=t) two-tail		0.052970097	0.352512793	0.964004399	0.195899132	0.622919934
	t Critical two-tail		1.980099876	1.980992298	1.974100447	1.976692198	1.982815274
EL	Mean	0.970524469	0.969709973	0.966211665	0.971956124	0.96649521	0.995174952
	Variance	7.13102E-05	0.000100227	7.74449E-05	0.000114952	0.000101797	0.000773163
	Observations	158	78	82	84	74	12
	Hypothesized Mean Difference		0	0	0	0	0
	df		133	158	139	123	11
	t Stat		0.618126783	3.650490396	-1.061269849	2.98098581	-3.060305816
	P(T<=t) one-tail		0.268774416	0.000177655	0.145203883	0.001732038	0.005423018
	t Critical one-tail		1.656391244	1.654554875	1.655889868	1.657336397	1.795884819
	P(T<=t) two-tail		0.537548832	0.000355309	0.290407766	0.003464076	0.010846037
	t Critical two-tail		1.977961264	1.975092073	1.977177724	1.979438685	2.20098516
FL	Mean	0.979713975	0.979978841	0.978312715	0.979346012	0.978658365	0.968953917
	Variance	0.000117534	2.86919E-05	4.58856E-05	8.8341E-06	1.20439E-05	0.001722666
	Observations	97	72	69	33	89	73
	Hypothesized Mean Difference		0	0	0	0	0
	df		148	162	125	117	79
	t Stat		-0.208731807	1.022871829	0.302525442	0.9095305	2.160242159
	P(T<=t) one-tail		0.417472305	0.153946732	0.381377185	0.182470006	0.016892574
	t Critical one-tail		1.655214506	1.654313957	1.657135178	1.657981659	1.664371409
	P(T<=t) two-tail		0.834944611	0.307893463	0.762754371	0.364940012	0.033785147
	t Critical two-tail		1.976122494	1.974715786	1.979124109	1.980447599	1.99045021

Table 20 - F-test (two sample for variance) results, WBI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	0.96658227	0.970051109	0.970773603	0.970111141	0.969598142	0.972730935
	Variance	7.75994E-05	7.7103E-05	0.000109381	0.000117115	9.29925E-05	0.000119675
	Observations	67	34	34	34	26	34
	df	66	33	33	33	25	33
	F		1.006437352	0.709443605	0.662590473	0.834469287	0.648417906
	P(F<=f) one-tail		0.504965293	0.117927261	0.078008684	0.274671912	0.067770281
	F Critical one-tail		1.69223579	0.62026433	0.62026433	0.597599661	0.62026433
SBL	Mean	0.797881853	0.811512696	0.812288546	0.800653632	0.800771217	0.840693935
	Variance	0.001105146	0.002031481	0.004796859	0.000731003	0.001860869	0.002335856
	Observations	66	31	34	32	31	28
	df	65	30	33	31	30	27
	F		0.544010348	0.2303896	1.511821682	0.593887384	0.473122629
	P(F<=f) one-tail		0.020755092	2.23115E-07	0.103898871	0.040568045	0.007329742
	F Critical one-tail		0.611791438	0.619231816	1.717938043	0.611791438	0.60319704
SCL	Mean	0.960778332	0.959416817	0.955230938	0.959826127	0.963396555	0.950841062
	Variance	0.000268603	0.000148288	0.000158726	0.000120942	0.000243194	0.00024851
	Observations	56	31	24	24	24	20
	df	55	30	23	23	23	19
	F		1.811361712	1.692248902	2.22092663	1.104484488	1.080854211
	P(F<=f) one-tail		0.04047545	0.08351929	0.019122833	0.408709819	0.443375635
	F Critical one-tail		1.749331453	1.873976147	1.873976147	1.873976147	1.988234971
SDL	Mean	0.977364185	0.973291514	0.976020008	0.972043585	0.97649841	0.97816934
	Variance	9.96772E-05	6.03936E-05	2.24408E-05	4.42385E-05	5.16204E-05	0.000177747
	Observations	65	32	24	32	20	24
	df	64	31	23	31	19	23
	F		1.650459192	4.441779621	2.253176544	1.930966078	0.560779802
	P(F<=f) one-tail		0.063959988	0.000102906	0.007508415	0.055517595	0.036362793
	F Critical one-tail		1.719525158	1.858509008	1.719525158	1.973522215	0.588471294

Table 21 - T-test (two sample assuming unequal variances), WBI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	0.96658227	0.970051109	0.970773603	0.970111141	0.969598142	0.972730935
	Variance	7.75994E-05	7.7103E-05	0.000109381	0.000117115	9.29925E-05	0.000119675
	Observations	67	34	34	34	26	34
	Hypothesized Mean Difference		0	0	0	0	0
	df		67	57	56	42	55
	t Stat		-1.874107794	-2.003776884	-1.644850482	-1.385991466	-2.842813222
	P(T<=t) one-tail		0.032638293	0.024927561	0.052801598	0.086532346	0.003131877
	t Critical one-tail		1.667916114	1.672028888	1.672522303	1.681952357	1.673033965
	P(T<=t) two-tail		0.065276585	0.049855121	0.105603197	0.173064693	0.006263755
	t Critical two-tail		1.996008354	2.002465459	2.003240719	2.018081703	2.004044783
SBL	Mean	0.797881853	0.811512696	0.812288546	0.800653632	0.800771217	0.840693935
	Variance	0.001105146	0.002031481	0.004796859	0.000731003	0.001860869	0.002335856
	Observations	66	31	34	32	31	28
	Hypothesized Mean Difference		0	0	0	0	0
	df		46	41	74	47	38
	t Stat		-1.502745352	-1.146756587	-0.440528565	-0.329760724	-4.277614706
	P(T<=t) one-tail		0.069869677	0.129065338	0.330419269	0.371523007	6.14403E-05
	t Critical one-tail		1.678660414	1.682878002	1.665706893	1.677926722	1.68595446
	P(T<=t) two-tail		0.139739355	0.258130676	0.660838537	0.743046013	0.000122881
	t Critical two-tail		2.012895599	2.01954097	1.992543495	2.011740514	2.024394164
SCL	Mean	0.960778332	0.959416817	0.955230938	0.959826127	0.963396555	0.950841062
	Variance	0.000268603	0.000148288	0.000158726	0.000120942	0.000243194	0.00024851
	Observations	56	31	24	24	24	20
	Hypothesized Mean Difference		0	0	0	0	0
	df		78	56	64	46	35
	t Stat		0.439886112	1.642271728	0.30361769	-0.677615266	2.394557158
	P(T<=t) one-tail		0.330618033	0.053069072	0.381202021	0.250704909	0.011064612
	t Critical one-tail		1.664624645	1.672522303	1.669013025	1.678660414	1.689572458
	P(T<=t) two-tail		0.661236067	0.106138145	0.762404042	0.501409819	0.022129225
	t Critical two-tail		1.990847069	2.003240719	1.997729654	2.012895599	2.030107928
SDL	Mean	0.977364185	0.973291514	0.976020008	0.971852962	0.97649841	0.97816934
	Variance	9.96772E-05	6.03936E-05	2.24408E-05	4.45116E-05	5.16204E-05	0.000177747
	Observations	65	32	24	31	20	24
	Hypothesized Mean Difference		0	0	0	0	0
	df		77	82	84	44	33
	t Stat		2.201992942	0.85553455	3.198285291	0.426820994	-0.269289403
	P(T<=t) one-tail		0.01532956	0.197374123	0.000975098	0.335795493	0.39469182
	t Critical one-tail		1.664884537	1.663649184	1.663196679	1.680229977	1.692360309
	P(T<=t) two-tail		0.03065912	0.394748246	0.001950195	0.671590986	0.789383639
	t Critical two-tail		1.991254395	1.989318557	1.988609667	2.015367574	2.034515297

The water band index (WBI) values for Wild Olive (Figure A-19) visibly have a similar pattern to the MSI values. The value distribution of the control plants differ but have a similar median and minimum values. BL3 (30mg/kg) has the lowest first and third quartile, median and minimum values, but also the highest variance. This may indicate that, although it dampens plant moisture stress, exposure to low concentrations of TNT may influence the storage and usage capacity of plant moisture.

A jump in WBI values is seen at BL4 (300mg/kg), as it has the highest first and third quartile values, and median value. The difference between the maximum and minimum values to that of the control plants are similar.

As with the NDWI, the differences in values for the WBI, in this case, are minimal, with all values for the surviving plants ranging between 0.90 and 1.00.

For BL7, the extreme distribution pattern again indicates that the cause of death of the plant may be moisture-related.

For River Bushwillow (Figure A-20), all plants had similar median values and similar distributions of values, with a slightly increasing trend with higher concentrations of TNT. The magnitude of the difference is so small that it may mean the WBI will be an insignificant tool to test for TNT contamination.

From the box plots for Soap Dogwood (Figure A-21) the same pattern emerges, with small distributions and similar median values.

Figure A-22, representing Sweet Thorn, shows the same sort of trend, except for EL7 (5000mg/kg) which has a significantly larger distribution range than the other plants, but it also has significantly fewer readings. This supports the notion that the plant may have suffered water-related stress before dying.

Figure A-23, representing White Stinkwood repeats the pattern seen in the other plants.

There is a correlation between the MSI for Transvaal Honey-bell Bush (Figure A-15) and the WBI for the same species (Figure A-24), where there seems to be an increasing trend in values from SAL3 toward SAL7 (30mg/kg to 5000mg/kg). This may indicate that the species store more water when contaminated with TNT, but struggles to use the moisture, leading to increased plant stress. Although the median WBI values seem to decrease with increased concentration of TNT, the third quartile values and median values are all higher than the control species. The distributions are relatively small and are exaggerated by the scale of the WBI axis.

Spekboom (Figure A-25) had WBI values below the range of what is considered normal for vegetation, but this again may be because the plants were often watered, while succulents prefer dry or arid conditions. Of all the specimens for this species, SBL7 (5000mg/kg) showed the most "normal" values, indicating the presence of a large amount of TNT may improve the plant's response to overwatering.

Natal Plum (Figure A-26) had values of between 0.94 and 0.98, with the control plant SCL1 and the plant subjected to 1200mg/kg TNT (SCL6) had both minimum and maximum values beyond this range. SCL6 also had a median value larger than any other plant, meaning that a dose of 1200mg/kg TNT may assist the plant in resisting water-related stress. Beyond that, SCL7 (5000mg/kg) had a significantly smaller distribution of values. The values for SCL7, in general, were also a lot lower than for the other plants.

There is a difference in distribution of WBI values for Kei Apple (Figure A-27) control specimens. SDL4 (300mg.kg) has a significantly smaller value distribution than the other contaminated plants, but only slightly lower than that of SDL2, a control plant. The magnitudes of the distributions for this species are, again, relatively small, and a random trend is seen with the median values, with both positive and adverse effects seen. All values for this species are still within the normal WBI range for plants.

5.5.6 Photochemical reflectance index

The photochemical reflectance index is an indicator of light use efficiency in plants. Effective light use indicates proper chlorophyll production within a plant, suggesting healthier plants. PRI values range between -1 and +1. -1 indicates ineffective light usage by the plant, while +1 indicates perfect light usage, and the common range for vegetation is between -0.2 and +0.2.

From Tables 22 to 25 (F and T-tests for trees and shrubs respectively) it is evident that all specimens of both shrubs and trees have mean values within the normal range. Using the T-test, most of the results indicated that there is no significant difference in PRI values between contaminated plants and control plants. Similar results are obtained for the T-test of the shrubs. When the F-test method is applied, a difference in variances is picked up for all shrubs and most trees.

Table 22 - F-test (two sample for variance) results, PRI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	-0.009322538	-0.015144592	-0.017189082	-0.013036561	-0.003223153	-0.074159091
	Variance	0.001492638	0.001986456	0.002916229	0.002838286	0.002429532	0.008413739
	Observations	208	98	98	96	98	22
	df	207	97	97	95	97	21
	F		0.751407756	0.511838552	0.525894263	0.614372953	0.1774049
	P(F<=f) one-tail		0.045826623	3.31592E-05	7.16187E-05	0.001945316	7.30549E-12
	F Critical one-tail		0.756752215	0.756752215	0.755443298	0.756752215	0.622199166
CL	Mean	-0.015872426	-0.01481952	-0.018037185	-0.01054995	-0.015058673	-0.006153292
	Variance	0.002432753	0.002841377	0.001894811	0.002083269	0.002681712	0.001844659
	Observations	155	86	80	81	80	95
	df	154	85	79	80	79	94
	F		0.856188126	1.283902642	1.167757512	0.907164186	1.318809125
	P(F<=f) one-tail		0.201894211	0.108462604	0.221667216	0.301442862	0.072369885
	F Critical one-tail		0.735320764	1.395509287	1.393268015	0.730691	1.366591725
DL	Mean	0.010496324	0.028667699	0.00685231	0.020346997	0.017812707	0.017720223
	Variance	0.001554432	0.000669256	0.001511315	0.001178406	0.001327771	0.001015383
	Observations	171	81	80	81	89	83
	df	170	80	79	80	88	82
	F		2.322628692	1.028529673	1.319097358	1.170707996	1.530882977
	P(F<=f) one-tail		2.00809E-05	0.451438021	0.081831207	0.206158262	0.015697447
	F Critical one-tail		1.387319372	1.389581897	1.387319372	1.370945552	1.382948261
EL	Mean	-0.004148108	-0.019396201	-0.01136273	0.001980905	-0.021294238	-0.035928828
	Variance	0.001361522	0.002750454	0.001557001	0.001377195	0.001540353	0.000851086
	Observations	158	78	82	84	74	12
	df	157	77	81	83	73	11
	F		0.495017269	0.87445169	0.988619654	0.883902704	1.599746735
	P(F<=f) one-tail		0.000107782	0.236606502	0.468400034	0.259961753	0.194529757
	F Critical one-tail		0.729931034	0.73321421	0.734764572	0.726378467	2.4378962
FL	Mean	-0.006919715	-0.018768332	-0.004989461	-0.010458532	-0.005389021	0.020670152
	Variance	0.001890323	0.001166922	0.001114394	0.001832881	0.001802304	0.003097777
	Observations	97	72	69	33	89	73
	df	96	71	68	32	88	72
	F		1.619923066	1.696279753	1.031339646	1.048837225	0.610219345
	P(F<=f) one-tail		0.016752623	0.011001047	0.476914118	0.411098628	0.011935642
	F Critical one-tail		1.450768168	1.459017356	1.67159077	1.414231175	0.698169939

Table 23 - T-test (two sample assuming unequal variances), PRI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	-0.009322538	-0.015144592	-0.017189082	-0.013036561	-0.003223153	-0.074159091
	Variance	0.001492638	0.001986456	0.002916229	0.002838286	0.002429532	0.008413739
	Observations	208	98	98	96	98	22
	Hypothesized Mean Difference		0	0	0	0	0
	df		168	145	143	155	22
	t Stat		1.111311511	1.294413965	0.612724697	-1.078780779	3.284732088
	P(T<=t) one-tail		0.13401109	0.098790054	0.270515789	0.141180686	0.001691161
	t Critical one-tail		1.653974208	1.655430251	1.655579143	1.654743774	1.717144374
	P(T<=t) two-tail		0.268022181	0.197580107	0.541031578	0.282361372	0.003382323
	t Critical two-tail		1.974185191	1.976459563	1.976692198	1.975387131	2.073873068
CL	Mean	-0.015872426	-0.01481952	-0.018037185	-0.01054995	-0.015058673	-0.006153292
	Variance	0.002432753	0.002841377	0.001894811	0.002083269	0.002681712	0.001844659
	Observations	155	86	80	81	80	95
	Hypothesized Mean Difference		0	0	0	0	0
	df		164	178	174	153	220
	t Stat		-0.150824415	0.344960872	-0.8270604	-0.115994434	-1.640196232
	P(T<=t) one-tail		0.440149789	0.365265528	0.204667799	0.45390453	0.051196685
	t Critical one-tail		1.654197929	1.653459126	1.653658017	1.654873847	1.651809286
	P(T<=t) two-tail		0.880299579	0.730531057	0.409335598	0.90780906	0.102393371
	t Critical two-tail		1.974534576	1.973380889	1.97369144	1.975590315	1.970805592
DL	Mean	0.010496324	0.028667699	0.00685231	0.020346997	0.017812707	0.017720223
	Variance	0.001554432	0.000669256	0.001511315	0.001178406	0.001327771	0.001015383
	Observations	171	81	80	81	89	83
	Hypothesized Mean Difference		0	0	0	0	0
	df		225	156	178	191	197
	t Stat		-4.362191674	0.688879464	-2.026078342	-1.49316977	-1.564370549
	P(T<=t) one-tail		9.80672E-06	0.245961194	0.022124795	0.068521396	0.059667754
	t Critical one-tail		1.651654074	1.654679996	1.653459126	1.652870547	1.652625219
	P(T<=t) two-tail		1.96134E-05	0.491922388	0.04424959	0.137042792	0.119335509
	t Critical two-tail		1.97056339	1.975287508	1.973380889	1.97246199	1.972079034
EL	Mean	-0.004148108	-0.019396201	-0.01136273	0.001980905	-0.021294238	-0.035928828
	Variance	0.001361522	0.002750454	0.001557001	0.001377195	0.001540353	0.000851086
	Observations	158	78	82	84	74	12
	Hypothesized Mean Difference		0	0	0	0	0
	df		116	155	169	135	14
	t Stat		2.301891784	1.373154269	-1.225498394	3.160459565	3.563428073
	P(T<=t) one-tail		0.011562776	0.085843773	0.111046304	0.000972439	0.001558353
	t Critical one-tail		1.658095744	1.654743774	1.653919942	1.656219133	1.761310136
	P(T<=t) two-tail		0.023125553	0.171687546	0.222092609	0.001944878	0.003116706
	t Critical two-tail		1.980626002	1.975387131	1.974100447	1.977692277	2.144786688
FL	Mean	-0.006919715	-0.018768332	-0.004989461	-0.010458532	-0.005389021	0.020670152
	Variance	0.001890323	0.001166922	0.001114394	0.001832881	0.001802304	0.003097777
	Observations	97	72	69	33	89	73
	Hypothesized Mean Difference		0	0	0	0	0
	df		166	163	56	183	132
	t Stat		1.98318519	-0.323336497	0.408546448	-0.242819068	-3.506089814
	P(T<=t) one-tail		0.024498055	0.37342743	0.342215317	0.404208753	0.000310926
	t Critical one-tail		1.654084713	1.654255585	1.672522303	1.653222803	1.65647927
	P(T<=t) two-tail		0.048996109	0.74685486	0.684430635	0.808417505	0.000621851
	t Critical two-tail		1.974357764	1.974624621	2.003240719	1.973011915	1.978098842

Table 24 - F-test (two sample for variance) results, PRI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	-0.012841323	-0.026894568	-0.02607157	-0.029140139	-0.030706877	-0.033112353
	Variance	0.001261847	0.001466106	0.001421798	0.001214288	0.001085931	0.001307239
	Observations	67	34	34	34	26	34
	df	66	33	33	33	25	33
	F		0.86067945	0.887501018	1.039165941	1.161995223	0.965276351
	P(F<=f) one-tail		0.29718728	0.333653884	0.463006585	0.346756899	0.440215255
	F Critical one-tail		0.62026433	0.62026433	1.69223579	1.812292331	0.62026433
SBL	Mean	-0.06495223	-0.079160925	-0.052390595	-0.066124234	-0.065104467	-0.083874449
	Variance	0.002007499	0.0017519	0.002500645	0.001542567	0.001752598	0.001478138
	Observations	66	31	34	32	31	28
	df	65	30	33	31	30	27
	F		1.145898249	0.802792645	1.301401795	1.145441715	1.358127292
	P(F<=f) one-tail		0.347655621	0.222483395	0.212378355	0.348116613	0.190974191
	F Critical one-tail		1.731217161	0.619231816	1.717938043	1.731217161	1.777013426
SCL	Mean	-0.014020436	-0.023118965	-0.035114203	-0.031571004	-0.068986506	0.002748297
	Variance	0.002500574	0.004151815	0.003973617	0.002939326	0.004600586	0.002698727
	Observations	56	31	24	24	24	20
	df	55	30	23	23	23	19
	F		0.602284594	0.629294282	0.850730545	0.543533897	0.926575387
	P(F<=f) one-tail		0.051216903	0.081468716	0.304937637	0.033303851	0.396032805
	F Critical one-tail		0.600093146	0.578887635	0.578887635	0.578887635	0.562164635
SDL	Mean	-0.056353548	-0.052666047	-0.072740156	-0.028329503	-0.019013979	-0.060580485
	Variance	0.002525465	0.002265204	0.000980277	0.001084649	0.000973363	0.002951224
	Observations	65	32	24	32	20	24
	df	64	31	23	31	19	23
	F		1.114895118	2.576278108	2.328371564	2.594575624	0.855734821
	P(F<=f) one-tail		0.377790654	0.006886996	0.005783365	0.011641333	0.305088799
	F Critical one-tail		1.719525158	1.858509008	1.719525158	1.973522215	0.588471294

Table 25 - T-test (two sample assuming unequal variances), PRI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	-0.012841323	-0.026894568	-0.02607157	-0.029140139	-0.030706877	-0.033112353
	Variance	0.001261847	0.001466106	0.001421798	0.001214288	0.001085931	0.001307239
	Observations	67	34	34	34	26	34
	Hypothesized Mean Difference		0	0	0	0	0
	df		62	63	68	49	65
	t Stat		1.785422168	1.698824615	2.206820702	2.294984426	2.678352273
	P(T<=t) one-tail		0.039542	0.047143	0.015353128	0.0130279	0.004679644
	t Critical one-tail		1.669804163	1.669402222	1.667572281	1.676550893	1.668635976
	P(T<=t) two-tail		0.079084	0.094286001	0.030706257	0.0260558	0.009359289
	t Critical two-tail		1.998971517	1.998340543	1.995468931	2.009575237	1.997137908
SBL	Mean	-0.06495223	-0.079160925	-0.052390595	-0.066124234	-0.065104467	-0.083874449
	Variance	0.002007499	0.0017519	0.002500645	0.001542567	0.001752598	0.001478138
	Observations	66	31	34	32	31	28
	Hypothesized Mean Difference		0	0	0	0	0
	df		63	61	69	63	59
	t Stat		1.52394895	-1.231976783	0.132177428	0.016325955	2.074394467
	P(T<=t) one-tail		0.066262947	0.111342838	0.44761432	0.493512972	0.021207277
	t Critical one-tail		1.669402222	1.670219484	1.667238549	1.669402222	1.671093032
	P(T<=t) two-tail		0.132525893	0.222685676	0.895228639	0.987025945	0.042414554
	t Critical two-tail		1.998340543	1.999623585	1.994945415	1.998340543	2.000995378
SCL	Mean	-0.014020436	-0.023118965	-0.035114203	-0.031571004	-0.068986506	0.002748297
	Variance	0.002500574	0.004151815	0.003973617	0.002939326	0.004600586	0.002698727
	Observations	56	31	24	24	24	20
	Hypothesized Mean Difference		0	0	0	0	0
	df		50	36	41	34	32
	t Stat		0.68085021	1.454844691	1.357595609	3.575380111	-1.251295244
	P(T<=t) one-tail		0.249553673	0.07718846	0.09100889	0.000536399	0.109948802
	t Critical one-tail		1.675905025	1.688297714	1.682878002	1.690924255	1.693888748
	P(T<=t) two-tail		0.499107346	0.154376921	0.182017781	0.001072797	0.219897605
	t Critical two-tail		2.008559112	2.028094001	2.01954097	2.032244509	2.036933343
SDL	Mean	-0.056353548	-0.052666047	-0.072740156	-0.028601605	-0.019013979	-0.060580485
	Variance	0.002525465	0.002265204	0.000980277	0.001118355	0.000973363	0.002951224
	Observations	65	32	24	31	20	24
	Hypothesized Mean Difference		0	0	0	0	0
	df		65	66	84	52	38
	t Stat		-0.352164667	1.835544456	-3.206030222	-3.991278083	0.332283166
	P(T<=t) one-tail		0.362927011	0.035465376	0.00095204	0.000103503	0.370750743
	t Critical one-tail		1.668635976	1.668270514	1.663196679	1.674689154	1.68595446
	P(T<=t) two-tail		0.725854023	0.070930751	0.001904081	0.000207005	0.741501487
	t Critical two-tail		1.997137908	1.996564419	1.988609667	2.006646805	2.024394164

As with the previous plots, it can be seen from Figure A-28, that the magnitude of variance for the photochemical reflectance index (PRI) for Wild Olive is relatively small. Patterns are still visible, with a slight drop in median value for BR3 when compared to the control plants, but a lower variance when compared to BL2. A small increase in median and third quartile values for BL4, BL5 and BL6 may indicate an improved usage of plant chemicals with increased TNT contamination, but the difference is so slight, that it may be negligible.

For River Bushwillow (Figure A-29), most readings were within the expected range for healthy vegetation, with a slight increase in values seen for the lower concentration plants (CL3, CL4 and CL5). There are outliers beyond the normal range. All plants have median values in the range of 0.

As with River Bushwillow, Soap Dogwood (Figure A-30) has the majority of readings within the normal range except for one outlier in the control plant CL2. It does not seem as if the TNT has a significant effect on the light efficiency of the plants. There is a slight increase in the size of value distribution for DL4, DL5 and DL6, but due to the small range of the readings, this may be circumstantial.

Sweet Thorn (Figure A-31) and White Stinkwood (Figure A-32) repeat this trend, where all readings, except for single outliers are within the normal range for the index, and no clear patterns emerge regarding the distribution of readings.

For all the shrubs studied, PRI values within the normal range for vegetation are found. The distribution of values has a small magnitude, as can be seen from Figure A-33, representing Transvaal Honey-bell Bush. Note the decrease in median values with an increase in TNT concentration. The distribution side also changes when comparing SAL3 and SAL4 with the control plants. The higher concentration specimens, SAL5 to SAL7) have similar distribution sizes to that of the control plants, albeit with smaller median values.

A sharp increase is seen for SBL4 (Spekboom; Figure A-34) in minimum, maximum and median values, but in general, all readings for the species were normal. Similarly, a drop in the median and minimum PRI values is visible for SBL3 (30mg/kg), while SBL7 (5000mg/kg) had the lowest median value. This pattern does seem to be random, as other contaminated plants have median values slightly higher or similar to the control specimens.

Natal Plum (Figure A-35) has highly random values for all samples. These values still fall within the normal range. SCL4 (300mg/kg) has a large distribution pattern, with a low median value, while SCL6 (1200mg) has a similar distribution size, but with a much lower median value. 5000mg/kg TNT may

have improved the light usage efficiency of the plant SCL7 slightly, because it has a distribution of values higher than that of the other plants.

There is no trend in values for the Kei Apple sample (Figure A-36), but the values fall within the normal range. Distribution of values for plants varies significantly. A prominent drop in median values is evident for SDL4 (300mg/kg), followed by a sharp increase in general values for SDL5 (600mg/kg) and SDL6 (1200mg/kg) respectively. This indicates that larger doses of TNT may improve the light use efficiency of the plant, but considering the high variability of values, this is doubtful.

5.5.7 Nitrogen index

The nitrogen index is used to determine nitrogen content in foliage. Sufficient nitrogen in plant foliage is necessary to promote plant health and growth potential. Due to the nitrogen in TNT, it was assumed that the plants may react with TNT in a way that affects their nitrogen uptake.

As with the other indices T and F-tests (Tables 26 and 27, and 28 and 29 for trees and shrubs respectively,) resulted in different results, with several of the results for trees stating no difference to the control plants, and most results for shrubs indicating no difference (T-test). With the exception of two plants, it was found that for F-test, differences in variances exist.

Table 26 - F-test (two sample for variance) results, NI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	-0.01828853	-0.02388939	-0.018346659	-0.022582872	-0.019523165	-0.002246048
	Variance	0.000108061	0.000216679	7.26012E-05	0.000113813	7.54056E-05	0.000221167
	Observations	208	98	98	96	98	22
	df	207	97	97	95	97	21
	F		0.498713112	1.48841708	0.949462671	1.433062087	0.488594889
	P(F<=f) one-tail		1.6862E-05	0.013860468	0.375240572	0.023027925	0.005932394
	F Critical one-tail		0.756752215	1.344489802	0.755443298	1.344489802	0.622199166
CL	Mean	0.631772777	0.647219687	-0.014636567	-0.009531652	-0.012798892	-0.007210748
	Variance	0.008281428	0.015768945	6.7276E-05	8.64747E-05	0.000102471	0.000101199
	Observations	155	86	80	81	80	95
	df	154	85	79	80	79	94
	F		0.525173273	1.890898555	1.471089411	1.241445925	1.257045986
	P(F<=f) one-tail		0.0002706	0.000973255	0.027998495	0.142759599	0.113930974
	F Critical one-tail		0.735320764	1.395509287	1.393268015	1.395509287	1.366591725
DL	Mean	-0.041597363	-0.04033454	-0.041652347	-0.044939908	-0.045266592	-0.040248071
	Variance	0.000112935	7.3293E-05	6.10048E-05	6.55353E-05	8.05075E-05	0.000113612
	Observations	171	81	80	81	89	83
	df	170	80	79	80	88	82
	F		1.540873934	1.851253281	1.723274243	1.402792957	0.994042973
	P(F<=f) one-tail		0.015257469	0.001206695	0.003399388	0.038914913	0.478655215
	F Critical one-tail		1.387319372	1.389581897	1.387319372	1.370945552	0.73766633
EL	Mean	-0.023135838	-0.023572694	-0.025530149	-0.022845979	-0.023637712	-0.016148896
	Variance	0.000101773	8.57775E-05	9.17408E-05	9.48052E-05	0.000114279	0.000153177
	Observations	158	78	82	84	74	12
	df	157	77	81	83	73	11
	F		1.186476731	1.109354145	1.073496123	0.890568209	0.664413716
	P(F<=f) one-tail		0.201629685	0.304479141	0.364072386	0.272413432	0.134426952
	F Critical one-tail		1.398966676	1.389873523	1.385633902	0.726378467	0.540515214
FL	Mean	-0.024000452	-0.025477767	-0.033235936	-0.021540346	-0.028651041	-0.027410657
	Variance	6.42603E-05	6.01577E-05	8.46911E-05	3.80946E-05	7.38025E-05	6.14059E-05
	Observations	97	72	69	33	89	73
	df	96	71	68	32	88	72
	F		1.068198496	0.758760901	1.686862954	0.870707258	1.046484921
	P(F<=f) one-tail		0.387610857	0.105950338	0.047127231	0.25303151	0.422807612
	F Critical one-tail		1.450768168	0.694776417	1.67159077	0.709221019	1.4481645

Table 27 - T-test (two sample assuming unequal variances), NI for trees

		Control	*3*	*4*	*5*	*6*	*7*
BL	Mean	-0.01828853	-0.02388939	-0.018346659	-0.022582872	-0.019523165	-0.002246048
	Variance	0.000108061	0.000216679	7.26012E-05	0.000113813	7.54056E-05	0.000221167
	Observations	208	98	98	96	98	22
	Hypothesized Mean Difference		0	0	0	0	0
	df		144	228	181	224	23
	t Stat		3.389460841	0.051777748	3.288707421	1.087470255	-4.933801729
	P(T<=t) one-tail		0.000451863	0.479375561	0.000604696	0.138998886	2.74838E-05
	t Critical one-tail		1.655504177	1.651564228	1.653315758	1.65168456	1.713871528
	P(T<=t) two-tail		0.000903725	0.958751121	0.001209393	0.277997773	5.49676E-05
	t Critical two-tail		1.976575066	1.970423195	1.973157042	1.970610961	2.06865761
CL	Mean	-0.015233033	-0.015755166	-0.014636567	-0.009531652	-0.012798892	-0.007210748
	Variance	0.000127212	7.7386E-05	6.7276E-05	8.64747E-05	0.000102471	0.000101199
	Observations	155	86	80	81	80	95
	Hypothesized Mean Difference		0	0	0	0	0
	df		213	207	191	176	216
	t Stat		0.398057671	-0.462714156	-4.148998318	-1.679073692	-5.841573779
	P(T<=t) one-tail		0.345493178	0.322027654	2.51158E-05	0.047456066	9.42205E-09
	t Critical one-tail		1.652038878	1.652248086	1.652870547	1.653557435	1.651938651
	P(T<=t) two-tail		0.690986356	0.644055309	5.02316E-05	0.094912133	1.88441E-08
	t Critical two-tail		1.971163885	1.971490392	1.97246199	1.973534388	1.971007472
DL	Mean	-0.041597363	-0.04033454	-0.041652347	-0.044939908	-0.045266592	-0.040248071
	Variance	0.000112935	7.3293E-05	6.10048E-05	6.55353E-05	8.05075E-05	0.000113612
	Observations	171	81	80	81	89	83
	Hypothesized Mean Difference		0	0	0	0	0
	df		191	204	201	206	162
	t Stat		-1.009356995	0.04609269	2.757336346	2.933019889	-0.947189931
	P(T<=t) one-tail		0.157040215	0.481640731	0.003182139	0.001868411	0.172476368
	t Critical one-tail		1.652870547	1.652357326	1.652469842	1.652284144	1.654313957
	P(T<=t) two-tail		0.31408043	0.963281462	0.006364278	0.003736823	0.344952736
	t Critical two-tail		1.97246199	1.971660889	1.971836507	1.971546669	1.974715786
EL	Mean	-0.023135838	-0.023572694	-0.025530149	-0.022845979	-0.023637712	-0.016148896
	Variance	0.000101773	8.57775E-05	9.17408E-05	9.48052E-05	0.000114279	0.000153177
	Observations	158	78	82	84	74	12
	Hypothesized Mean Difference		0	0	0	0	0
	df		166	172	175	136	12
	t Stat		0.330814452	1.803282924	-0.217701302	0.339255821	-1.908053444
	P(T<=t) one-tail		0.370600918	0.036547016	0.413957739	0.367470158	0.040296362
	t Critical one-tail		1.654084713	1.653760949	1.653607437	1.656134988	1.782287556
	P(T<=t) two-tail		0.741201837	0.073094033	0.827915478	0.734940316	0.080592723
	t Critical two-tail		1.974357764	1.973852169	1.973612462	1.977560777	2.17881283
FL	Mean	-0.024000452	-0.025477767	-0.033235936	-0.021540346	-0.028651041	-0.027410657
	Variance	6.42603E-05	6.01577E-05	8.46911E-05	3.80946E-05	7.38025E-05	6.14059E-05
	Observations	97	72	69	33	89	73
	Hypothesized Mean Difference		0	0	0	0	0
	df		156	134	71	180	157
	t Stat		1.207027936	6.718030043	-1.825127004	3.807716152	2.781035755
	P(T<=t) one-tail		0.114624212	2.40051E-10	0.036094056	9.60958E-05	0.003041104
	t Critical one-tail		1.654679996	1.656304542	1.666599658	1.653363013	1.654617035
	P(T<=t) two-tail		0.229248424	4.80102E-10	0.072188112	0.000192192	0.006082207
	t Critical two-tail		1.975287508	1.977825758	1.993943368	1.973230823	1.975189163

Table 28 - F-test (two sample for variance) results, NI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	-0.019750703	-0.019082626	-0.01816812	-0.019193122	-0.019106084	-0.019623605
	Variance	5.81638E-05	7.86341E-05	9.16403E-05	0.000108367	7.48039E-05	6.18266E-05
	Observations	67	34	34	34	26	34
	df	66	33	33	33	25	33
	F		0.739676093	0.63469693	0.536729879	0.777549952	0.940756202
	P(F<=f) one-tail		0.148348314	0.058684608	0.016040273	0.20706268	0.406812371
	F Critical one-tail		0.62026433	0.62026433	0.62026433	0.597599661	0.62026433
SBL	Mean	-0.009396962	-0.010445746	-0.008536511	-0.010674331	-0.009212963	-0.015777851
	Variance	4.47803E-05	2.42224E-05	5.67833E-05	3.6509E-05	4.17343E-05	5.2388E-05
	Observations	66	31	34	32	31	28
	df	65	30	33	31	30	27
	F		1.848715896	0.788616727	1.226553139	1.072985843	0.854781725
	P(F<=f) one-tail		0.033119156	0.205038565	0.269925111	0.426627479	0.297533678
	F Critical one-tail		1.731217161	0.619231816	1.717938043	1.731217161	0.60319704
SCL	Mean	-0.063297304	-0.065072489	-0.074178502	-0.069805533	-0.06767337	-0.074560293
	Variance	0.00057206	0.000614347	0.000428406	0.000356718	0.000407052	0.00034632
	Observations	56	31	24	24	24	20
	df	55	30	23	23	23	19
	F		0.93116607	1.335320913	1.603672675	1.405372065	1.651825265
	P(F<=f) one-tail		0.400071439	0.22584217	0.107264767	0.186590651	0.113893928
	F Critical one-tail		0.600093146	1.873976147	1.873976147	1.873976147	1.988234971
SDL	Mean	-0.015979536	-0.019248333	-0.014309266	-0.017844812	-0.015630715	-0.019593096
	Variance	9.56877E-05	9.00825E-05	7.15851E-05	7.44886E-05	5.46893E-05	0.000105279
	Observations	65	32	24	32	20	24
	df	64	31	23	31	19	23
	F		1.062223421	1.336699377	1.284594791	1.74966051	0.90889474
	P(F<=f) one-tail		0.437488834	0.222213134	0.224677247	0.087139918	0.369826019
	F Critical one-tail		1.719525158	1.858509008	1.719525158	1.973522215	0.588471294

Table 29 - T-test (two sample assuming unequal variances), NI for shrubs

		Control	*3*	*4*	*5*	*6*	*7*
SAL	Mean	-0.019750703	-0.019082626	-0.01816812	-0.019193122	-0.019106084	-0.019623605
	Variance	5.81638E-05	7.86341E-05	9.16403E-05	0.000108367	7.48039E-05	6.18266E-05
	Observations	67	34	34	34	26	34
	Hypothesized Mean Difference		0	0	0	0	0
	df		58	55	52	41	65
	t Stat		-0.374586708	-0.838364741	-0.276880105	-0.333093585	-0.077542612
	P(T<=t) one-tail		0.354666996	0.202727354	0.391484917	0.370380514	0.469215049
	t Critical one-tail		1.671552762	1.673033965	1.674689154	1.682878002	1.668635976
	P(T<=t) two-tail		0.709333993	0.405454709	0.782969834	0.740761028	0.938430098
	t Critical two-tail		2.001717484	2.004044783	2.006646805	2.01954097	1.997137908
SBL	Mean	-0.009396962	-0.010445746	-0.008536511	-0.010674331	-0.009212963	0.250296122
	Variance	4.47803E-05	2.42224E-05	5.67833E-05	3.6509E-05	4.17343E-05	0.008308574
	Observations	66	31	34	32	31	28
	Hypothesized Mean Difference		0	0	0	0	0
	df		78	60	67	61	32
	t Stat		0.868022017	-0.561465642	0.947005787	-0.12930914	-2.005963984
	P(T<=t) one-tail		0.194022552	0.288285685	0.173519467	0.448769236	0.026687842
	t Critical one-tail		1.664624645	1.670648865	1.667916114	1.670219484	1.693888748
	P(T<=t) two-tail		0.388045104	0.576571371	0.347038933	0.897538473	0.053375683
	t Critical two-tail		1.990847069	2.000297822	1.996008354	1.999623585	2.036933343
SCL	Mean	-0.063297304	-0.065072489	-0.074178502	-0.069805533	-0.06767337	-0.074560293
	Variance	0.00057206	0.000614347	0.000428406	0.000356718	0.000407052	0.00034632
	Observations	56	31	24	24	24	20
	Hypothesized Mean Difference		0	0	0	0	0
	df		60	50	55	51	43
	t Stat		0.323924855	2.05394857	1.29960403	0.839445109	2.146545412
	P(T<=t) one-tail		0.3735607	0.022613915	0.099578819	0.202568709	0.018756654
	t Critical one-tail		1.670648865	1.675905025	1.673033965	1.67528495	1.681070703
	P(T<=t) two-tail		0.747121401	0.04522783	0.199157637	0.405137418	0.037513309
	t Critical two-tail		2.000297822	2.008559112	2.004044783	2.00758377	2.016692199
SDL	Mean	-0.015979536	-0.019248333	-0.014309266	-0.017503407	-0.015630715	-0.019593096
	Variance	9.56877E-05	9.00825E-05	7.15851E-05	7.31174E-05	5.46893E-05	0.000105279
	Observations	65	32	24	31	20	24
	Hypothesized Mean Difference		0	0	0	0	0
	df		63	47	67	41	39
	t Stat		1.578706293	-0.791354287	0.778586298	-0.170073567	1.492907211
	P(T<=t) one-tail		0.059705897	0.216356446	0.2194823	0.432894368	0.071753962
	t Critical one-tail		1.669402222	1.677926722	1.667916114	1.682878002	1.684875122
	P(T<=t) two-tail		0.119411795	0.432712893	0.4389646	0.865788737	0.143507923
	t Critical two-tail		1.998340543	2.011740514	1.996008354	2.01954097	2.02269092

Due to the nitrogen in TNT, it was expected that the nitrogen index (NI) would correlate with the increase in available nitrogen as a result of an increase in TNT concentration. From Figure A-37, this is not the case. NI values for the plants differ greatly, even between control plants. The only plant to show an increased nitrogen as expected is BL7, which was exposed to 5000mg/kg of TNT. The distribution of BL3 (30mg/kg) shows a much larger variation of values than any of the other specimens.

From Figure A-38 (River Bushwillow) an increase of values within the whole distribution with an increase in TNT concentration. It also looks as if the distribution range increases with an increase in TNT concentration. The magnitude of the distributions is small, though, with no values exceeding -0.04 and 0.02.

Contrary to the T and F-test results, visually it seems as if there is little variance between plants exposed to TNT and control plants for Soap Dogwood (Figure A-39). DL3 and DL4 have slightly higher median values than the control species, while DL5 and DL6 have lower median values. DL7 (5000mg/kg) has similar distribution patterns to the lower concentrations, meaning that any changes may not have been due to TNT.

Again, Figure A-40 (Sweet Thorn) shows a decrease in NI values for EL4 (300mg/kg), but plants with higher concentrations of TNT than EL4 have higher median values. EL7 has a relatively large distribution of values, indicating a relatively high nitrogen intake before dying.

Figure A-41, representing White Stinkwood, shows random NI values, with FL4 (300mg/kg) having a distribution with the lowest values overall. FL6 has slightly higher values when compared to the other plants, possibly indicating improved nitrogen usage in the plant, but FL6 and FL7 (1200mg/kg and 5000mg/kg) only have slightly lower values. This shows that the differences may have been due to other circumstances than TNT contamination.

Figure A-42, the NI box plots for Transvaal Honey-bell Bush, shows that all of the plants, except for SAL6 (1200mg/kg), have similar median values, and variances that are not dissimilar in magnitude to the control plants. SAL4 (300mg/kg) has a slightly larger variance, but the range of values between maximum and minimum for the whole species may be small enough to be insignificant.

The values for Spekboom (Figure A-43) follow suit, with the majority of NI values for most specimens being distributed at around -0.01. SBL7 (5000mg/kg) is an exception, as it has the lowest overall values for the plants of that species. This indicates that the shock dose of TNT may have adversely influenced the nitrogen utilisation of the plant.

There is a big difference in value distribution of the control plants (the median NI value for SCL2 is lower than the 25^{th} quantile limit of SCL1) for Natal Plum (Figure A-44), but when comparing the distribution patterns of the contaminated plants, to SCL2, a positive trend is visible. Considering the minimal differences in absolute value, this trend may also be circumstantial. Thus it is doubtful whether these differences were caused by varying TNT contamination.

Similarly, the random nature of Kei Apple's distributions (Figure A-45) is likely to be attributed to other factors, including the initial chemical composition of soil or organic matter contamination after the study started. Similarly, the differences between values are minimal.

5.6 Summary

In general, there was a trend in the REP of the studied plants. Plants exposed to 30mg/kg TNT had different REP profiles to that of the control plants. The significance of this is that the concentration of TNT around leaking anti-personnel mines tend to be 30mg/kg. The red-edge position can be useful as an indicator of the presence of antipersonnel mines if used with care.

Note, that in Tables 30 and 31, red cells indicate that there is no significant difference between the control and the contaminated plants (accept null hypothesis), while green cells suggest that there is a significant difference (reject the null hypothesis).

From Tables 30 and 31, highly varied results were obtained when comparing the different indices using the F-test method. For the NI, only Soap Dogwood (DL) showed that there is significant variance between all the contaminated plants and the control plants. Soap Dogwood also showed definitive variance in REP values when using the F-test method, while all other tree species have varied results. This indicates that Soap Dogwood may be utilised as an indicator species for the detection of TNT at all measured concentration levels when using the nitrogen index or the red-edge position.

When the T-test results are examined, a clear difference in results is visible when compared to the F-test results. Except for Wild Olive (BL) and the NDWI results for River Bushwillow (CL), the null hypothesis for all plants for all indices was rejected, as there is significant variance in the samples (the null hypothesis of the study assumes equality of variance). These broad differences in sample variances indicate that any of the indices may be used for the detection of TNT, under the assumption that no environmental factors influence the outcome. As stated previously, this study is done under the assumption that environmental factors had a negligible effect on the results of the study. Further research is suggested in a later chapter, where sample plants will be housed in a greenhouse, limiting environmental factors.

From Table 31, a similar pattern emerges. When considering the F-test results, most species of shrub had a significant difference in variance when compared to the control plants. When considering the T-test results, the null hypothesis is rejected for each plant for all concentration levels of TNT. This indicates that there is a significant variance between samples, but that the means of contaminated plants do not differ significantly from the control species. This provides the opportunity for further research, where the data can be analysed by a statistician to determine a suitable hypothesis testing model.

The fact that the shrubs had a relatively high percentage of cases where the null hypothesis is rejected indicates that there may be a case of a window of opportunity. Doubt is cast over this due to an outright rejection of the null hypothesis for all plants using the T-test. It may be worthwhile to test a window of opportunity theory, as well as a simulated continuous leakage.

The small range of values found for some indices, such as the nitrogen index, and the fact that most of the plants had normal values for water-based indices such as the water-band index indicates that these indices are not suitable for use in landmine detection. This is especially relevant when considering that in the field, readings would not be taken in ideal conditions, meaning any difference in value caused by external interference would lead to false alarms.

Table 30 - Summarised results for F-test and T-test results for trees

		NI		NDWI		REP		MSI		WBI		PRI	
Species	*Plant*	*F-test result*	*T-test result*	*F-test result*	*T-test result*	*F-test result*	*T-test result*	*F-test result*	*T-test result*	*F-test result*	*T-test result*	*F-test result*	*T-test result*
BL	3	Accept	Reject	Accept	Accept	Accept	Reject	Accept	Accept	Accept	Reject	Accept	Accept
	4	Reject	Accept	Reject	Accept	Accept	Reject	Reject	Reject	Reject	Accept	Accept	Accept
	5	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Accept	Accept	Accept	Accept
	6	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Accept	Accept
	7	Accept	Reject	Accept	Reject	Reject	Accept	Accept	Reject	Accept	Reject	Accept	Reject
CL	3	Accept	Reject	Accept	Accept	Accept	Reject	Accept	Reject	Accept	Reject	Reject	Reject
	4	Reject	Reject	Reject	Reject	Accept	Reject	Reject	Reject	Reject	Reject	Accept	Reject
	5	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Accept	Reject
	6	Accept	Reject	Reject	Accept	Accept	Reject	Reject	Reject	Reject	Reject	Reject	Reject
	7	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject
DL	3	Reject	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Reject	Reject
	4	Reject	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject
	5	Reject	Reject	Accept	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Accept	Reject
	6	Reject	Reject	Accept	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Accept	Reject
	7	Reject	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Reject	Reject
EL	3	Accept	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject
	4	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Reject	Reject
	5	Accept	Reject	Accept	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Reject	Reject
	6	Reject	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Reject	Reject
	7	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject
FL	3	Accept	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Reject	Reject	Reject	Reject
	4	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject
	5	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Accept	Reject
	6	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Accept	Reject
	7	Accept	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject

Table 31 - Summarised results for F-test and T-test results for shrubs

		NI		NDWI		REP		MSI		WBI		PRI	
Species	*Plant*	*F-test result*	*T-test result*	*F-test result*	*T-test result*	*F-test result*	*T-test result*	*F-test result*	*T-test result*	*F-test result*	*T-test result*	*F-test result*	*T-test result*
SAL	3	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Reject	Reject
	4	Reject	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Reject	Reject	Reject	Reject
	5	Accept	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Reject	Reject	Accept	Reject
	6	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Accept	Reject
	7	Reject	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Reject	Reject	Reject	Reject
SBL	3	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject
	4	Reject	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Reject	Reject
	5	Accept	Reject	Reject	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject
	6	Accept	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject
	7	Reject	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject
SCL	3	Reject	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Reject	Reject	Reject	Reject
	4	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Reject	Reject
	5	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Reject	Reject
	6	Accept	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject
	7	Accept	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Reject	Reject
SDL	3	Accept	Reject	Accept	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Accept	Reject
	4	Accept	Reject	Accept	Reject	Reject	Reject	Accept	Reject	Reject	Reject	Reject	Reject
	5	Accept	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject
	6	Accept	Reject	Reject	Reject	Reject	Reject	Accept	Reject	Accept	Reject	Reject	Reject
	7	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject	Reject	Reject

5.7 Comparison to UPLC QToF study

A UPLC QToF study was done to detect anomalies in the composition of the vegetation matter. UPLC QToF refers to Ultra Performance Liquid Chromatography Quadrupole Time of Flight of mass spectrometry (Gupta et al. 2013). It is a technique used for the identification of compounds in a mixture, as well as the quantity of the components. Each component compound separates from the mixture at a given time.

Chlorophyll content of plant biomass separates in the region of 15 and 18 minutes using UPLC QToF. This is relatable to the red-edge position (REP) detected in hyperspectral sensing, as the REP is dependent on the chlorophyll content of the plant.

The pilot study included samples from *Ilex Mitis* (Cape Holly), *Olea Europaea subsp. Africana* (Wild Olive), *Celtis Africana* (White Stinkwood) and *Caffra Dovyalis* (Kei Apple). It is important to note that the sample for Cape Holly, which died out earlier during the study, may have included vegetation other than Cape Holly, such as weeds.

Figures 47 to 50 represent UPLC QToF spectral readings extracted from the zone indicative of chlorophyll content.

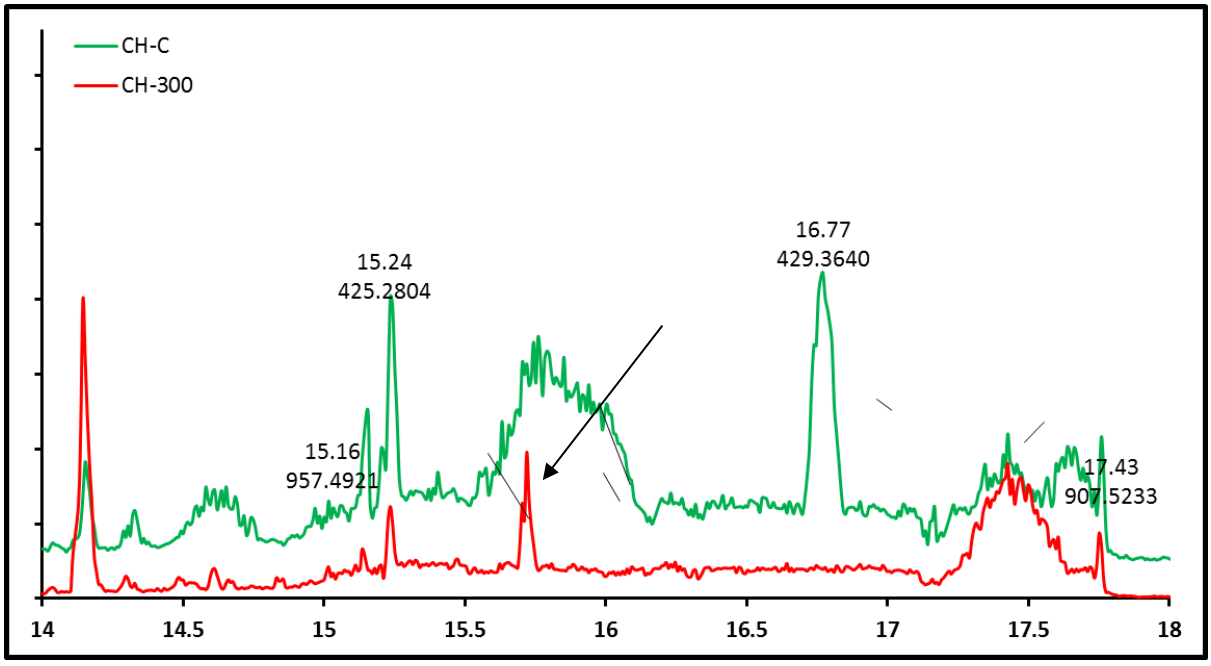

Figure 47 - UPLC QToF spectral reading, Cape Holly (green line = control; red line = 300mg/kg TNT), chlorophyll region (Dr X Peter)

From Figure 47, it is seen that there is suppression in the chlorophyll region (marked by arrow). The suppression indicates that even after four years since the inception of the study, residual TNT in the soil still affects the health of the vegetation.

Figure 48 represents UPLC QToF spectral readings for Wild Olive. As with the readings for Cape Holly, a general suppression in the region can be seen, but there is a spike in the reading between 16 minutes and 16.5 minutes. When compared to the REP box plots for plant BL4 (300mg/kg), a deduction is made that this spike may correlate with the lower median value and lower REP values for the plant. It is still to be investigated which type of chlorophyll causes this phenomenon.

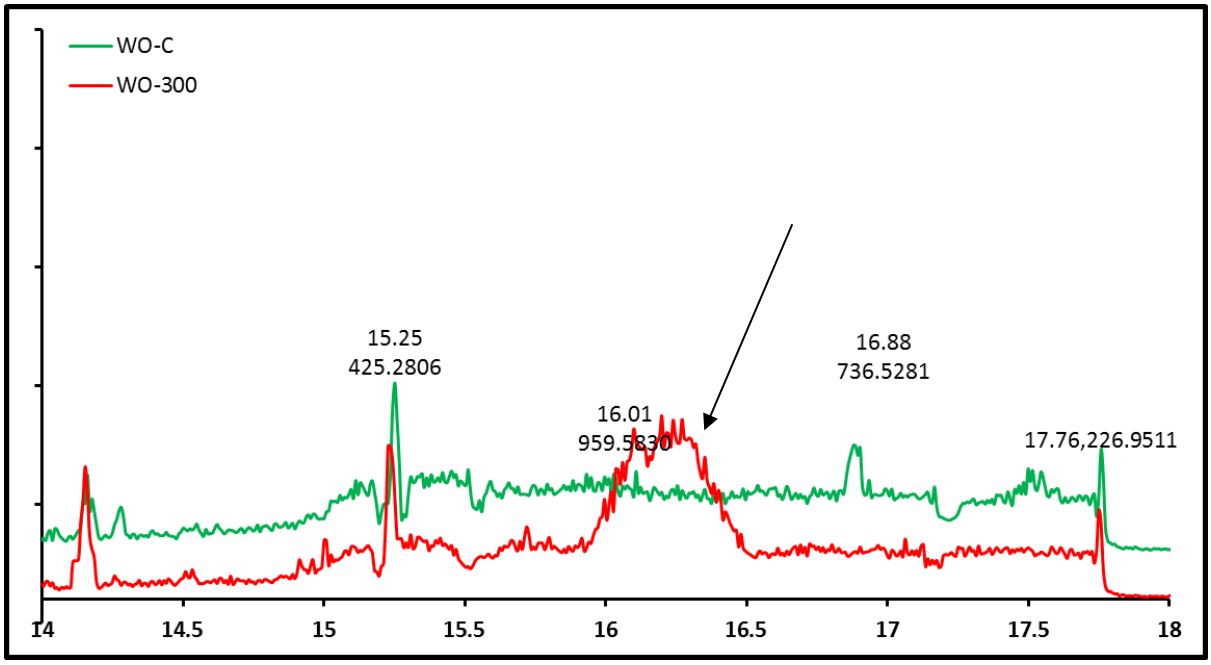

Figure 48 - UPLC QToF spectral reading, Wild Olive (green line = control; red line = 300mg/kg TNT), chlorophyll region (Dr X Peter)

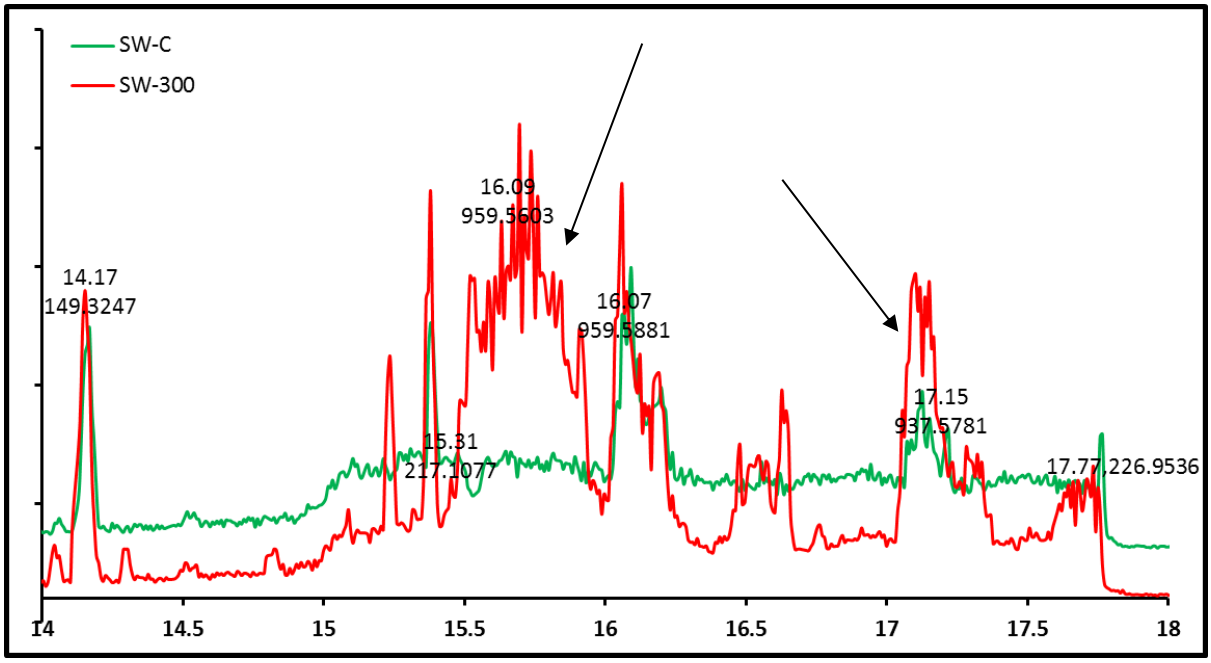

Figure 49 - UPLC QToF spectral reading, White Stinkwood (green line = control; red line = 300mg/kg TNT), chlorophyll region (Dr X Peter)

From Figure 49, multiple spikes in the chlorophyll region are noticed. Prominent spikes between 15 minutes and around 16.5 minutes, and 17 minutes and 17.5 minutes are present. These may represent different chlorophyll types, and also warrants further investigation. When compared to the REP box plot for White Stinkwood, FL4 (300mg/kg) has a similar median value to FL1 (control), but has a lower variability than the control plant, but also lower maximum and minimum values. This may indicate that the UPLC QToF results and hyperspectral readings correlate. This also indicates that a window of opportunity exceeding three years may exist.

A clear difference is visible from Figure 50 (Kei Apple) between 15.5 minutes and 16.5 minutes. This is like the Wild Olive, albeit half a minute earlier. This may indicate that the presence of TNT has an influence on different types of chlorophyll for various plants. This is also in contrast to Cape Holly, which shows no significant difference in signature apart from the reading magnitudes.

When comparing the readings from Figure 50 with the REP of SDL5 (Figure 37), (600mg/kg), which shows significantly higher median and upper values than any of the control plants (SDL1 and SDL2), it may be assumed that the two studies correlate.

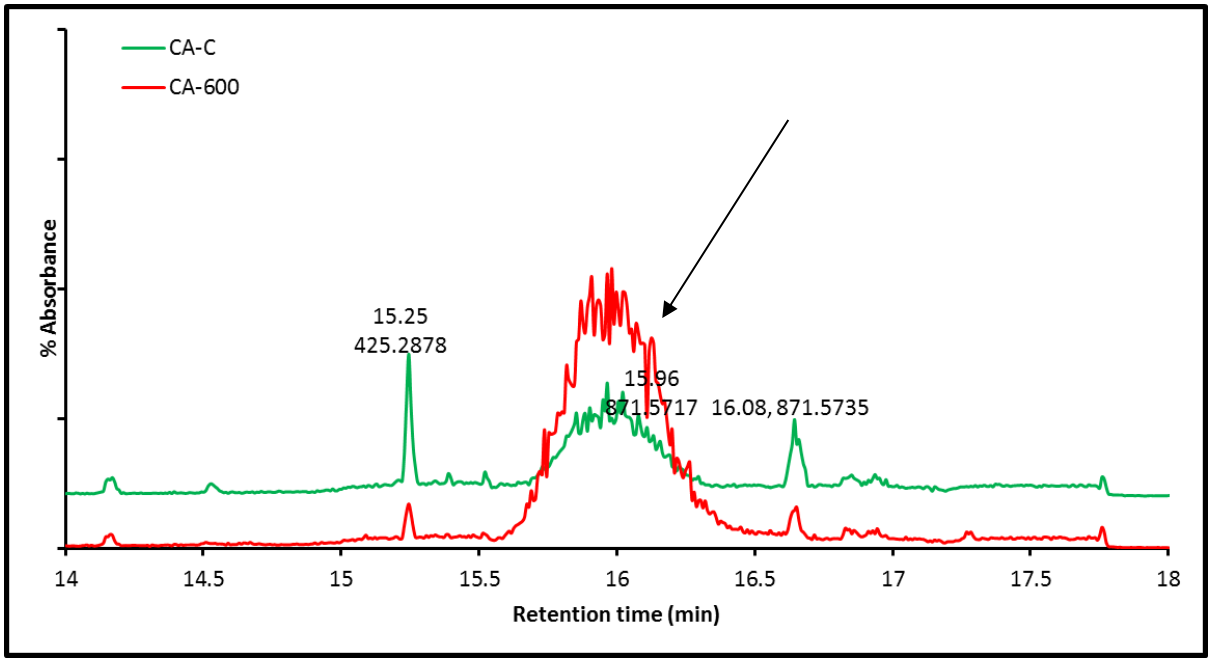

Figure 50 - UPLC QToF spectral reading, Kei Apple (green line = control; red line = 600mg/kg TNT), chlorophyll region (Dr X Peter)

Please note that figures 47 to 50 have been used, with permission, as was supplied by Dr Xolani Peter of the CSIR, without amendments or alterations.

Chapter 6. ANSWER TO RESEARCH QUESTIONS

The purpose of this study was to attempt to answer the research questions set out in the initial phase of the study. Analysis of data collected in the field was done, and results were generated to answer the following questions:

6.1 What is the physiological and spectral response to the leaching of TNT into the soil of South African indigenous trees?

A mixed response was observed during the study. Physically, some of the trees tended to resist environmental changes better than others. What was noticed was that trees exposed to 600mg/kg TNT had longer green cycles than other plants. Conversely, plants exposed to high dosages of TNT, such as 1200mg/kg and 5000mg/kg tended to be visually less healthy than other plants. Even in the same species, varying responses to TNT exposure was noticed.

As was previously mentioned, either a poison or fertiliser effect was expected. It was found that both effects could manifest in the same species of plant, depending on TNT exposure. Attributing this response only to TNT exposure is an assumption because there was also variation in control plant health.

Spectrally, this mixed response was also seen. In the case of Soap Dogwood, highly variable results were found, with no clear trend to indicate whether the plants were poisoned or fertilised by the TNT. In other cases, such as with White Stinkwood, all of the exposed plants tended to be less healthy than the control species. The plant health for the exposed plants seemed to increase with the concentration of TNT.

Thus, to answer this research question: The tree species used for this study had physical and spectral responses to TNT contamination. These reactions were highly variable, ranging from a positive health effect to deteriorated health. Intra-species variation was also noted. The observed poison and fertiliser effects were also supported by the UPLC QToF analysis, that showed both spikes and dips in chlorophyll content for contaminated plants.

6.2 Will different types of indigenous/cosmopolitan plants react differently to the leaching of TNT into their soil?

The species of trees used in this study was complemented with five species of grass and four species of shrub. One of the selection criteria for these plants was that they should have either a cosmopolitan distribution or be indigenous to Southern Africa.

The grass study was unsuccessful because most of the plants died out early during the study. Fortunately, some useful observations could be made. Firstly, the grass experiment should be

redesigned in future to include grasses in their natural environment, or grass species should be used that are suited to grow in containment. Also, it was noticed that the addition of TNT to the soil of the grasses and trees triggered an increase of bees in the immediate area. Using bees to detect landmines is a known method of detection. It was also noticed that some animals that would eat the grasses tended to prefer grasses exposed to lower concentrations of TNT.

Physically, the shrub species reacted adversely to the TNT exposure, with foliage browning as shown in Figure 28. They seemed to recover well after exposure, but again, mixed results were obtained. The shrub species displayed trends of declining health, displaying a poison effect, but in the case of Kei Apple, it was noticed that plants contaminated with 600mg/kg and 1200mg/kg showed a prominent spike in health.

Thus, as with the trees, both the poison and fertiliser effect was evident, but may be attributed to several factors, not exclusively TNT contamination. This is due to the variability of results even between the two control plants.

Different plants thus may react differently to the leaching of TNT into their soil. This reaction may manifest as a general decline in health, or increase, depending on the concentration of TNT. It may also influence the ability of the plant to react to environmental changes. There is a definite physiological variation to the health of the plant with the initial exposure.

6.3 Do specific spectral bands tend to be better indicators of TNT contamination than others?

It was found that the red-edge position was the vegetation index that had the best correlation with TNT exposure. Statistical analysis showed that none of the other tested indices showed a prominent correlation between the value of the index and TNT contamination.

Thus, spectral bands in the red, near-infrared and infrared areas of the electromagnetic spectrum proved to be better indicators of TNT contamination. Variances in the red-edge position were useful in investigating responses of plant health to the contamination of TNT.

Spectral bands between the ranges of 680 and 780nm represent the spectral range where the red-edge position of plants is found. For the calculation of the red-edge position, as per Cho and Skidmore (2006), spectral values at 700nm, 740nm, 760nm and 780nm are needed and are thus relevant spectral bands in the indication of TNT contamination.

Chapter 7. OUTCOME OF RESEARCH OBJECTIVES

Certain objectives were proposed at the start of the study. Four of the six initial objectives were achieved, but due to time frame limitations and issues with the sensor, two objectives were not met.

7.1 Capture as much spectral reflectance data as possible from the available plant species, as is possible in the projected timeframe, using in situ hyperspectral remote sensing

During the study, the number of visits to Paardefontein where readings of trees were possible exceeded fifty. For the shrubs, these visits were more than 30. This provided a significant sample base for statistical analysis. Throughout the study, a total of 4658 readings were taken in total.

Several scheduled visits did not yield any readings due to inclement weather, sensor issues or issues beyond the control of the involved people. The grass study was, unfortunately, unsuccessful, but a further reconsideration and redesign of the experiment may have positive results in future.

All readings were taken using the ASD field spectrometer, as proposed in the methodology, which is a hyperspectral sensor which can detect spectral reflectance between 350nm and 2500nm.

This objective was sufficiently achieved to do a comparative study. Both long-term and short-term studies were possible, rendering results that warrant possible further research.

7.2 Consult further literature and improve literature review to determine theoretical soundness of methodology

A literature review was done to support the concept, methodology and findings of this study. This ensures that the study is based on proper scientific principles and that the result of this study will be of value to any further application and research in the field.

The literature review also provides a basis of comparison for the study, as well as supporting the usage of hyperspectral remote sensing to perform the study. Sufficient literature review was done to support the case of this study, meaning that this objective was sufficiently met.

7.3 Test the collected data using the different vegetation indices to determine whether exposure to TNT creates differences in spectral reflectance

As discussed in the methodology, seven vegetation indices were proposed to be analysed to determine whether TNT affects the spectral reflectance of plants. The indices were calculated by extracting the relevant spectral reflectance for each of the required bandwidths.

Statistical analysis was done to determine whether a correlation exists between the index and TNT exposure, and the results thereof noted. The results were also presented to a statistician for verification, and to assist in the understanding thereof.

This means that this objective was achieved.

7.4 Identify possible spectral bands which show correlation to the concentration of TNT in the soil

From the statistical testing of the vegetation indices, it was determined that the spectral bands between 680nm and 780nm were found to be most suitable for the detection of TNT. These bands include the bands required to calculate the red-edge position, which was the vegetation index most appropriate for the detection of TNT.

7.5 Determine whether a correlation exists between the plants' spectral reflectance and weather occurrences around the time of measurement

Time limitations and scheduling issues meant that it was not possible to compare the spectral readings and weather events during the study. This would have supported some of the findings of this study but was unfortunately not achievable.

It is possible to include this as an objective for any future research, as historical data can be requested from the South African Weather Service.

7.6 Compare canopy readings to leaf clip readings to determine whether the methodologies developed can be practically used in actual fieldwork

As is discussed in the limitation chapter of this document, an issue with the sensor’s battery significantly reduced the number of readings possible during each visit to Paardefontein. This meant that canopy readings were not possible. The basis of this study was to compare readings taken during Smit (2013) with leaf clip readings taken during this study.

As real-world applications of hyperspectral remote sensing would likely involve canopy readings, leaf clip and canopy readings should be compared. Findings from this study and any future research have to be replicable when using canopy readings to verify the practical suitability of the methodology.

This can be addressed in further research, starting with the greenhouse study, which will be designed to include significantly fewer plants.

Chapter 8. LIMITATIONS

8.1 Assumptions and disallowances

The project was performed under the assumption that the only variable between the plants was the differing concentrations of TNT. Of course, this is not true. The plants themselves were not identical, and the soil content may have differed between plants of the same species. Drainage characteristics may also have differed between plants.

As is discussed below, the amount of water administered to each plant was not monitored. Thus plants from the same species may have received differing amounts of water. This is relevant because if a plant received more or less water than others in the same species, any of the indices that are related to moisture content might be influenced. Also, while TNT only has a solubility of about 20g per litre of water, residual TNT may be physically removed from the soil due to water washing nutrients, including residual TNT, out of the ground.

In this regard, the project design did not allow for the simulation of topography. The project was planned in such a way that plants are not subject to sloping. In other words, a level minefield was simulated. This disregards water runoff and does not simulate landmines leaking upslope of vegetation. In an actual minefield, one expects topography to have some influence, and this can be addressed in future research.

8.2 Weather, watering and environmental issues

The plants were subjected to semi-natural conditions. This meant that they were exposed to weather conditions, animals, insects and other plants. The plants were housed without any cover, meaning that they were exposed to any weather conditions prevalent at the time. These conditions include rain, sun, heat waves and drought.

Due to the nature of the project, several external factors influenced the outcome of the study. These include natural factors, as well as technical and artificial issues. As stated in the methodology, the plants were kept in the same immediate environment. They were, however, subject to the care of the staff of the farm, meaning that watering and maintenance of the area may have been irregular. It is practice for the staff to take a compulsory break around Christmas, with only security staff remaining. This means that the plants may have had extended periods without proper watering. This is of limited concern, seeing as all of the plants would have been exposed to this factor together.

Another limitation regarding the care and maintenance of the plants was that when water was given, which was usually scheduled for twice a week, the amount of water given to each plant was not monitored. The significance of this is that some plants in a range may have been subjected to higher levels of watering than others. This means that some of the indices' results may have been skewed due

to water stress. As mentioned in the results, *Potulacaria Afra*, which is a succulent shrub, over-watering may have adversely affected the health of the study group. In other cases, the watering scheduled could not be followed by staff due to issues such as the water vehicle not working, or no water being available on the farm. This meant that plants were not manually watered for extended periods. Whenever it was noticed that the containers that the plants were kept in had any standing water, the water was removed.

Other environmental factors which may have influenced this study is the high volumes of rain in 2014, which may have been a factor of the grass study failing. When the grasses were collected from ARC Roodeplaat, they were severely filled with water, and the stress of the relocation, as well as the high volumes of water, may have resulted in some of the grass specimens dying.

Toward the end of 2015, and for most of 2016, South Africa experienced a severe drought, meaning the plants were exposed to high temperatures and insufficient natural rainfall. Manual watering of the plants was also kept to a minimum during the drought, due to the scarcity of water in the area as well as water usage restrictions. This may have influenced spectral readings taken during this period, but all the plants were exposed to identical conditions, reducing the significance of the drought for inter-species variability.

8.3 Fauna

As stated in the findings chapter, the plants were housed in a secure enclosure. Some small animals, such as rabbit or antelope, may have still been able to access the plants. This was visible due to grasses regularly being eaten, in some cases to such an extent that it was impossible to take any readings.

The presence of bees also hindered the process of taking readings. It was noticed that the presence of honey bees seemed to increase in the area after TNT had been administered to the plants. As Dr Schmitz is allergic to bees, and to avoid any personal injury, they were avoided, and the number of readings taken on that day would be limited. Although they were a regular presence around the plants, the amount of times bees negatively impacted on the study was limited.

Wasps, praying mantises, birds and snakes were also commonly noticed in the area around the plants. Apart from two, isolated cases of snakes seeking refuge in the bags in which the grass species were kept, the above fauna never prohibited the taking of readings. In the event of wasps and snakes, they were avoided where possible. No cases of bites or bee stings occurred during the study.

8.4 Paardefontein staff and facilities

Staff arrangements at Paardefontein sometimes led to the office or facilities being unmanned when readings were scheduled. Readings were then either rescheduled or cancelled, meaning that the original plan of taking bi-weekly readings was not possible.

8.5 ASD spectrometer and readings

While the utmost care was taken to ensure that the ASD instrument was properly maintained and functioning correctly, sensor issues also limited the number of readings which were taken, as well as possibly impacting on the quality of readings. The ASD spectrometer was originally released with two batteries, which ensured that it was possible to take multiple readings per plant specimen during each visit to Paardefontein. Toward the beginning of the study, one of the batteries failed, reducing the amount of readings possible per plant per session to two. In other cases, the laptop paired to the scanner was unable to connect to the device, meaning that no readings could be taken for that day.

The sensor is not weatherproof, meaning that readings could only be taken under dry conditions. If it was raining on a day that was scheduled for to take readings, the session had to be postponed or cancelled. It was also noticed that connectivity issues between the laptop and ASD spectrometer were more frequent during hot or windy days.

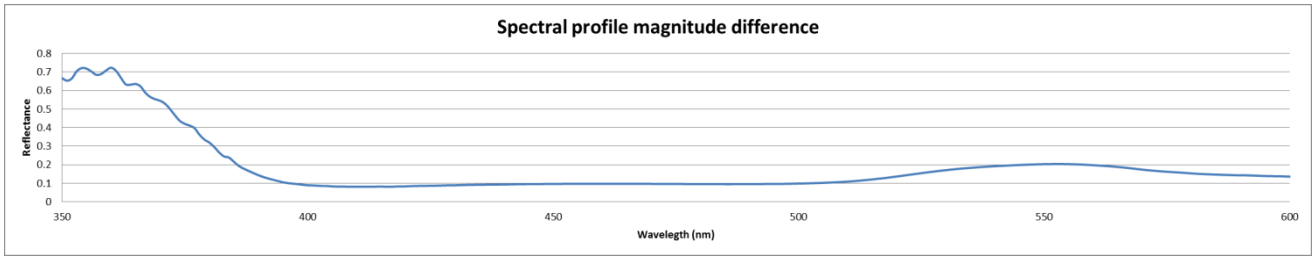

Figure 51 - Static in 350nm to 430nm range

During taking readings, it was noticed that for some wavelengths, erroneous readings were generated. Static was noticed in the wavelength region between 350nm and 430nm. In Figure 51, small cyclic peaks and depressions are visible, while readings for longer wavelengths generate a smooth line. Although noticeable, these readings did not influence the outcome of the project as it was in a bandwidth area not used for any analysis. It was also noticed that a “step” at about 1000nm was present when taking readings. Figure 52 displays a slight, abrupt dip in reflectance values. Both these artefacts varied in magnitude between readings, and in the case of the static, sometimes propagated as negative values.

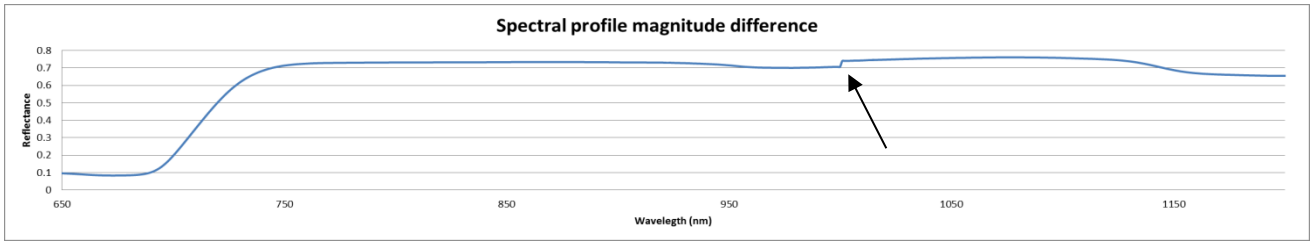

Figure 52 - "Step" artefact in readings at 1000nm

These values may be attributed to a calibration issue with the spectrometer. They have been present in all readings taken and used for this study, but since they propagate at bandwidths not utilised in the analysis, they have been ignored.

What was also noticed was that in some cases, subsequent readings taken on the same day for the same plant might have different magnitudes. The spectral profile may have been similar, but one profile may be significantly lower. Figure 53 displays this difference in magnitudes for subsequent readings for EL1 (Sweet Thorn, control). This is the reason for using an average value of readings when doing the analysis. Also, note the static in the profiles between 350nm and 430nm, as well as the artefact in the profiles at 1000nm.

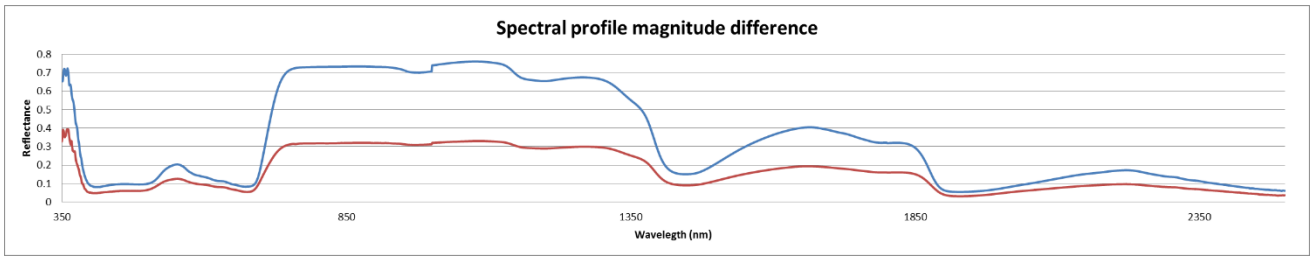

Figure 53 - Spectral magnitude difference, Sweet Thorn control plant, 2014-12-15

What was noticed when taking readings at Paardefontein was that the difference in magnitude usually happened when the foliage coverage or arrangement in the leaf clip mechanism of the sensor was insufficient. The ideal reading is one where the aperture of the leaf clip mechanism is completely covered, or mostly covered by the foliage sample. If there is a significant uncovered surface area, readings tended to have a reduced magnitude. This was usually corrected in the field by adjusting the sample area on the sensor aperture.

When readings were taken, in some cases it was unavoidable to include brown or yellow foliage in a leaf clip sample. Even in the event of evergreen plants, browning of the leaves is still normal, as the older foliage is shed. In such cases, a typical yellow spectral profile was noticed. This profile is characterised by a gradual increase in reflectance in the red to infrared, in contrast with the noticeable steep increase in reflectance in this bandwidth area.

Figure 54 is an example of a typical green spectral profile (blue line) and a characteristic yellow profile (red line). This example is of Cape Holly, the species of tree which died out before the end of the study. The green profile was taken of one of the control plants on 6 June 2013, and the yellow profile was taken on the same day, for the 30mg/kg plant. It is important to note that TNT was not administered to the plants at this time. It is also important to note that although these profiles are typical of green and yellow plants, spectral signatures of different plants are unique, and may have different reflectance values.

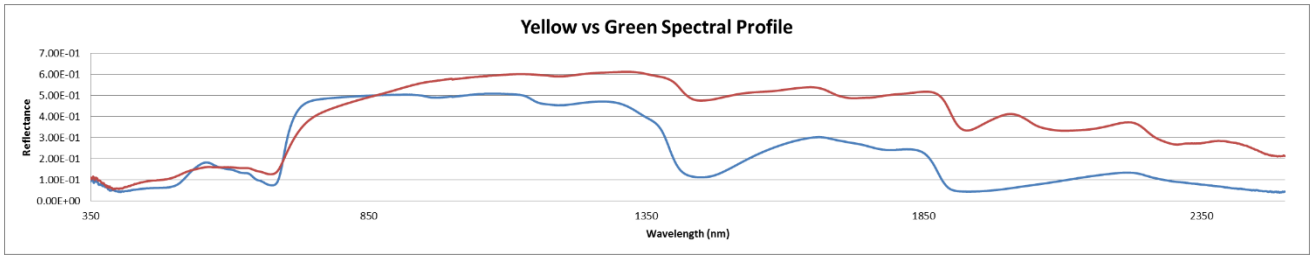

Figure 54 - Comparison of green (blue line) and yellow (red line) spectral profiles, Cape Holly

8.6 Scheduling conflicts

It was not always possible to arrange suitable meetings during this project, either to take readings at Paardefontein or to discuss administrative matters regarding the project. These were usually caused by either other professional or personal commitments. Such scheduling issues were easily resolved, and seldom negatively impacted on the outcome of the project.

As the sensor is an asset of the CSIR, it is available for use to several members of staff. Due to booking conflicts, the sensor was not always available to use for scheduled visits to Paardefontein. This issue was usually resolved by rescheduling visits, but in some cases, long term bookings of the sensor meant that some visits had to be cancelled.

Chapter 9. SIGNIFICANCE OF RESEARCH

This research aims to assist in the mammoth task of rendering the world landmine-free. If any landmines can be detected and successfully be removed using this, and any subsequent research, the chances of innocent civilians being hurt by landmines are reduced.

Should the project have positive results, and the theory that plants contaminated by explosives have differences in spectral reflectance signatures to that of healthy, uncontaminated plants be found to be viable, the methodology here with further development can be applied in the field of humanitarian demining. Also, if spectral bands showing major clear signs of TNT contamination can be isolated and verified, a multispectral sensor can be developed specifically for landmine detection. A further positive development may be a combined airborne sensor, light enough to fit on a UAV, light aircraft or helicopter, which can significantly increase the area being scanned per unit of time. It might also allow for existing space-borne platforms to be used for this purpose.

It is not the intent of the research to provide a fool-proof tool to detect hidden landmines, or even to detect individual mines. It is meant to be used in conjunction with other devices or sensors in the search for mines. The aim is to reduce the number of man-hours needed to find and define possible minefields. Should the methodology prove successful, a mine-detection system can be designed that contains several sensors, such as multispectral sensors, ground-penetrating radar, and metal detectors, or multi or hyperspectral sensors can be added to existing mine-detection platforms. This means that people may spend less time physically looking for landmines, but rather rely on remotely sensed data in identifying possible minefields. This will, hopefully, provide a means to minimise the possibility of demining teams setting off landmines by accident, causing physical harm or even death.

Should the presence of TNT in soil be detectable using hyperspectral remote sensing, further research can be done to test for contamination by other elements and substances found in landmines, EXPs, or UXOs, such as RDX, plastic explosives, lead, iron or gunpowder.

While the research proposed is specifically aimed at the field of humanitarian demining, the application of the research may reach beyond that. The indices used in this project can be and have been applied in the areas of mining, water engineering, precision farming and environmental management. Although the findings of this project have a substantial degree of uncertainty, a refined model may also have applications in the defence sector, including mine clearance.

During this study, possible future research has been identified. The study as-is does not account for the continuous leaching of TNT into the soil, but rather simulates a single contamination. This means that

with continuous watering and rain, the concentration of TNT may be reduced as it is washed from the soil.

It was suggested that a similar study takes place with plants situated in a greenhouse, to control factors such as moisture in the plants, ambient temperatures and the concentration of TNT in the soil. External factors, such as droughts, frost and heat waves can then be eliminated, and the amount of water the plants receive can be precisely controlled. The concentration of TNT in the plant soil can also be controlled, by continuously administering a dose of TNT with the watering of the plants. This will simulate a real-world situation, where a landmine degrades and continuously leaches TNT into the soil.

Different substances may also have different effects. This study focuses on the effects of TNT on plants, mainly due to the easy availability thereof, but other explosives are used in warfare, including RDX and C4. If possible, the effects of such substances may be tested similarly.

Lastly, as stated previously, the focus of humanitarian mine detection research is on hybrid devices. A study investigating the effectiveness of a mine-detection device that utilises hyperspectral or multispectral remote sensors, together with other sensors, such as GPR, should also be investigated, as well as the viability of having such a system on an unmanned platform, either aerial or terrestrial.

As stated earlier in this text, topographic and hydrologic factors have not been tested in this study. Further research in this area may prove valuable, and possible research may include the influence certain soil types may have on the TNT leaching process. Topographic factors can also be investigated, such as slope, and the effect it has on the concentration of TNT in areas down slope.

Chapter 10. ARTICLES, PAPERS AND PRESENTATIONS

The proposal and initial results of this study were presented at the Geneva International Centre for Humanitarian Demining at Denel Land Systems, Lyttleton, Pretoria, in June 2015. It was positively received by the attendants.

A research paper was prepared in conjunction with Dr Xolani Peter, Dr Peter Schmitz and Dr Antony Cooper, discussing the outcome of the study comparing ultra-performance liquid chromatography and hybrid quadrupole orthogonal time of flight spectrometry of leaf samples taken from contaminated plants, and the results of this study.

An article is also being prepared to submit to a South African geoscience journal, namely the South African Journal of Geomatics.

Chapter 11. FUTURE RESEARCH

Although this project had relatively inconclusive results, analysis of the red-edge position did show some promise. Further research has already been planned and submitted for approval at the CSIR.

11.1 Greenhouse study

External influences had a profound effect on the plants used for this study. A small-scale study was designed to fit greenhouse conditions. Figure 55 shows the greenhouse used for the follow-up study. This means that factors such as temperature differences, exposure to water (irrigation controller pictured in Figure 56), and the influence of fauna and flora can be better controlled, and in some cases eliminated.

Figure 55 - Greenhouse at CSIR, Pretoria

Figure 56 - Irrigation control unit, greenhouse study

The greenhouse study commenced at the end of 2016, with a reduced amount of plants relative to what was used at Paardefontein. Shrub and grass species have been acquired, and are housed in a greenhouse on the CSIR's main campus in Pretoria. (Figures 57 and 58) The plants are monitored, and TNT will be administered by trained professionals, similarly to this study, and readings will be taken with the ASD spectrometer on a regular basis.

Figure 57 - Shrubs used for greenhouse study

Figure 58 - Grasses used for greenhouse study

Ultra performance liquid chromatography and hybrid quadrupole orthogonal time of flight spectrometry will also be done on the plants by Dr Peter, as explained in an earlier chapter. This will be done at regular intervals, and the results of the two studies will be compared.

11.2 Simulated mine field

A redesign of the grass study is warranted due to the results of the tree and shrub study. The use of established grasses in their natural environment would be preferred, and this eliminates any stress or adverse factors in moving and rehousing the plants.

A possible area to create a simulated minefield has been identified on Paardefontein. Again, a similar methodology will be followed as with this study, but under fully natural conditions. Plants will be established plants and will be exposed to all natural factors in the area. Paardefontein is situated in a vegetation biome called Central Sandy Bushveld (SANBI, 2012), dominated by grasslands, and includes shrubs, trees and succulents.

The planned study area will be roughly 215m x 272m, of which 135m x 215m will be a control area. A secondary control site will be situated on a neighbouring private farm. The test site will be divided into a grid pattern, and various concentrations of TNT will be administered to the area. Holes will be dug, and the soil will be mixed with TNT that has been dissolved in acetone to render it unusable. This mixture will be returned to the ground to simulate a leaking AP mine.

Readings will be taken on a bi-weekly basis, and the simulation will be done for six weeks.

11.3 RPAS monitoring

Should the simulated minefield study have promising results, the use of a remotely piloted aircraft system (RPAS) will be explored. A suitable RPAS will be fitted with a multispectral sensor, where canopy readings can be taken of the simulated minefield. These canopy readings can be compared to the leaf clip readings gathered during the simulated minefield study.

Unmanned vehicles have a great potential when applied to the geomatics field (Al-Tahir: 2015). Unmanned systems such as CATUAV have already shown great promise in the detection of minefields in Eastern Europe, and the possible addition of HS remote sensing systems to existing mine detection systems will greatly increase the value of these systems.

Should the RPAS phase of the study yield positive results, the research would have achieved its objective, and a usable system that can detect landmines in a practical environment can be explored.

11.4 Other studies

This study was done using only TNT. Other studies have been performed for gas leak detection systems, as well as water leak detection. Further studies can be conducted to determine the effect of unexploded ordnance, which may include chemicals such as lead, and compounds such as gunpowder. The effects of lead on plant health have been studied, but a combination of elements and compounds in explosives and weapons can be investigated. Systems to detect other unexploded remnants of war and improvised explosive devices can also be investigated.

The readings generated for this study will be kept and made available with the permission of the University and CSIR to any person who wishes to perform any further analysis. The data can be requested from the author, Dr Schmitz, or the Department of Geography, Geoinformatics and Meteorology at the University of Pretoria.

Chapter 12. CONCLUSION

As with Smit (2013), mixed results were seen in this study. Vegetation indices such as the MSI and NDWI yielded insignificant correlation to the concentration of TNT in the plant soil. However, some positive results were gathered, and valuable lessons were learned.

It was clear that the REP may prove to be the vegetation index that will indicate the presence of landmines in an area. Although mixed results were found using the REP as an indicator, it proved that both the fertiliser effect, as well as the poison effect were detectable. Different concentrations of TNT yielded both the poison effect, as well as the fertiliser effect in the same species of plant. This leads to the conclusion that, when looking for minefields, it is not necessarily a case of looking for positive or negative differences, but rather any differences.

As the long-term study, the trees especially served mixed results. Even in the same species, varying effects of TNT were detected and differed significantly with the concentration of TNT. In the shrub species, the trend was more negative, with plants exposed to TNT appearing to be under more stress, and less green than control plants. This difference between trees and shrubs warrants a redesign of the grass study, which is important due to the prominence of grasses in open areas.

It is also possible that a window of opportunity may exist, and future research may prove this, but the correlation of REP values and chlorophyll suppression detected using chromatography and spectrometry indicates that TNT has a long-lasting presence in soil, even after an event where a single leakage happened. This correlation also shows that TNT does affect the health of plants, meaning further research into the topic is warranted. The more profound differences in the index values for the shrubs, relative to the trees, support the notion that a window of opportunity may exist. This may be tested using several short-term measurements, or a continuous leak simulation.

Usage of the REP as a means of mine detection is ideal, as several sensors already exist that have the capacity to sense infrared and near infrared. This means that it is not necessary to develop an entirely new sensor. The REP formula for this study is a refined version of the formula, but until a sensor is prepared by this formula, existing systems can be used. These systems range from spaceborne sensors, such as Landsat, to multispectral handheld devices.

From this study, it is also evident that hyperspectral and multispectral systems may not necessarily be applied to pinpoint landmine positions, but rather serve as area reduction systems. The significance of this is that less time and resources will be spent looking for landmines in areas which may be unaffected. Ultimately, the goal is to reduce the amount of time and resources it takes to find minefields, and rather

apply them to areas known to be affected. This may reduce immediate contact with landmines, and hopefully assist in saving lives.

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APPENDIX A – BOX PLOTS

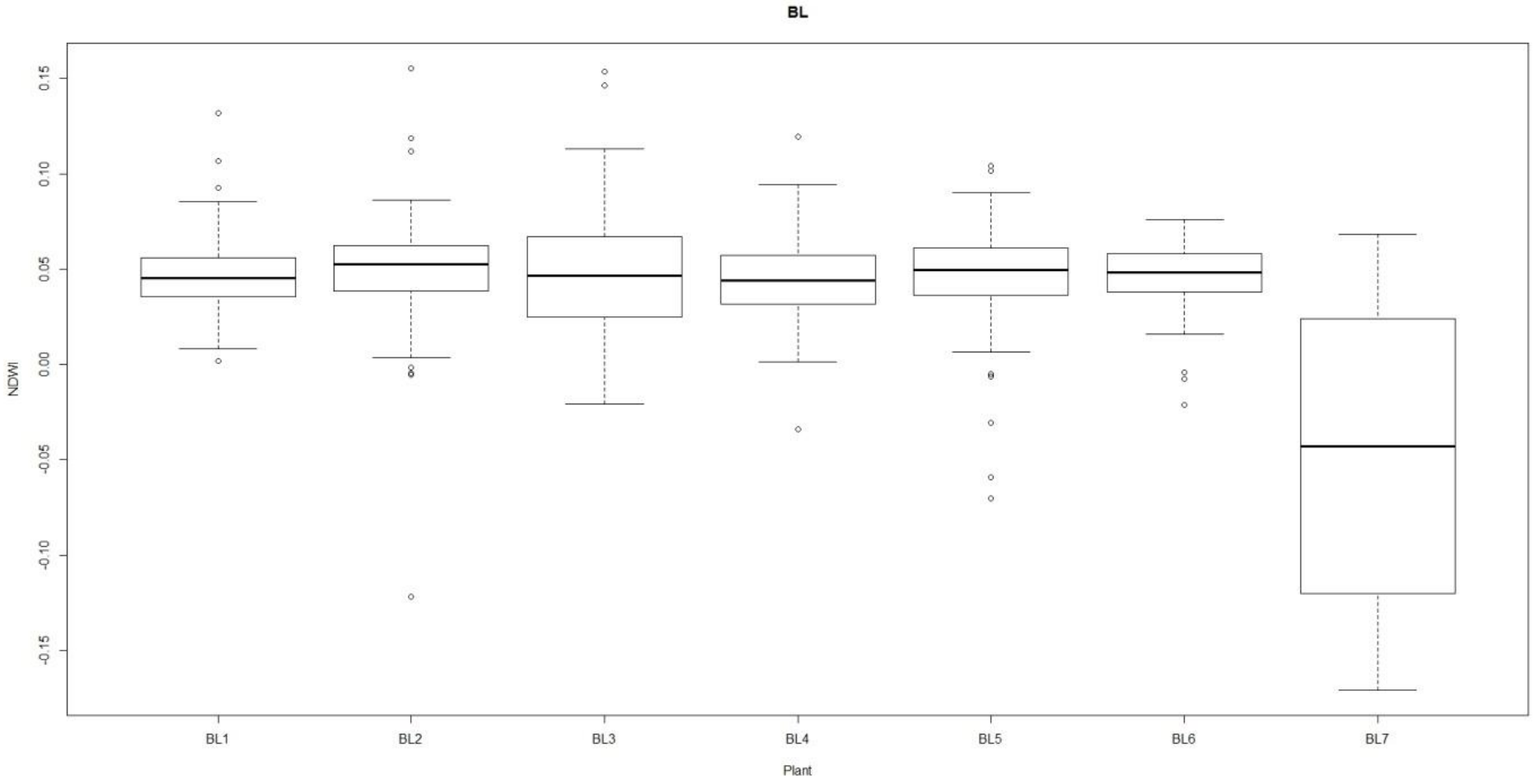

Figure A-1 - Box plot for NDWI, from leaf clip readings for Wild Olive

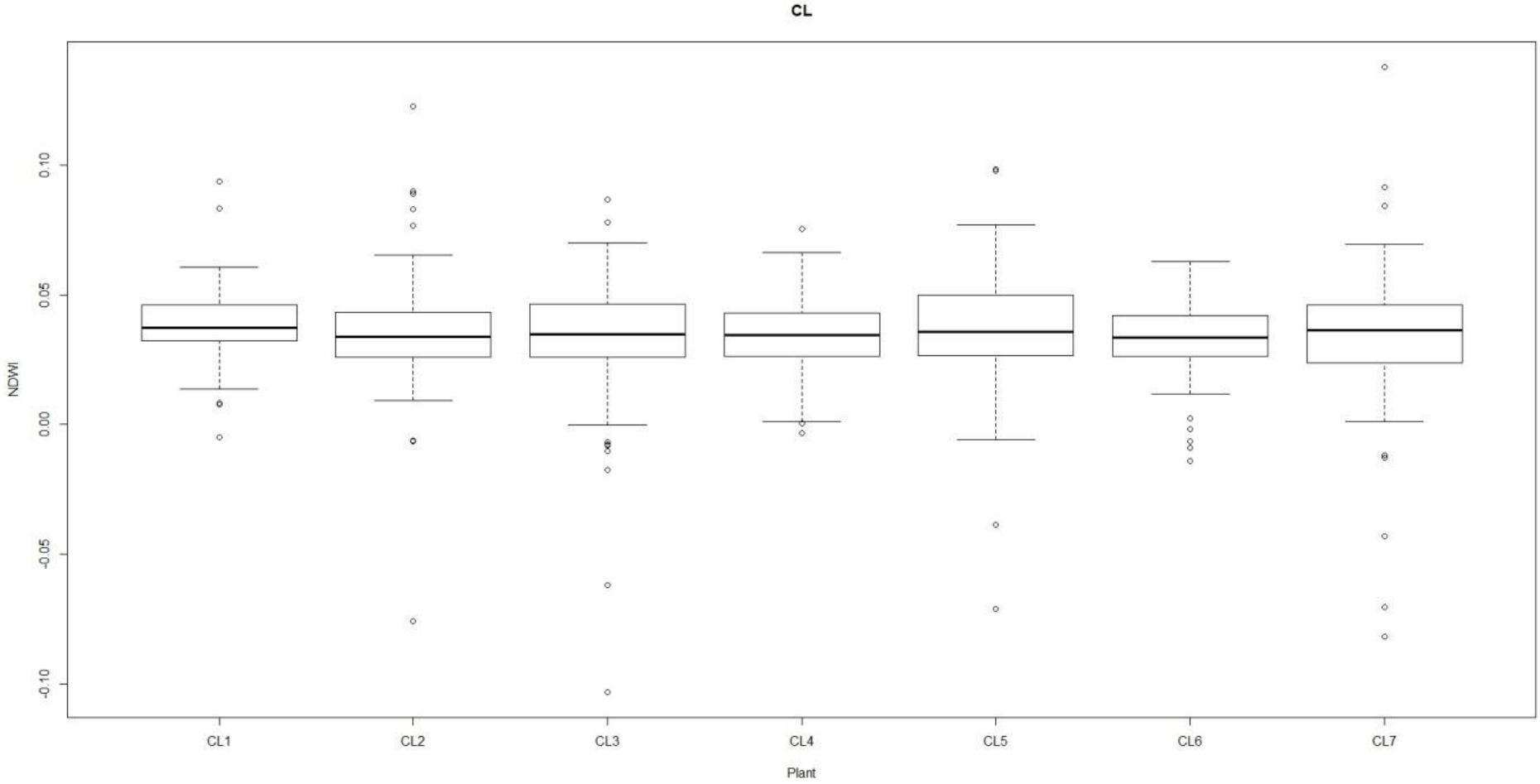

Figure A-2 - Box plot for NDWI, from leaf clip readings for River Bushwillow

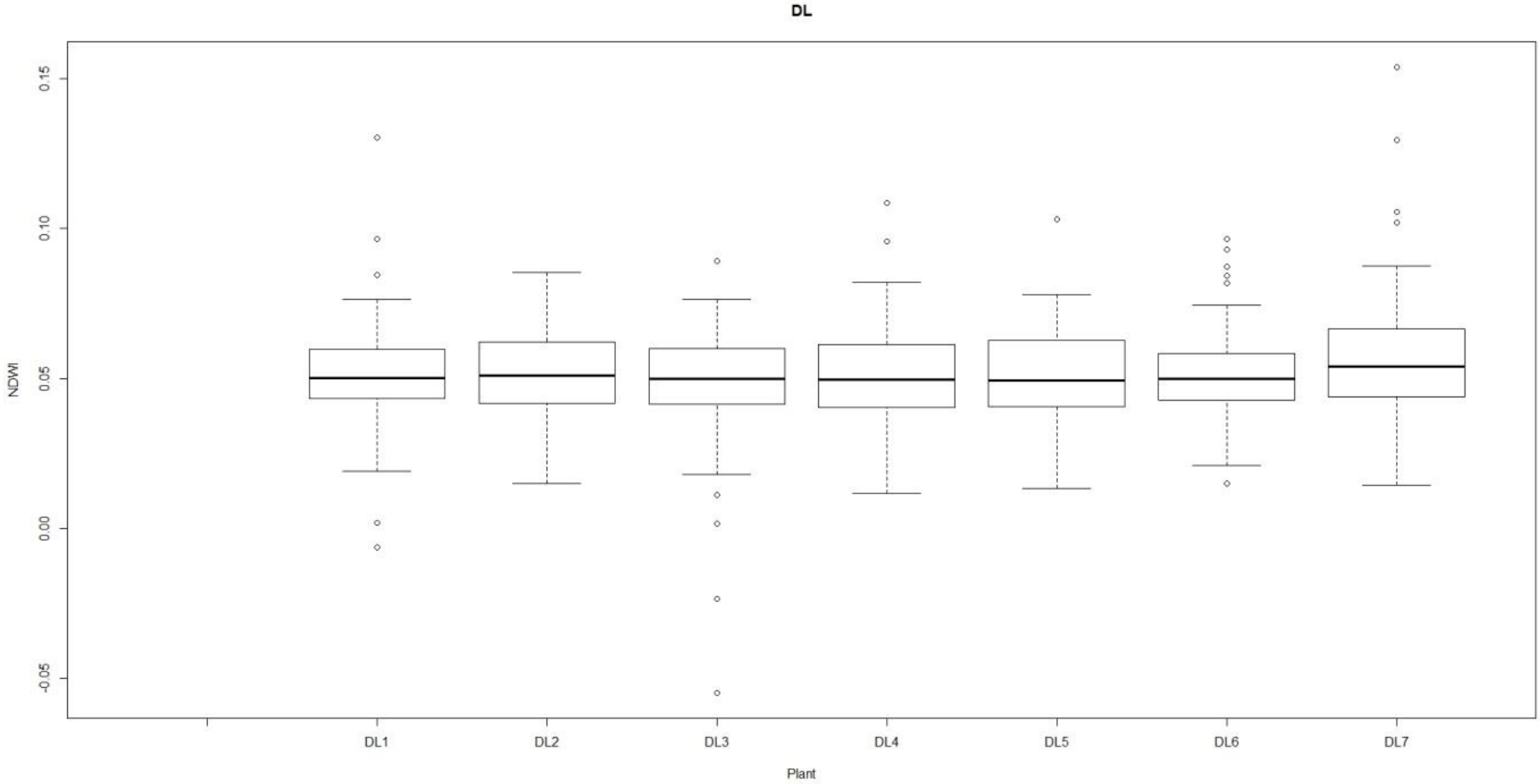

Figure A-3 - Box plot for NDWI, from leaf clip readings for Soap Dogwood

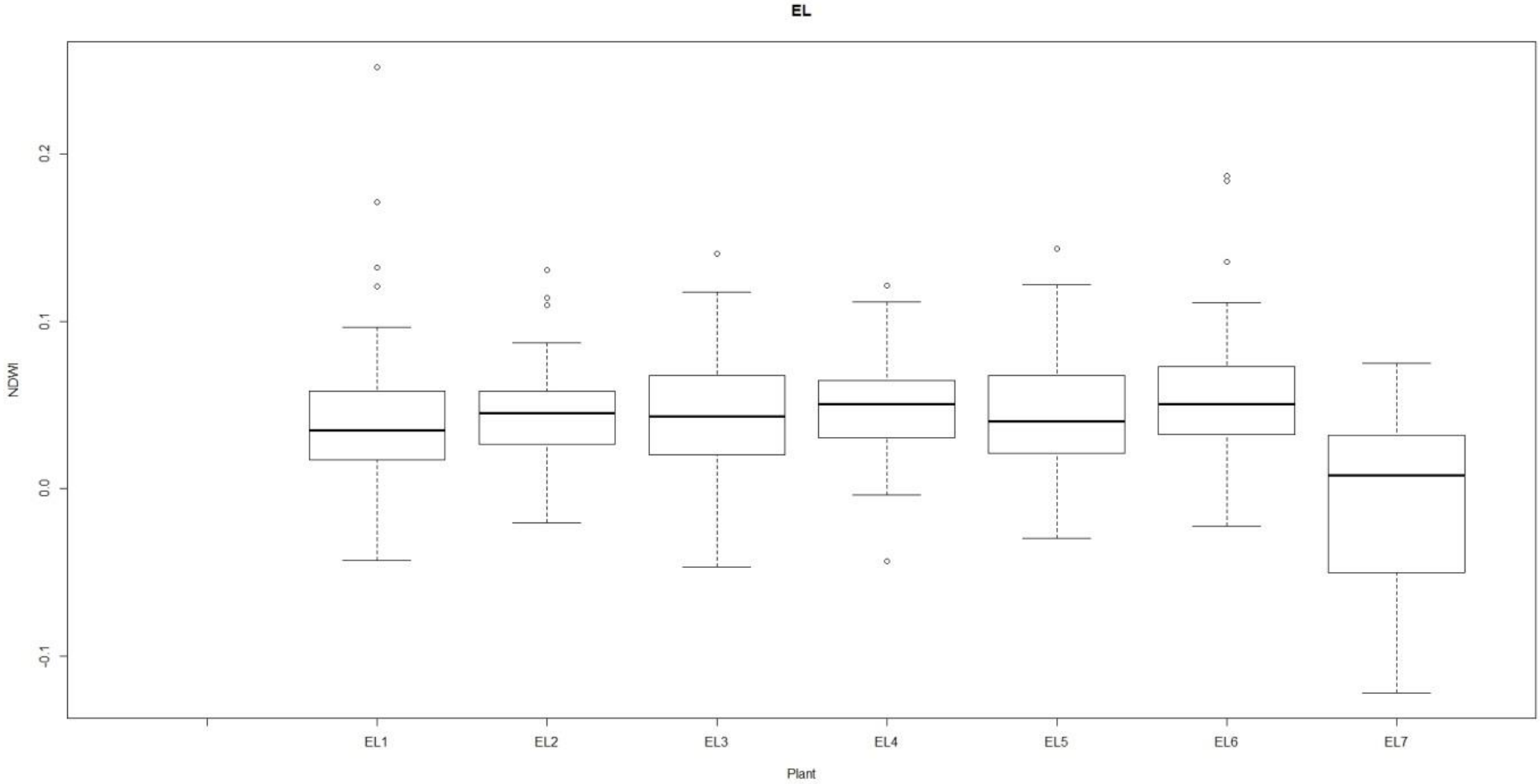

Figure A-4 - Box plot for NDWI, from leaf clip readings for Sweet Thorn

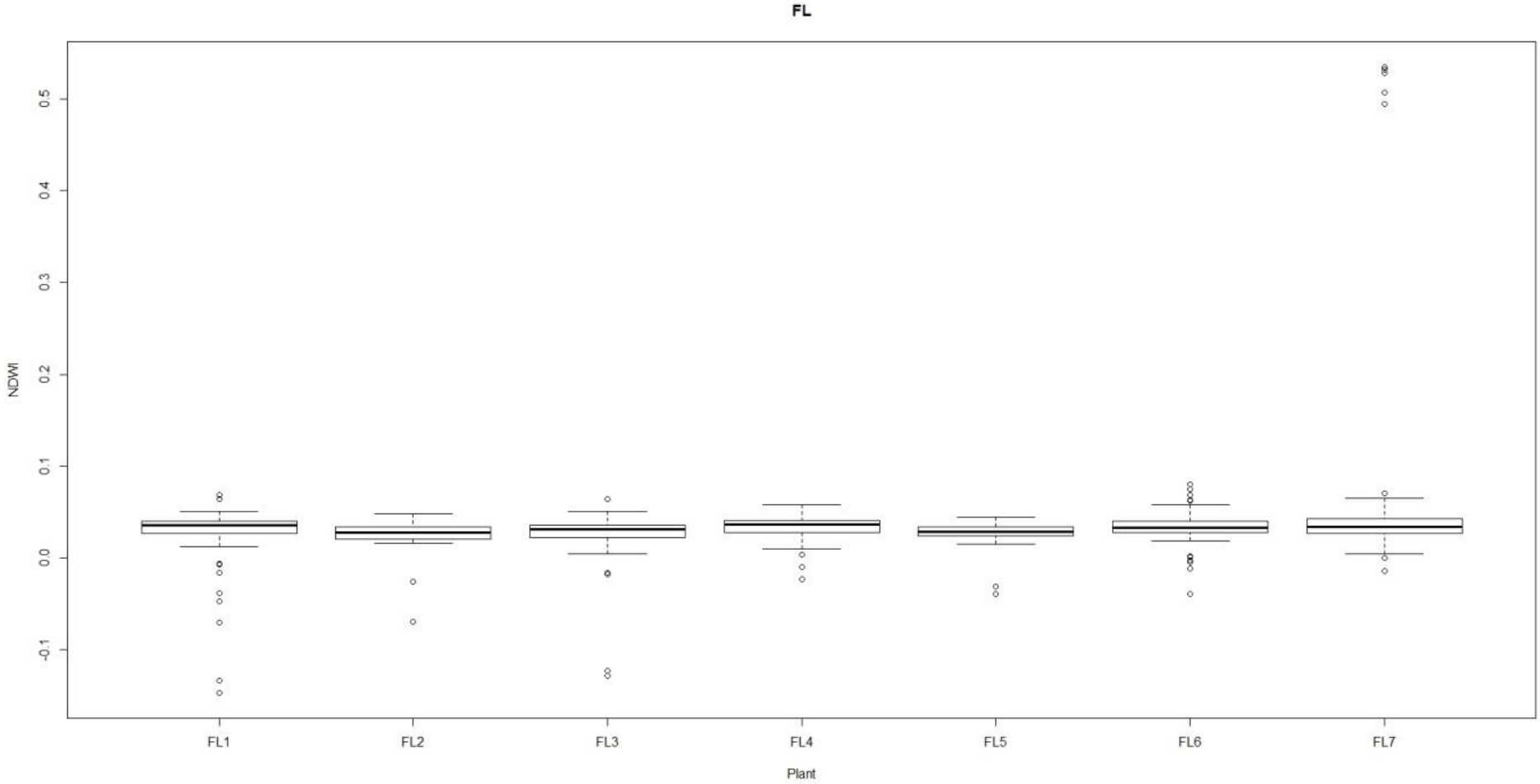

Figure A-5 - Box plot for NDWI, from leaf clip readings for White Stinkwood

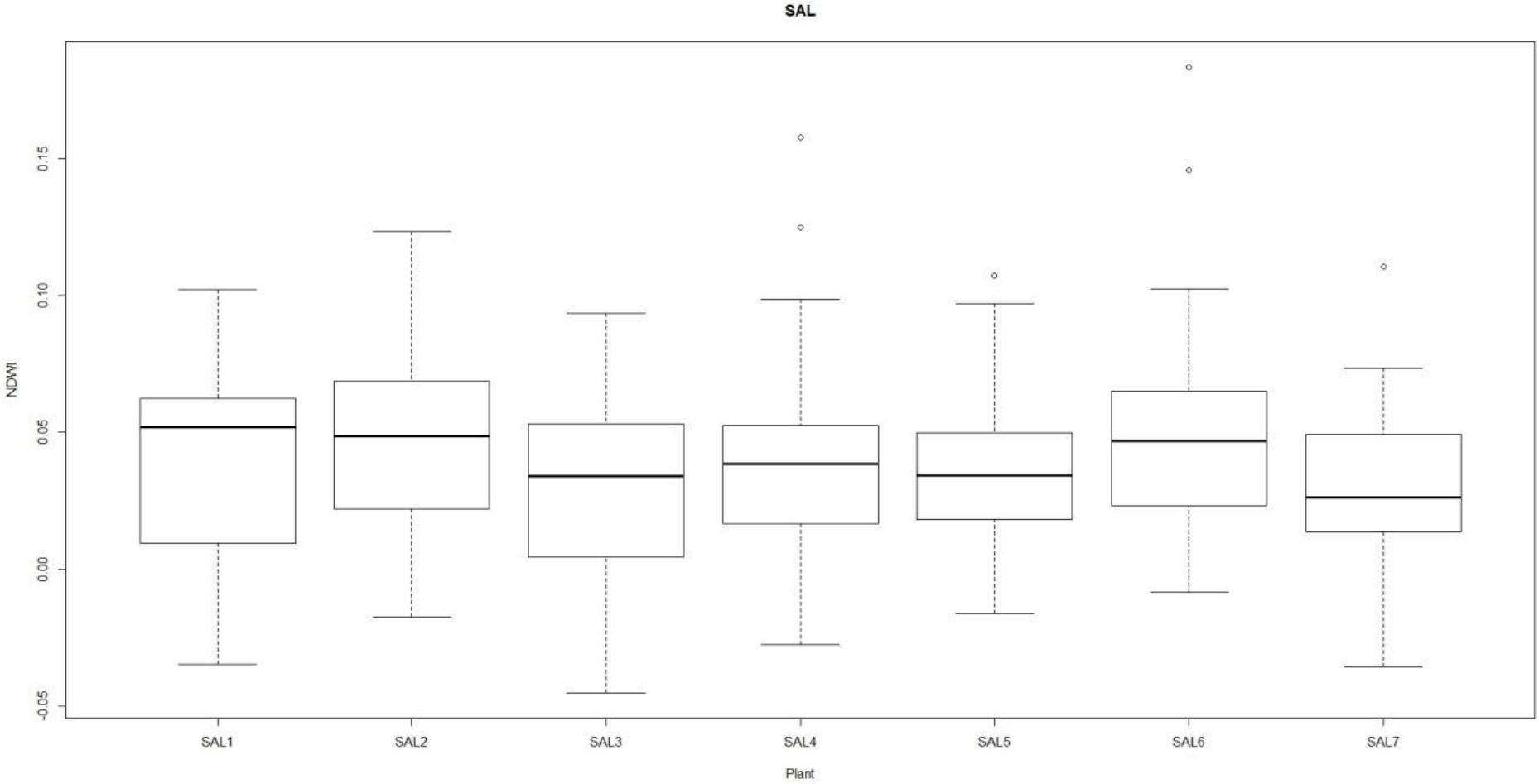

Figure A-6 - Box plot for NDWI, from leaf clip readings for Freylinia Tropica (Transvaal Honey-bell Bush)

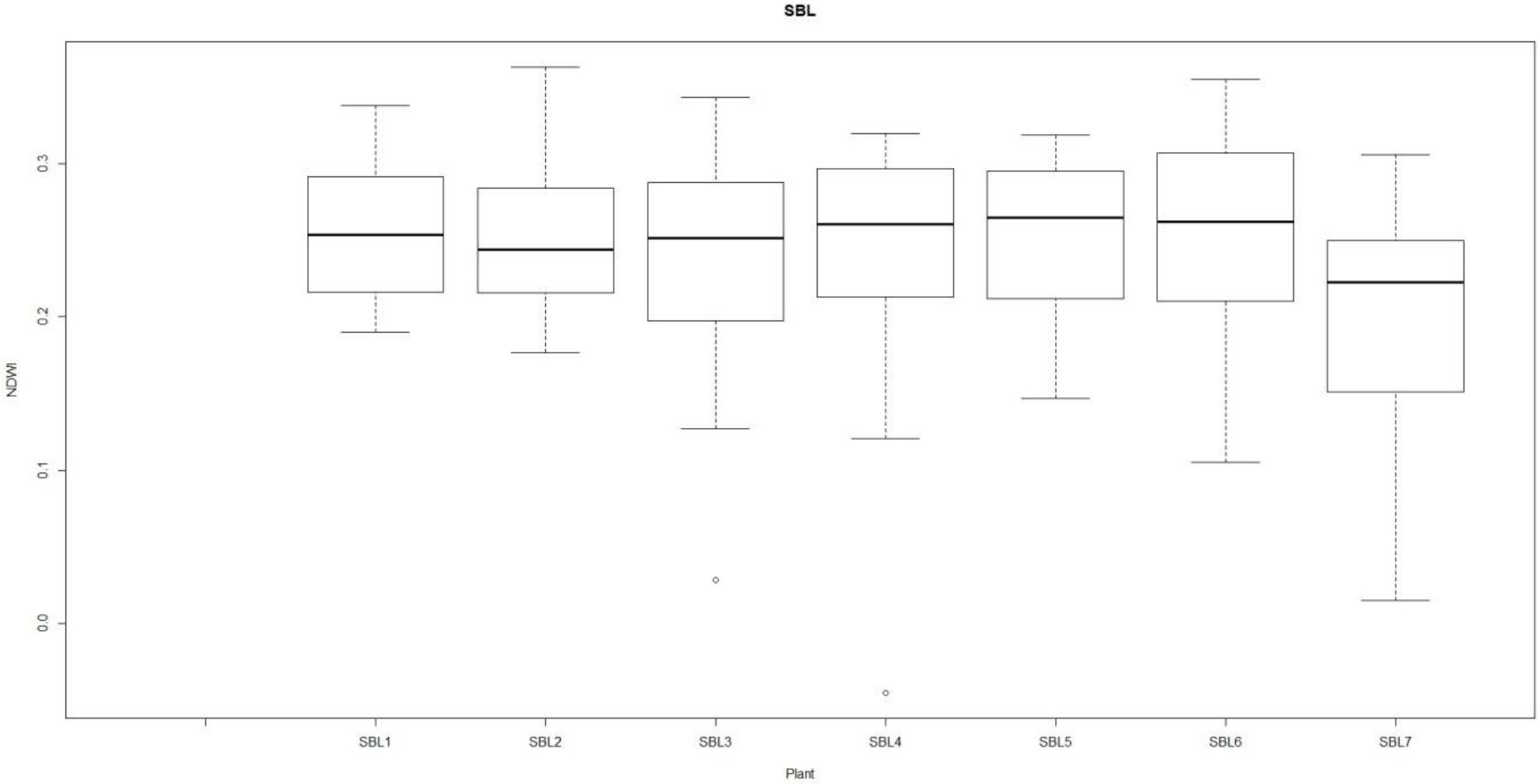

Figure A-7 - Box plot for NDWI, from leaf clip readings for Portulacaria Afra (Spekboom)

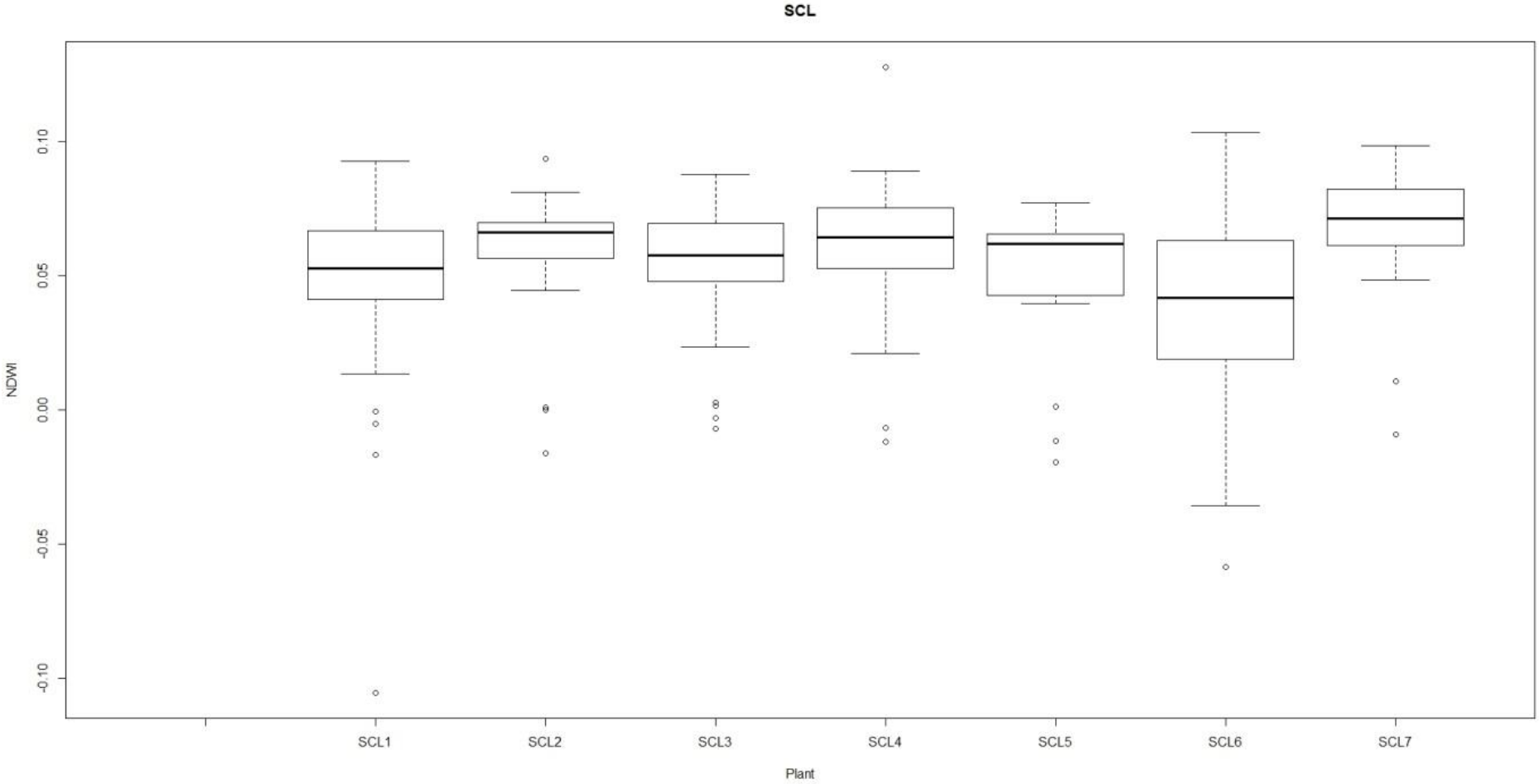

Figure A-8 - Box plot for NDWI, from leaf clip readings for Carissa Macrocarpa (Natal Plum)

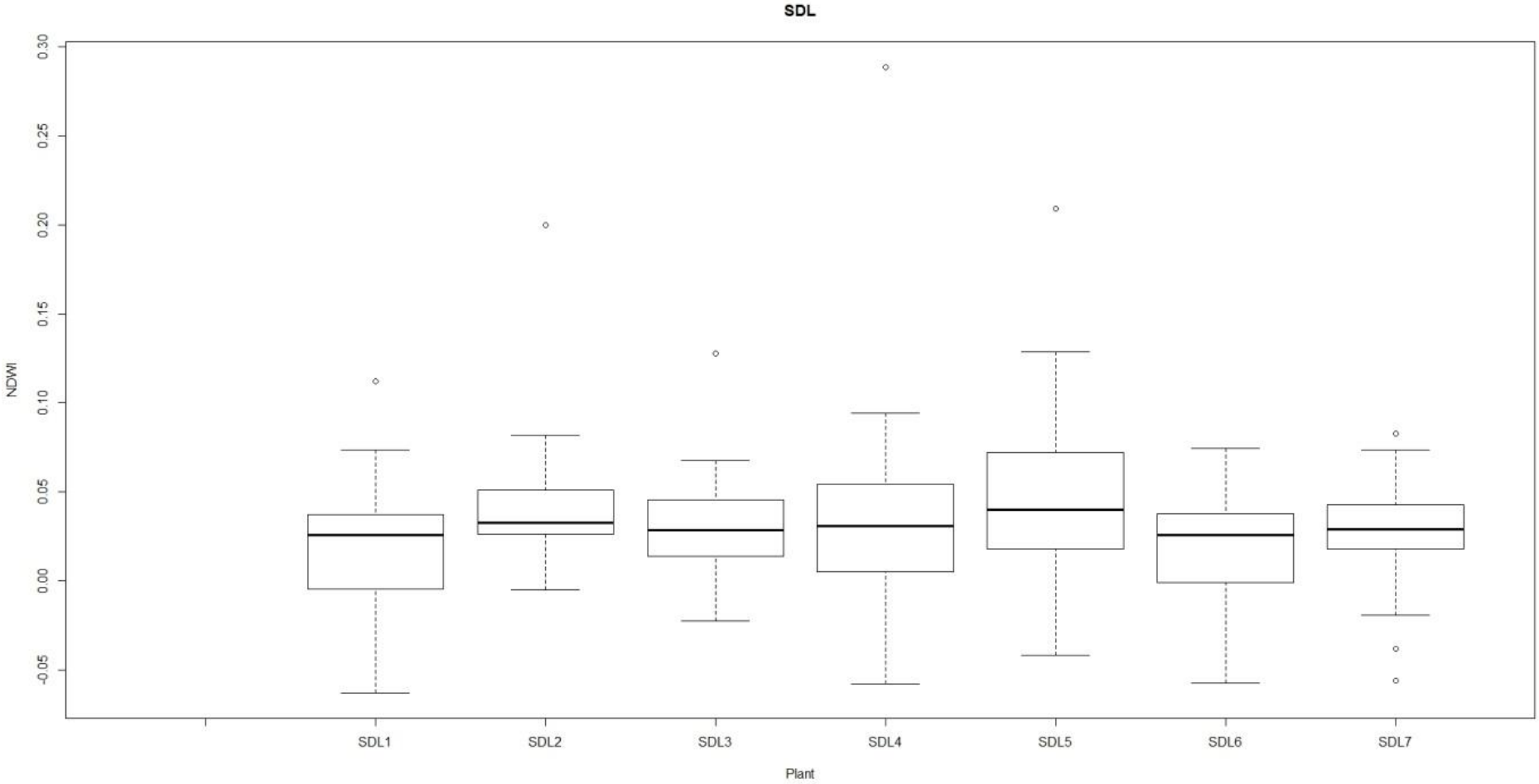

Figure A-9 - Box plot for NDWI, from leaf clip readings for Dovyalis Caffra (Kei Apple)

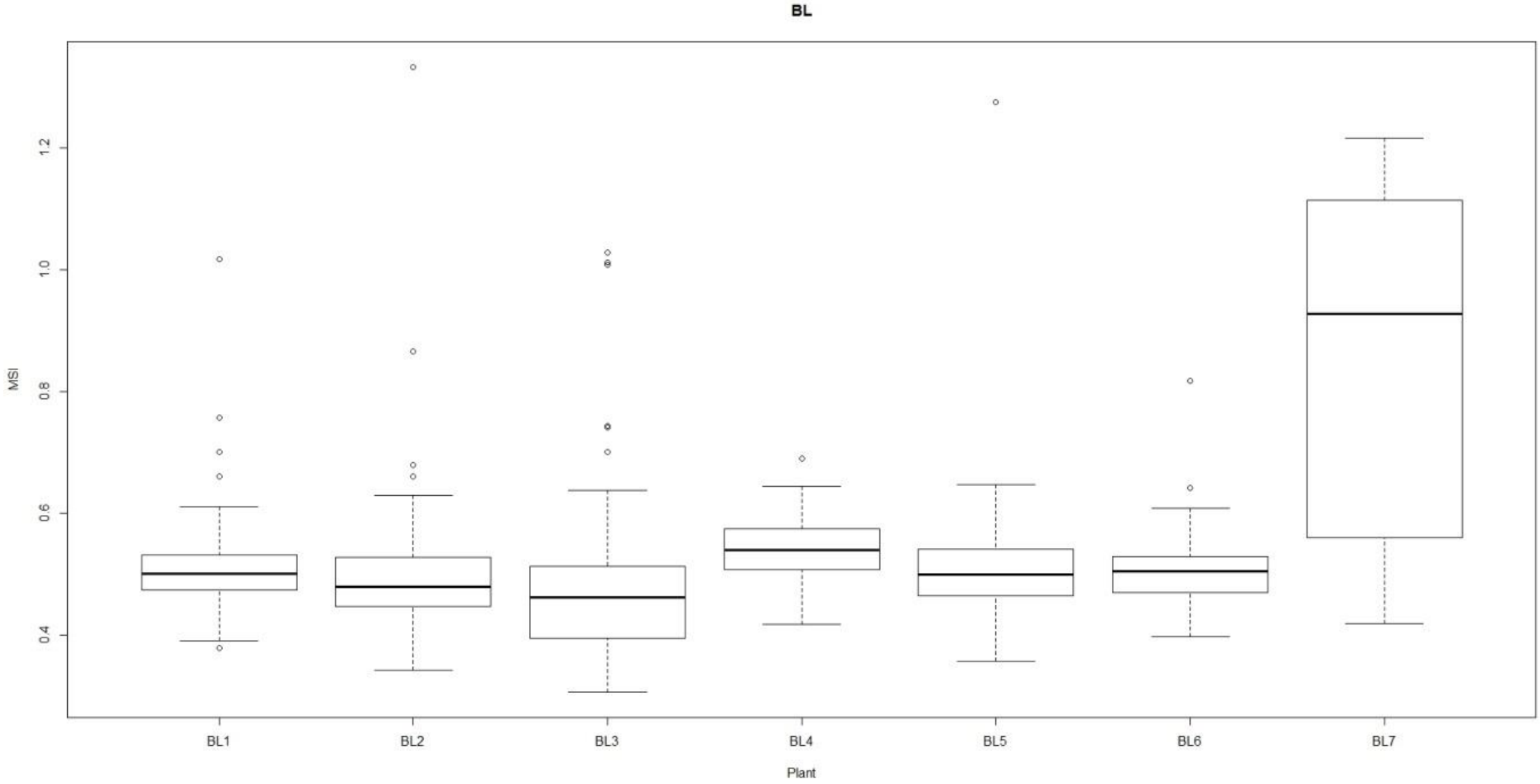

Figure A-10 - Box plot for MSI, from leaf clip readings for Wild Olive

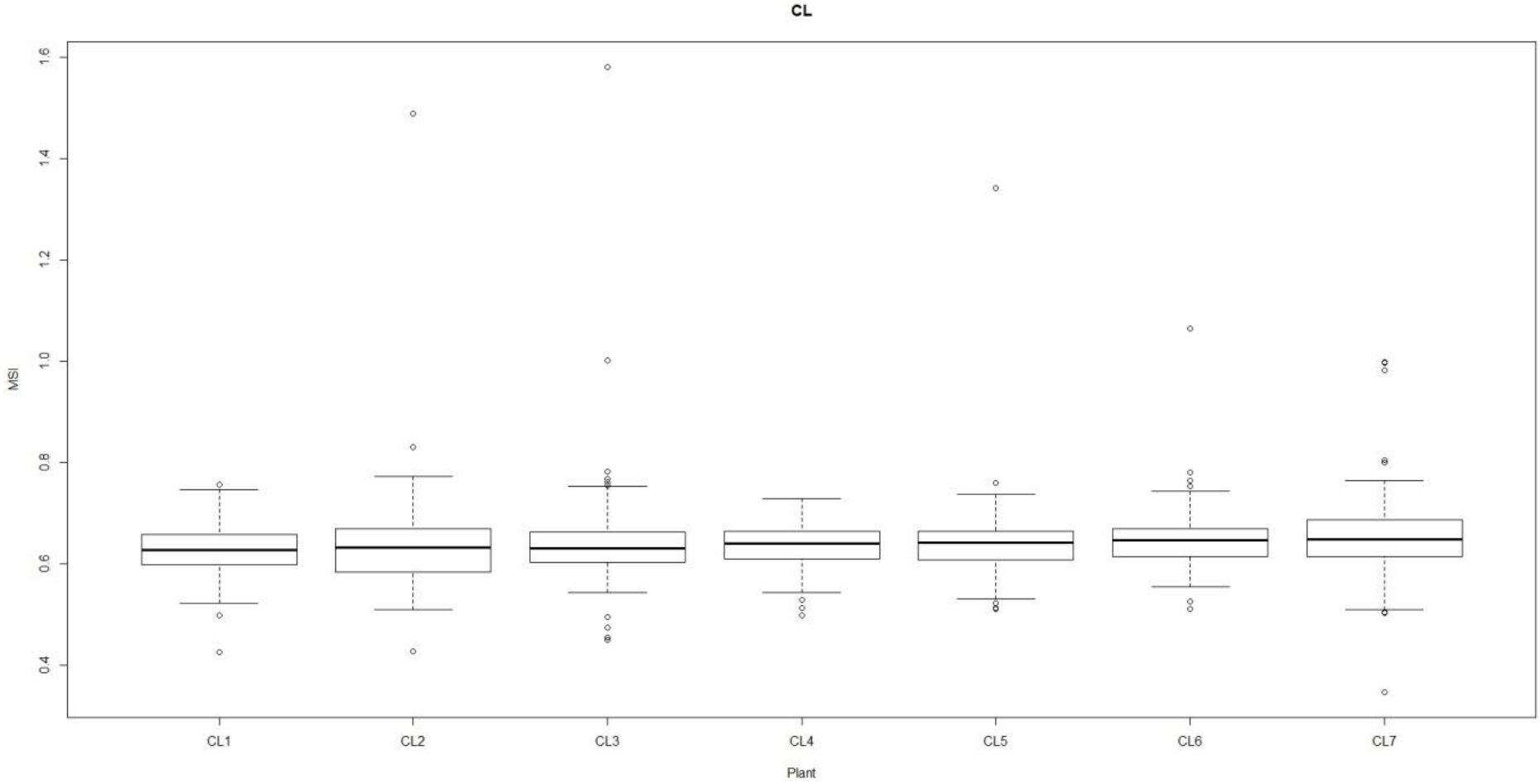

Figure A-11 - Box plot for MSI, from leaf clip readings for River Bushwillow

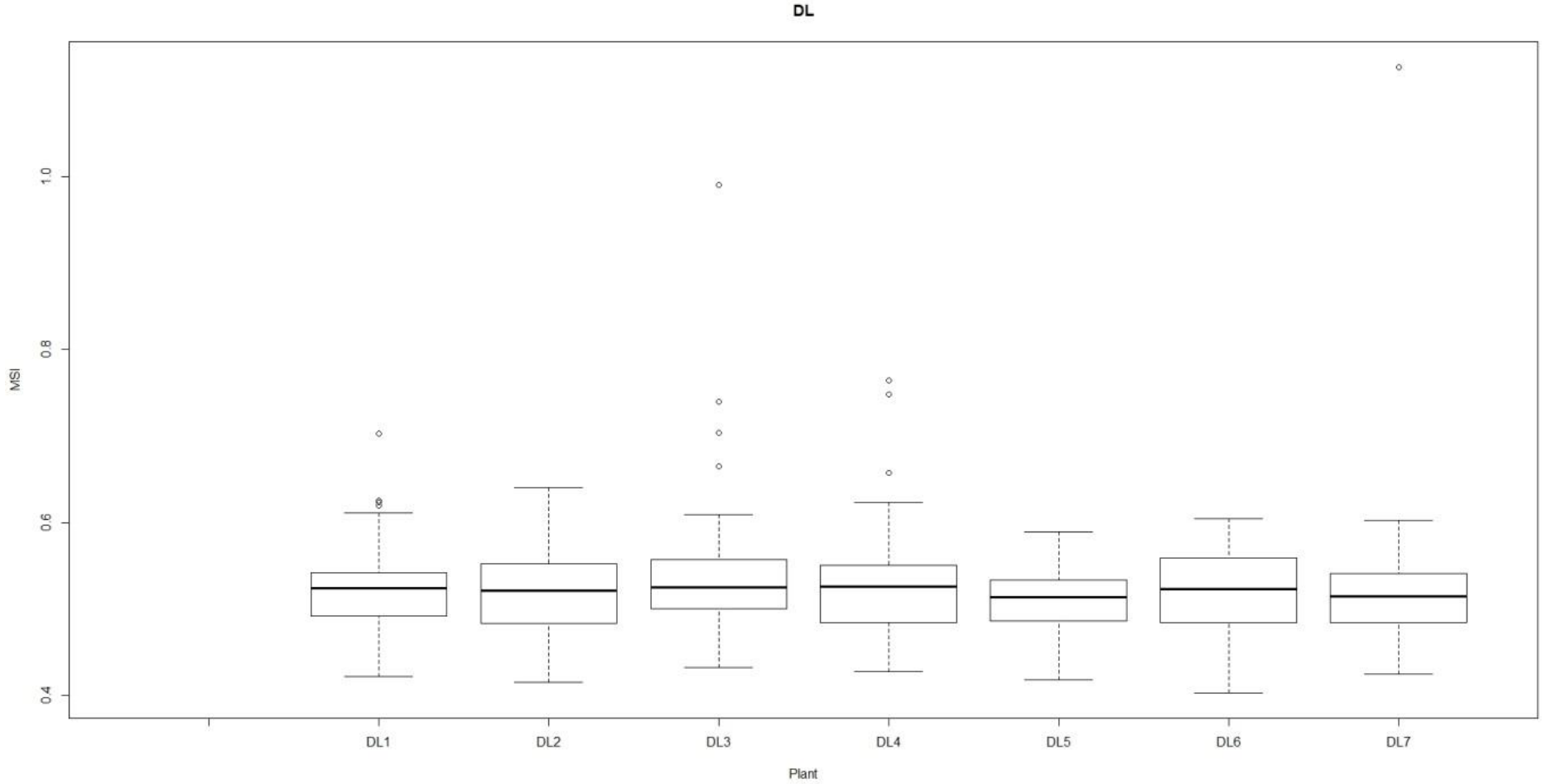

Figure A-12 - Box plot for MSI, from leaf clip readings for Soap Dogwood

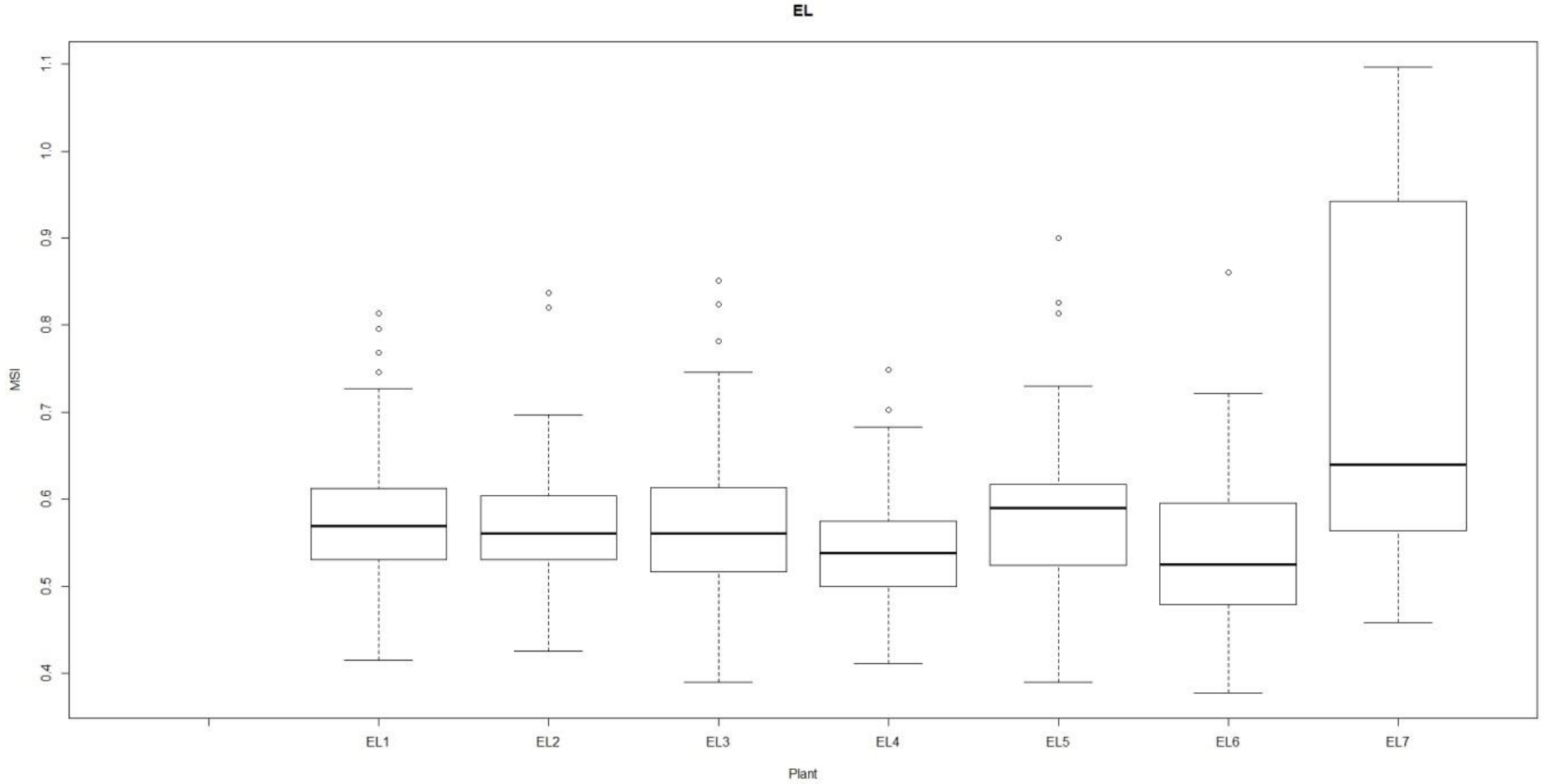

Figure A-13 - Box plot for MSI, from leaf clip readings for Sweet Thorn

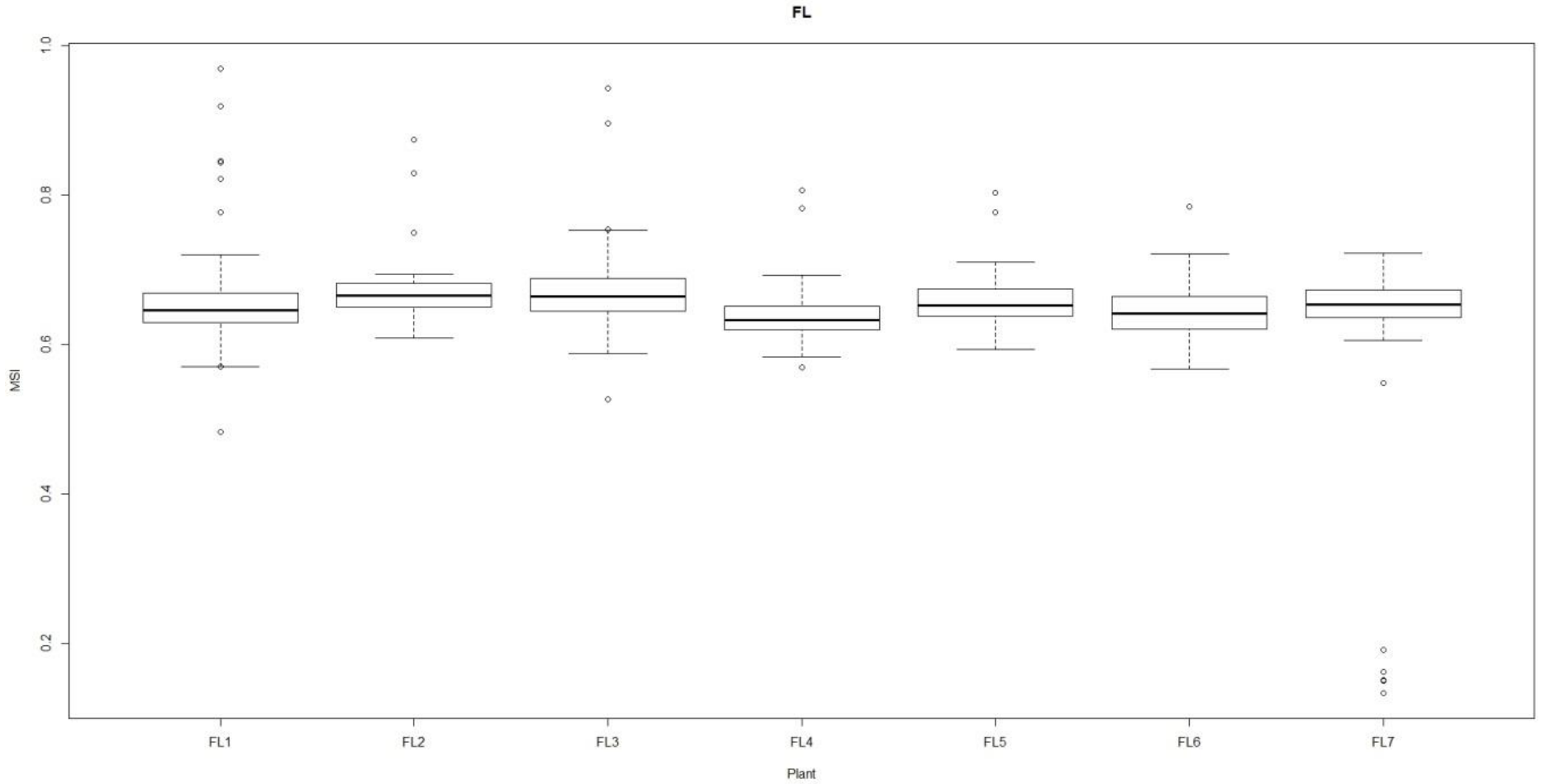

Figure A-14 - Box plot for MSI, from leaf clip readings for White Stinkwood

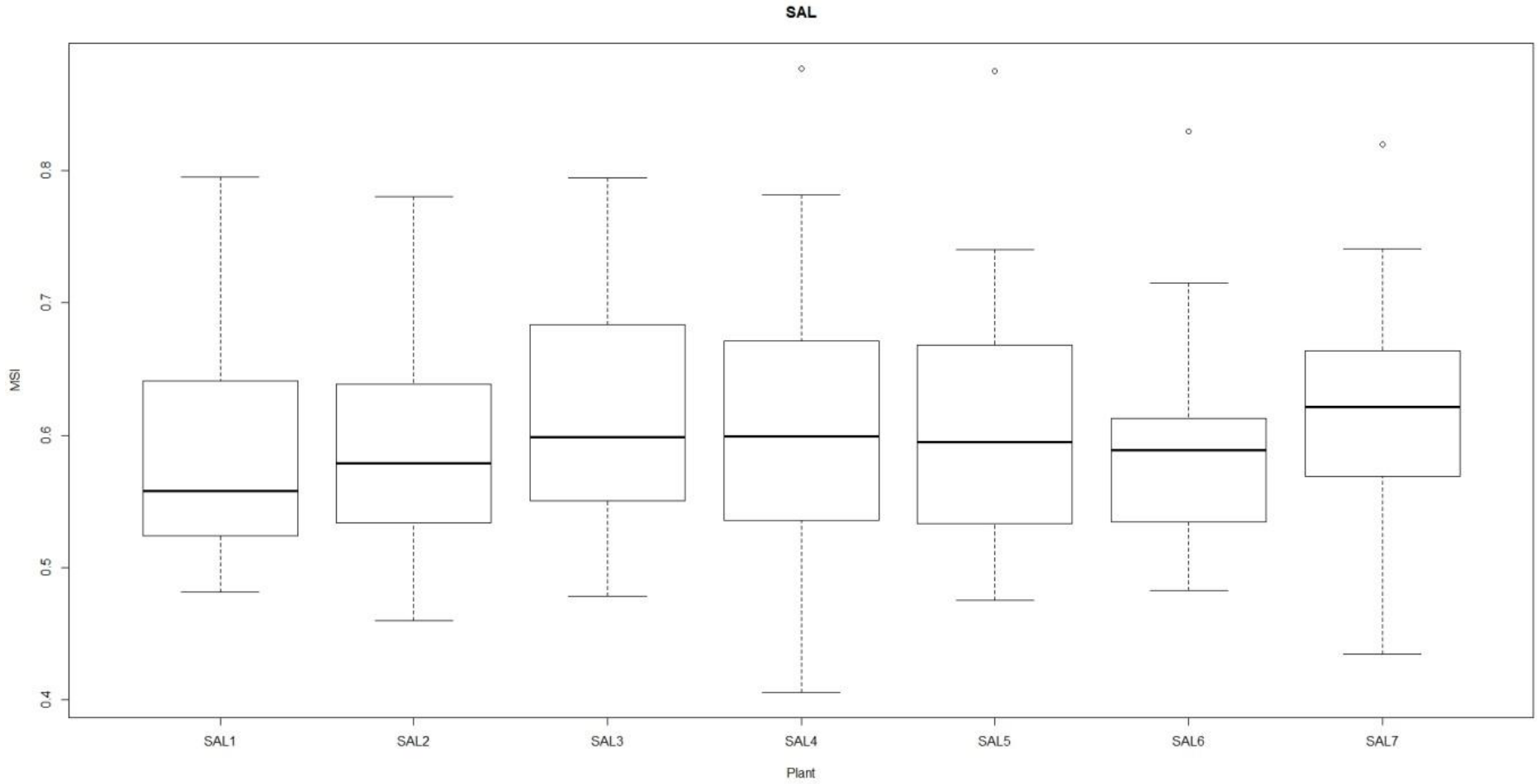

Figure A-15 - Box plot for MSI, from leaf clip readings for Freylinia Tropica (Transvaal Honey-bell Bush)

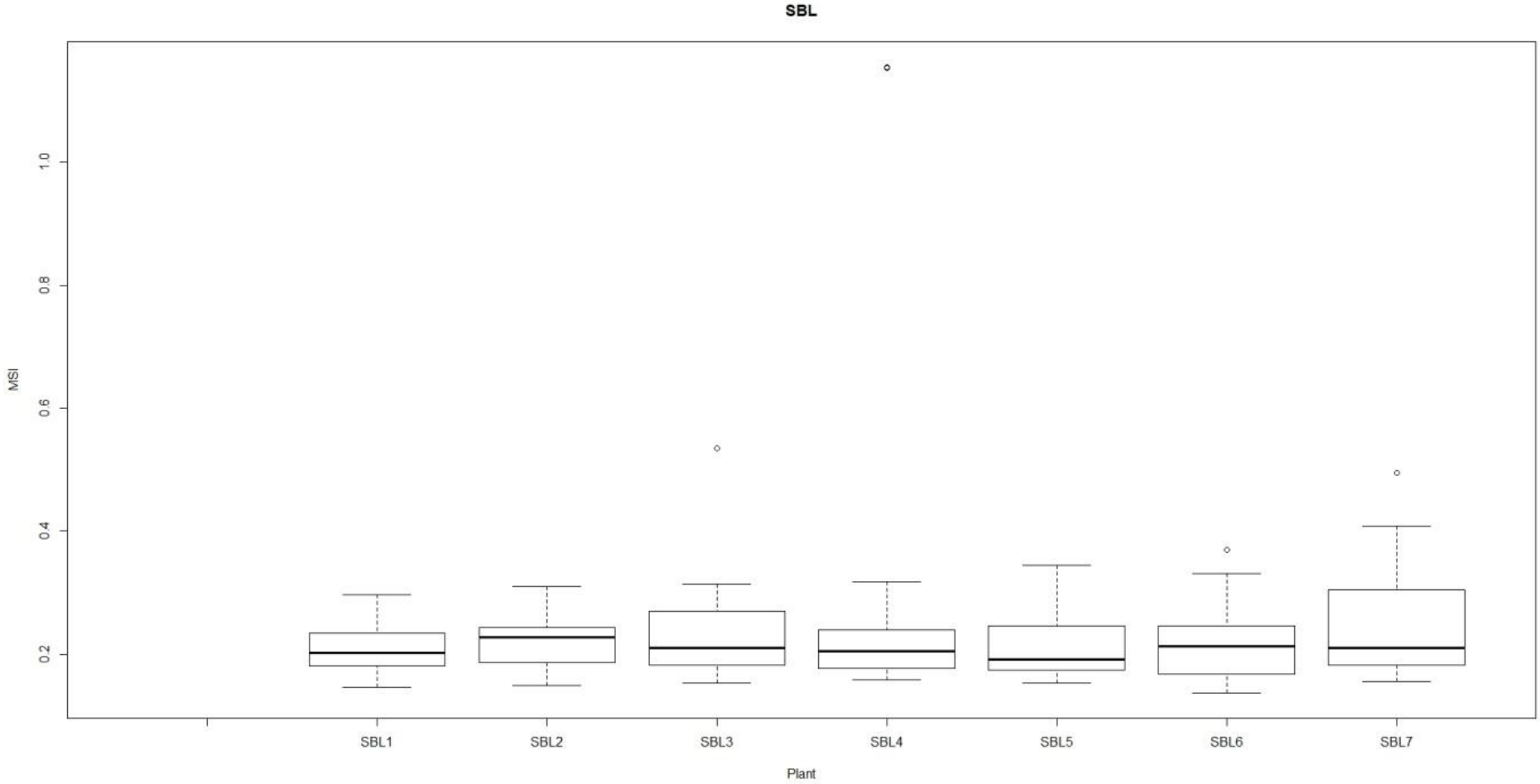

Figure A-16 - Box plot for MSI, from leaf clip readings for Portulacaria Afra (Spekboom)

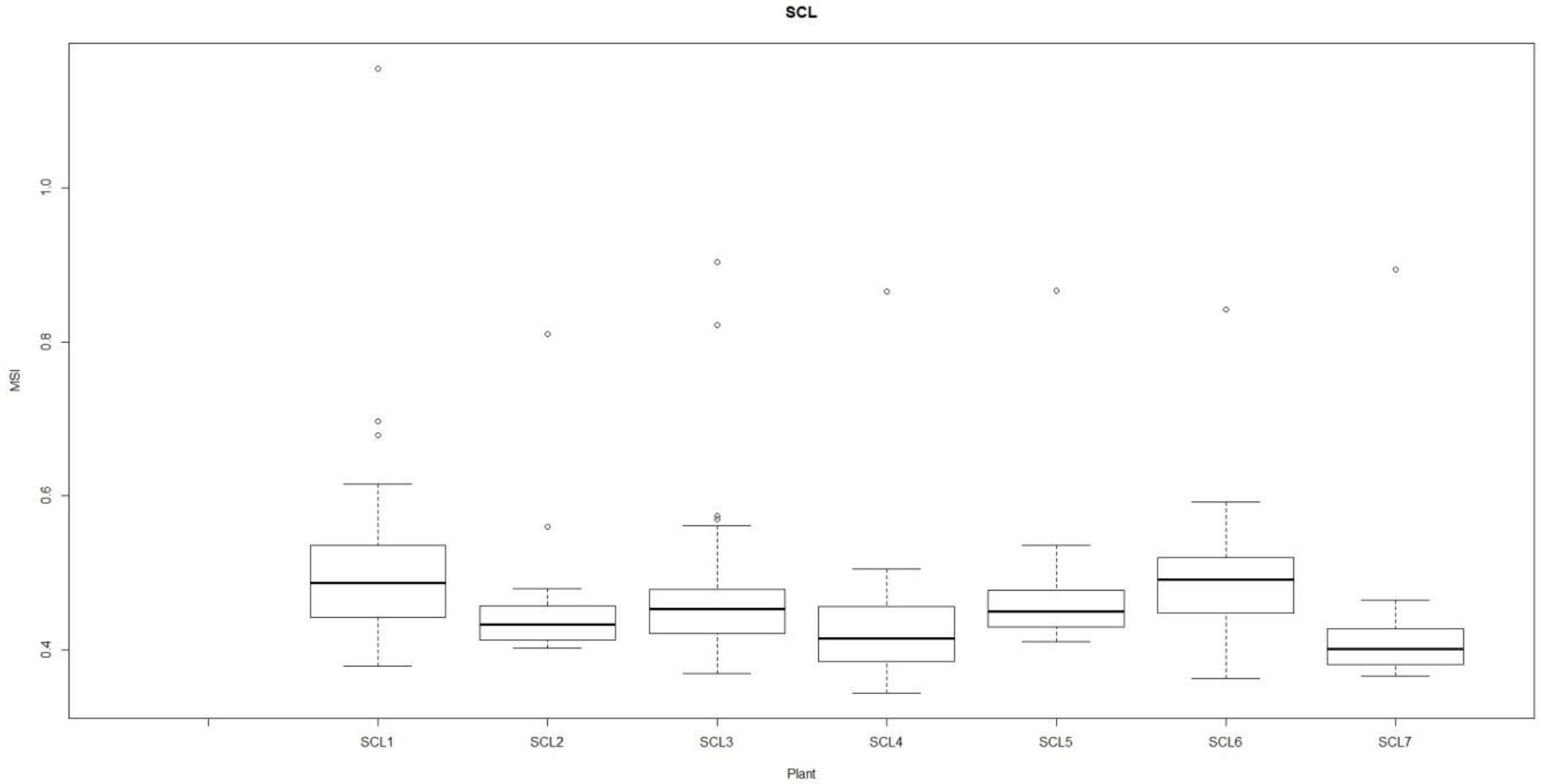

Figure A-17 - Box plot for MSI, from leaf clip readings for Carissa Macrocarpa (Natal Plum)

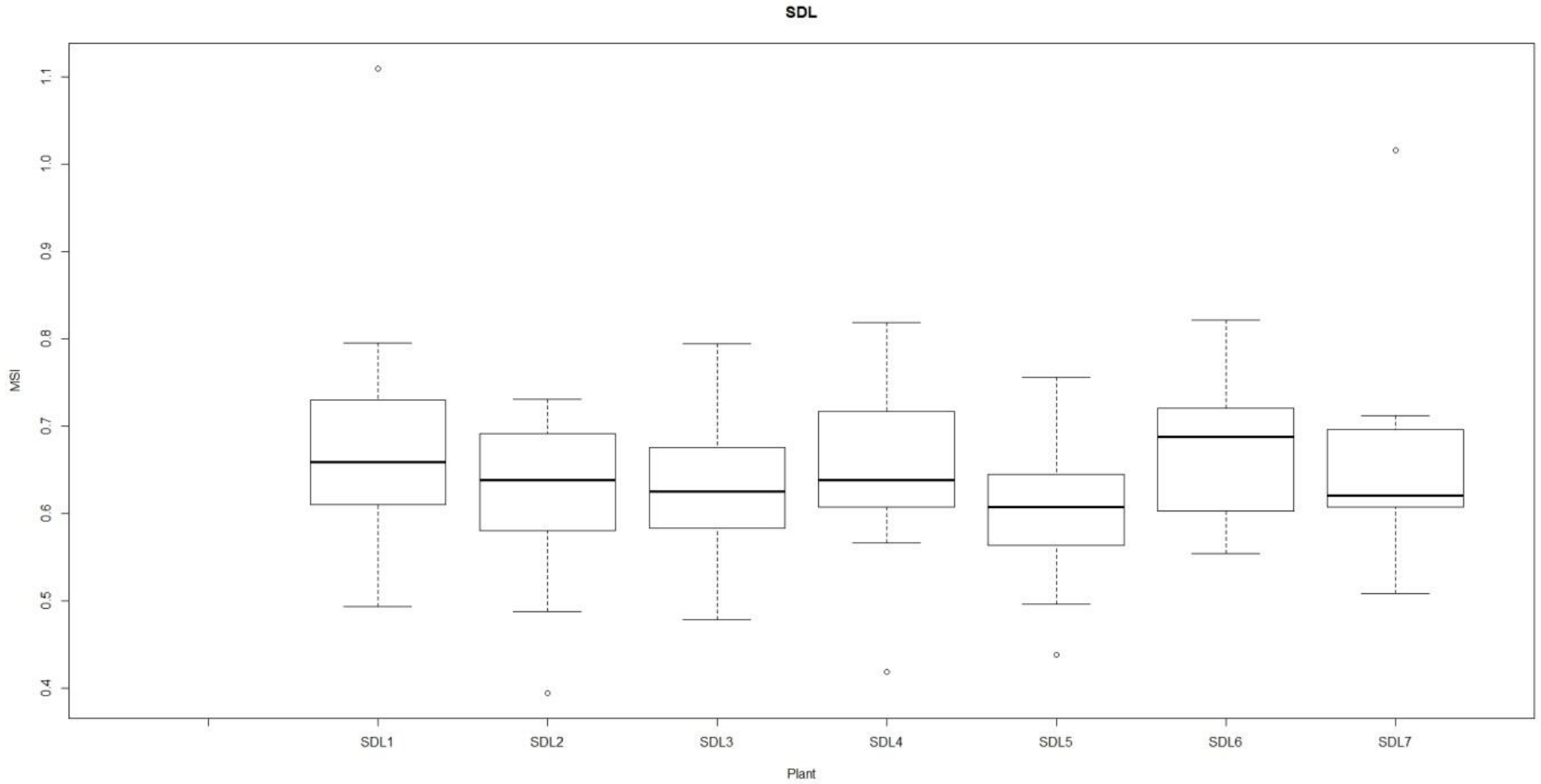

Figure A-18 - Box plot for MSI, from leaf clip readings for Dovyalis Caffra (Kei Apple)

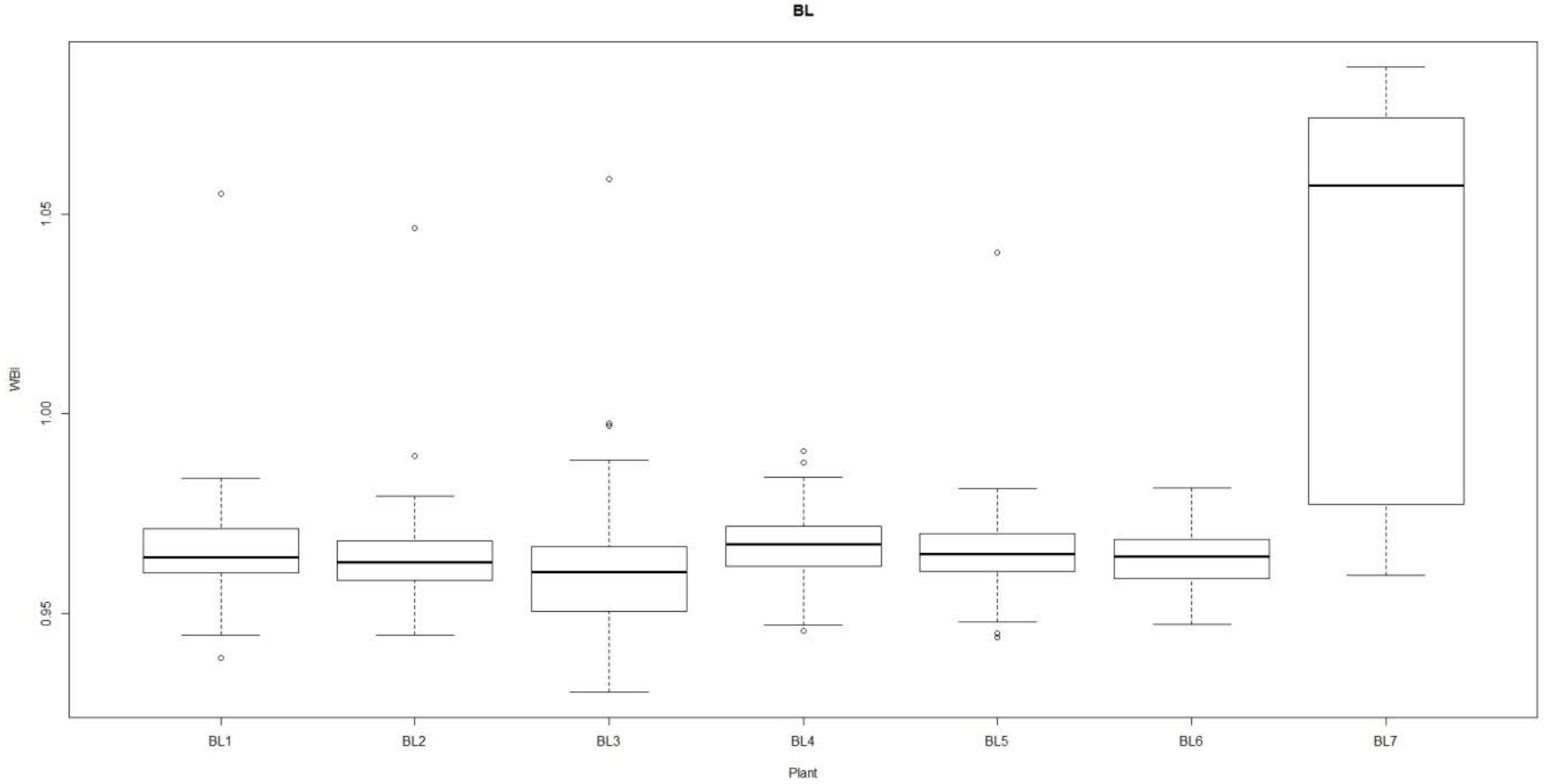

Figure A-19 - Box plot for WBI, from leaf clip readings for Wild Olive

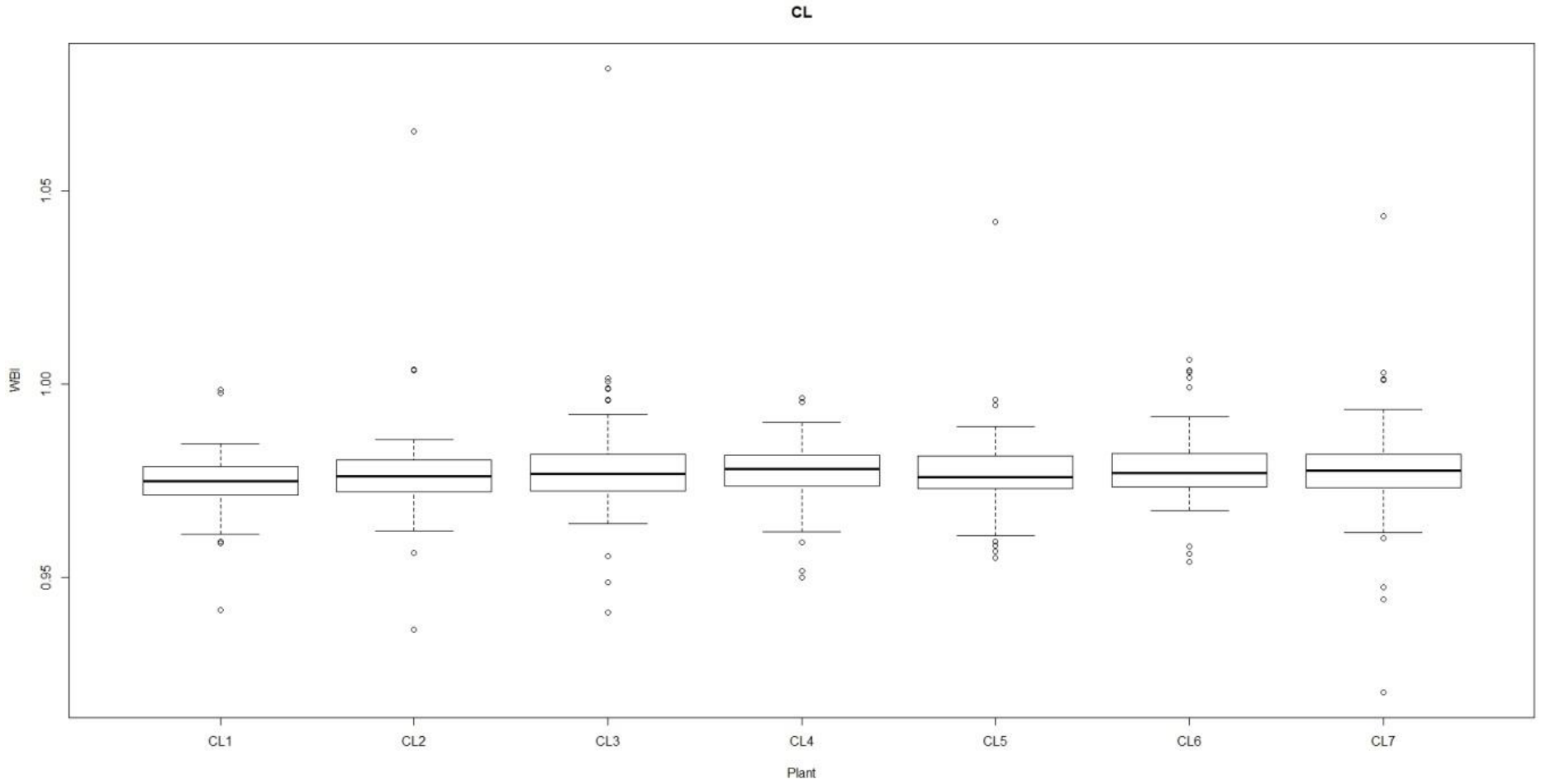

Figure A-20 - Box plot for WBI, from leaf clip readings for River Bushwillow

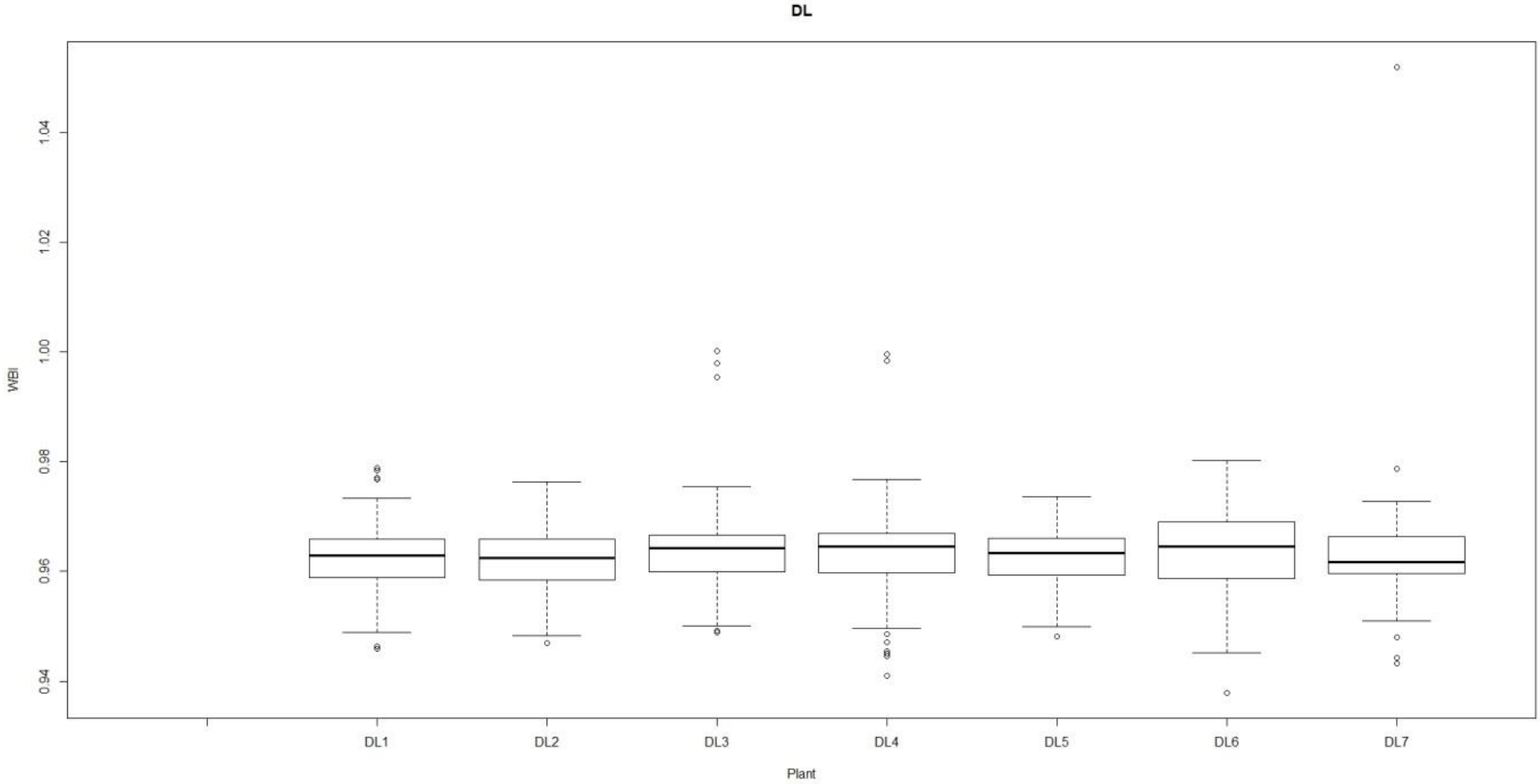

Figure A-21 - Box plot for WBI, from leaf clip readings for Soap Dogwood

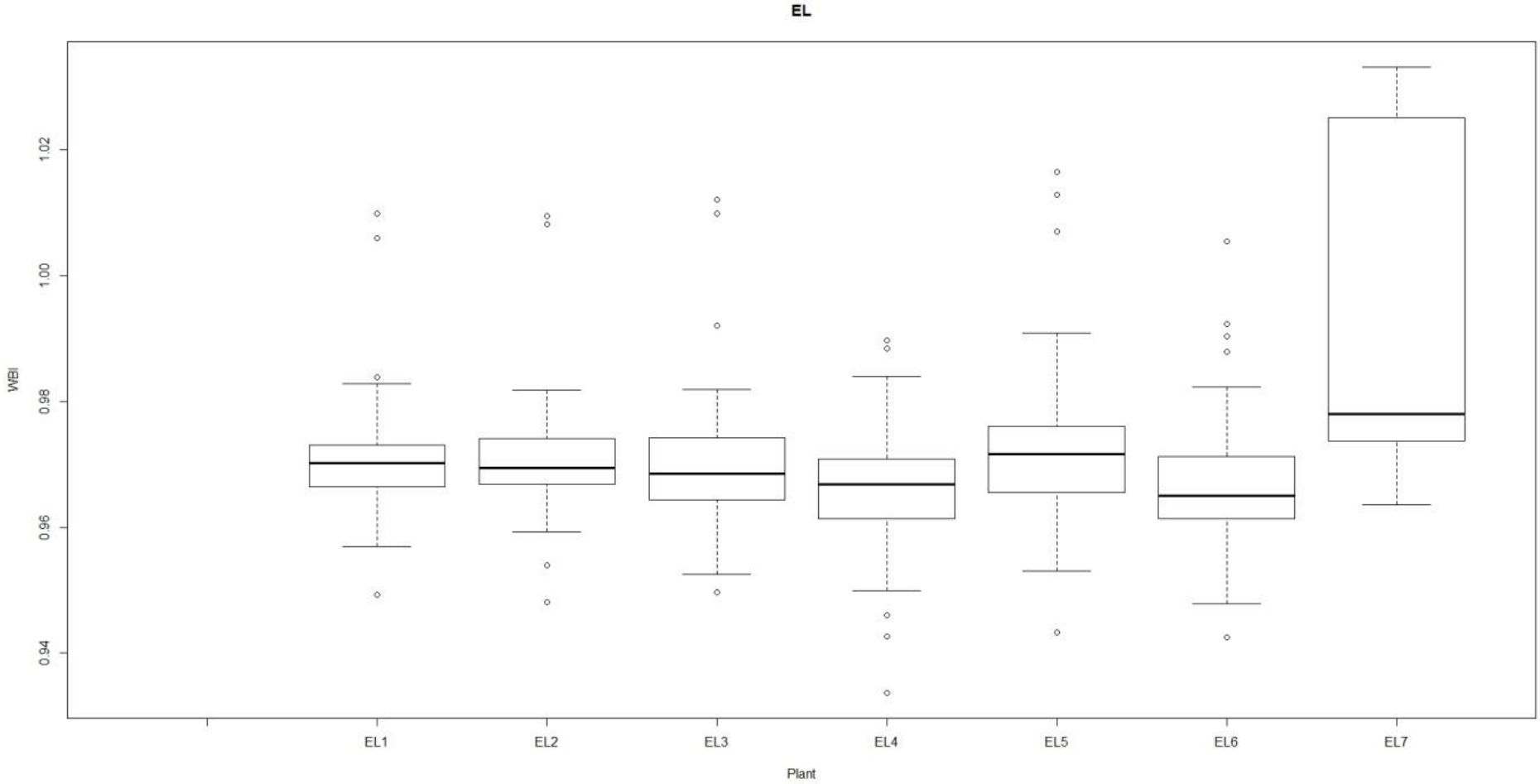

Figure A-22 - Box plot for WBI, from leaf clip readings for Sweet Thorn

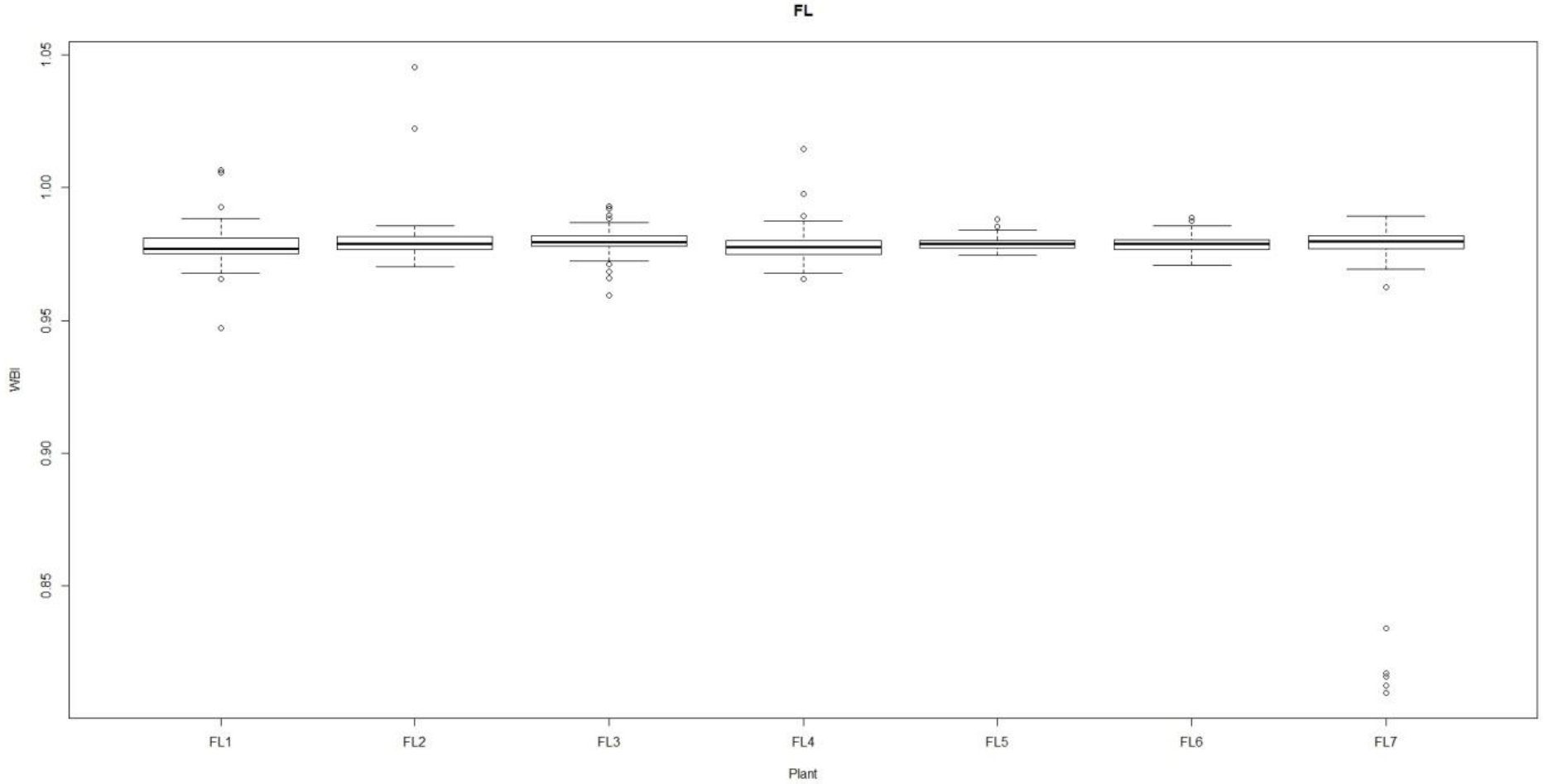

Figure A-23 - Box plot for WBI, from leaf clip readings for White Stinkwood

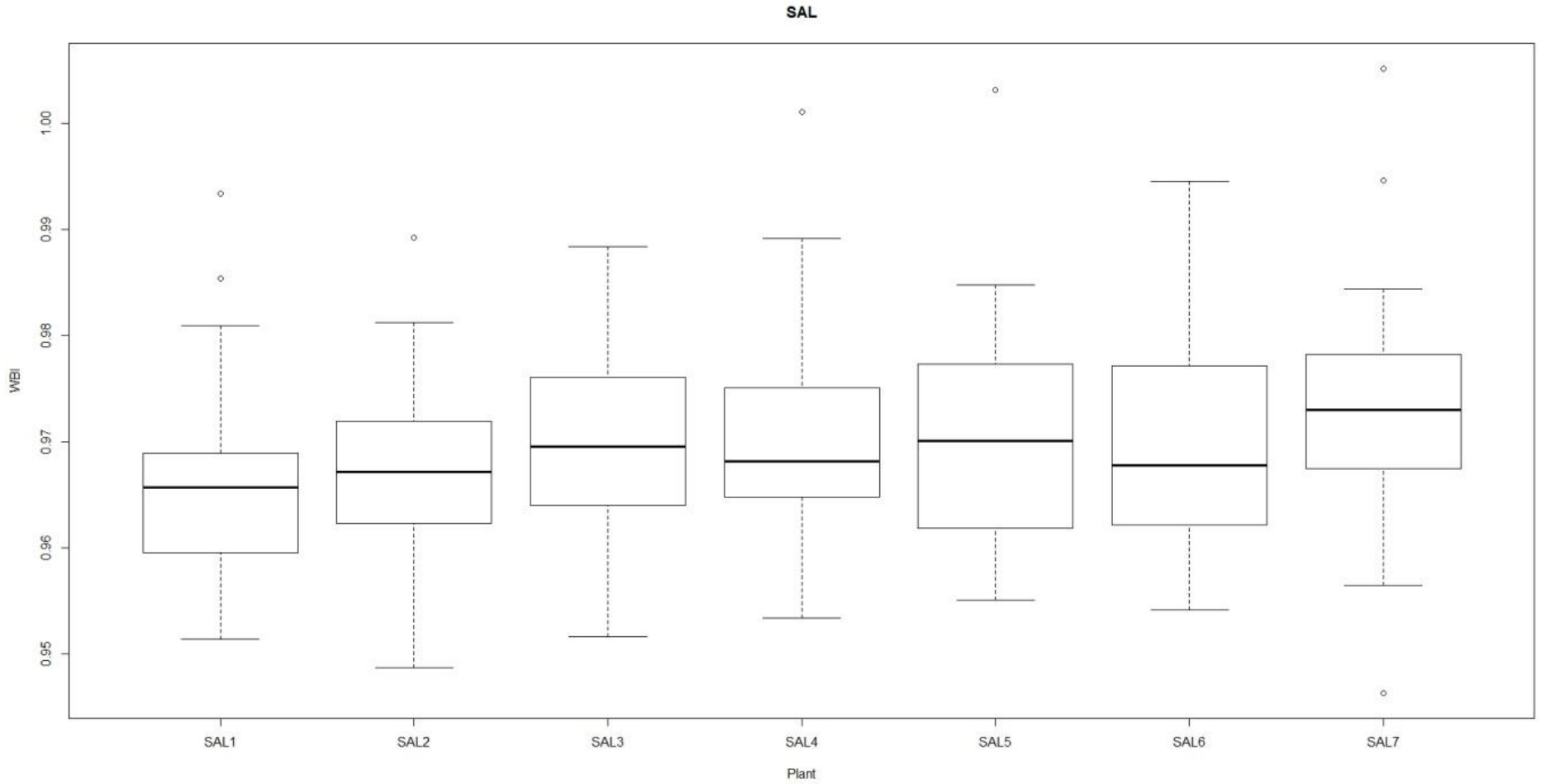

Figure A-24 - Box plot for WBI, from leaf clip readings for Freylinia Tropica (Transvaal Honey-bell Bush)

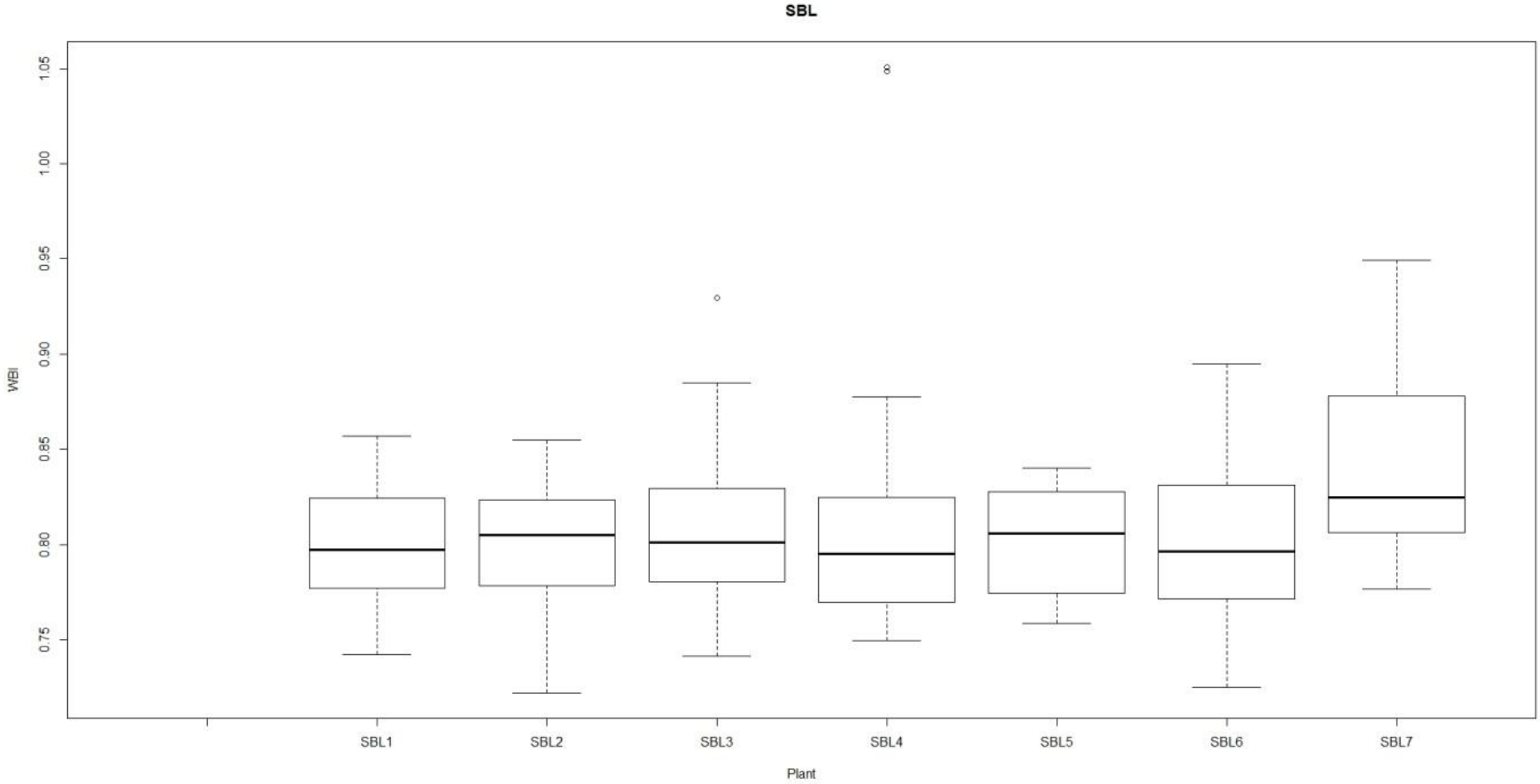

Figure A-25 - Box plot for WBI, from leaf clip readings for Portulacaria Afra (Spekboom)

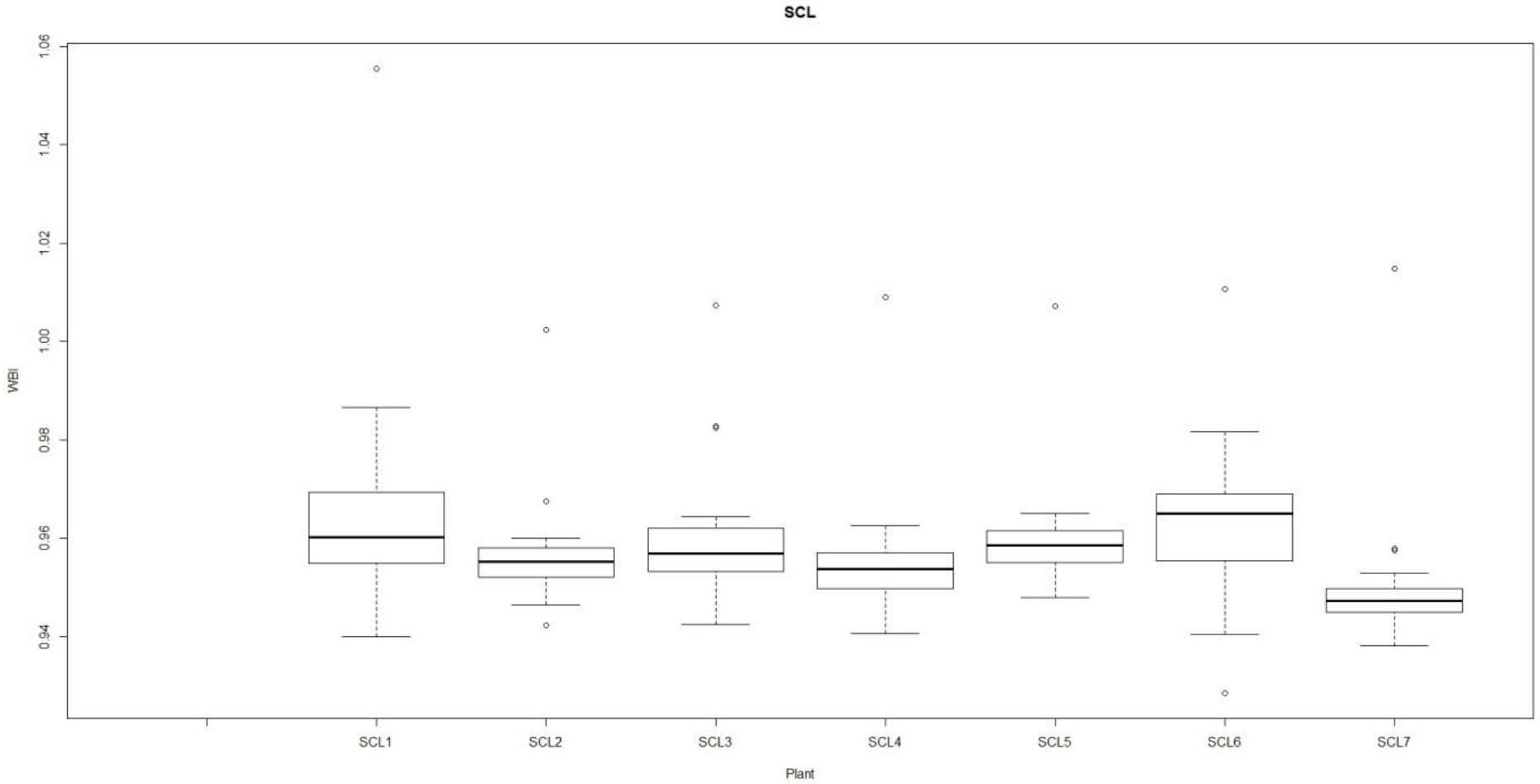

Figure A-26 - Box plot for WBI, from leaf clip readings for Carissa Macrocarpa (Natal Plum)

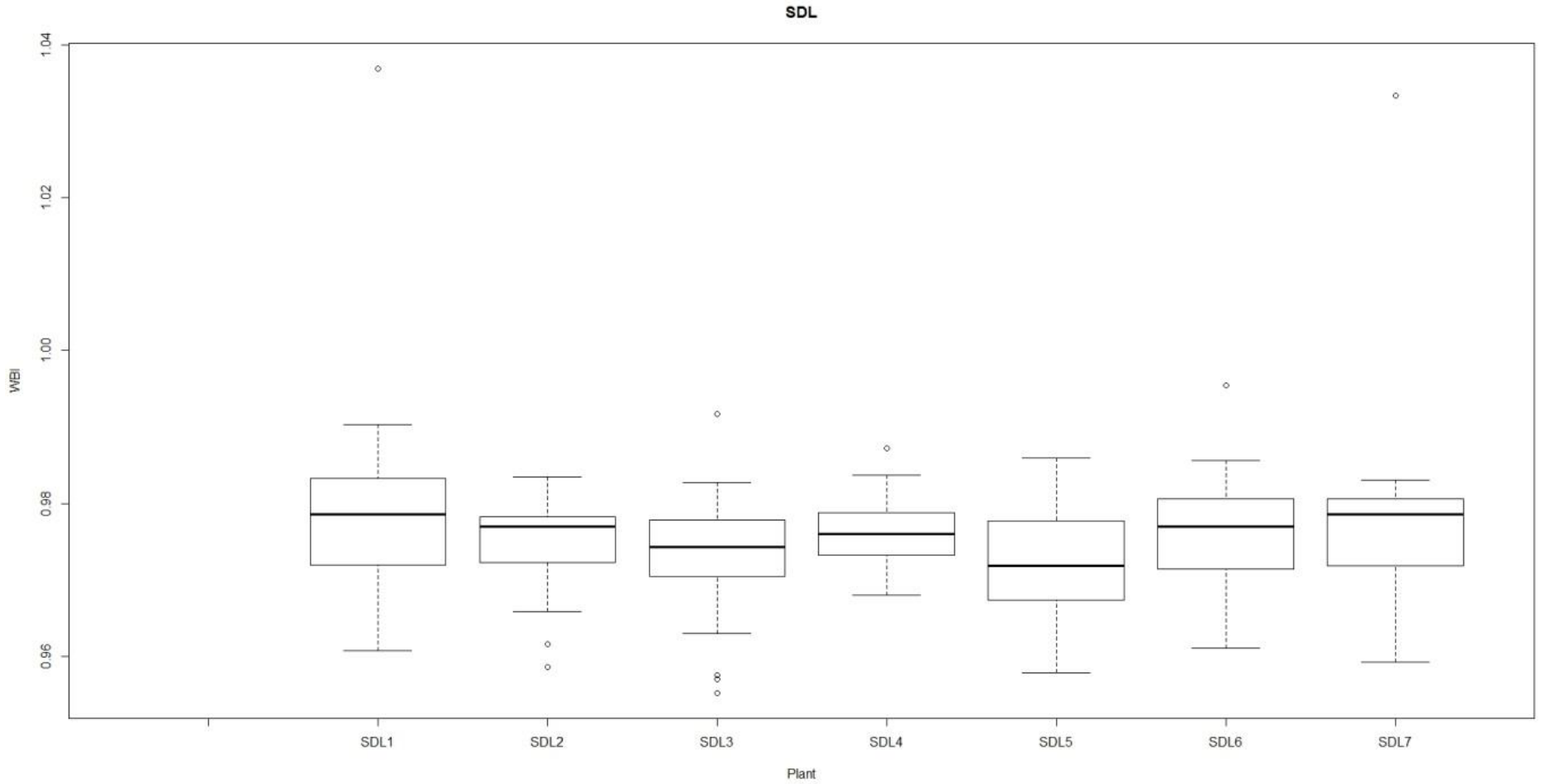

Figure A-27 - Box plot for WBI, from leaf clip readings for Dovyalis Caffra (Kei Apple)

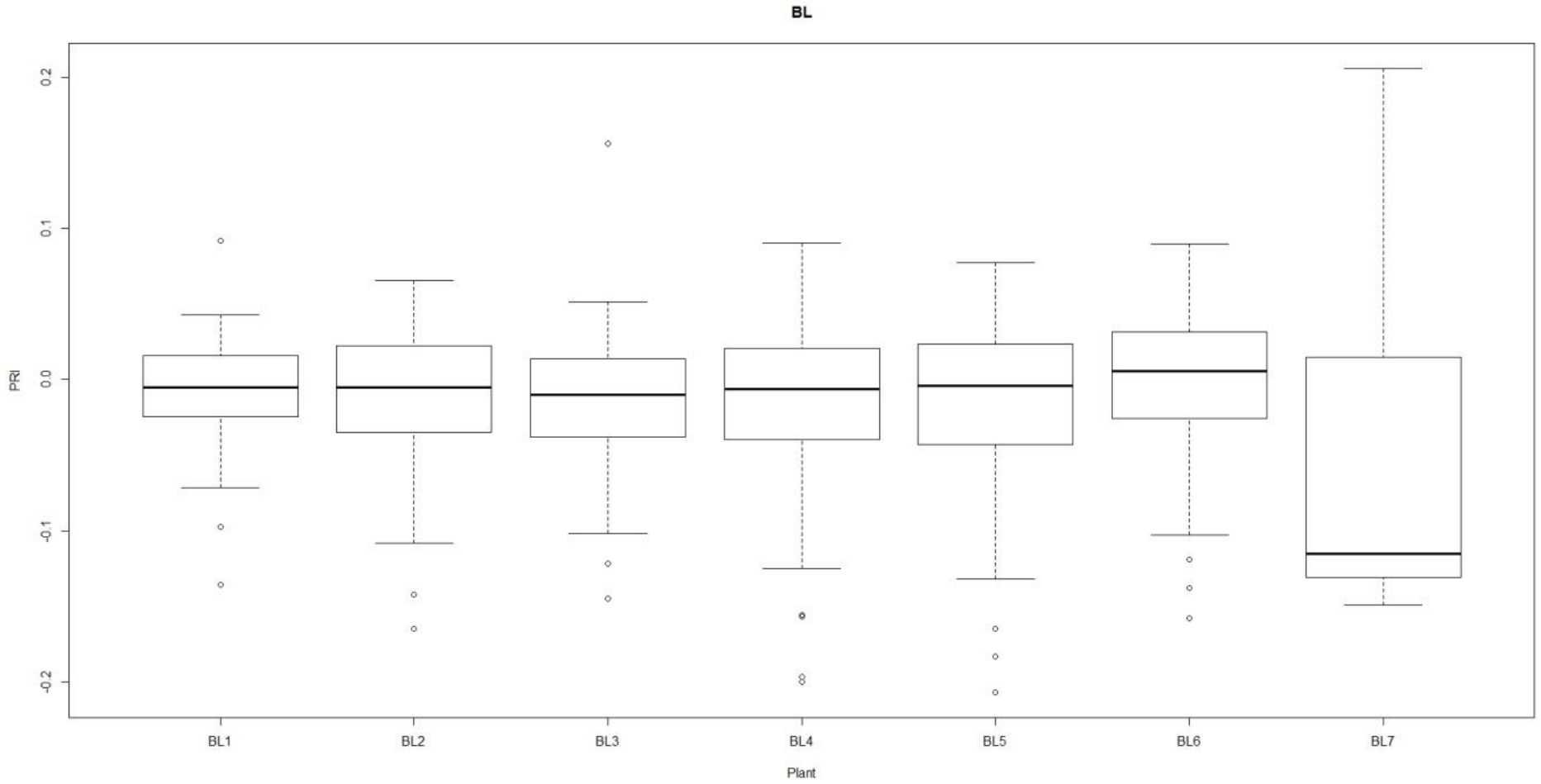

Figure A-28 - Box plot for PRI, from leaf clip readings for Wild Olive

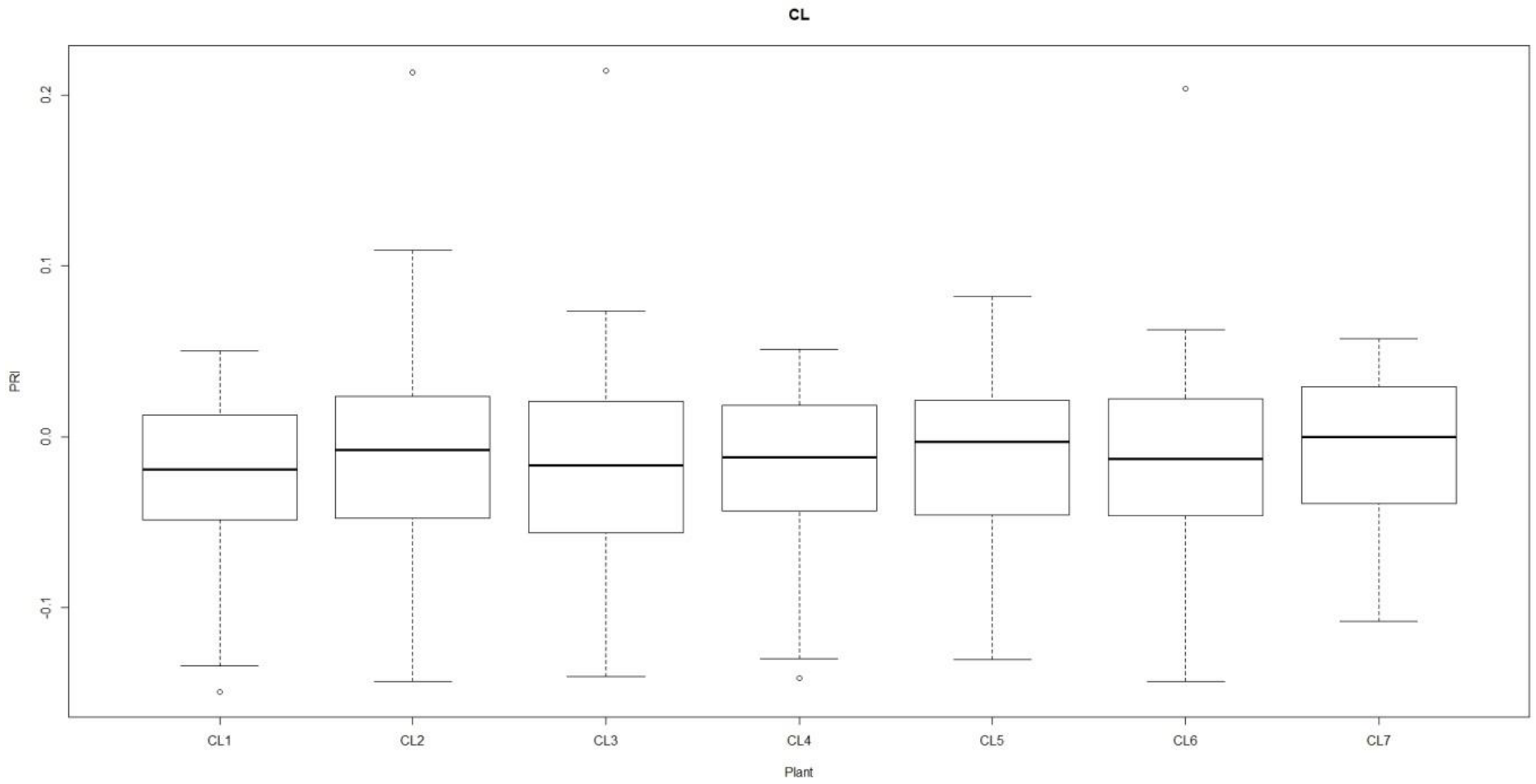

Figure A-29 - Box plot for PRI, from leaf clip readings for River Bushwillow

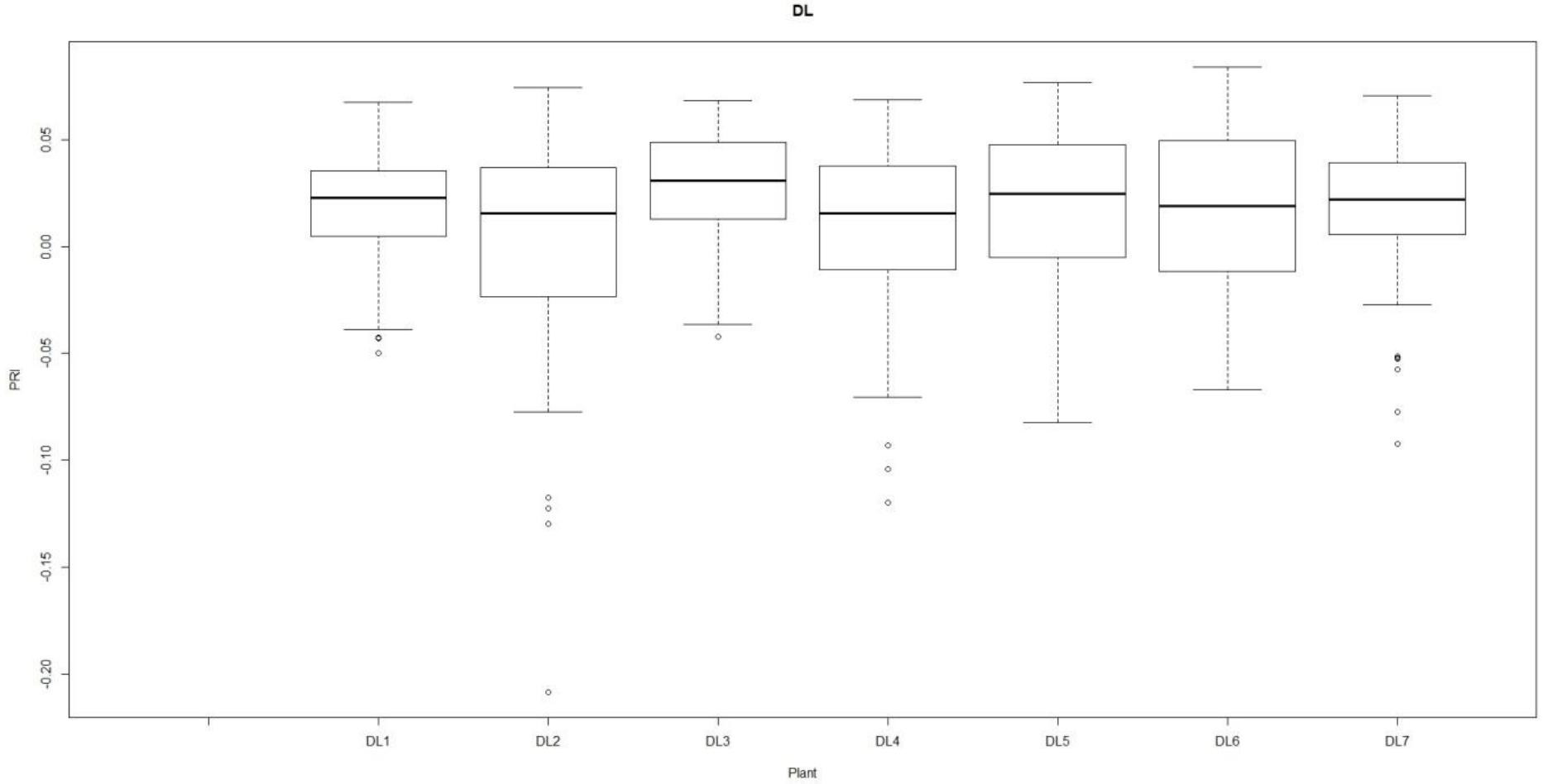

Figure A-30 - Box plot for PRI, from leaf clip readings for Soap Dogwood

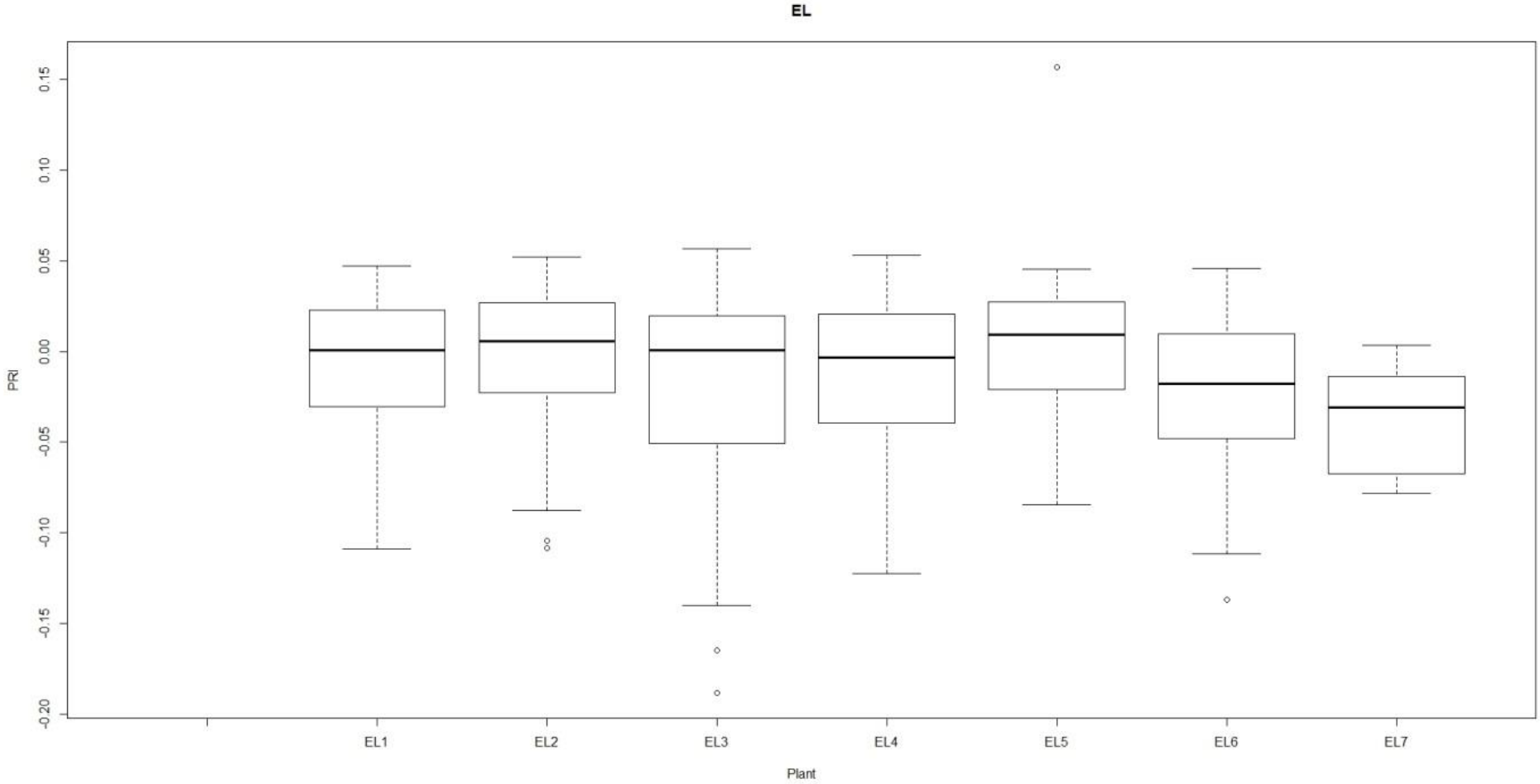

Figure A-31 - Box plot for PRI, from leaf clip readings for Sweet Thorn

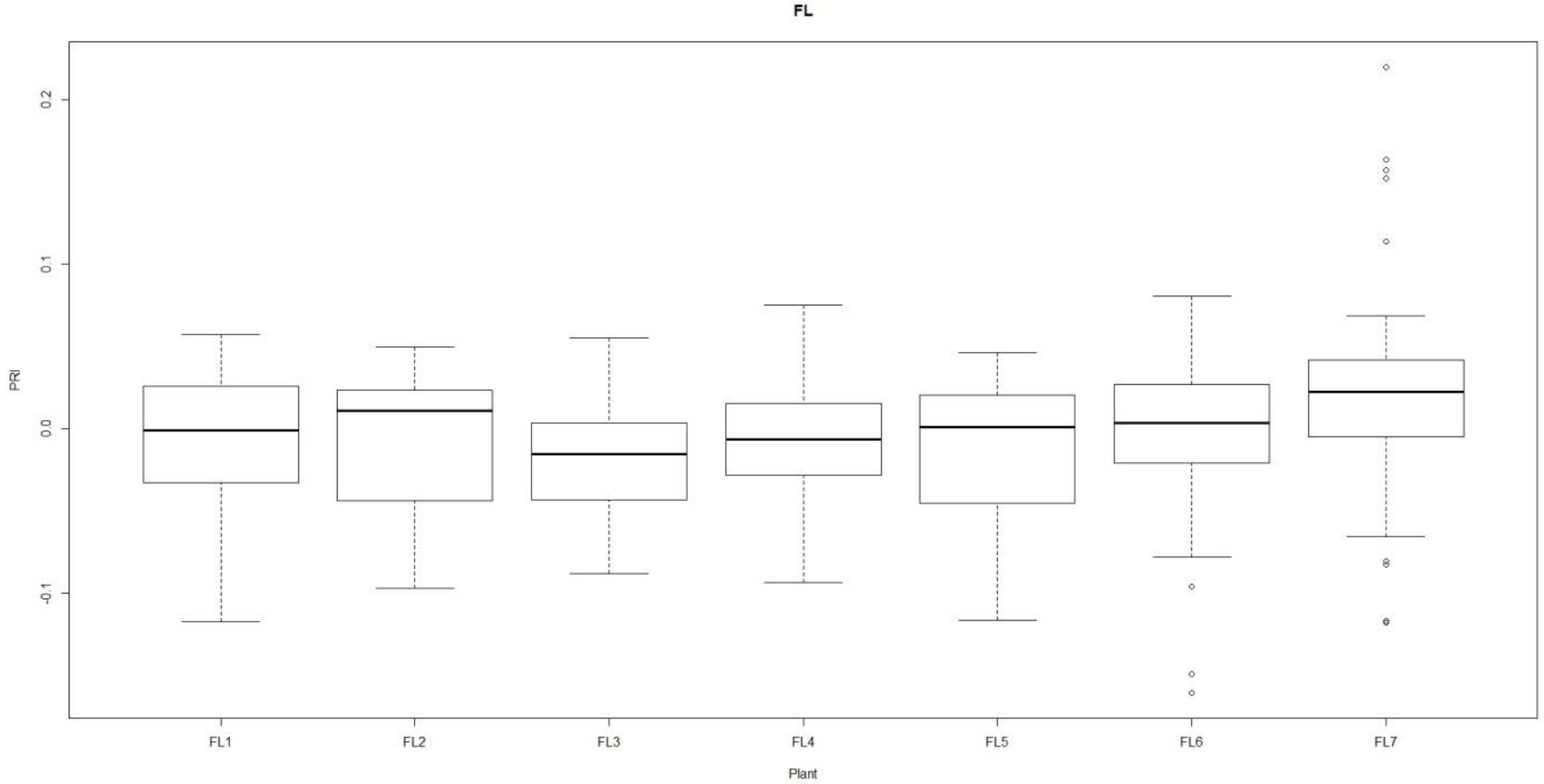

Figure A-32 - Box plot for PRI, from leaf clip readings for White Stinkwood

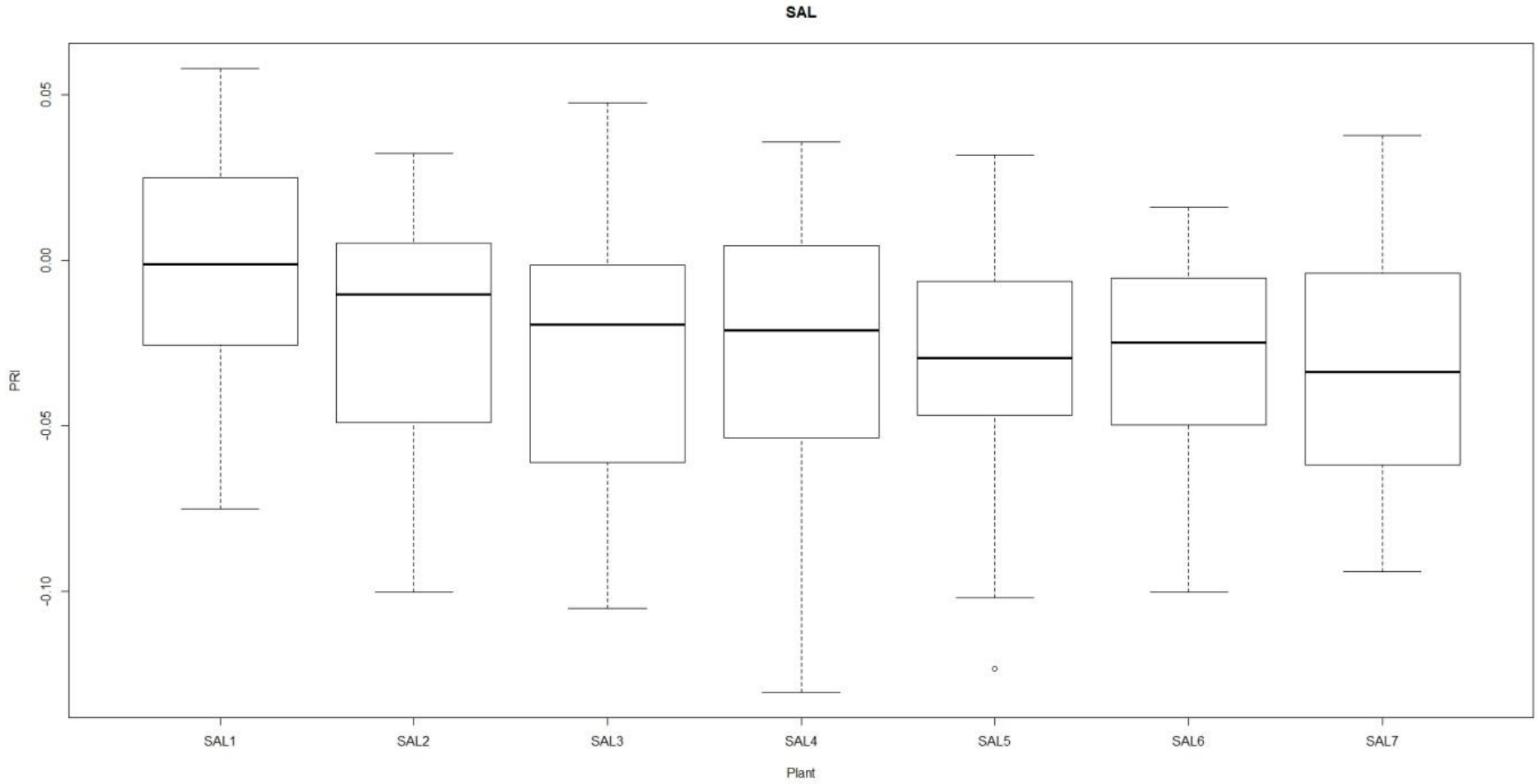

Figure A-33 - Box plot for PRI, from leaf clip readings for Freylinia Tropica (Transvaal Honey-bell Bush)

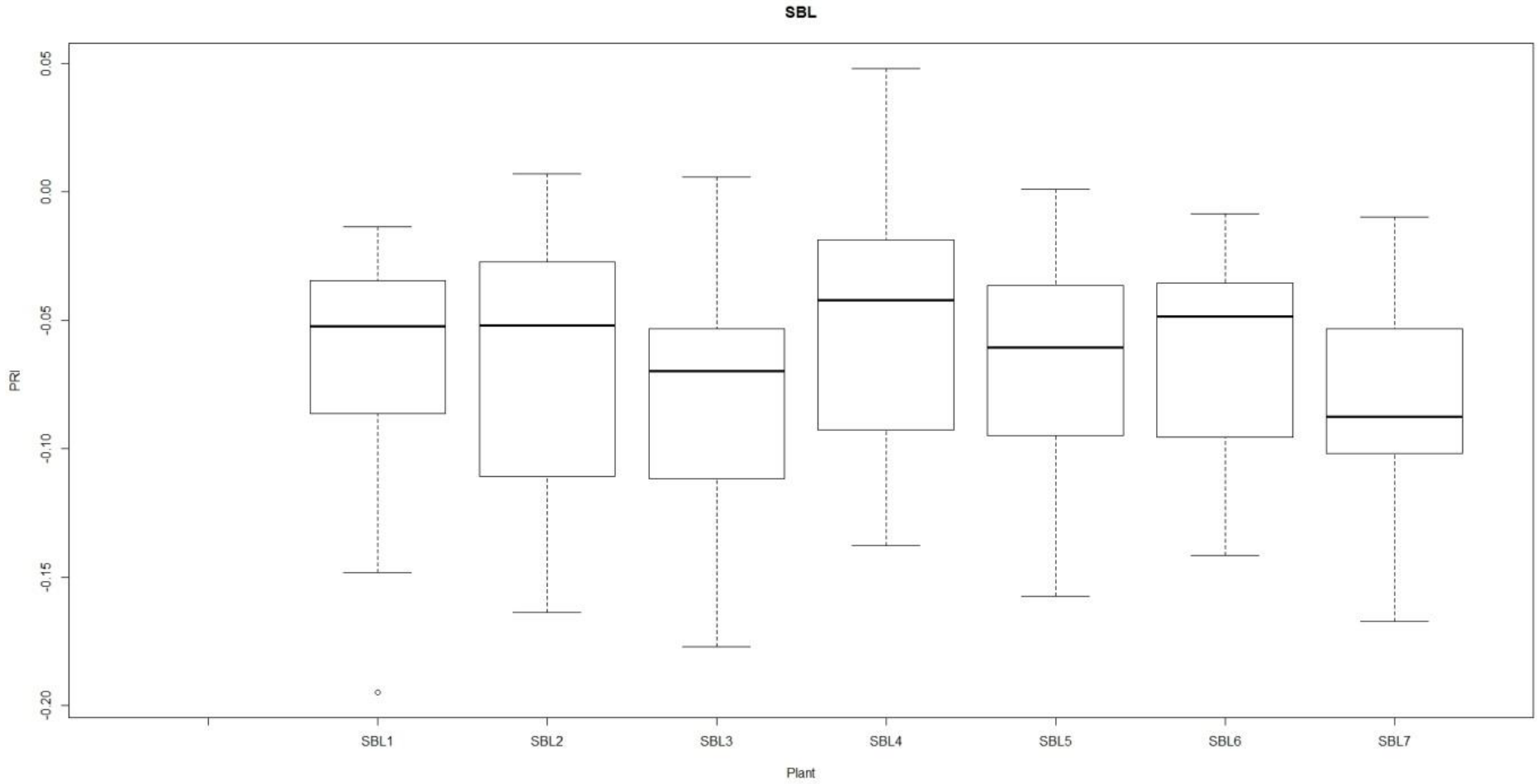

Figure A-34 - Box plot for PRI, from leaf clip readings for Portulacaria Afra (Spekboom)

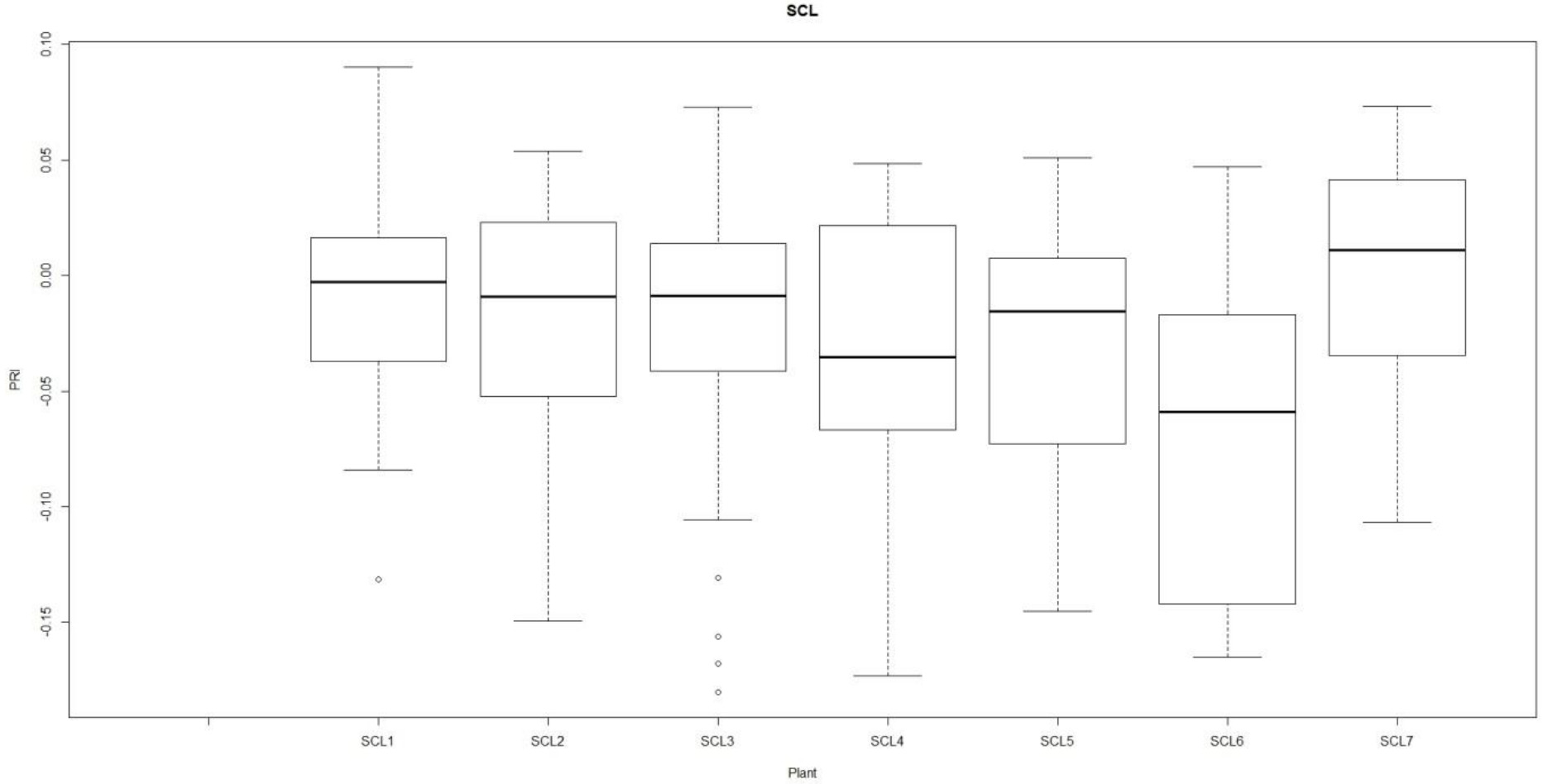

Figure A-35 - Box plot for PRI, from leaf clip readings for Carissa Macrocarpa (Natal Plum)

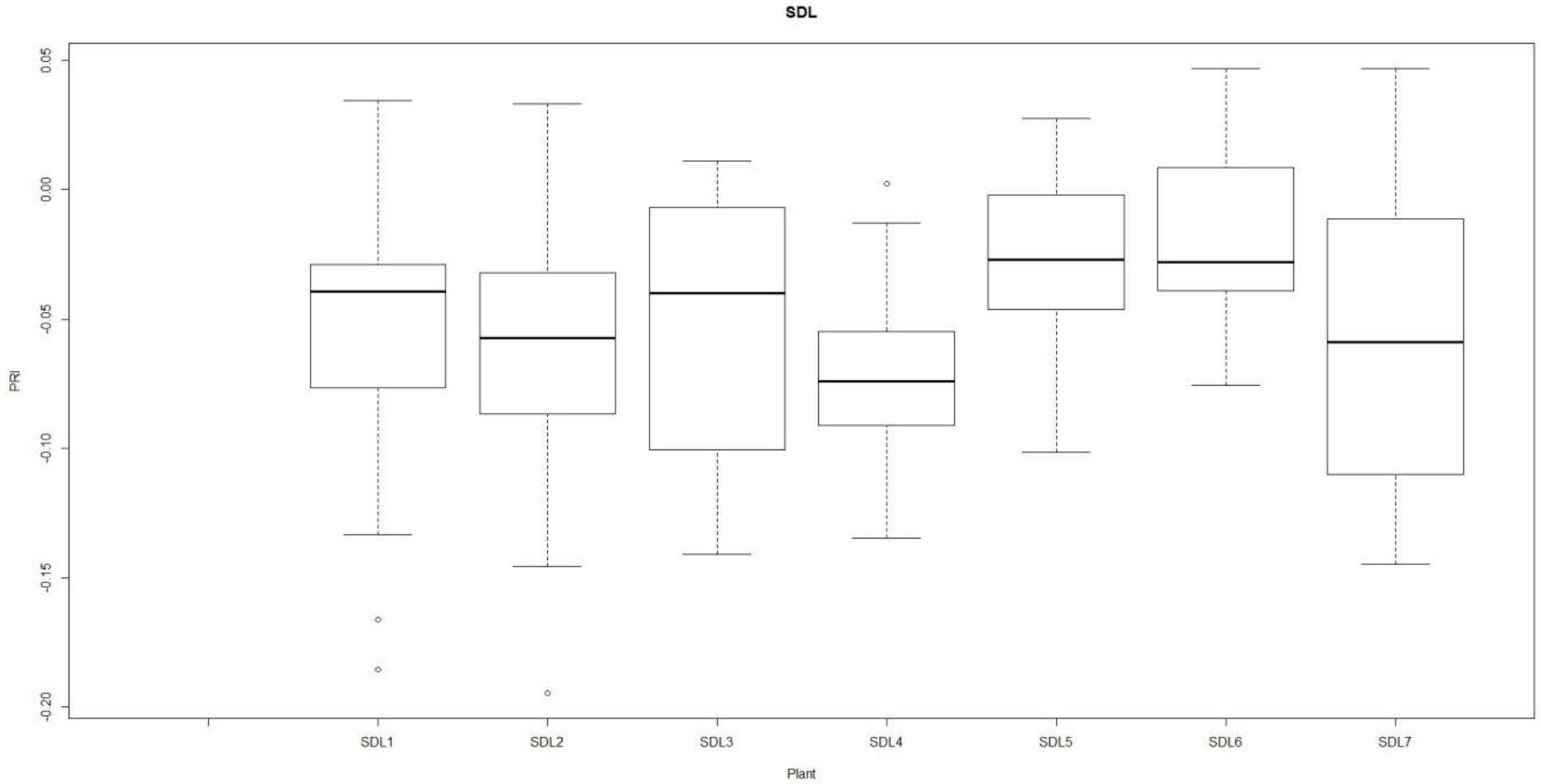

Figure A-36 - Box plot for PRI, from leaf clip readings for Dovyalis Caffra (Kei Apple)

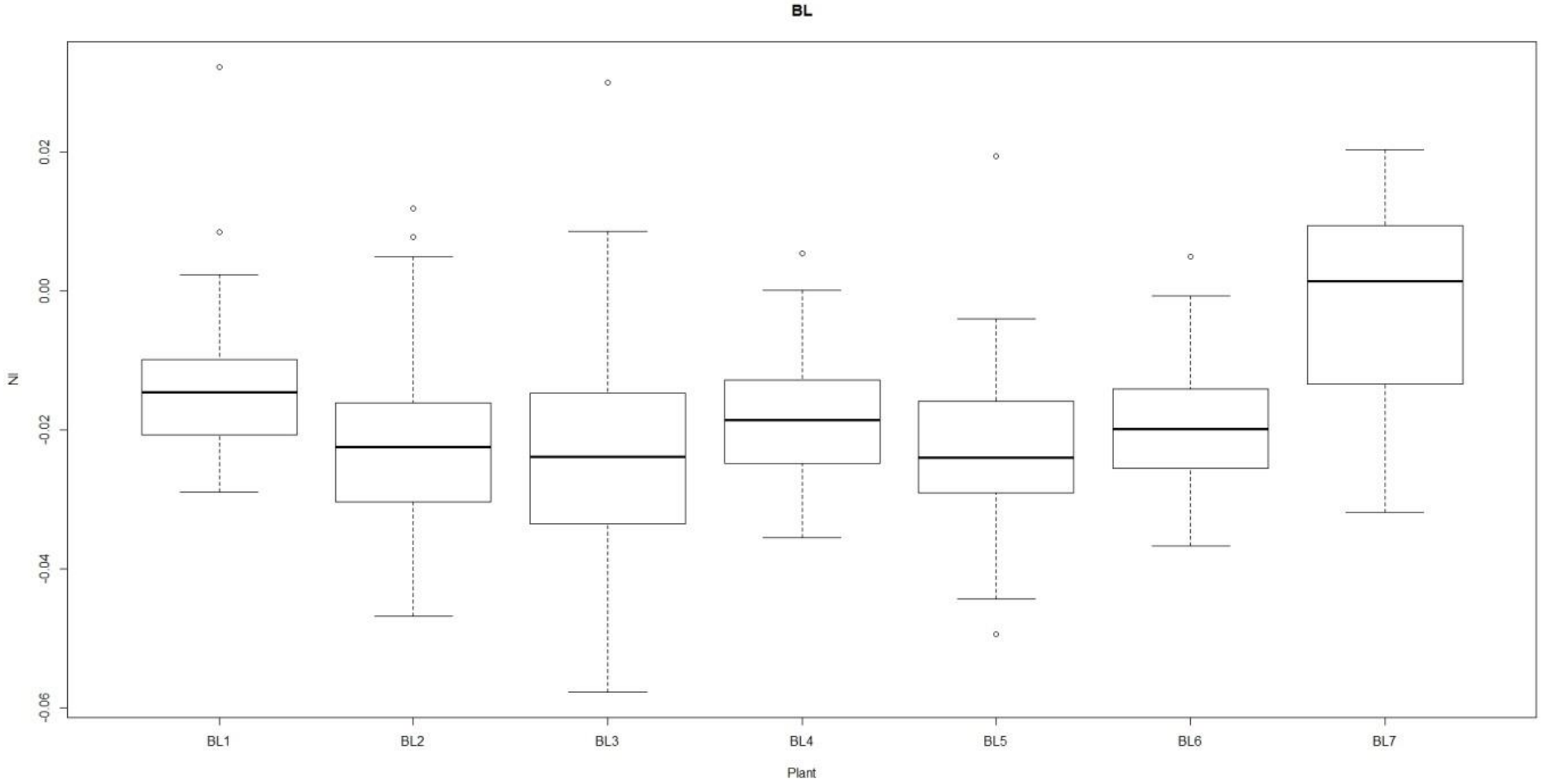

Figure A-37 - Box plot for NI, from leaf clip readings for Wild Olive

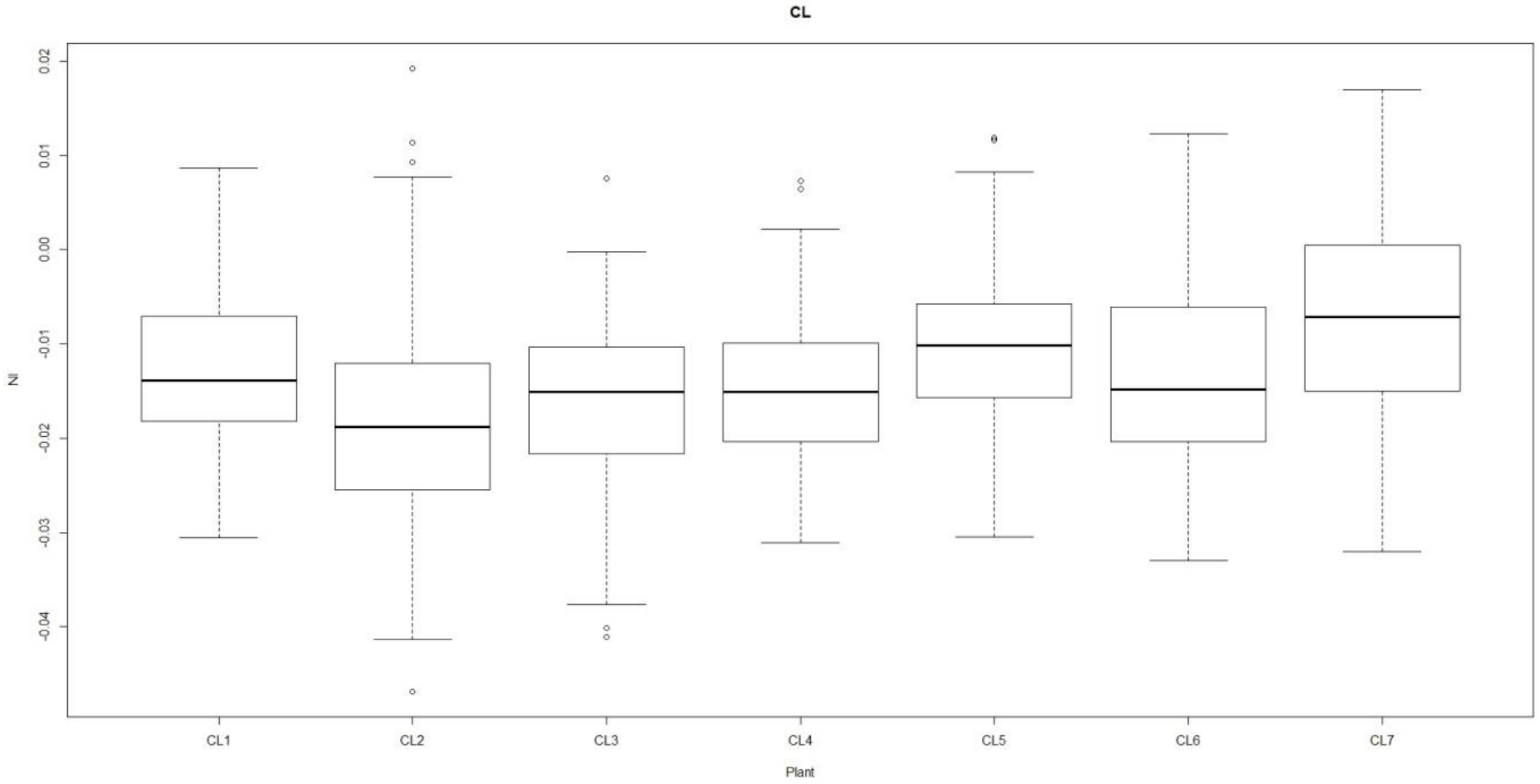

Figure A-38 - Box plot for NI, from leaf clip readings for River Bushwillow

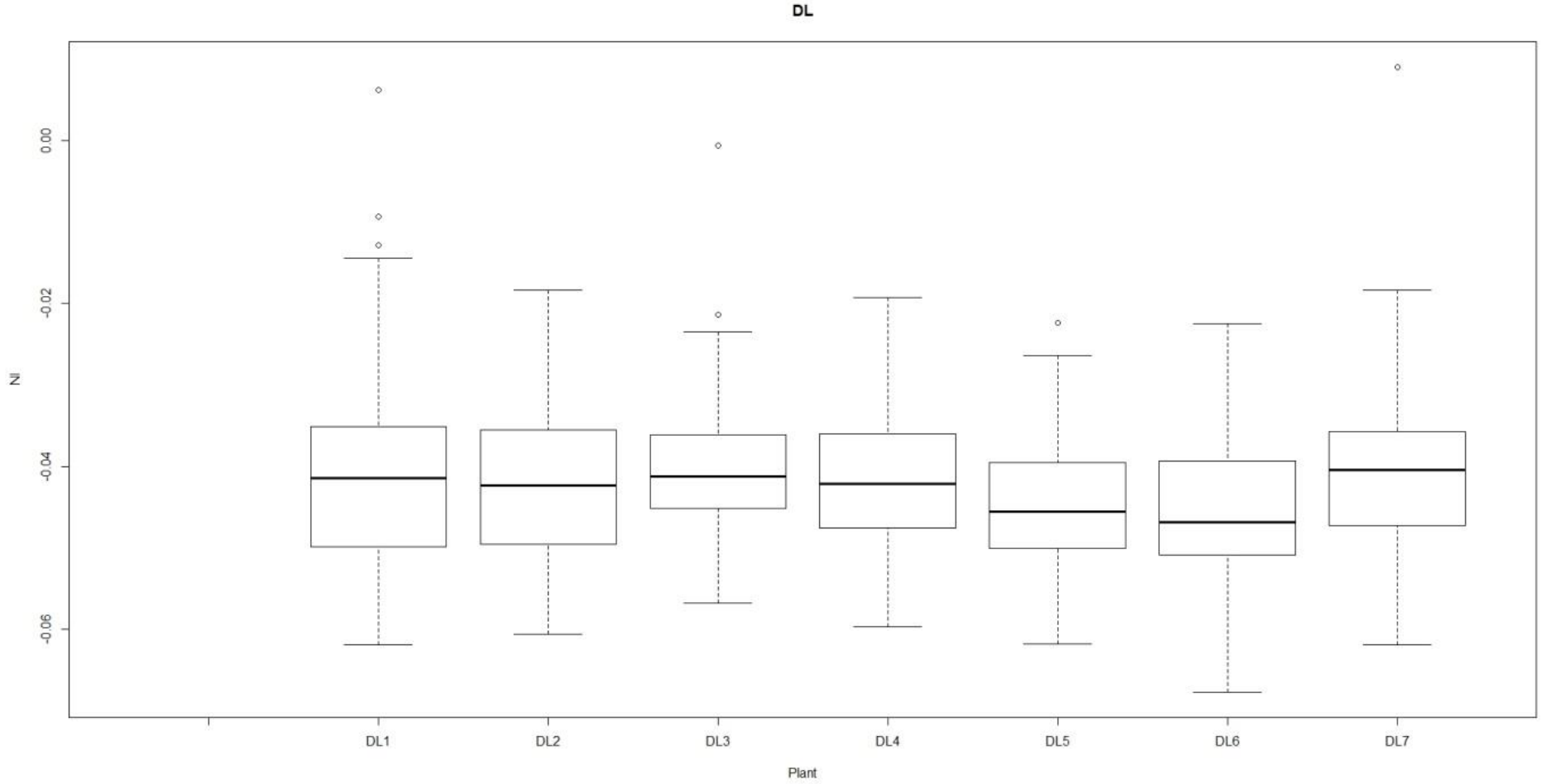

Figure A-39 - Box plot for NI, from leaf clip readings for Soap Dogwood

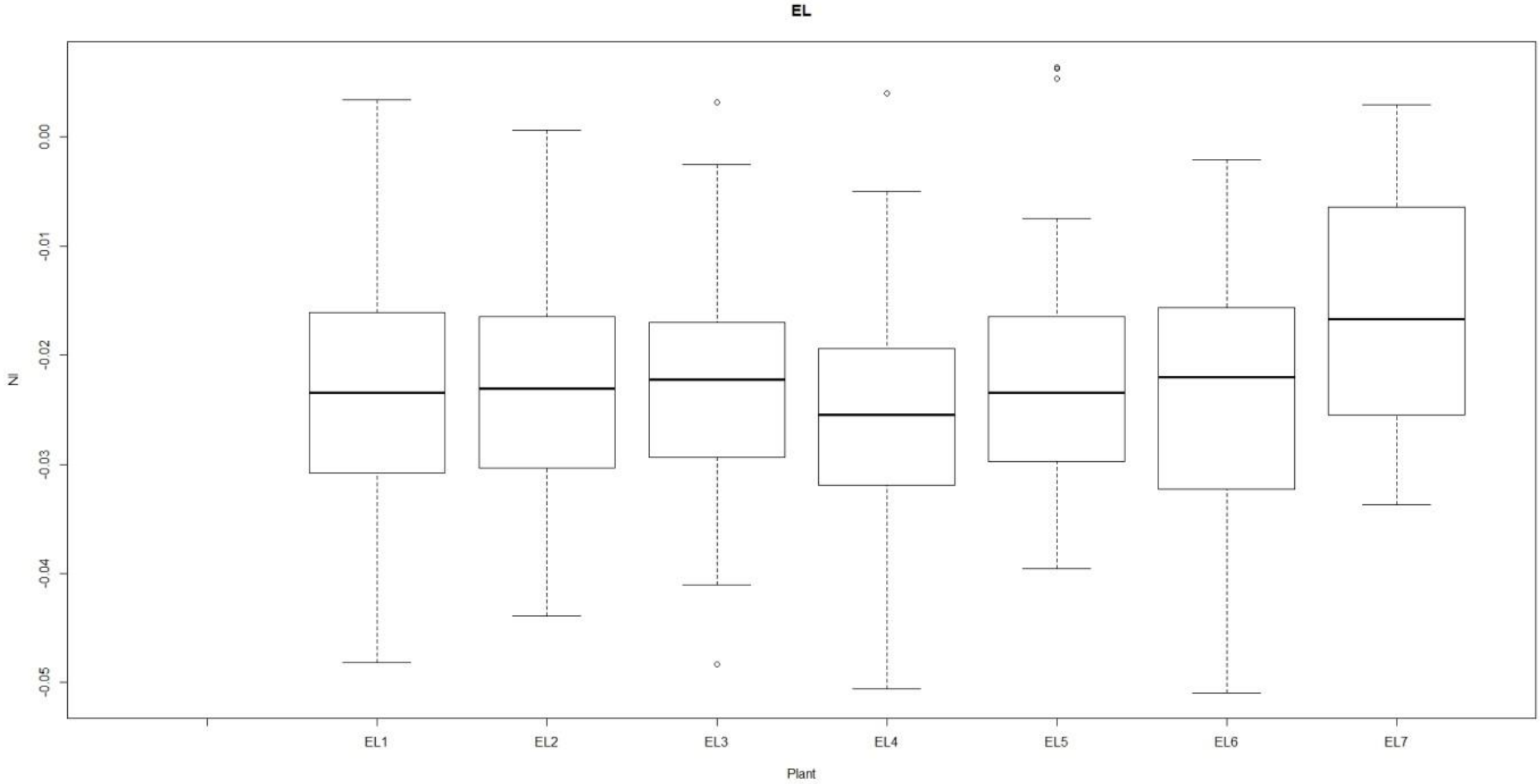

Figure A-40 - Box plot for NI, from leaf clip readings for Sweet Thorn

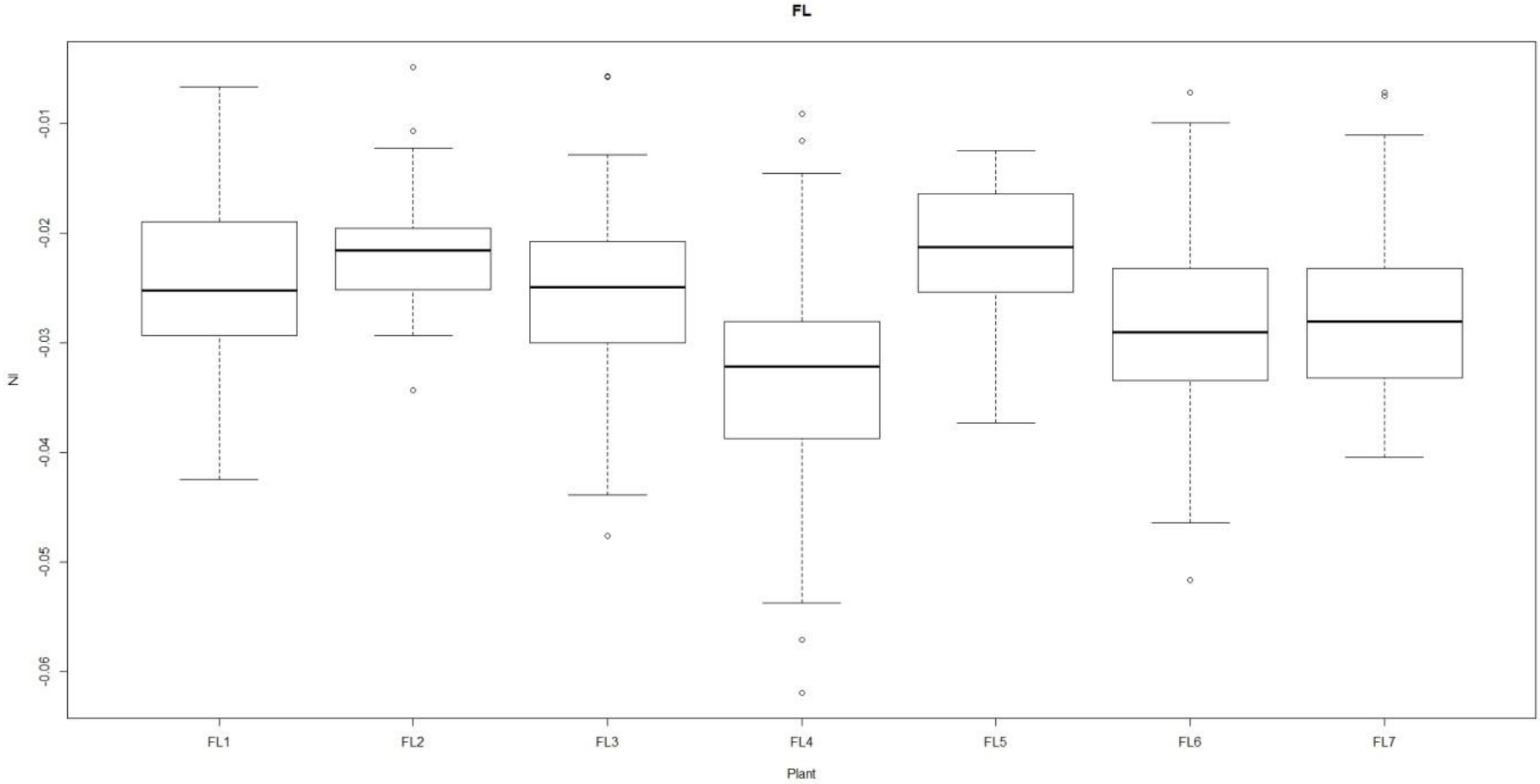

Figure A-41 - Box plot for NI, from leaf clip readings for White Stinkwood

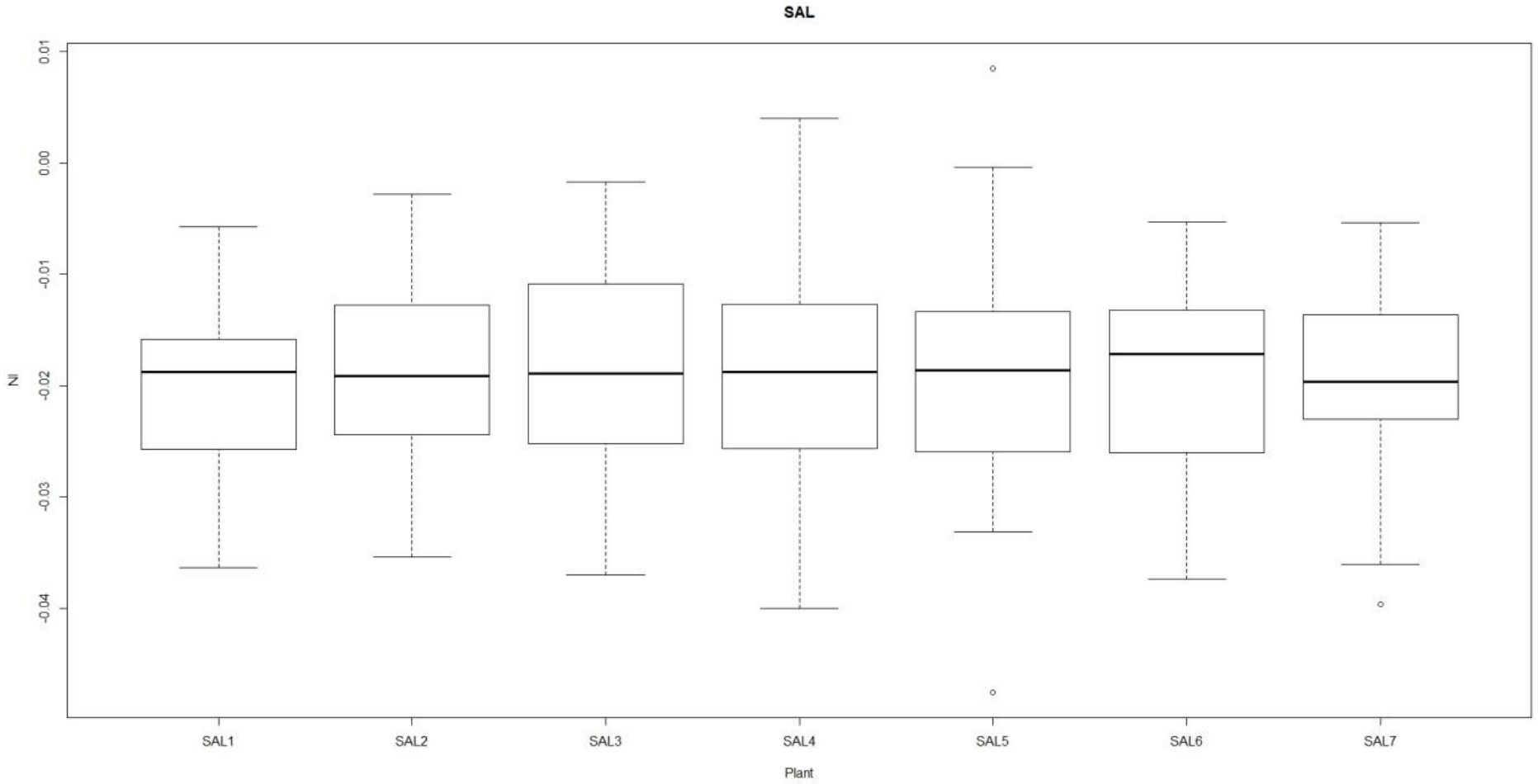

Figure A-42 - Box plot for NI, from leaf clip readings for Freylinia Tropica (Transvaal Honey-bell Bush)

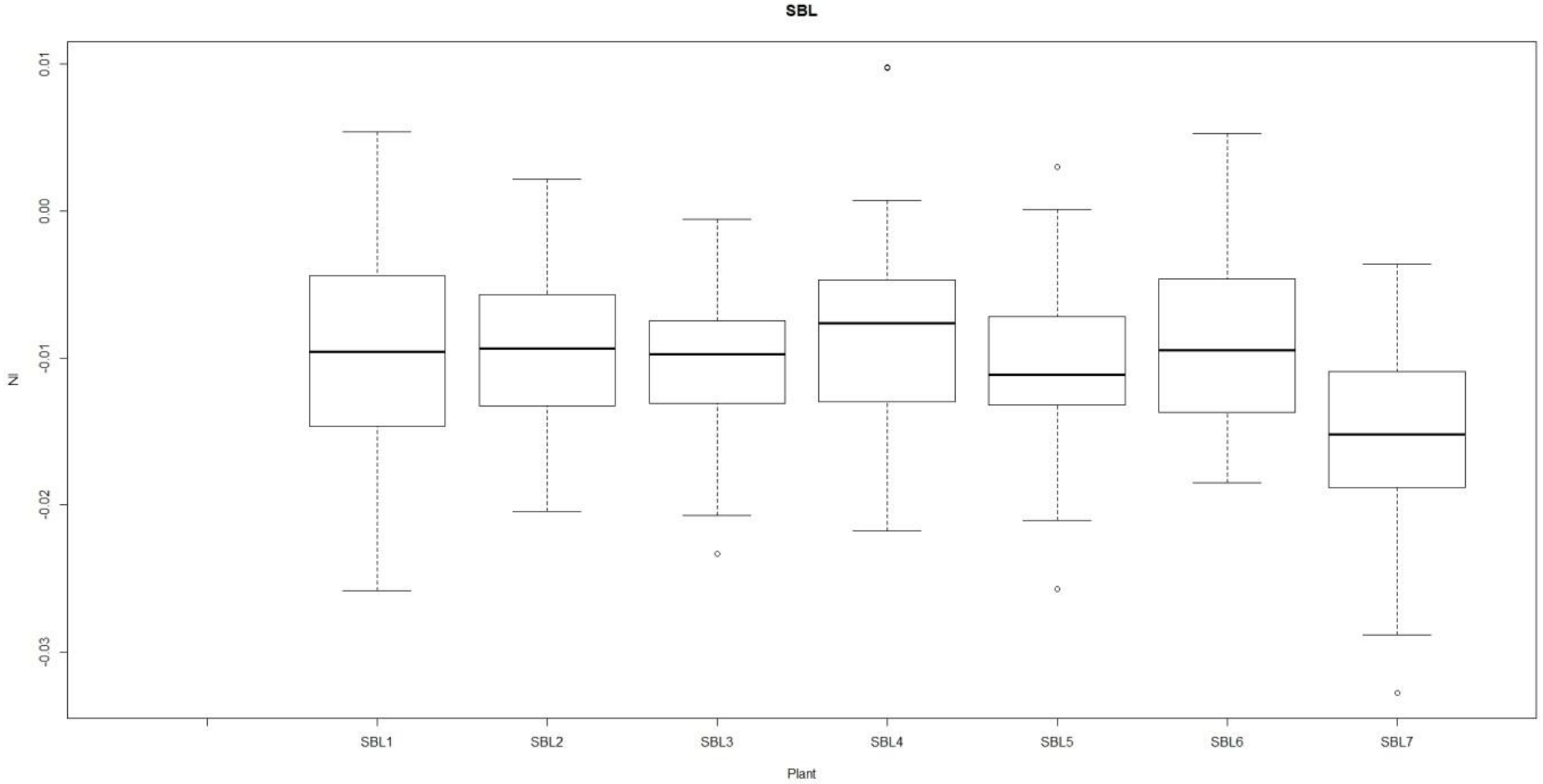

Figure A-43 - Box plot for NI, from leaf clip readings for Portulacaria Afra (Spekboom)

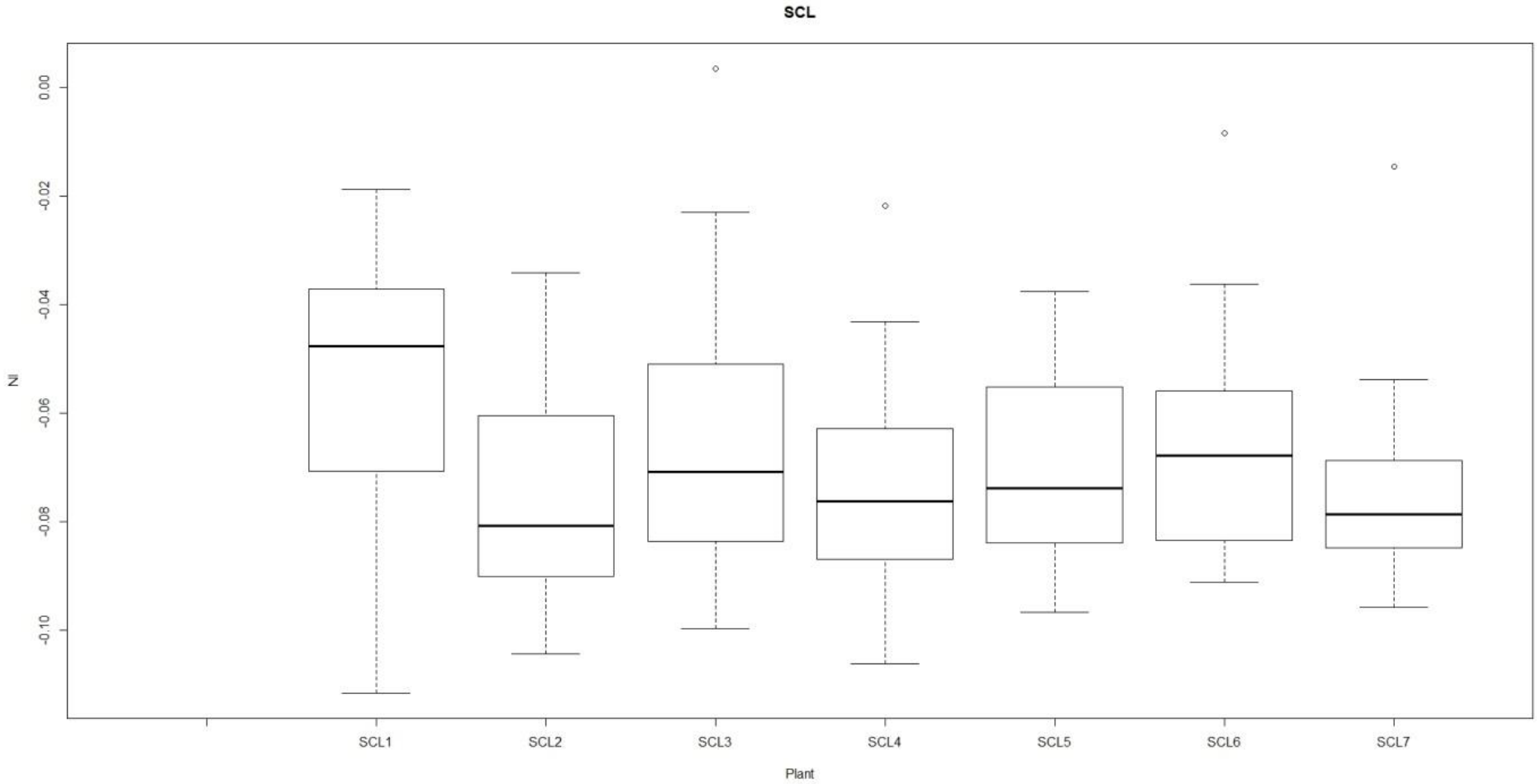

Figure A-44 - Box plot for NI, from leaf clip readings for Carissa Macrocarpa (Natal Plum)

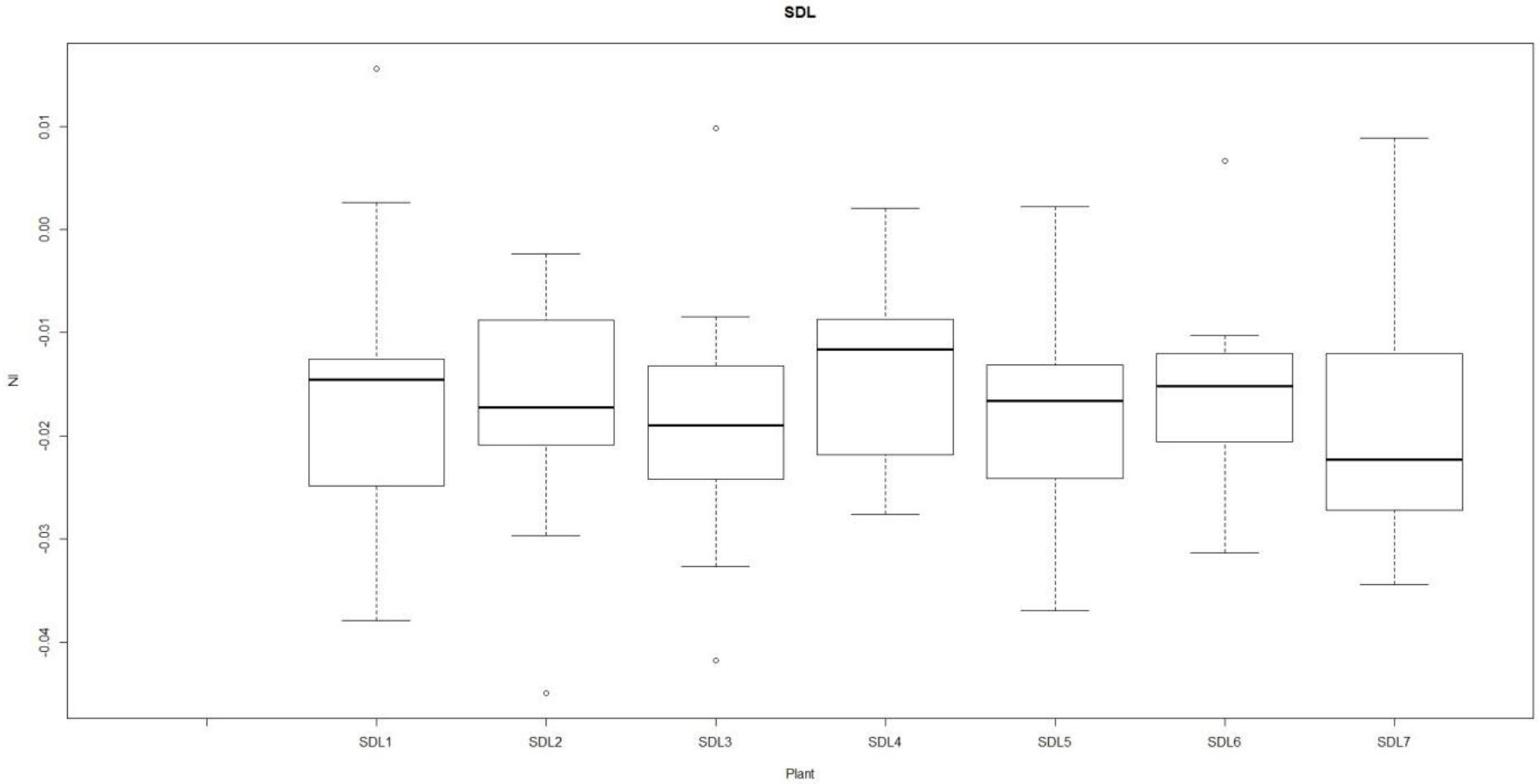

Figure A-45 - Box plot for NI, from leaf clip readings for Dovyalis Caffra (Kei Apple)

APPENDIX B – R CODE TO GENERATE BOX PLOTS

```
BL <- read.csv("BL.csv", header=T)
CL <- read.csv("CL.csv", header=T)
DL <- read.csv("DL.csv", header=T)
EL <- read.csv("EL.csv", header=T)
FL <- read.csv("FL.csv", header=T)
SAL <- read.csv("SAL.csv", header=T)
SBL <- read.csv("SBL.csv", header=T)
SCL <- read.csv("SCL.csv", header=T)
SDL <- read.csv("SDL.csv", header=T)
boxplot(BL$REP~BL$Plant,main="BL",xlab="Plant",ylab="REP")
boxplot(CL$REP~CL$Plant,main="CL",xlab="Plant",ylab="REP")
boxplot(DL$REP~DL$Plant,main="DL",xlab="Plant",ylab="REP")
boxplot(EL$REP~EL$Plant,main="EL",xlab="Plant",ylab="REP")
boxplot(FL$REP~FL$Plant,main="FL",xlab="Plant",ylab="REP")
boxplot(SAL$REP~SAL$Plant,main="SAL",xlab="Plant",ylab="REP")
boxplot(SBL$REP~SBL$Plant,main="SBL",xlab="Plant",ylab="REP")
boxplot(SBL$REP~SBL$Plant,main="SBL",xlab="Plant",ylab="REP")
boxplot(SCL$REP~SCL$Plant,main="SCL",xlab="Plant",ylab="REP")
boxplot(SDL$REP~SDL$Plant,main="SDL",xlab="Plant",ylab="REP")
boxplot(BL$NI~BL$Plant,main="BL",xlab="Plant",ylab="NI")
boxplot(CL$NI~CL$Plant,main="CL",xlab="Plant",ylab="NI")
boxplot(DL$NI~DL$Plant,main="DL",xlab="Plant",ylab="NI")
boxplot(EL$NI~EL$Plant,main="EL",xlab="Plant",ylab="NI")
boxplot(FL$NI~FL$Plant,main="FL",xlab="Plant",ylab="NI")
boxplot(SAL$NI~SAL$Plant,main="SAL",xlab="Plant",ylab="NI")
boxplot(SBL$NI~SBL$Plant,main="SBL",xlab="Plant",ylab="NI")
boxplot(SBL$NI~SBL$Plant,main="SBL",xlab="Plant",ylab="NI")
boxplot(SCL$NI~SCL$Plant,main="SCL",xlab="Plant",ylab="NI")
boxplot(SDL$NI~SDL$Plant,main="SDL",xlab="Plant",ylab="NI")
boxplot(BL$NDWI~BL$Plant,main="BL",xlab="Plant",ylab="NDWI")
boxplot(CL$NDWI~CL$Plant,main="CL",xlab="Plant",ylab="NDWI")
boxplot(DL$NDWI~DL$Plant,main="DL",xlab="Plant",ylab="NDWI")
boxplot(EL$NDWI~EL$Plant,main="EL",xlab="Plant",ylab="NDWI")
boxplot(FL$NDWI~FL$Plant,main="FL",xlab="Plant",ylab="NDWI")
boxplot(SAL$NDWI~SAL$Plant,main="SAL",xlab="Plant",ylab="NDWI")
boxplot(SBL$NDWI~SBL$Plant,main="SBL",xlab="Plant",ylab="NDWI")
boxplot(SBL$NDWI~SBL$Plant,main="SBL",xlab="Plant",ylab="NDWI")
boxplot(SCL$NDWI~SCL$Plant,main="SCL",xlab="Plant",ylab="NDWI")
boxplot(SDL$NDWI~SDL$Plant,main="SDL",xlab="Plant",ylab="NDWI")
boxplot(BL$MSI~BL$Plant,main="BL",xlab="Plant",ylab="MSI")
boxplot(CL$MSI~CL$Plant,main="CL",xlab="Plant",ylab="MSI")
boxplot(DL$MSI~DL$Plant,main="DL",xlab="Plant",ylab="MSI")
boxplot(EL$MSI~EL$Plant,main="EL",xlab="Plant",ylab="MSI")
boxplot(FL$MSI~FL$Plant,main="FL",xlab="Plant",ylab="MSI")
boxplot(SAL$MSI~SAL$Plant,main="SAL",xlab="Plant",ylab="MSI")
boxplot(SBL$MSI~SBL$Plant,main="SBL",xlab="Plant",ylab="MSI")
boxplot(SBL$MSI~SBL$Plant,main="SBL",xlab="Plant",ylab="MSI")
boxplot(SCL$MSI~SCL$Plant,main="SCL",xlab="Plant",ylab="MSI")
boxplot(SDL$MSI~SDL$Plant,main="SDL",xlab="Plant",ylab="MSI")
boxplot(BL$WBI~BL$Plant,main="BL",xlab="Plant",ylab="WBI")
boxplot(CL$WBI~CL$Plant,main="CL",xlab="Plant",ylab="WBI")
boxplot(DL$WBI~DL$Plant,main="DL",xlab="Plant",ylab="WBI")
boxplot(EL$WBI~EL$Plant,main="EL",xlab="Plant",ylab="WBI")
boxplot(FL$WBI~FL$Plant,main="FL",xlab="Plant",ylab="WBI")
boxplot(SAL$WBI~SAL$Plant,main="SAL",xlab="Plant",ylab="WBI")
boxplot(SBL$WBI~SBL$Plant,main="SBL",xlab="Plant",ylab="WBI")
boxplot(SBL$WBI~SBL$Plant,main="SBL",xlab="Plant",ylab="WBI")
boxplot(SCL$WBI~SCL$Plant,main="SCL",xlab="Plant",ylab="WBI")
boxplot(SDL$WBI~SDL$Plant,main="SDL",xlab="Plant",ylab="WBI")
boxplot(BL$PRI~BL$Plant,main="BL",xlab="Plant",ylab="PRI")
boxplot(CL$PRI~CL$Plant,main="CL",xlab="Plant",ylab="PRI")
boxplot(DL$PRI~DL$Plant,main="DL",xlab="Plant",ylab="PRI")
boxplot(EL$PRI~EL$Plant,main="EL",xlab="Plant",ylab="PRI")
boxplot(FL$PRI~FL$Plant,main="FL",xlab="Plant",ylab="PRI")
boxplot(SAL$PRI~SAL$Plant,main="SAL",xlab="Plant",ylab="PRI")
boxplot(SBL$PRI~SBL$Plant,main="SBL",xlab="Plant",ylab="PRI")
boxplot(SBL$PRI~SBL$Plant,main="SBL",xlab="Plant",ylab="PRI")
boxplot(SCL$PRI~SCL$Plant,main="SCL",xlab="Plant",ylab="PRI")
boxplot(SDL$PRI~SDL$Plant,main="SDL",xlab="Plant",ylab="PRI")
```