Enhancing Community Conservation Efforts for Pest Plant Eradication Using Low-Altitude Remote Sensing

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Abstract

Invasive plant species in New Zealand are a significant threat to biodiversity. These invasive plants were introduced during earlier settlements via different pathways. Regional councils and conservation groups attempt to these rebuild native flora and fauna communities by restoring, reducing, and halting human environmental impacts including the spread of invasive plants. The current method to detect invasive plants involve on-ground searches, which are slow, infrequent, and costly. Invasive plants require early, rapid detection and management. Remote sensing in modern literature has been used as a novel way of detecting invasive plants in remote areas. This method is favoured as it is faster, more cost-effective, and thus able to be performed regularly in contrast with current methods used.

This study detected the invasive plants Woolly Nightshade, Moth Plant, Gorse, and Sweet Pea Shrub using low-altitude high-resolution drones on Moturoa Island in the Bay of Islands, New Zealand. A Phantom 4 Professional UAV paired with a MicaSense RedEdge Sensor was used to collect the imagery. To detect the invasive plants, we used three classification techniques in ArcGIS: pixel-based Maximum Likelihood, object-based Support Vector Machine and Random Trees. We tested nine segmentation parameters for each classier. Out of the nine segmentation parameters, parameters 2 and 8 performed the best for Random Trees and Support Vector Machine with an average of 60% and Kappa of 54%. However, Maximum Likelihood did not perform adequately with segmentation parameters 2 and 8; instead, it performed best with segment 9. The accuracy results for that parameter were 56%, with a kappa value of 50%.

This research examined the need for a suitable sampling size, effects on accuracy in relation to the timing of imagery acquisition, segmentation settings and the effects of shadows on plant spectral reflectance. This research can directly benefit the Northland Regional Council, community-led restoration projects, and researchers in this field efficiently by enabling prompt detection of invasive plants.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signed:

Date: 26/02/2022

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Abbreviations

Act - Biosecurity Act 1993

ANN - Artificial Natural Network

DOC - Department of Conservation

DSM - Digital surface models

DT - Decision Tree

GCP - Ground control points

GNR- Good Neighbour Rule

GPS - Global Positioning System

KNN - K-nearest Neighbour

NGOs – Non-Governmental Organisations

NDVI - Normalised Difference Vegetation Index

NDWI - Normalised Difference Water Index

NIR - Near-infrared

NPD - National Policy Direction for Pest Management

NPPA - The National Pest Plant Accord

MDL - Motu Roa Development Limited

ML - Maximum Likelihood

OA- Overall accuracy

R2 - R- squared

RE - Red Edge

RF - Random Forest

RGB - Red, Green and Blue

RT - Random Trees

SPOT - Satellite Pour ll'Observationde la Terre

SVM - Support Vector Machine

TAG - Technical Advisory Group

UAV - Unmanned Aerial Vehicle

Chapter 1: Introduction

1.1 Background

For thousands of years, people have intentionally and unintentionally transported and traded plant species worldwide (Iannone et al., 2020; Lovatt, 2011). Many of those introduced species now reside in areas outside of their native habitats. Some of those species have become naturalised in their new habitats, meaning that they have a self-sustaining and reproducing population in a specified geographic area, without the need for human intervention (Lovatt, 2011).

The majority of those introduced and naturalised species pose no threat to their new environments (Jones et al., 2011; Mafanya et al., 2017); however, some introduced and naturalised species can have a negative impact on the environment and economy (Jones et al., 2011; Mafanya et al., 2017). These harmful species are referred to as invasive species (Iannone et al., 2020; Lovatt, 2011). They can proliferate, reproduce rapidly, disperse well, and tolerate a large range of environmental conditions (Baron et al., 2018; Jones et al., 2011; Mafanya et al., 2017; Paz-Kagan et al., 2019). This is because the natural predators, competitors, diseases, and parasites that keep invasive species numbers in check in their natural habitats are often absent when invasive species populate a new area. (Colautti & MacIsaac, 2004; Iannone et al., 2020; Lovatt, 2011). Invasive plant species can affect vertebrates, invertebrates, soil microbes, ecological habitats, fire regimes, trophic structures, and food webs in their new habitats. They can also affect ecosystem processes, such as nutrient cycling, soil sedimentation, and hydrological cycles (Baron et al., 2018; Jordan et al., 2008; Reid et al., 2009).

Currently, there are 200 invasive plant species naturalised in New Zealand with a growth rate of 10% from 2010 to 2015 (Craig et al., 2000; Department of Conservation, 2019; Ministry for the Environment & Stats NZ, 2019). Due to the introduction of invasive plant species, more than 10,000 native plants and animal species are considered threatened or at risk of extinction. These include 56% of vascular plants, 23% of mosses, hornworts, liverworts, and 10% of lichens (Ministry for the Environment & Stats NZ, 2019). The estimated annual costs in relation to damage and management of invasive species is approximately $500 million NZD (Lovatt, 2011). In the United States, invasive plant damage, management and control, cost approximately $137 billion USD every year (Huang & Asner, 2009).

Several organisations within New Zealand manage invasive plants. These range from national government agencies, regional councils, and industry groups to local Māori organisations, non-governmental organisations (NGOs), landowners, land occupiers, community groups, and the public (Hulme, 2020). These organisations conduct pest management activities to protect New Zealand's economy, environment, and socio-cultural values (Bourdôt et al., 2018; Champion, 2005).

Invasive plants require early detection and management. Nevertheless, the current advised methodology to monitor and detect invasive plants by government and NGOs is to locate them at ground level manually. Regional councils report that the geographical areas of concern are discovered via information from the public, council staff and Department of Conservation (DOC) staff (Bourdôt et al., 2018; Ministry for the Environment & Stats NZ, 2019). There are two issues with this method. Firstly, the staff from DOC, regional councils, and other NGOs do not go beyond the sites of interest. The second issue is that it is time-consuming, requires appropriate regular monitoring, and is practically suboptimal for long-term management. Specifically, regarding the local population, the majority lack the knowledge of invasive plants and their effects on the environment, the economy, and the welfare of animals and humans. This leads to A majority of pest-plants being ignored.

Remote sensing drones are a novel, rapid, and cost-efficient technique used alongside mapping to indicate new sites of interest and locate invasive plants (Lishawa et al., 2017). This method allows invasive plants to be located and eliminated shortly after detection (Lishawa et al., 2017). Having visual distribution maps or models of invasive species hotspots will help communities, governments, NGOs, and the wider public to efficiently detect invasive plant species (Lishawa et al., 2017).

In this thesis, I test the accuracy and abilities of an off the shelf drone with a multispectral sensor to detect Woolly Nightshade (Solanum mauritianum Scop.), Gorse (Ulex europaeus L.), Moth Plant (Araujia sericifera Brot.) and Sweet Pea Shrub (Polygala myrtifolia L.). These species are highly prevalent in New Zealand and are often the target of eradication efforts by local government and community organisations. The methods of this thesis can be used as a guide for local communities and charities that want to incorporate geospatial science in effectively detecting invasive plants. In addition, it can be extended for use by government agencies at a local and national level especially for Doc staff that want to expand the areas of interest for majority threatening invasive plants.

1.2 Aim of research

This research aims to enhance community conservation efforts for pest plant eradication using low-altitude unmanned aircraft. The object of this study is to;

- Find the optimal classifier for the detection of invasive plants using a commercially available multispectral camera.

The case study uses a small private sanctuary island called Moturoa at the mouth of Kerikeri inlet in the Bay of Islands, New Zealand (Avery, 2010). Since the sanctuary's establishment, shareholders have planted over 60,000 native trees (Avery, 2010; Jones et al., 2011). However, invasive plants such as Gorse, Sweet Pea Bush, Moth Plant and Woolly Nightshade have been a significant problem for the residents of Moturoa, as they pose a severe threat to native flora (Avery 2010).

1.3 Structure of the thesis

Chapter 2 discusses background information on restoration in New Zealand as well as invasive plant management. This section also discusses applications of remote sensing to detect invasive plants.

Chapter 3 introduces the four invasive plants of the study, including environmental impacts, management methods and botanical information. This section also introduces the study site, the methods of acquiring the imagery, and the classification process.

Chapter 4 presents the results of this thesis.

Finally, Chapter 5 discusses my results in relation to the current literature and other aspects of the study. This chapter also provides a critical evaluation of the research and its methods.

Chapter 2: Literature review

2.1 Background of restoration in New Zealand

There are limited areas where human influence on ecosystems is yet to occur (Godet & Devictor, 2018; Heywood & Iriondo, 2003). Human influence puts pressure on ecosystems and habitats, causing species to decline. This results in decreased biodiversity, degradation of habitats, species loss, and species fragmentation (Craig et al., 2000; Heywood & Iriondo, 2003; Towns & Daugherty, 1994). For example, in New Zealand, the arrival of Polynesians and European settlers caused a significant impact on the environment (Saunders & Norton, 2001). Introduced plants and animal species by Polynesians and European settlers have caused the extinction of seven native plant species (Ministry for the Environment & Stats NZ, 2019). Another example of human impact since settlement is the removal of 70% of native forests, initially from the Polynesians burning practices and subsequently from the Europeans deforestation for settlement, agriculture, and trade (Ministry for the Environment & Stats NZ, 2019). More recently, the total area of native forest reduced by 16,108 hectares between 1996 and 2012 (Ministry for the Environment & Stats NZ, 2019). The loss of native plant areas enhances the spread of invasive plants. Smith (2019) stated some of the most common traits of invasive plants is the ability to thrive, germinate and disperse in disturbed habitats. Certain invasive plants such as Moth Plant and Gorse thrive in disturbed sites such as those that were previously covered by native plants (Gränzig et al., 2021a; Waipara et al., 2006). Similarly, Buffelgrass (*Pennisetum ciliare*) grow is disturbed lands including roadside, cliff faces, valley flats and drainages (Elkind et al., 2019). In South Africa, invasive plant Woolly Nightshade has been further spread in disturbed lands by frugivores as their fruit is more available than native plant fruits (Schor et al., 2015).

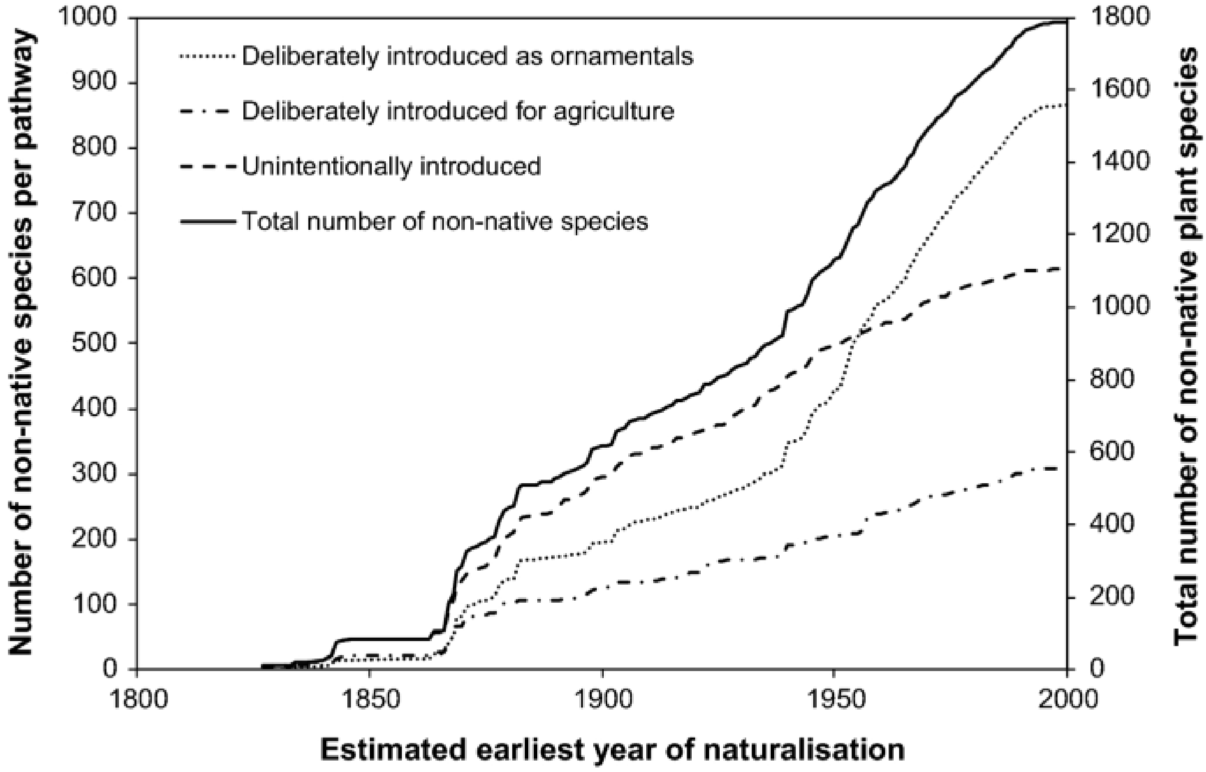

Figure 1: The total number of naturalised plants over the last 200 years by different pathways. Image reproduced from Hulme (2020)

Figure 1 illustrates the growth of non-native plant species since Europeans settlement. The left y-axis refers to the number of non-native species per pathway. A pathway refers to a human activity that has advertently or inadvertently introduced a new species into an area. The right y-axis shows the total number of native plant species.

The number of non-native plant species naturalised since European settlement in New Zealand has grown steadily since the 1800s (Figure 1) and these have become naturalised via three different pathways. The pathways in Figure 1 refer to three which these were, deliberately introduced as ornamental, deliberately introduced for agricultural, and unintentionally introduced. Deliberately introduced ornamentals becoming the greatest source of naturalisation since the 1950s (Hulme, 2020). The significant increase number of non-native plant species was enough of a concern to initiate the introduction and passing of the Noxious Weed Act (1900). This is the first example of a legislation to actively manage non-native plant population levels anywhere in the world (Hulme, 2020).

More recently, New Zealand created the Department of Conservation (DOC) on April 1st 1987, through the Conservation Act (1987) (Craig et al., 2000; Towns & Daugherty, 1994). DOC was assigned to manage and conserve New Zealand's natural and historical heritage. The creation of DOC Restoration Islands is an example of an attempt to rebuild native flora and fauna communities of by restoring, reducing, and halting human environmental impact (Avery, 2010; Craig et al., 2000; Saunders & Norton, 2001; Towns & Daugherty, 1994; Veitch, 2001). Conservation actions, such as eradicating pests, removing invasive plants, and continuously maintaining the habitat on said islands are performed following DOC guidelines (Avery, 2010; Craig et al., 2000; Towns & Daugherty, 1994). These islands contain rich biodiversity and are a refuge for species that are endangered on the mainland. Some examples of DOC Restoration Islands in New Zealand includes Tiritiri Matangi, Mercury Islands, Aotea (Great Barrier) and Te Hauturu-o-Toi (Little Barrier) (Avery, 2010; Towns & Daugherty, 1994; Veitch, 2001). There are also private restoration islands such as Moturoa in the Bay of Islands, where owners have been eradicating pest plants such as Moth Plant and Woolly Nightshade since the 1980s (Avery, 2010).

2.2 Invasive plants in New Zealand

There are 27,000 introduced species and 2,000 of those are naturalised species in New Zealand in comparison to 2,500 native species (Lovatt, 2011). Two hundred of the 2,000 naturalised species are invasive (Ministry for the Environment, 2007). The regional councils and government departments have a cooperative agreement called 'National Pest Plant Accord' (NPPA), which works alongside the Biosecurity Act (1993) (Act) to prevent, reduce, or eliminate invasive plant species. The NPPA is a list of invasive plants that require management. The Act is the legislation that facilitates said management. The NPPA list is controlled by the Technical Advisory Group (TAG), and they determine which unwanted species get included on the NPPA list using predefined criteria such as the negative impacts on the environment (Champion, 2005).

The legislation purpose is to mitigate the effects of harmful organisms on the economic wellbeing, the environment, human health, and the enjoyment of the natural environment (*Biosecurity Act*, 1993). The legislation also provides the list of unwanted organisms. The Act also aims to reduce the impacts of these organisms on Māori and their cultural traditions (Part 5, Section 54) (Champion, 2005). The harmful plants outlined are described by the Act to pose significant negative impacts and are difficult to control once established. Section 5 of the Act enables the development of national or regional pest and pathway management plans and small-scale management programmes aimed at eradicating or effectively managing harmful organisms. In part 5, section, 52, 53, 56 and 100, the Act illustrates the steps required for enforcing the prevention of sale and distribution of harmful organisms. There are both National Strategic Plans and Regional Strategic Plans to enable the management of pest plants.

The National Policy Direction for Pest Management (NPD) is a framework for regional councils and NGOs to use when developing their pest control (Bourdôt et al., 2018; Ministry for Primary Industries, 2013). The NPD framework was based on the foundations provided by Act.

The Act part 5, section 56 states that any plan must clearly describe the outcomes of a pest management strategy (Bourdôt et al., 2018). There are five programmes to serve as guidance for regional councils and NGOs provided within the Act. These are highlighted in Table 1 below (Bourdôt et al., 2018). If the invasive plant is in either the Exclusion, Eradication Progressive Contained, or Sustained Control categories, councils are required to give the geographic area of the plant (National Policy Direction for Pest Management, 2015 [Part 4, Section C, clause i]). In Part 8 Section 1 of the NPD and Act section part 5, Section 56, clause 3, there is the 'Good Neighbour Rules' (GNR). These outline the responsibilities of property owners in terms of the management of those invasive plants.

Table 1: Act program definition and goals. Reproduced Ministry for Primary Industries, (2013).

Program	Definition
Exclusion	The process of preventing the establishment of the subject present in New Zealand but not yet established in a particular area
Eradication	Reducing the infestation level to zero in short to medium terms.
Progressive containment	Gradually reduce distribution of the subject.
Sustained control	Limiting the impact of the subject and supress it from spreading to other properties.
Value of a place	Protected by excluding or eradicating risk factors from the place, or by containing, reducing, or controlling the risk factors within the place in a way that protects the value of a place.

There are currently 14 regional pest management plans in New Zealand. While there are numerous pest plants in each region, the regional council's focus is to control the most harmful pest plants. Some pest plants may be common in some regions but absent in others. Appendix 1 shows the 14 regional pest plant management aims and their programs for the four invasive plants of this study. The level of prioritisation and management for each region is different. This is because the four invasive plants have different growth rates in different parts of New Zealand. Most new sites detected are usually alerted to the council by the public, although the Horizon Council argued that the public usually report plants that are not defined as invasive. This means that the council is required to first confirm the new sites before taking any action. The processes of detecting new sites of invasive plants is slow under the majority of regional councils, and thus chances of the spread of plants is high. While it is useful and informative for some councils to use Global Positioning System (GPS) software to locate pest plants on maps, these maps are not generally shared with the public. The majority of maps that are shared are the ones with high-interest regions and yet they do not show hotspots of pest plants. Depending on the program type, many sites require monitoring for several years, and a defined area of an invasive plant is required to be removed each year. Some of the invasive plants are required to be removed with the GNR. However, several councils mentioned the public misinformation on which plants are invasive (Hawkes Bay Regional Pest Management Plan, n.d.; Horizons Regional Pest Management Plan, 2017). To start with, there are many invasive plants for each region to control. Some of those invasive plants have similar appearance and Similarities with native plants and thus creates a confusion among the public. Additionally, in order for a plant species to be classified as invasive, regional councils require time, resources and changes to the planning process. During that planning process, the classification of 'invasive' can be opposed for political or commercial reasons.

Despite that, there are conservation community-based groups that aim to educate the public around invasive plants, including how to detect, remove and eradicate them completely from sites of interest. An example of one of these groups in north Auckland is Pest-Free Kaipatiki (https://www.pestfreekaipatiki.org.nz). Some of their work includes Native plant nurseries , compost collection, reserve restorations, stream care and encouraging zero waste management.

2.3 Community management of invasive plants

Community-based restoration groups play a significant role in managing invasive plant and animal pests, planting native plants, translocating native species, and achieving restoration and enhancement of native species and habitats (Sullivan & Molles, 2016). There are more than 600 current community environmental groups across New Zealand that have the aim of restoring degraded sites and improving habitats for native flora and fauna. The New Zealand biodiversity strategy states the need to support community actions designed to ensure the preservation of New Zealand's unique native biodiversity (Peters et al., 2015). Examples of current well-known NGOs and community groups in New Zealand include Forest & Bird, Ark in the Park, Restore Hibiscus & Bays, Pupuke Birdsong Project, and Kaipātiki Project Incorporated. These organisations are dependent on volunteers to perform conservation tasks. This is beneficial as this approach educates the public around invasive plants and their impacts on native flora and fauna.

DOC and communities also work in partnership to restore native ecosystems on public and private land (Sullivan & Molles, 2016). There are entire islands being given a specific designation for the protection and promotion of native flora and fauna some include Tiritiri Matangi, Mercury Islands, Great Barrier or Aotea, Little Barrier/Te Hauturu-o-Toi, Rotoroa Island and Moturoa Island in the Bay of Islands (Avery, 2010; Galbraith, 2013; Ritchie, 2012; Towns & Broome, 2003; Veitch, 2001). In addition, community groups on those islands actively participate in managing pest plants (Avery, 2010; Galbraith, 2013; Ritchie, 2012; Towns & Broome, 2003; Veitch, 2001).

Communities, like councils, use the Pest Plant Accord List and the website ‘weed busters’ for information on invasive plants that occur in their sites. The difference between community groups and councils is that there is no set program for community groups. Community groups can have various goals, including full ecosystem restoration, environmental quality monitoring pest plant control, species management and control, sustainability, planting, education on invasive plants and habitat restoration, to name a few. Applications such as ecoTrack are recommended to enable community engagement in tracking invasive pest species. The app includes monitoring of target species, and tracking weed control activities (Restore Hibiscus & Bays, n.d.).

The currently advised method of detecting invasive plants is a physical search (Timmins & Braithwaite, 2003). This is more challenging on islands than on the mainland. Costs of travelling to the islands mean searches are less frequent than on the mainland, leading to irregular observations of new invasive plants. Flowering seasons are vital to detecting many invasive plants in order to differentiate them from native plants. Not being on the islands during that time can create issues in spotting them in the future (Timmins & Braithwaite, 2003). The idea of also travelling to islands is costly as the majority of those islands do not have public facilities such as supermarkets or housing enough for all volunteers. Instead, the volunteers are required to bring their food supplies and their camping gear. While this is not a significant issue for many volunteers, it can seem challenging for others who have not previously participated in these projects.

As a result, infrequent searches, seasonality challenges, incorrect site prioritisation, and detecting new weed incursions are the critical issues with physical searches for invasive plants on the mainland and islands. As a result, it is more difficult for small community-based conservation groups to find hotspots of invasive plants and create management plans and goals to eradicate them. An example of this was seen on Lady Alice Island, where infrequent searches for invasive plants led to the establishment of Mexican devil (*Ageratina adenophora*), to the extent to which it is now unlikely to be eradicated (Timmins & Braithwaite, 2003). Established invasive plants on islands are more challenging to eradicate than areas which have only been recently exposed to non-native species. For example, on Curvier Island, five years of removal of Moth Plant (*Araujia sericifera*) were unsuccessful since the plant was already well established when found. This is an example of failure to detect invasive plants in the early stages. Delayed detection of invasive plants and reinvasion from the mainland would make it very unlikely for eradication (Timmins & Braithwaite, 2003).

In response, Soubry et al. (2021) emphasise the need for using remote sensing to monitor invasive species. Using UAV can help improve field surveying and detection of invasive plants that are on high slopes or cliff faces (Bolch et al., 2021). UAVs can cover large geographic areas at lower costs than traditional surveying and detection of invasive plants (Bolch et al., 2021; Marzialetti et al., 2021). They are also time-efficient, agile and provide valuable, accurate maps of invasive plants (Bolch et al., 2021; Marzialetti et al., 2021). Marzialetti et al. (2021) emphasised that UAVs have improved community group surveying and mapping efforts in inaccessible regions such as grasslands and wetlands.

2.4 Remote sensing and invasive plants

2.4.1 Review of remote sensing in ecology applications

In 1958, Charles Elton published a paper called 'The Ecology of Invasions by Animals and Plants'. This was the first example of the use of remote sensing to detect invasive plant species (Vaz et al., 2018). The Landsat Programme launched across the 1970s and in the 1980s were the first multispectral and hyperspectral satellites (Vaz et al., 2018). Since then, many more satellites have been launched, such as the Satellite Pour ll'Observationde la Terre (SPOT). Early studies attempted to map invaded habitats through satellite imagery during that time. (Vaz et al., 2018). Retrospect, those attempts at the time were limited in their abilities to accurately detect invasive Plants. These challenges are elaborated in the next section. In the early 2000s, unmanned aerial vehicles were commercially available, this steered a new direction for detecting invasive plant species (Vaz et al., 2018). Figure 2 shows the total number of publications by year with the main themes as “plants” and “Remote sensing” and the increase of published articles from the early 2000s. Remote sensing and plant publications were from various disciplines, including remote sensing technology, photographic imaging science, ecology, plant science, multi-disciplinary geoscience, environmental science, engineering, forestry, and agronomy. In Figure 3 we can see the themes of published papers with the main themes as “plants” and “Remote sensing”

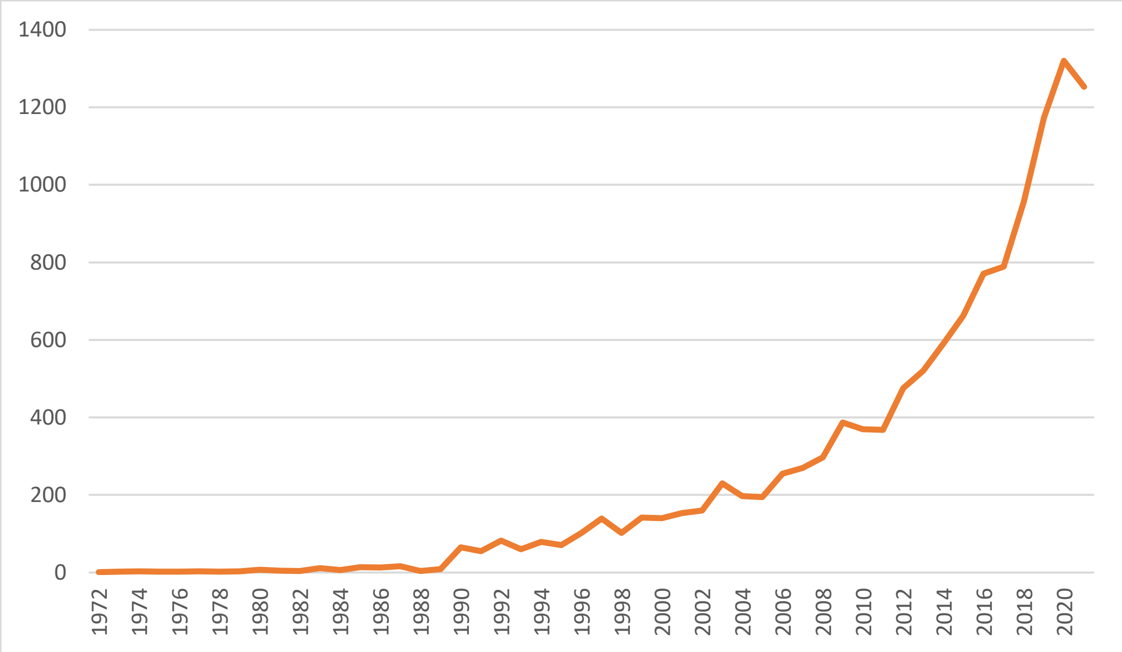

Figure 2: Total Publications by Year of "Remote sensing" and "plant in topic search in Web of Science.

Figure 3: Fields that included "Remote sensing" and "plant" in topics search in Web of Science.

2.4.2 Review of platforms

Remote sensing is a technique used to gather valuable insights/information about the earth without any physical contact with the items or areas under observation by specific instruments mounted on aeroplanes, satellites, and other platforms such as unmanned aerial vehicles (UAVs) (Aggarwal, 2004; J. B. Campbell & Wynne, 2011; Ouyang et al., 2011; Weng, 2013). Platforms in remote sensing refers to a vehicles which have instruments or sensors mounted on them (Sanderson, 2010; Weng, 2013). Some of those sensors on such platforms have different attributes which can determine what the sensor can be used for (Weng, 2013). Some of these attributes include time of image acquisition, the distance the sensor is from the object of interest, the location, and the coverage of the area (Weng, 2013). In remote sensing, platforms are categorised in three classes, ground based, airborne and spaceborne (Aggarwal, 2004; J. B. Campbell & Wynne, 2011; Ouyang et al., 2011; Weng, 2013). These platform types and average flight altitude are shown in Figure 4.

In 1858, Gaspard-Félix Tournachon took aerial photos using an airborne hot air balloon in France. This was the first remote sensing vehicle used to acquire imagery of the earth. Airborne platforms today include aircraft and unmanned aerial vehicles. Unmanned aerial vehicles (UAVs) are currently the most used platform in remote sensing. UAVs are favoured by the public because it is low-risk, low-cost, and systematically observe natural phenomena at high spatial-temporal resolution (Ivošević et al., 2015; Ouyang et al., 2011; Simic Milas et al., 2018; Weng, 2013). They can also acquire imagery up to 150 metres in altitude above the controller. These platforms are often controlled on ground by the user (Weng, 2013; Pajars 2013). Scientists started using UAV based platforms in the early 2000s once UAVs became commercially available (Vaz et al., 2018). The lower cost of UAVs allowed for data acquisition for multiple applications, including invasive plant species mapping (Alvarez-Taboada et al., 2017; Casas et al., 2021; Martin et al., 2018; Marzialetti et al., 2021; L. Wang et al., 2021). Other platforms such as aircrafts can acquire imagery between 3km to 12 km altitude (J. B. Campbell & Wynne, 2011).

Ground based remote sensing involves the gathering of data on the ground. Usually, the data acquired includes an object’s spectral reflectance for image calibration. A radiometric calibration considers the irradiance measurement, camera exposure data, and the position of the sensor relative to the sun (directional measurements) (Pajares, 2015). This type of correction is essential for accurate quantitative measurements of the imagery. Radiometric collaboration ensures all imagery is exposed appropriately, reducing over and under exposure of images. It allows reflected light to be measured in five different spectral bands. The MicaSense RedEdge sensor produced by MicaSense, Inc. includes radiometric calibration.

Spaceborne platforms including satellites are the most used remote sensing platform. Satellites is one of the platforms that acquires imagery with the highest altitude of over 700km (Sanderson, 2010). TIROS-1, launched in 1960, was the first Satellite primary designed for climatological and meteorologically observations. It also laid the foundations for the creation of future land observation satellites, such as Landsat 1 (ERTS-1), launched in 1972 (J. B. Campbell & Wynne, 2011).

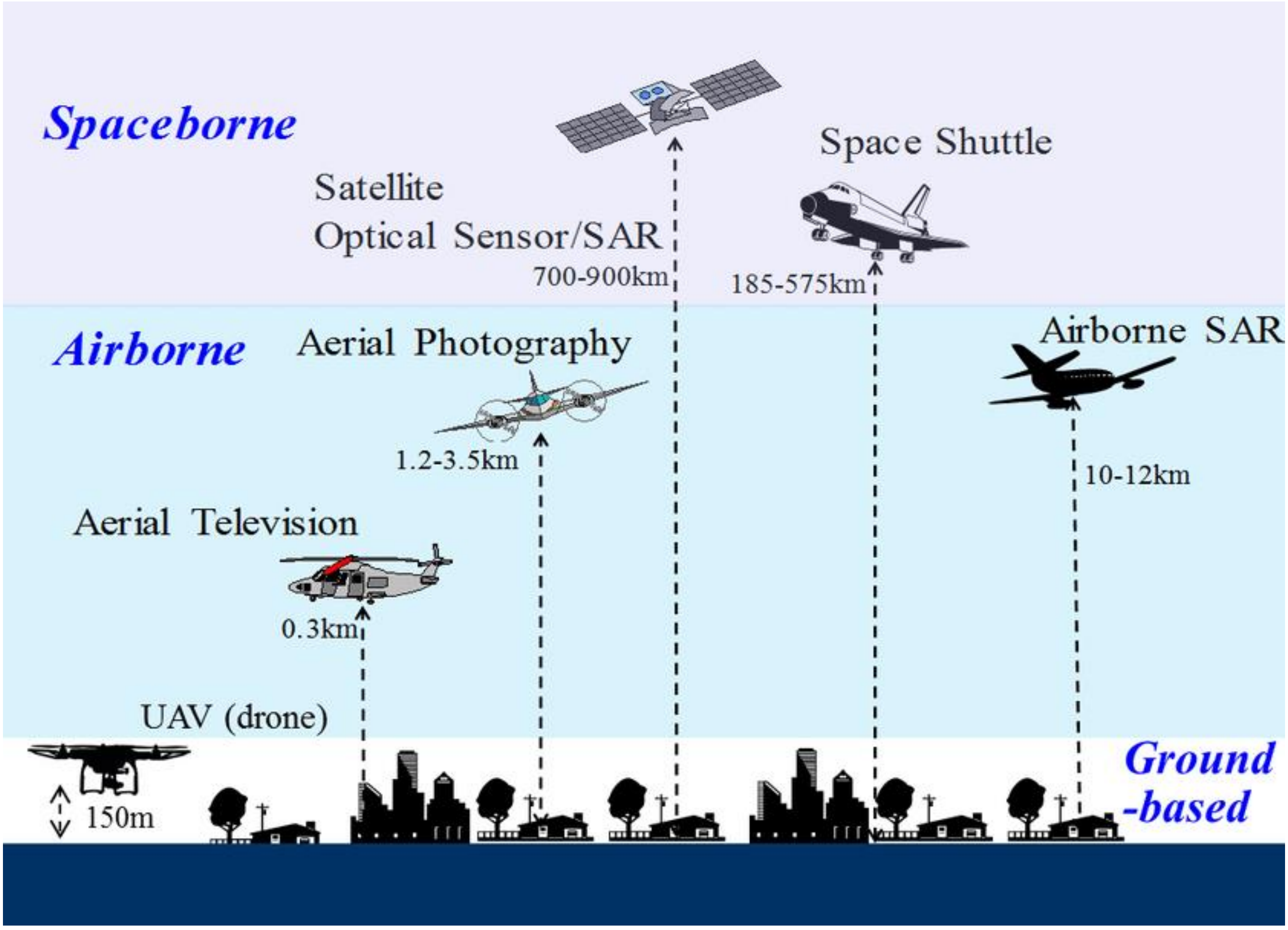

Figure 4: Remote sensing platforms and their flight height retrieved from Yamazaki et al. (2016)

2.4.3 Review of sensors mounted on platforms

There are two types of sensors in remote sensing: passive sensors that use an external energy source such as the sunlight, and active sensors that use an energy source such as radar or laser. Active sensors send signals to Earth, which objects either reflect, absorb, or transmit. The reflected signals are sent back to the sensors and are then measured (Aggarwal, 2004; J. B. Campbell & Wynne, 2011; Simic Milas et al., 2018). Satellites such as SPOT, Landsat, Worldview (Aggarwal, 2004; J. B.

Campbell & Wynne, 2011) as well as UAV such as DJI (Da-Jiang Innovations, Guangdong, 2006) Phantom 3, 4, and Matrice 600 Pro (Dash et al., 2019; Horning et al., 2020; Laporte-Fauret et al., 2020) are all examples of passive sensor.

Sensors and platforms affect imagery's spectral, temporal, and spatial resolution. A spatial resolution refers to the number of pixels in the image. The more pixels there are, the higher the resolution (Ouyang et al., 2011; Weng, 2013; Xue & Su, 2017). The spatial resolution may vary depending on the height at which the imagery is captured (Dash et al., 2019). For invasive plant detection, high spatial and spectral resolution is required. A lower resolution of more than 1 metre can produce blurry imagery, which in return can produce lower accuracy (Zhao Xuan Zhang, 2014).

The frequency with which a sensor views the exact location is called the temporal resolution (Liang & Wang, 2019). The exact location’s of a sensors imagery capture rate can vary from days to weeks to months (Ouyang et al., 2011; Weng, 2013; Xue & Su, 2017). The temporal resolution is often associated with satellite and manned aircraft rather than UAVs. This is because UAVs allow for the repetitive collection of data for a location anytime, unlike satellites that require sensors to return to the exact location over a longer period of time (Ouyang et al., 2011; Weng, 2013; Xue & Su, 2017).

The spectral resolution is the number of spectral bands in the sensing device. Sensors gather information between visible light to the infra-red wavelength range (Campbell & Wynne, 2011). Sensors can have multiple bands. For example, a red, green, and blue (RGB) sensor would have three bands that range from 400nm to 700nm. Multispectral sensors have additional bands that extend beyond the visible light spectrum, including near-infrared (NIR) and Red Edge (RE), where the bands can range from 700 nm — 1mm (Aggarwal, 2004). The most used sensors in the literature were RGB, Multispectral and Hyperspectral (Bannari et al., 1995; A. Wang et al., 2019).

Figure 5: MicaSense RedEdge Camera (Left), DJI Phantom Series 4 Aircraft (Right) UAV Image Acquisition.

The MicaSense company produces MicaSense RedEdge Sensor (Figure 5). The RedEdge Sensor contained five high-precision sensors independent of each other (Figure 5). The wavelengths extend from the visible to non-visible light spectrum range (400 nm — 900 nm). Table 2 presents the five sensors and the centre wavelength for each. The benefit of this sensor is that it had radiometric properties, which allowed for the conversion of raw digital numbers into absolute reflectance or sensor reflectance into surface reflectance values. Figure 6 shows the RedEdge band wavelength relationship with typical plant reflectance and filter transmissivity. The Red Edge (RE) and Near-Infrared (NIR) are suitable for distinguishing plants for this study.

Table 2: Wavelength centres of MicaSense RedEdge Sensor. Table reproduced from MicaSense-RedEdge, 2015.

Band	Band Name	Centre Wavelength (nm)
1	Blue	475
2	Green	560
3	Red	668
4	Near-Infrared (NIR)	840
5	Red Edge (RE)	717

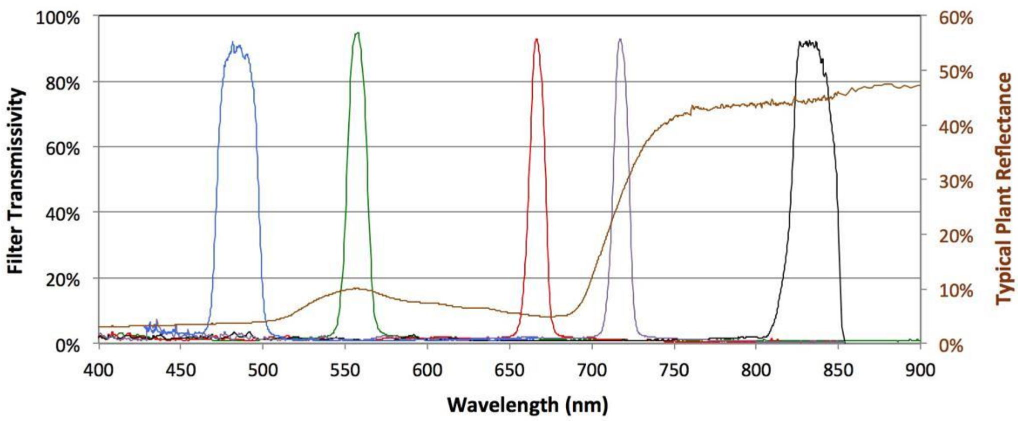

Figure 6: MicaSense RedEdge band wavelength relationship with typical plant reflectance and filter transmissivity. Graph reproduced from MicaSense-RedEdge, 2015.

Review of postprocessing software

In remote sensing, there are a number of software's that are used to postprocess imagery taken by platforms. The software that were used in the literature included, Multi-View Environment (Wijesingha et al., 2020; Wu et al., 2019), VisualSFM (Lehmann et al., 2017), Agisoft Metashape (Ahmed et al., 2021; Laporte-Fauret et al., 2020; Marzialetti et al., 2021; Papp et al., 2021) DroneDeploy (Casas et al., 2021) and

Pix4D Mapper (Abeysinghe et al., 2019; M. J. Campbell et al., 2020; Casas et al., 2021; Kedia et al., 2021; L. Wang et al., 2021; X. Yang et al., 2021). Pix4D Mapper was chosen for this thesis as it has an easy to use interface, is reliable and optimised for the Micasense Red Edge.

Pix4D Mapper is an image mosaicking software. The software has five main steps: initial processing, point cloud densification and orthomosaic, digital surface model generation, and quality reporting. The initial process computes the geolocation of each image using advanced automatic aerial triangulation and bundle block adjustment. The point cloud densification was set to full process instead of rapid. The full extent is time-consuming; however, produces higher accuracy results regarding the resolution of the imagery. The point cloud and mesh were built on the automatic tie points and point densification and 3d texture mesh. The third step was the DSM, orthomosaic and index creation. This step created the distal surface model, enabling the orthomosaic and reflectance map computation. The orthomosaic is based on orthorectification with perspective distortions removed from the images whereas the reflectance map produced the value of each pixel.

2.4.4 Review of remote sensing for invasive species.

Satellites are some of the earliest platforms used to acquire imagery for invasive species (Vaz et al., 2018). They provide large multi-scale spatial resolution, various temporal imagery for monitoring vegetation, obtain imagery without being on the ground (Vaz et al., 2018). However, in comparison to UAVs, satellite images have not been successfully used by operators to detect invasive plants due to low spectral and spatial resolution. Visible range and NIR satellite images are affected by cloud cover, making it a challenge for researchers to obtain long-term datasets (Bradley, 2014; Mafanya et al., 2017; Pajares, 2015; Xue & Su, 2017). For example, Müllerová et al. (2013) detected giant hogweed (*Heracleum mantegazzianum*) at a regional level with a UAV and compared it to Rapid Eye 2010, which had a resolution of five metres. Müllerová et al. (2013) stated that giant hogweed plant detection required very high resolution; however, using a UAV for large spatial areas could be overwhelming and, therefore, a suboptimal method. Despite the limitations of the UAV, they concluded that high-resolution platforms of less than 0.5 meters are required to detect invasive plants for early detection.

UAVs have some limitations in imagery acquisition, specific weather requirements, scale and legal constraints (de Sá et al., 2018; Müllerová, Bartaloš, et al., 2017; Müllerová, Brůna, et al., 2017). Although Müllerová, Brůna, et al. (2017) stated that there is no standardised data processing, this allows for creativity and exploration of different tools to combine with remote sensing. UAVs have no standardised way of pre-processing the data or determining which software to use (Müllerová, Brůna, et al., 2017). This is due to each study requiring specific technical attributes. This is due to each study requiring specific technical attributes. Software is yet to be designed to meet this goal. Weather can be problematic, to drones such as DJI Phantom 4 can only fly in wind conditions less than 10 m/s and requires little to no rain. As well as that, UAVs are mainly appropriate for an area cover of 1-10 km depending on the platform capability. For studies that require a wider area cover, other remote platforms such as manned aircraft or satellite should be used. Lastly, there are legal constraints in urban, private, commercial and airport zones.

The Phantom 4 can fly as low as 2 meters and up to a maximum of 6000 metres away using a remote control via tablets or smartphones although, this is illegal under part 101 rules drone use in New Zealand (Civil Aviation Authority of New Zealand, 2021; DJI, n.d.). It has a vertical accuracy GPS positioning of ±0.5 m and horizontal GPS positioning of ±1.5 m. The benefit of this aircraft is that it can be temperate range from 0 to 40 Degree Celsius. The drone can fly in slightly windy conditions; however, for the accuracy of imagery and wind resistance tolerance of 10 m/s, the drone is typically only flown during sunny with the wind of less than 10 m/s. With rainfall, the clouds can affect the spectral reflectance of the different plants to be the same. High winds can also blow away the aircraft and affect the image acquisition process.

2.5 Review of methods for processing UAV data

2.5.1 Pixel and object-based

There are two commonly used image classification techniques which are paired with classification methods in literature. The image classification techniques are pixel-based and object-based, and the classification methods are supervised and unsupervised. Supervised image classification requires the user to specify the groups of pixel values for each class before the analysis, and the unsupervised method relies on the computer to cluster the pixel values (Blaschke, 2010). For this literature review, I focused on the supervised classification method, which I used for this thesis.

Pixel-based classification is a traditional image classification approach that assigns pixels of different values into known categories. The disadvantage of assigning pixels into known categories can result in a salt and pepper pattern. This is problematic, as objects may have pixel values similar to another object leading to a misclassification. This is unsuitable as it neglects spatial and textural information of neighbouring pixels.

Unlike pixel-based approaches, object-based classification removes the salt and pepper effect. It classifies objects using image segmenting tools to provide edge detection and feature extraction (Blaschke, 2010). This classification approach has been significantly popular in the last decade (Blaschke, 2010). Figure 7 illustrates the salt and pepper effect of pixel-based classification compared to object-based classification, which did not have the effect (Powell & Brooks, 2008).

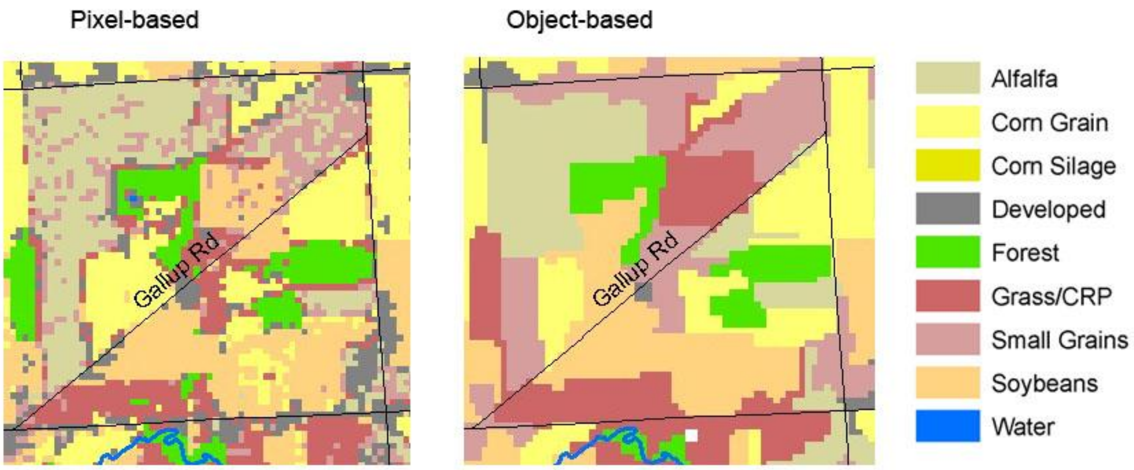

Figure 7: Comparison of pixel-based classification vs. object-based classification.
Note. These image classifications were produced by Powell and Brooks in 2004*, comparing pixel-based classification to object-based classification. From Land Use Land Cover Mapping in the Tiffin River Watershed by R. Powell and C. Brooks, 2008, Michigan Tech Research Institute (MTRI), p. 18 (https://www.researchgate.net/publication/254599984_Land_Use_Land_Cover_Mapping_in_the_Tiffin_River_Watershed). Public Domain*

Pixel-based classification is commonly used for biodiversity mapping including environmental monitoring of invasive plants (Dash et al., 2019; Kedia et al., 2021; Laporte-Fauret et al., 2020; Tay et al., 2018); mapping plant communities in wetlands ; ecology and conservation mapping (D. J. Hill et al., 2017; Horning et al., 2020); and mapping plant communities in coastal habitats (de Sá et al., 2018). Similarly, object-based applications include invasive plant detection (Liu et al., 2017; Tesfamichael et al., 2018; Wijesingha et al., 2020; X. Yang et al., 2021), monitoring invasive plants in different landscapes (Martin et al., 2018; Wu et al., 2019), ecology and conservation (Marzialetti et al., 2021), and environmental monitoring of freshwater ecosystems (Chabot et al., 2018; Hung et al., 2014).

Currently, many research papers argue that object-based image analysis is preferred as compared to pixel-based image analysis. For example, Yang et al. (2021) detected leafy spurge in 2015 and 2017 using object-based classification and had an overall accuracy (OA) of 78% and 75%, respectively. Similarly, (Wu et al., 2019) detected *Mikania micrantha* with an accuracy of 93.25%. Wijesingha et al. (2020) mapped *Lupinus polyphyllus Lindl* with an average accuracy of 88%. However, some research papers have argued against the assumption that object-based perform better than pixel-based image classification (Abeysinghe et al., 2019; Horning et al., 2020; Madurapperuma et al., 2020; Mafanya et al., 2017; Müllerová, Brůna, et al., 2017; Ouyang et al., 2011; Whiteside et al., 2011). Mafanya et al. (2017) and Ouyang et al. (2011) compared object-based and pixel-based image analysis approaches to determine best for plant scientific applications such as invasive plant detection. Mafanya et al. (2017) compared object-based and pixel-based mapping Midnight Lady (*Harrisia pomanensis*). They found that supervised pixel-based imagery had the highest OA of 87.7%, compared to supervised object-based imagery, with 85.5% OA (Mafanya et al., 2017). Ouyang et al. (2011) also detected the invasive plant *Spartina alterniflora* using pixel and object-based classification using 11 models. The accuracy range of the 11 models was between 78% and 87%. Mafanya et al. (2017) and Ouyang et al. (2011) emphasised that there is no significant evidence that object-based performance was greater than pixel-based. Similarly, Abeysinghe et al. (2019) compared pixel-based and object-based classifiers in detecting *Phragmites* using four original bands (green, red, RE, NIR). The pixel-based classier had the highest accuracy compared to object-based classifiers as the pixel-based approach identified small patches of *Phragmites* in the estuary.

2.5.2 Spectral reflectance

The differences in accuracy in the literature are due to plants having a similar spectral reflectance (Qian et al., 2020). Each plant has its specified chemical composition and has a spectral signature and spectral reflectance (Aggarwal, 2004; Jackson & Huete, 1991). When solar radiation hits an object, it is reflected, absorbed, or transmitted (Aggarwal, 2004; Jackson & Huete, 1991). As a result, each object interacts with the electromagnetic spectrum differently (Kumar & Singh, 2013). The reflected and transmitted information about the object is sent to sensors and produces a spectral signature (J. B. Campbell & Wynne, 2011). The most suitable bands for remote sensing for vegetation classification are in the NIR region (Bannari et al., 1995; de Sá et al., 2018). The band presents more than 90% of information related to vegetation in comparison to other bands such as green, red, or blue (Bannari et al., 1995).

Chlorophyll content controls the majority of the spectral response of leaves as it absorbs sunlight and is responsible for photosynthesis (Yang et al., 2017). Campbell and Wynne (2011) stated that chlorophyll does not absorb sunlight equally, whereas blue and red light are absorbed, and green light is reflected. Therefore, NIR is said to show the reflectance of living vegetation, not green. This spectrum allows for detecting vegetated, and non-vegetated surfaces as vegetated surfaces will reflect much darker colours than the vegetated areas (Campbell & Wynne, 2011; Yang et al., 2017). Yet despite this concept, vegetation is still misclassified in literature (de Sá et al., 2018; Gränzig et al., 2021b; Marzialetti et al., 2021; Müllerová, Bartaloš, et al., 2017; Tay et al., 2018; X. Yang et al., 2021). That is due to some plant species having a similar spectral signature, and often machine learning algorithms fail to recognise them as different plant species. That can cause further errors in the classification stage (Qian et al., 2020).

To overcome this challenge, recent studies have used seasons of different plants to differentiate between species with a similar spectral signature (de Sá et al., 2018; Gränzig et al., 2021b; Marzialetti et al., 2021; Müllerová, Brůna, et al., 2017; Tay et al., 2018; X. Yang et al., 2021). For example, Paz-Kagan et al. (2019) detected *Acacia saligna* and *Acacia salicina* during flowering seasons and achieved an accuracy of 97.3%. Similarly, Müllerová, Brůna, et al. (2017) detected Giant Hogweed (*Heracleum mantegazzianum*) during flowering and non-flowering periods. Accuracy when flowering was up to 100% but, dropped later in the vegetation season to approximately 60%. Similarly, Gränzig et al. (2021) distinguished Gorse (*Ulex europaeus)* successfully from other plant species during the flowering period and had an accuracy of 85%. However, flowering plants are not the only possible way to increase the accuracy and detectability of plants as Müllerová, Brůna et al. (2017) detected knotweed post-flowering stage of developing red stems. These red stems were visible enough understorey for the sensors on the drones to detect it and classify it as Knotweed.

The supervised methodology is referred to as spectrally pure classes, as training samples are unique and distinguishable. The user can create polygons around these "spectrally pure" groups of pixels or segments to define the classes, and the tool harvests the pixel value ranges within the polygons (Blaschke, 2010). That means the user will train and create samples for each class. Each class has unique pixel values that help distinguish them from other classes. The unsupervised method, in contrast, relies on the computer to cluster the pixel values. This method generally is not used as often as supervised classification. That is because unsupervised classification is time-consuming and does not produce as "spectrally pure" classes as a person inputting the data. Instead, the user generally inputs several classes for the computer, using a range of possible values according to the input raster's statistics and creating these classes.

Next, the tool attempts to classify each pixel based on the values clustered in the data space. Once that is complete, the user is required to classify the classes created (Blaschke, 2010).

2.6 Review of classification algorithms for vegetation classification

2.6.1 Image classifications

Choosing the appropriate classifier is necessary for classification accuracy (Xie et al., 2008). There are many possibilities to categorise classifiers using different types of learning and data distribution assumptions. The main two types of classifiers used in the literature are parametric and non-parametric (Abeysinghe et al., 2019). A parametric model has a fixed number of parameters with a normal distribution. Non-parametric models do not have to be normally distributed and do not have a fixed number of parameters. This method is more flexible in dealing with the data. However, unlike parametric methods, non-parametric method are slow and require large amounts of data. Due to its flexibility, non-parametric classifiers are favoured over parametric classifiers in the literature (Kumar & Singh, 2013). Parametric classifier examples are K-nearest Neighbour (KNN), and Maximum Likelihood (ML) (Xie et al., 2008) and non-parametric classifiers include Decision Trees (DT), Random Trees (RT), Random Forest (RF), Artificial Natural Network (ANN), and Support Vector Machine (SVM) (Sravanthi & Sarma, 2021). Table 3 shows the list of the three most commonly used classifiers and the literature that used them.

Table 3: List of the three classifiers used in literature

Classifier	Method	Reference
Support Vector Machine	Non-parametric	(Abeysinghe et al., 2019; Argüello et al., 2021; Casas et al., 2021; Holden et al., 2021; Müllerová et al., 2013; Papp et al., 2021; Rupasinghe & Chow-Fraser, 2019; Samiappan et al., 2017; Tesfamichael et al., 2018; Wu et al., 2019; Z. Zhou et al., 2018)
Maximum Likelihood	Parametric	(Abeysinghe et al., 2019; Madurapperuma et al., 2020; Müllerová, Bartaloš, et al., 2017; Nhamo et al., 2018; Whiteside et al., 2011; Z. Zhou et al., 2018)
Random Trees/ Random Forest	Non-parametric	(Argüello et al., 2021; Baron et al., 2018; Bolch et al., 2021; Chabot et al., 2018; Cheţan et al., 2017; Dash et al., 2019; de Sá et al., 2018; Elkind et al., 2019; Gränzig et al., 2021b; D. J. Hill et al., 2017;

	Holden et al., 2021; Kattenborn et al., 2019; Kedia et al., 2021; Killick & Blanchon, 2018; Laporte-Fauret et al., 2020; Laso et al., 2020; Martin et al., 2018; Michez et al., 2016; Müllerová, Bartaloš, et al., 2017; Tesfamichael et al., 2018; L. Wang et al., 2021; Wijesingha et al., 2020)

ML is one of the most widely used classifiers in the literature. It assumes a normal distribution of data and calculates the probability of a pixel belonging to a specific class (Abeysinghe et al., 2019). The pixels are assigned to classes based on their probability value. Müllerová, Bartaloš, et al. (2017) compared ML and SVM to detect Giant Hogweed (*Heracleum mantegazzianum*). SVM performed poorly in detecting Giant Hogweed compared to ML. The main disadvantage of this classifier is the assumption that the input data value is normally distributed. Abeysinghe et al. (2019) compared SVM, ML, and NN classier in detecting Phragmites. The SVM classier outperformed NN and ML by producing the highest accuracy of over 90% compared to 82% and 88%, respectively. However, Abeysinghe et al. (2019) mentioned that ML could detect the Phragmites class at higher levels than the other classes as it could detect small pixel values. This means the salt and pepper effect can be used as an advantage in similar cases to Abeysinghe et al. (2019) study.

RT is a non-parametric classifier that uses Leo Breiman's Random Forest Algorithm. Various training data samples and subsets were used to generate individual decision trees in RT (Kislik 2020). These decision trees make several decisions based on the rank order of priority for every pixel that has been classified (Hnusuwan et al., 2020). RT can handle extensive data with no normal distribution assumption, making it suitable for large areas. However, this classifier is sensitive to sampling data (Belgiu & Drăgu, 2016). Unlike SVM, it requires several sampling designs to get accurate results. That can be a limitation to specific scenarios where the presence of IPs is low. Instead, it is advised to acquire data during suitable seasons to easily distinguish and detect the plants (Belgiu & Drăgu, 2016). Peerbhay et al. (2016) detected Woolly Nightshade using RT classifier. The detection of the invasive plant in forest margins, open areas and riparian zones had accuracies of 91.33%, 85.08%, and 67.90%, respectively. Kattenborn et al. (2019) also used RT to detected *Pinus radiatia*, *Ulex europaeus* and *Acacia dealbata*. The results of the research had an accuracy of 70%, 77% and 90% for *P.radiatia, U.europaeus, A.dealbata*, respectively.

SVM is a non-parametric classifier. Unlike ML, this classifier does not assume the data to have a normal distribution. It also does not depend on the number of trees or ranking based on sampling size (Abeysinghe et al., 2019). Instead, it generates a system of equations to ovulate pixel values by assigning these values to training samples (Jackson, 2019). The advantages of SVM are that they can be trained with a limited number of the sample (Mountrakis, 2011). That method performs best due to being less susceptible to black noise, correlated bands, and an unbalanced number of sizes of training sites within each class (Akar & Güngör, 2012). That is often a limitation in other classifiers like ML. SVM also uses convexity of the cost function, which is particularly useful for classification. The disadvantage of this classier approach is that it is not optimal for dealing with noisy data, which can often be the case in vegetation mapping. Another common issue discussed is that mislabelling of objects can dramatically degrade OA (Mountrakis, 2011). Samiappan et al. (2017) used SVM to detect common reed (*Phragmites australis*). The OA of the study using the classifier was 91%. Rupasinghe and Chow-Fraser (2019) used SVM to detect Phragmites australis. The OA for the study was 88.5%.

For this thesis, the three classifiers used were ML, RT, and SVM because they are available on ArcGIS Pro. This is necessary as community groups and non-government volunteer programs such as Motu Roa Development Limited' are offered a Non-Profit Organisation Program which provides low-cost access to ESRI's software, content, and resources to support their missions (Esri, n.d.-a).

2.6.2 Accuracy Assessment

Accuracy assessment is a term used to describe the degree of correctness of classified classes compared to the actual ones. For example, a map derived from image classification is recognised as accurate only if it provides a true representation of the site of interest (Xie et al., 2008). Confusion matrix tables give information on the Overall Accuracy, User Accuracy, Producer Accuracy, Kappa and Estimate for each class.

The User Accuracy (U-Accuracy) column shows false positives or omissions when pixels are incorrectly classified as a known class when they are not. U-Accuracy is also referred to as errors of commission or type 1 errors. Reading data from the rows of the table computes the error rate. According to the reference data, the "Total" row represents the number of points that should have been classified as each class. The accuracy column for the producer indicates errors of commission and false negatives.

Table columns contain the data used to compute this error rate. The error of omission, or type 2 error, is also referred to as "producer's accuracy". The total column displays the number of points classified as a particular class according to the classified map.

The Kappa statistic of agreement gives an overall assessment of the accuracy of the classification. The Kappa statistics vary between 0 to 1 showing the confusion matrix of the agreement between classified random points (Chen et al., 2015). The literature Chen et al. (2015), Okwuashi et al. (2012), and Shivakumar & Rajashekararadhya (2018) divided the statists into various of 0 to 1 to five to six classes. Shivakumar and Rajashekararadhya (2018) had five classes, a kappa value below 0.40 was poor, a kappa value between 0.41 to 0.60 was a moderate agreement, values between 0.61 to 0.75 had a good agreement, values between 0.76 to 0.80 had an excellent agreement and values above 0.81 had an almost perfect agreement. Chen et al. (2015) and Okwuashi et al. (2012) had six categories with different interpretations of kappa values than the Shivakumar and Rajashekararadhya (2018) interpretations. Chen et al. (2015) and Okwuashi et al. (2012) based their categories on Viera (2005). The values in Chen et al. (2015) and Okwuashi et al. (2012) that have 0 Kappa accuracy were regarded to have poor management, between 0 to 0.2 was regarded as slight agreement, between 0.21 to 0.4 was a fair agreement, 0.41 to 0.6 is a moderate agreement, 0.61 to 0.80 was a substantial agreement and above 0.8 was an almost perfect agreement. Table 4 shows the kappa value interpretation.

Table 4: The Kappa value interpretation.

Kappa Statistics	Interpretation
<0.00	Poor agreement
0.00 - 0.20	Slight agreement
0.21 - 0.40	Fair agreement
0.41 - 0.60	Moderate agreement
0.61 - 0.80	Substantial agreement
0.80 - 1.00	Almost Perfect agreement

Note. Retrieved from “Understanding interobserver agreement" by A. Viera and J. Garrett, 2005, *Family Medicine, 37(5), p. 362.*

2.7 Invasive plants of study

For this study I selected four plants for detection through low altitude remote sensing; these four plants are Woolly Nightshade, Sweet Pea Shrub, Moth Plant and Gorse. They are all found to the southwest of Ponga Hollow on Moturoa Island (Figure 8 and Figure 14). Detection of these plants has proven to be difficult and poses a significant challenge for shareholders of Moturoa Island. In the following section, background information such as the spread, appearance, impacts and distribution of each plant is explained.

Figure 8: Satellite image of Moturoa Island

2.7.1 Moth Plant

Figure 9: Moth Plant flower, leaves and pod from left to right.
From Phil Bendle Collection, CitScihub, n.d.
(https://www.citscihub.nz/Phil_Bendle_Collection:Araujia_hortorum_(Moth_plant)).

Background and spread

Moth Plant (*Araujia sericifera*) is a fast-growing evergreen climbing vine native to Southern Brazil, and Argentina (Waipara et al., 2006; Winks & Fowler, 2000). The Moth plant has been introduced as an ornamental plant in many countries around the world, and it has been naturalised or become invasive in a number of countries. It is considered invasive in Australia, South Africa, the United States of America (California), Israel, Italy, and Spain (Ramírez & Anderson, 2019; Waipara et al., 2006; Winks & Fowler, 2000). In New Zealand, it was recorded as being naturalised since 1888 but it was only regarded as invasive in the late 1990s, by which time it was spreading abundantly in Auckland City (Waipara et al., 2006; Webb et al., 1995; Winks & Fowler, 2000).

Appearance

The vine has a woody stem that can be up to 40mm in diameter, a fast-growing evergreen (Ramírez & Anderson, 2019; Timmins & Braithwaite, 2003). The vine produces sticky milk sap and a scent when the stems or leaves are broken off (Ramírez & Anderson, 2019; Timmins & Braithwaite, 2003). The vine can climb up to 5–7 metres in height. During the flowering season, which in New Zealand occurs between December and May, white flowers with pinkish petals are formed. The flowers then produce large fruit, which contain up to 400 seeds as seen in Figure 9 (Winks & Fowler, 2000).

Distribution and Detectability

The Moth Plant mechanism for dispersal is wind (Ritchie, 2012; Waipara et al., 2006). First, the large fruits remain on the vine and become dry. It then splits, allowing the approximately 400 seeds to spread on a parachute of fine silky tufts (Waipara et al., 2006; Winks & Fowler, 2000). Since the plant can climb to up to six metres in height, this allows seeds the opportunity to travel several hundred metres in the air (Waipara et al., 2006). As a result, these seedlings establish quickly. Seeds can remain viable for more than five years (Elliott et al., 2009; Ritchie, 2012; Winks & Fowler, 2000).
It usually inhabits warm climates and is found in loose, fertile soil in frost-free areas of moderate to high rainfall (Waipara et al., 2006; Winks & Fowler, 2000). This vine prefers semi-shaded areas but tolerates open areas with total exposure to the sun once it has climbed to the canopy of the plants (Coulston, 2002; Winks & Fowler, 2000). In terms of remote sensing and the detection of Moth Plants in forests, there is a high chance of low to no detection as plants are only exposed to view from above once they have climbed fully into the canopy. However, in urban areas, the plant is exposed more as it climbs over fences and on vacant lands (Elliott et al., 2009).

Impacts

In its native range, the vine is used for medicinal, ornamental, and industrial purposes (Ramírez & Anderson, 2019; Winks & Fowler, 2000). The Moth plant in New Zealand, Australia and South Africa is considered a serious invasive plant as it can cause substantial environmental damage (Elliott et al., 2009; Waipara et al., 2006; Winks & Fowler, 2000). The plant is slow-growing in shaded areas until changes in environmental conditions occur, such as exposure to the sun and an increase in moisture soil levels, then the plant starts to spread quickly, smothering native plants (Coulston, 2002; Ramírez & Anderson, 2019). Over time, the vine can completely cover shrubs and trees. As it grows and gets heavier, eventually, branches can start breaking. In some cases, the vines have been reported to be wrapping around their branches so tightly that they become girded (Ramírez & Anderson, 2019; Waipara et al., 2006). In addition to that, the vine is known to compete with other species for water and nutrients (Ramírez & Anderson, 2019; Waipara et al., 2006).

In Australia, the dark brown ripe seeds of the Moth Plant were tested as feeding material for poultry. Poultry death occurred within 24 hours of feeding on 5-15 g of the seedling. Although it is not common in Australia, the plant is suspected of poisoning cattle and poultry (Winks & Fowler, 2000). In additionally, the sticky milk sap produced by the vine is known to irritate the skin of humans (Ramírez & Anderson, 2019; Timmins & Braithwaite, 2003; Winks & Fowler, 2000).

2.7.2 Woolly Nightshade

Figure 10: Woolly Nightshade juvenal, flowers and unripe berries left to right.
Notes Woolly Nightshade. From Phil Bendle Collection, CitScihub, n.d.
(https://www.citscihub.nz/Phil_Bendle_Collection:Solanum_mauritianum_(Woolly_Nightshade)).

Background and spread

Woolly Nightshade (*Solanum mauritianum*) is a tropical tree native to Brazil and Uruguay in South America (Olckers, 2011; Peerbhay et al., 2016). In the last century, this plant may have been deliberately propagated throughout the world as an ornament due to its mauve/purple flowers and abundant fruit attracting birds to residential gardens (Olckers, 2011). It was naturalized in New Zealand in 1883 (Allan, 1940).

Today it is an invasive plant species in South Africa, Fiji, Hawaii, New Zealand, Australia, Mauritius, and Madagascar (Olckers, 2011).

Appearance

Woolly Nightshade is a multi-branched shrub or small tree that usually grows between two and four metres tall (although it can reach a height of 10 m under the right conditions) with whitish, soft-woody stems (Peerbhay et al., 2016). It has a strong odour and a life span of up to thirty years. The entire plant is covered in dense, felt-like hairs. It has large, grey-green, ovate-elliptical, simple leaves, which can reach 40 centimetres long and 30 centimetres wide. Each leaf has a pointed tip and a wedge-shaped base. Petioles range from three to nine centimetres in length. It has long, hairy yellowish trichomes which are star-shaped and densely tomentose (Olckers, 2011). As seen in Figure 10, it produces dense clusters of mauve to purple flowers (15-20 mm in diameter) with yellow anthers. This is followed by a cluster of round green unripe berries, leading to yellow and white berries when ripening approximately 1cm in diameter (Olckers, 2011).

Distribution and Detectability

In New Zealand, this pest-plant is found in heavily disturbed forests, light gaps, shrubland, estuaries, and wetlands (McGregor, 1999). Woolly Nightshade is known to have various ways of spreading into a new habitat (McGregor, 1999; Peerbhay et al., 2016). In New Zealand, Australia, and South Africa, the most common is through frugivorous birds dispersing the seeds (McGregor, 1999; Olckers, 2011; Ritchie, 2012; Schor et al., 2015; van den Bosch et al., 2004). In addition to frugivorous birds, it has been observed in South Africa spreading through monkeys such as the Vervet Monkey (Chlorocebus pygerythrus) (Schor et al., 2015). In South Africa, bird dispersal agents have switched to eating Woolly Nightshade fruit, affecting the dispersion of the seeds of several native plants (Schor et al., 2015). This is problematic as the fruit is abundant throughout the year and a predictable food source for fruit-eating birds and mammals (Schor et al., 2015; van den Bosch et al., 2004). This will further cause the plant to overcrowd and shade with dense stands by hindering other plant species' growth (Schor et al., 2015). It can grow in both open sites and semi-shaded areas (Schor et al., 2015).

Woolly Nightshade has a distinct green colour and is generally identified easily. I predicted that the spectral signature of this species is distinctive, allowing the software to distinguish it easily from other plants. During the flowering season, it produces unique purple flowers. The leaf colour of Woolly Nightshade allows for further distinguishability from other plants. A challenge for detection may occur where individuals occur under the canopies of other species. Horizons Regional Pest Management Plan (2017) stated that the spread of Woolly Nightshade is estimated to have occupied 100 ha of production land and 630 ha of commercial forestry, marginal land and urban areas with scattered infestations in Manawatū-Whanganui region of North Island in New Zealand.

Impacts

Due to the two-year reproduction cycle, large seed mass, and rapid growth rate of the Woolly Nightshade, it is a highly invasive species that can out-compete the indigenous flora (Olckers, 2011; Schor et al., 2015). Impacts from Woolly Nightshade include displacement of native vegetation, hindering of forestry activities, attracting agricultural pests, poisoning livestock and invertebrates, and posing health risks to humans (McGregor, 1999; Olckers, 2011; Schor et al., 2015). Woolly Nightshade's green berries contain alkaloid chemicals toxic to humans and animals (McGregor, 1999; Olckers, 2011). There have been reports of fatal poisonings of pigs and cattle in Queensland, Australia (McGregor, 1999). When it is dislodged during mechanical clearing operations, the fine hairs (trichomes) on stems and leaves can cause irritation and respiratory problems (Olckers, 2011). In addition to that, Woolly Nightshade is an allopathic plant meaning it produces toxins that poison the soil (Mushtaq & Siddiqui, 2018). The absence of understorey vegetation is commonly observed in Woolly Nightshade woodlands, which is thought to result from the allopathic effects (van den Bosch et al., 2004).

Van den Bosch et al. (2004) investigated the impacts of Woolly Nightshade on seed germination of the native shrub *Hebe Stricta* in New Zealand. Throughout the 22-day period, the seeds were tested for germination on soils on filtered paper with three different concentrated treatments. The first treatment was with the leaves of Woolly Nightshade, the second was the stem of Woolly Nightshade, and root leachates of Woolly Nightshade. To simulate field conditions, rainwater was used as a control treatment. A significant allelopathic effect was seen in this study, where 54% of seeds treated with rainwater germinated, while 0% of seeds germinated when treated with 100% Woolly Nightshade leaf leachate treatment. In regards to root leachates, only 31% of seeds germinated. As well as its allopathic properties, Woolly Nightshade is said to use a self-grooming mechanism to drop discarded leaves onto the forest floor, thus preventing the establishment of *H. Stricta* during regeneration (van den Bosch et al., 2004). In ecologically sensitive areas such as native shrublands, Woolly Nightshade's allelopathic properties justify eradicating this plant since eradication will result in more native seeds germinating (Mushtaq & Siddiqui, 2018; van den Bosch et al., 2004).

2.7.3 Gorse

Figure 11: Gorse flowers (left) pods (middle) and Bush (right). From Phil Bendle Collection, CitScihub, n.d. (https://www.citscihub.nz/Phil_Bendle_Collection:Ulex_europaeus_(Gorse)).

Background and spread

Gorse (Ulex europaeus), originally from Western Europe (R. Hill et al., 2001), is abundant along the western coasts of continental Europe and in the British Isles, but it is much less common inland. It has become naturalised in Norway, Sweden, Poland and Switzerland (Anderson & Anderson, 2010).

Gorse was intentionally introduced as a hedge plant to contain livestock, as fodder, and even to comfort colonist nostalgia. (Anderson & Anderson, 2010). Despite growing in New Zealand as early as 1835, it was not declared an invasive species until the passing of an Act of Parliament in 1900 (R. L. Hill et al., 2000; Magesan et al., 2012). It was deliberately introduced across the landscape as a hedge plant (Magesan et al., 2012). In Australia, it was planted for the same reasons before 1845. According to Leary et al. (2005), Gorse is believed to have been introduced to Hawaii in imported sheep wool before 1910, then again in the 1930s after cattle replaced sheep on extensive rangelands. It now covers 4,097 hectares on Hawaii Island alone. The introduction of Gorse to other parts of its exotic range may have occurred accidentally when European colonists imported animals and hay. It is considered an invasive weed in Hawaii, Australia, Chile, Costa Rica, New Zealand, and the Atlantic coastal areas of North America (Anderson & Anderson, 2010).

Appearance

Gorse is a spiky shrub (2-3 m tall) with many branches in young plants, but it becomes bare of leaves at the base as plants age. Gorse mature leaves are spines that have deep furrows, whereas new leaves are spinless. As seen in Figure 11, Gorse had yellow, pea-like flowers that bloomed from May to November. In some instances, it has been noted that they bloom all year (Magesan et al., 2012). The seeds are enclosed in hairy seed pods (13-25 mm long) that mature to black and explode when mature (Anderson & Anderson, 2010).

Distribution and Detectability

Evergreen and vigorous, Gorse can colonise many areas, including disturbed ground, depleted pasture, eroded areas, and forest gaps (Anderson & Anderson, 2010; Richardson & Hill, 1998) MacCarter & Gaynor 1980). Gorse seedlings cannot compete strongly with tall vegetation but are effective colonizers of disturbed ground (Ritchie, 2012). Plantation forests and poorly managed pastures in New Zealand often have this weed (Magesan et al., 2012; Ritchie, 2012). The most common way this plant is spread is via the explosion of the seed pods. Seeds spread up to 5 m away from the parent plant upon explosion (R. Hill et al., 1996; Ritchie, 2012). The second most common way is through farm machinery as Gorse invasion along road margins is evidence of seeds becoming embedded in the mud (MacCarter & Gaynor 1980). The seeds are viable in the soil for 20-30 years, and they can produce approximately 34,000 seeds per square metre per year (MacCarter & Gaynor 1980; (Anderson & Anderson, 2010; R. L. Hill et al., 2000).

Gorse can only grow in regions where there is little shade (MacCarter & Gaynor, 1980; Ritchie, 2012). The yellow flowers bloom from May to November in New Zealand, which helps distinguish this plant. Gorse grows on the edges of forests and paddocks, coastal cliff faces, riverbeds and other open disturbance sites such as slip faces. It often establishes densely packed shrub monocultures that exclude all other plants over extensive areas (MacCarter & Gaynor, 1980; Auckland Regional Pest Management Plan, 2020). In urban areas, it grows on roadsides, disturbed lands, cliff faces, and on stream beds. It also competes with other invasive plants such as Woolly Nightshade (*Horizons Regional Pest Management Plan*, 2017). However, as old stands of Gorse begin to senesce, light penetrates to the ground allowing native seedlings to establish in large numbers.

Impacts

Gorse has many impacts on native flora in many countries. Its impacts include damage to ecosystem services, changes to ecosystems/habitat alteration, modification of fire regimes, hydrology, nutrient regimes, successional patterns, and loss of native species habitats (Anderson & Anderson 2010). Gorse is a nitrogen-fixing species (Magesan et al., 2012). McQueen et al. (2006) and Goldstein et al. (2010) have noted that Nitrogen-fixing species are typically pioneers in disturbed environments such as fire-prone ecosystems. However, extra nitrogen can affect ecosystem processes such as nitrogen deposition, soil acidification, and microbiologically mediated soil processes such as mineralization, immobilization, nitrification, denitrification, and emission of nitrous oxide and methane (Goulding et al. 1998; Fageria & Stone 2006). Additionally, recent concerns about rising nitrate concentrations in surface water have drawn attention to nitrogen leaching (Goldstein et al., 2010). As well as that, a high standing biomass of Gorse poses a severe fire risk, especially in areas near forest margins, thus threatening the environment in areas with high conservation values (Richardson and Hill, 1998). Although Magesan et al. (2012) stated that Gorse could provide a nursery for native seedlings, Harris et al. (2001) have noted that Gorse is replacing native Kânuka (Kunzea ericoides) and Mânuka (Leptospermum scoparium) as the early successional species in many areas.

2.7.4 Sweet Pea Shrub

Figure 12 Sweet Pea Shrub flowers

Notes Sweet Pea Shrub. From Phil Bendle Collection, CitScihub, n.d. (https://www.citscihub.nz/Phil_Bendle_Collection:Polygala_myrtifolia_(Sweet_pea_shrub)).

Background and Spread

Sweet Pea Shrub (*Polygala myrtifolia*) is a small tree or shrub native to southern and south-eastern South Africa (Adair et al., 2011; Webb, 1980). It is considered invasive in New Zealand, Australia, and the United States of America (Southwest California) (Adair et al., 2011; Smith, 2019; Webb, 1980). The first recorded recording of Sweet Pea Bush in New Zealand was in 1870 (Webb, 1980). In New Zealand, Sweet Pea Shrub is commonly found in the Auckland region. It is found in the rest of the North Island except for Gisborne, and on the South Island it is found in Nelson (Webb, 1980). In Western Australia, it has been listed as a high priority for removal. In New Zealand, it is considered a harmful organism in some regions meaning any sales or trade of this plant is prohibited (Webb et al., 1995).

Appearance

Sweet Pea is a perennial legume-like shrub that grows up to 2 metres in height. Branches are covered in short, curly hairs when they are young. The stems are woody, smooth, and many-branched. Alternate, oval, and smooth leaves appear throughout. As seen in Figure 12, the purple flowers look like Sweet Pea Shrubs and bloom all year round. The seeds are dark brown in colour and hairy in texture (Webb et al., 1995). It can flower and seed when it reaches two years of age and can flower for over a decade (Adair et al., 2012; Webb, 1980).

Disturbance and detection

It grows in various locations such as in forest margins, rocky surfaces, dunes, open grasslands, riparian areas, and disturbed lands (Adair et al., 2012). It can tolerate hot to moderately cool temperatures, poor and rocky soil, drought, salt, semi-shaded areas, and wind. However, Sweet Pea is known to not grow in frost affected areas, saturated soils (waterlogging), or grazed land (Adair et al., 2012). Although most seeds drop close to the parent plant, wind, and water disperse sweet Pea Shrub seedlings. Up to 2,000 seedlings per m2 can establish and the seeds can remain viable in the soil for two to three years Up to 2,000 seedlings per m2 can establish and the seeds can remain viable in the soil for two to three years (Webb et al. 1995). It can mature in 2 years (Adair et al., 2012). Since it is mainly found in forest margins, near coastlines, dunes, and riparian areas, the seeds fall in close proximity to the plant, which once germinated, creates an area around the plant of seedlings which go through the same process, spreading the plant over a large surface area (Adair et al., 2012; Smith, 2019).

Impacts

Sweet Pea Shrub in Australia, New Zealand and California is known to hinder the success of native species. It does this by producing a vast amount of seedlings in a relatively short period compared to native species, thus negating the ability of native seedlings to propagate in the area (Adair et al., 2011). In addition, in coastal parts of Australia and New Zealand, it is known to outcompete and once grown, the leaves can shade-out low growing coastal shrubs by producing many long-lived seeds (Adair et al., 2011).

2.8 Plant Detectability

Moth Plant can grow in shaded conditions and flourish once they break through the canopy (Figure 13). Once it has climbed to the top of a tree/ shrub or grasses, it spreads quickly and later smothers plants surrounding it. Moth Plant might also be growing under trees, shrubs, or forests, and thus the drone will not detect it. Therefore, it will be challenging to detect their seedlings/ juvenile plants as well as the vines that have not reached the canopy. However, their white flowers and pods can make them easier to detect during the flowering season.

Woolly Nightshade can tolerate conditions that are not favourable to detection from UAVs, such as growing in shades. However, Woolly Nightshade has different coloured leaves compared to native plants. The leaves, which are grey-green and purple flowers, help distinguish this plant easily using spectral reflectance. In addition, the leaves appear soft and furry, unlike native and other invasive plants. Therefore, there is a low probability of misclassifying this plant. Woolly nightshade juvenile plants are also likely to be detected due to the size and shape of the leaves. The leaves have a large surface area, allowing a low-altitude UAV to detect them more easily.

Unlike Woolly Nightshade and Moth Plant, Gorse requires full sun exposure to grow, making it theoretically easier to detect. Gorse less than 30 cm in diameter is less likely to be detected due to the spareness and shapes of the leaves seen in Figure 11. In addition, the growth of young Gorse plants allows the soil to be more exposed from a low altitude UAV perspective. Young Gorse plants are therefore unlikely to be detected. Sweet Pea Shrub is more likely to be found in large dense forms. However, Sweet Pea Shrub can grow in partial shade under trees, tall grass, and tall shrubs, making it difficult to detect. These purple plant flowers, which bloom all year round, make them distinguishable and easy to detect.

Figure 13: Moth Plant growing over other plants.
Notes Moth Plants. From Phil Bendle Collection, CitScihub, n.d.
(https://www.citscihub.nz/Phil_Bendle_Collection:Araujia_hortorum_(Moth_plant)).

Chapter 3: Material and methods

3.1 Study Area

Moturoa Island is one of the many restoration islands and sanctuaries in New Zealand. The shareholders management includes removing invasive plant and animal pests, plant native trees, translocate native species, and restore native flora and fauna (Sullivan & Molles, 2016). Moturoa Island is managed by 'Motu Roa Development Limited' (MDL), and this company owns the land, buildings, livestock, plants, and equipment. The company has 25 shareholders who collaboratively make decisions that affect the island. In 1959, one shareholder registered the island under the Wildlife Act 1953 due to the significance of its black rocks, and as a result, the island was recognised as a wildlife sanctuary in 1960. In 1976, shareholders changed their policy on the planting of flora. The new policy consisted of planting native trees and creating a refuge for native wildlife instead of the previous policy concerned with planting non-native trees for commercial purposes. The native fauna is dependent on the native flora, and thus the island's primary effort and goal was to remove non-native species (Avery, 2010).

In 1985, MDL began utilising casual wildlife workers and assigned them various tasks, including removing invasive plants such as Woolly Nightshade. In April 1990, the Offshore Island Research Group completed a report at the shareholders' invitation. The Offshore Islands Research Group's recommendation and the Restoration Plan Report indicated the need to detect and eradicate weeds to minimise their adverse impacts and promote the growth and establishment of native flora and fauna (Avery, 2010).

While the island shareholders and caretakers have eliminated animal pests, the island still has pest plants such as Moth Plant (*Araujia sericifera*), Alligator Weed (*Alternanthera philoxeroides*), Woolly Nightshade (*Solanum mauritianum*), Sweet Pea Bush (*Polygala myrtifolia*), Gorse (Ulex europaeus), Pampas (*Cortaderia selloana*) and Climbing Asparagus (*Myrsiphyllum scandens*). These pest plants threaten to disrupt the propagation of native flora. In addition, if these pest plants continue to spread, they will permanently alter the island's environment (Avery, 2010). Table 5 lists the invasive plant species found on the island.

Table 5: The list of invasive plants on Moturoa Island

Name	Scientific Name
Moth Plant	*Araujia sericifera*
Woolly Nightshade	*Solanum mauritianum*
Ink Weed	*Phytolacca octandra*
Bone Seed	*Chrysanthemoides moniliferassp*
Pampas Grass	*Cortaderia selloana*
Gorse	*Ulex europaeus*
Wilding Pines	*Pinus contorta*
Rat Tail Grass	*Sporobolus africanus*
Agapanthus	*Agapanthus praecox subsp. orientalis*
Taiwan Cherry	*Prunus campanulata*
Wild Ginger	*Asarum*
Sweet Pea Shrub	*Polygala myrtifolia*
Wireweed	*Polygonum aviculare*

Research location map

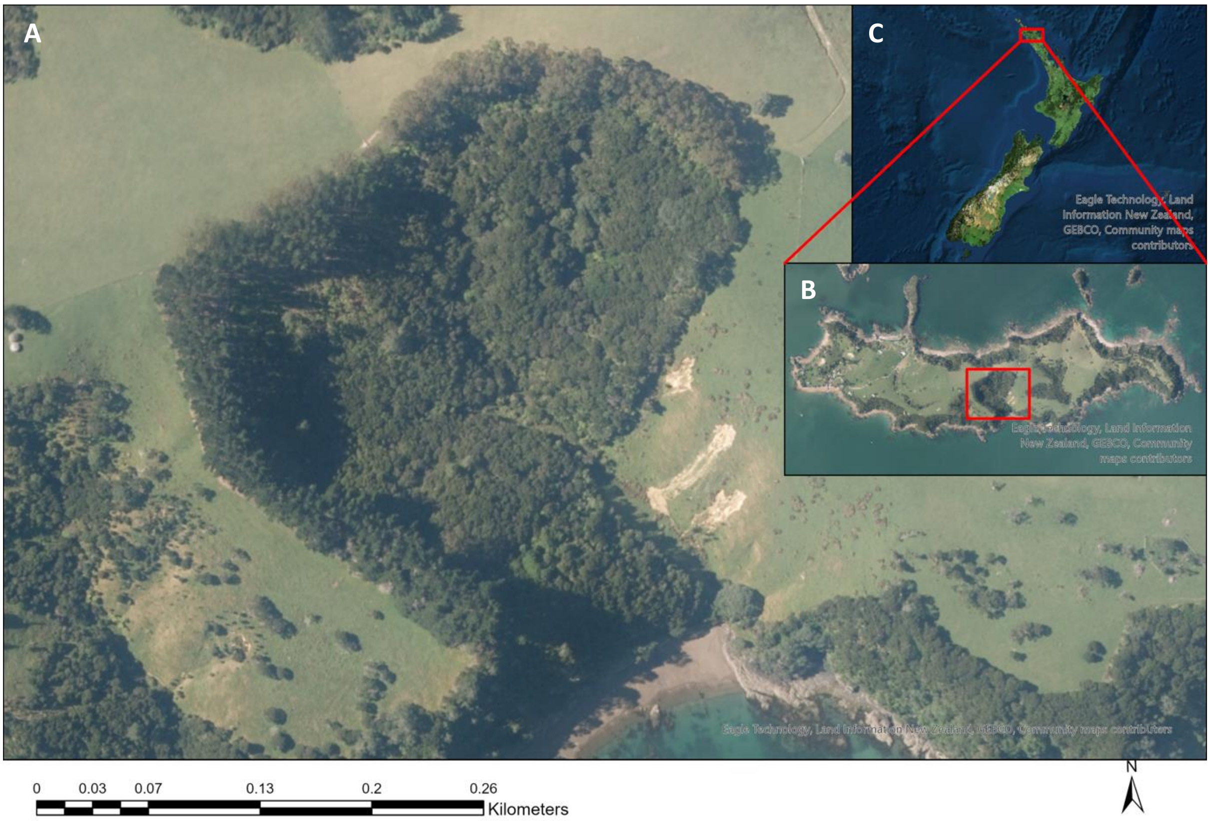

Figure 14: (a) Satellite image of Ponga Hollow, (b) Satellite image Moturoa Island with Ponga Hollow highlighted in a red box, (c) Satellite image of New Zealand, highlighting location of Moturoa Island.

3.1.1 Case Study

The study site is Ponga Hollow, on Motorua Island, and the central location of the study was 35° 12.703'S 174° 5.4626'E. Since the beginning of restoration efforts by MDL, Table 6 lists the native plant species that have been planted in the area by volunteers and shareholders. Currently, within Ponga Hollow, exotic trees such as Pine are being removed and replaced with native plants. Those exotics are left to decay on site. When they are cut down, there is usually an absence of understorey plants. As a result, many invasive plants such as Moth Plant (*Araujia sericifera*), Alligator Weed (*Alternanthera philoxeroides*), Woolly Nightshade (*Solanum mauritianum*), Sweet Pea Bush (*Polygala m*yrtifolia), Gorse (Ulex europaeus), Pampas (*Cortaderia selloana*) and Climbing Asparagus (*Myrsiphyllum scandens*) invade the area as seen in Figure 15.

Figure 15: Ponga Hollow ground photos.

The southwest area of Ponga Hollow has the highest concentration of invasive plants. This is an example of how invasive plants in New Zealand propagate more easily and spread more quickly than native plants in disturbed areas (Waipara et al., 2006; Winks & Fowler, 2000). Intervention by MDL is needed to promote the growth of native plants. Without the intervention, invasive plants could dominate the area. The challenge within Ponga Hollow for manual searches is that certain areas are inaccessible. Remote sensing is particularly useful in these inaccessible areas as it allows a convenient and accurate method to map the invasive plants and removes the time and expense of searching hard to reach areas.

Table 6: List of native plants in Ponga Hollow

Maori Name	English Name	Scientific Name
Akeake	Hopbush	*Dodonaea viscosa*
tī kōuka	Cabbage tree	*Cordyline australis*
Houpara	Five Finger	*Pseudopanax lessonii*
Kānuka	White tea-tree	*Kunzea ericoides*
Karaka	New Zealand laurel	*Corynocarpus laevigatus*
Karamu	-	*Coprosma robusta*
Karo	Stiffleaf Cheesewood	*Pittosporum crassifolium*
Houhere	Lacebark	*Hoheria populnea*

Mānuka	New Zealand tea-tree	*Leptospermum scoparium*
Ngaio	Mousehole tree	*Myoporum laetum*
Pohutukawa	New Zealand Christmas tree	*Metrosideros excelsa*
Kaikomako		*Pennantia corymbosa*
Purple Akeake	Purple hopbush	*Dodonaea viscosa purpurea*
Manatu	Ribbonwood	*Plagianthus regius*
Tarata	Lemonwood	*Pittosporum eugenioides*
Taupata	Glass plant	*Coprosma repens*
Wharangi	-	*Melicope ternata*
Mahoe	Whiteywood	*Melicytus ramiflorus*
-	-	*Coprosma macrocarpa subsp. minor*

3.2 Data Collection

Figure 16 shows the workflow that I used to collect the data on Moturoa Island. The flight preparation criteria included weather and timing of data acquisition. The data needed to be collected between 11-2 pm to avoid shadowing effects while also having no severe weather or wind speed greater than 10 m/s,

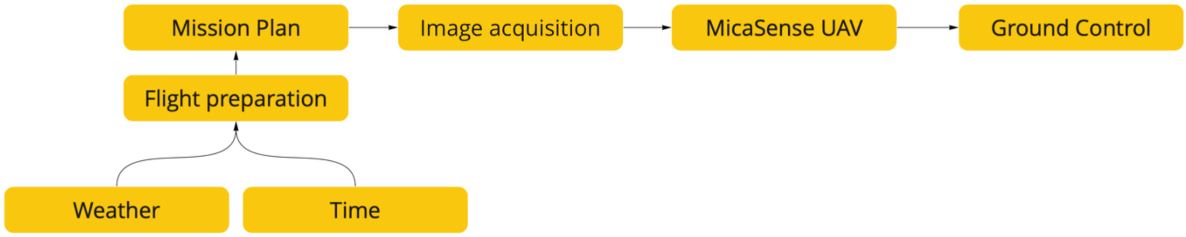

Figure 16: Workflow of image collection

Sensor and Aircraft

The DJI Phantom Series 4 aircraft with a customised mount for the MicaSense RedEdge Sensor collected all aerial imagery for this thesis. Phantom 4 Aircraft is a UAV made by the Da-Jiang Innovations technology company. The modified Phantom 4 with RedEdge sensor can achieve a 15-minute flight time and it has a max wind resistance tolerance of up to 10 m/s.

Training validation and calibration

Between the 12th and 30th January 2020, the Garmin eTrex 20 handheld GPS was used to capture the location of the four plant species targeted for this study. We collected ten locations for each species in the following cover size classes: 10-30 cm, 31-100 cm and 101 to 300 cm diameter. At every plant we collected a five-minute GPS average resulting in an accuracy level if two to three metres. In total, each plant species had approximately 30 location points.

Radiometric calibration

MicaSense RedEdge sensor radiometric calibration panels were used for each band and were placed on-site to be calibrated. I used the MicaSense reflectance panel before and after each flight to allow for calibration during postprocessing. Figure 17 shows the radiometric calibration panels taken with the MicaSense RedEdge Sensor.

Figure 17: Radiometric calibration panels from Left (Red, Blue, Green, NIR, RED) taken with MicaSense RedEdge Sensor.

3.2.1 Image acquisition

In this project, the data was acquired on July 12th 2020. The imagery was collected between 11 and 1 pm to minimise shadows. Two thousand six hundred thirty single images were collected for the entire site with a frontal and side overlap of 70%. Fifteen ground control points (GCP) were collected for this study to georeference the horizontal and vertical accuracy of the study area (Oniga et al., 2018). These points were collected with the Garmin eTrex 20 handheld GPS with waypoint averaging. The points were added to the orthophotos using the ArcGIS tool import GCP and Manage GCP. The points were imported as a CSV file.

UAV Data Processing

Post Processing - photogrammetry

The workflow for image processing is shown in Figure 18. The raw images were then imported into the Pix4DMapper Desktop (version 4.6.1) to generate reflectance, orthomosaic, digital surface models (DSM), 3D meshes, and point clouds. The RGB imagery from the inbuilt Phantom 4 sensor and the multispectral imagery from the MicaSense RedEdge were geotagged. The coordinate project system used was WGS 84 / UTM zone 60S (EGM96 Geoid). Then, I used the multispectral template on Pix4DMapper for processing the imagery. I changed a number of settings on this template to match my requirements.

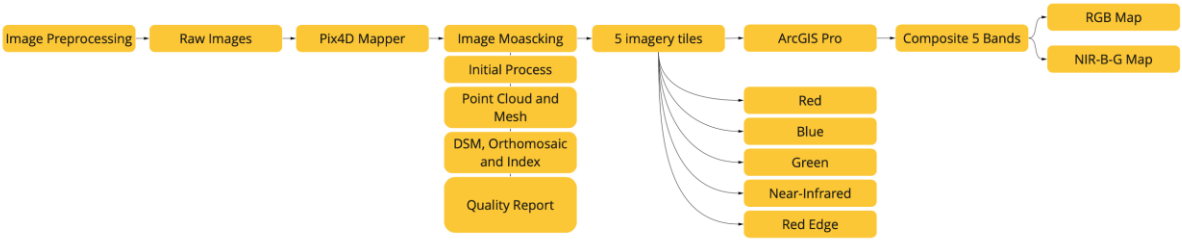

Figure 18: Workflow of image processing.

Image tiling and raster dataset

The five bands (Green, Red, Blue, Red edge, NIR) produced by Pix4D Mapper were composited to create a single multispectral image using Composite Bands (Data Management) tool by ArcGIS Pro (version 2.8.3). This was used to create a new raster dataset based on a specific band combination and order. In addition, the RGB band composition was used as a visual aid in selecting training areas for classification and validation processes, and the NIR-B-G was used for segmentation and analysis purposes (Table 7).

Table 7: Band composition order created from Composite Bands tool

Raster image	Band Composition
Ponga_Multi_RGB.tif	Red-Green-Blue
Ponga_Multi.tif	NIR-Green-Blue

3.2.2 Image classification and accuracy assessment

Figure 19 shows the work flow I used to classify the multispectral imagery. For this thesis, I used the supervised classification method using three classifiers. These were: SVM , RT and ML. The supervised classification method classes were created in ArcGIS Pro using the 'classification schema' and 'training samples' tools. The classification schema reflects on the number and type of classes to use. The classification scheme was used for this research based on the invasive plants to be detected. For this research, a total of eight classes were used: logs, grass, water, Gorse, Woolly Nightshade, Sweet Pea, trees, and shadow.

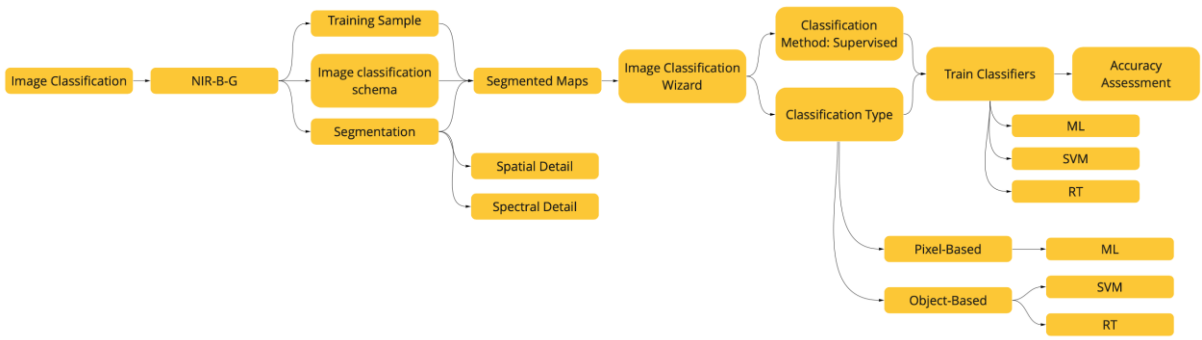

Figure 19: Workflow of image classification

The training sample assigns pixel values to classification schema classes. Training Samples Manager creates training samples for each class category in the schema and provide information about the number and size of samples to help improve the accuracy of a classification model. For each class, we used different shapes to capture them. Each class was trained at least 20 times. Details of the classes used and the number of samples are seen in Table 8.

Table 8: Training sample manager classes and samples

Class	samples	Description
logs	70	logs, visible tree branches and Sand
trees	101	Native plants in Ponga Hollow
Woolly Nightshade	22	Woolly Nightshade (Solanum mauritianum)
grass	31	Grasses, dried grass
shadow	31	Dark shaded areas of plants
Sweet Pea	24	Sweet Pea Shrub (Polygala myrtifolia)
Gorse	23	Gorse (Ulex europaeus)
water	22	Water

With each pixel assigned to a class, segmenting of the map was then completed. Using this process, neighbouring pixels that were similar in colour and had similar shape characteristics were combined. I segmented the raster image Ponga_Multi.tif, which had a band composition of NIR-Green-Blue using different parameter sets. Each segmented map had different spectral and spatial detail. I created nine segmented maps, each with a different spectral and spatial detail, to understand their effects on the classifiers accuracy.

I tested various levels of spectral detail, spatial detail, and minimum segmentation size to determine the optimal segmentation parameters for detection of invasive plants. The spectral and spatial detail range between 1 to 20. The spectral detail value sets the spectral characteristics of objects. The lower the spectral detail value, the more smoothing occurs, less detection between objects. For plant detection, the higher the spectral value, the greater the discrimination between the different plant species. The spatial detail value gives the proximity between objects: the lower the values, the more spatially smoothed the objects area. For plant detection, the smaller the values create a smoother outcome combining different plants as opposed to larger values separating the different plants.

I only focused on two parameters for this study, spatial detail, and spectral detail. A total of nine segmentation parameter settings were generated to decide which had the best boundaries for segments. I chose the lowest spectral detail of 10 and the greatest of 20, and the lowest spatial detail of 5, and the highest of 20. The segmentation parameters settings that I used are shown in Table 9 below. These settings were chosen to determine which parameter setting preformed best and if the parameter settings produced different results with each image classifier.

Table 9: Parameter settings used segment the orthomosaic map

Parameter	1	2	3	4	5	6	7	8	9
Spectral Detail	20	20	20	20	15	15	15	10	10
Spatial Detail	20	15	10	5	5	10	15	10	5

3.2.3 Image Classifiers

In this study, ML was used in the pixel-based classification and SVM, and RT classifiers were used in the object-based classification. SVM and RT are non-parametric parameters, which means they do not assume data distribution while ML does. I set RT to the maximum number of 50 trees, a maximum tree depth of 30, and a maximum number of 1000 samples per class. I also set the SVM parameter to the default number of 500 maximum number of samples per class. The accuracy points were created using the tool “Create Accuracy Assessment Points (Image Analyst)”. I used equalized stratified random as it created the same number of random points for each class. I used ground truth data for the target field. I examined each random point and determined the accurate class in the attribute table. In addition, confusion matrix tables were created once all the random points were classified. The image analysis tool Compute Confusion Matrix (Image analyst) created the Confusion Matrix tables. These tables contain information on the overall accuracy, user accuracy, producer accuracy, and estimate for each class for user and producer. This process was repeated for each segmented map.

Chapter 4: Results

4.1 Image pre-processing and mosaic

MicaSense RedEdge Sensor acquired two thousand six hundred and thirty red, green, blue, NIR and RE images on July 12th, 2020, and processed them on Pix4D Mapper software (version 4.6.1). This image set covers an area of 0.075 km2 (18.50 ha) over the Ponga Hollow southwest region. The image's calibrated percentage was 95%. The quality report from the Pix4D mapper stated that the spatial resolution was 5.16 cm, with a median number of 5084.36 matches per calibrated image. We used 10 out of the 15 ground control points (GCPs) to adjust the data to the true ground. Figure 20 shows the GCP locations used for georeferencing the map.

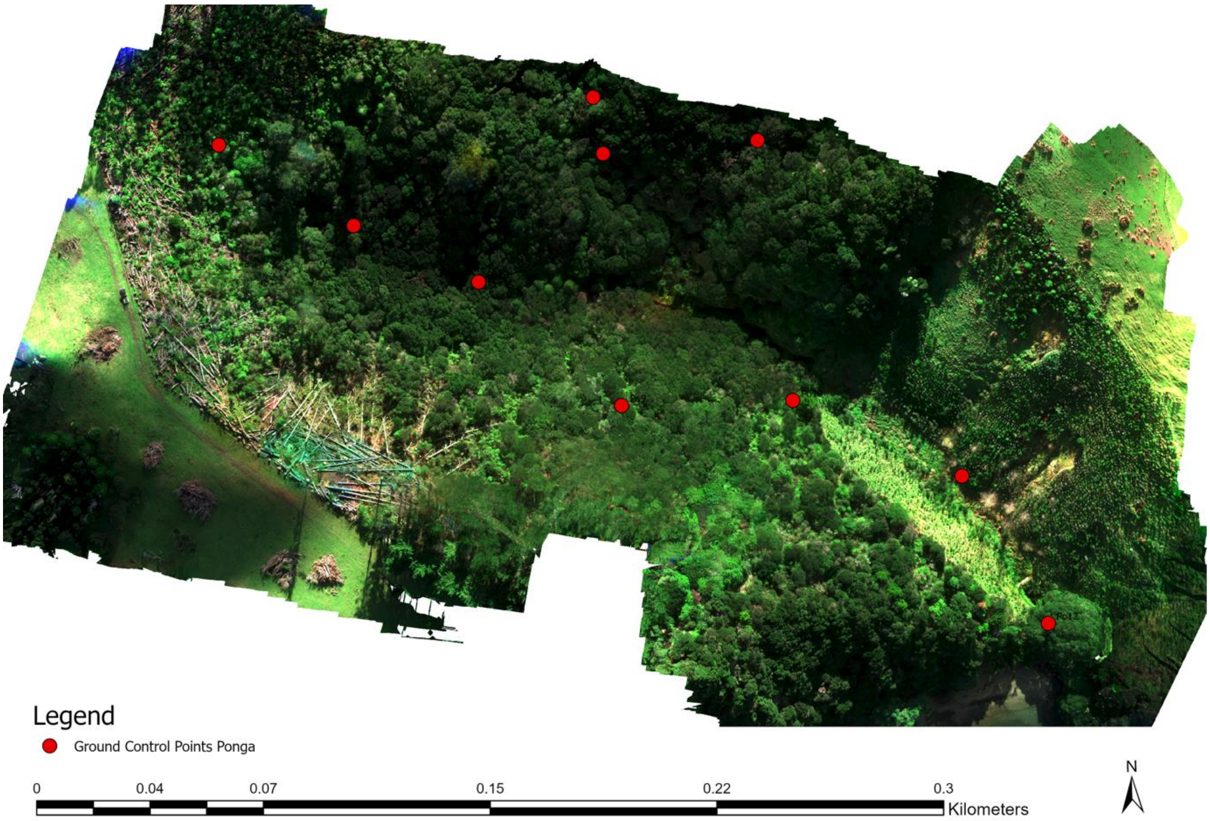

Figure 20: Ground Control Points

4.2 Image processing

The composite band image did not produce an accurate natural coloured map, thus changes to stretch type parameters were completed directly through the histogram graph. I chose stretch type 'precent clip' with Red, Green, and Blue between 0 and 0.08. After obtaining the most accurate natural colour visualisation, the band combination was changed to NIR, Green, and Blue. Figure 21 (A) shows the RGB orthomosaic before changing the stretch, and Figure 21 b shows the orthomosaic after changing the stretch. Figure 22 shows the training validation points for the plants investigated in this thesis.

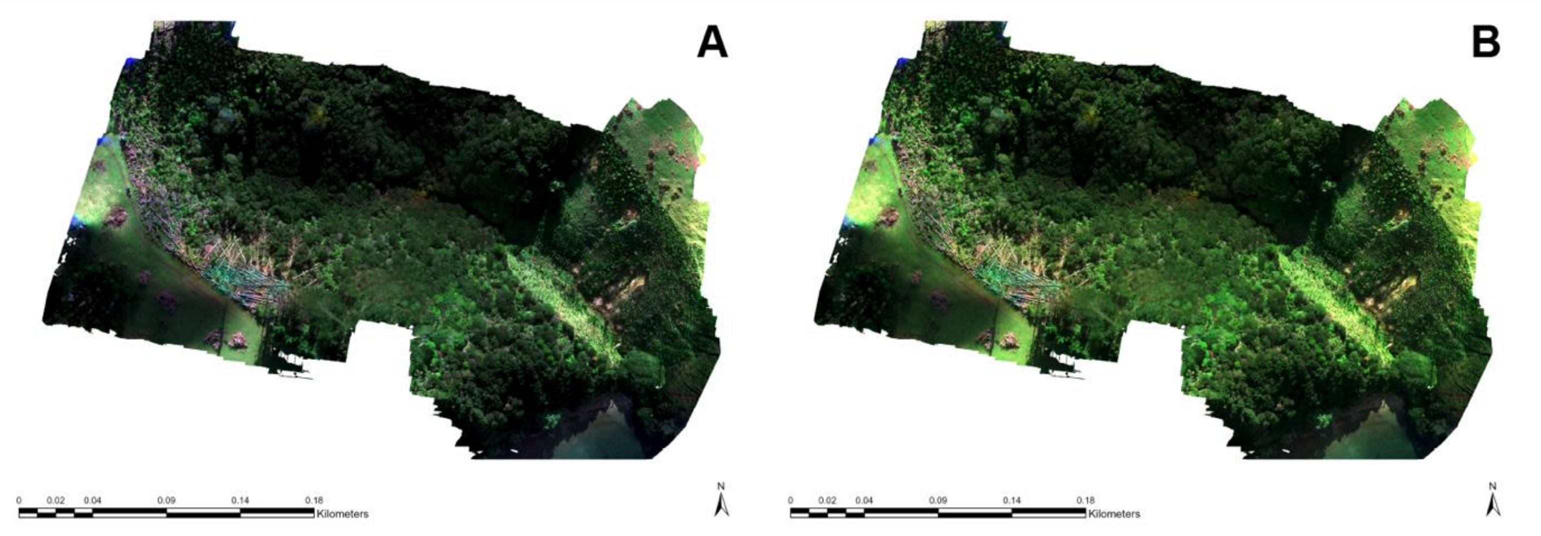

Figure 21: Mosaiced imagery Before correction (A) after correction (B)

Table 10: MicaSense band centre wavelength and their names in ArcGIS

Band	MicaSense Band Name	ArcGIS Bands	Centre Wavelength (nm)
1	Blue	Band_3	475
2	Green	Band_2	560
3	Red	Band_1	668
4	Near-Infrared (NIR)	Band_4	840
5	Red Edge (RE)	Band_5	717

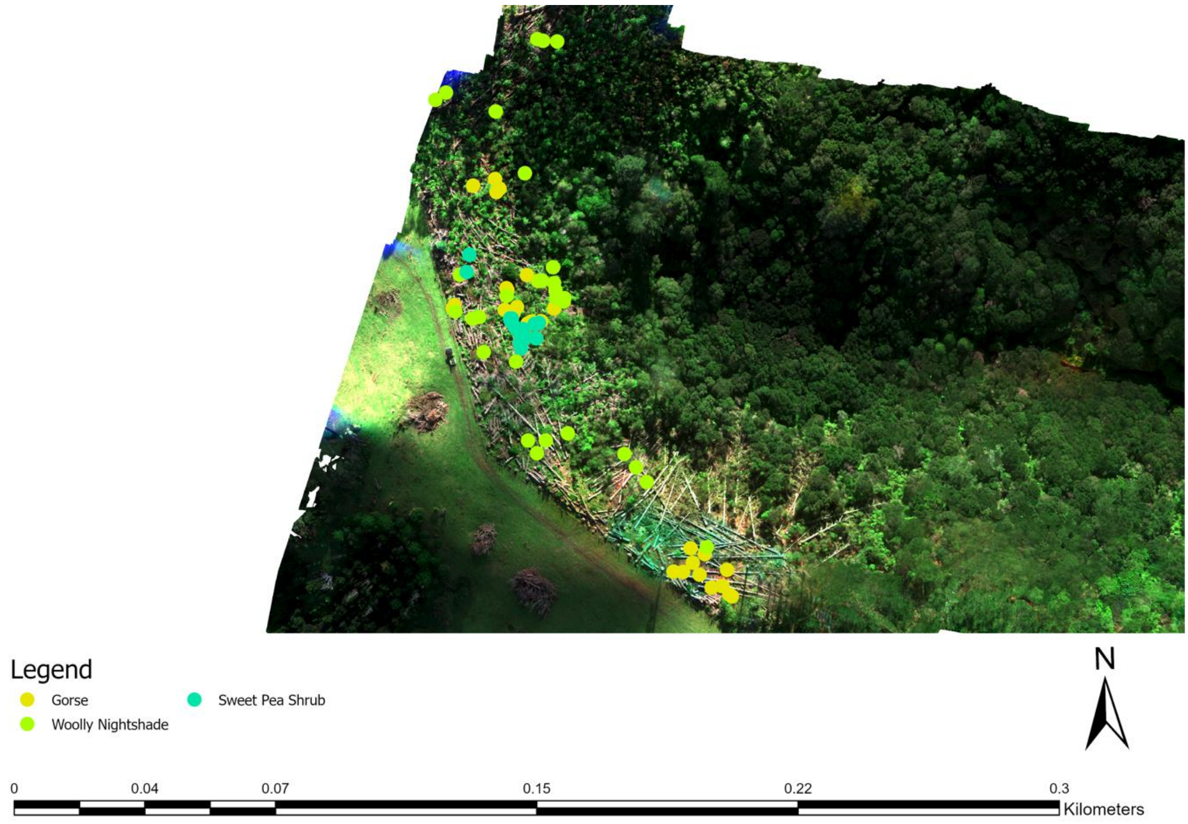

Figure 22: Training Validation of Woolly Nightshade, Gorse, and Sweet Pea Shrub.

4.2.1 Spectral reflectance

The spectral signature of the plants is shown in Figure 23 and scatter plot graphs in Figures 24 to 26. The plots and graphs were used to determine which band to use to create the false colour image. Image scatter plots can show the relationship between either bands and objects or between two bands. This plot can determine valuable information on the features of the images. In ArcGIS, the scatter plot shows the R-squared (R^2), which states the correlations between the two variables being examined. High R^2 values indicate a strong correlation and therefore indicate similarities. For our study, low correlation bands were required to distinguish and separate multiple features from the imagery (Esri, n.d.-b). We examined the relationship between bands red and green, bands NIR and green, and bands red edge and green. Band_2 (Green) and Band_4 (NIR) correlation was $R^2 = 0.69$ (Figure 24), while Band_1 (Red) and Band_2 (Green) had an $R^2 = 0.8$ (Figure 25). Band_5 (Red Edge) and Band_2 (Green) (Figure 26) had R^2 of 0.88. Band_2 (Green) and Band_4 (NIR) had the lowest correlation, while Band_2 (Green) and band_5 (Red Edge) had the highest correlation of 0.88.

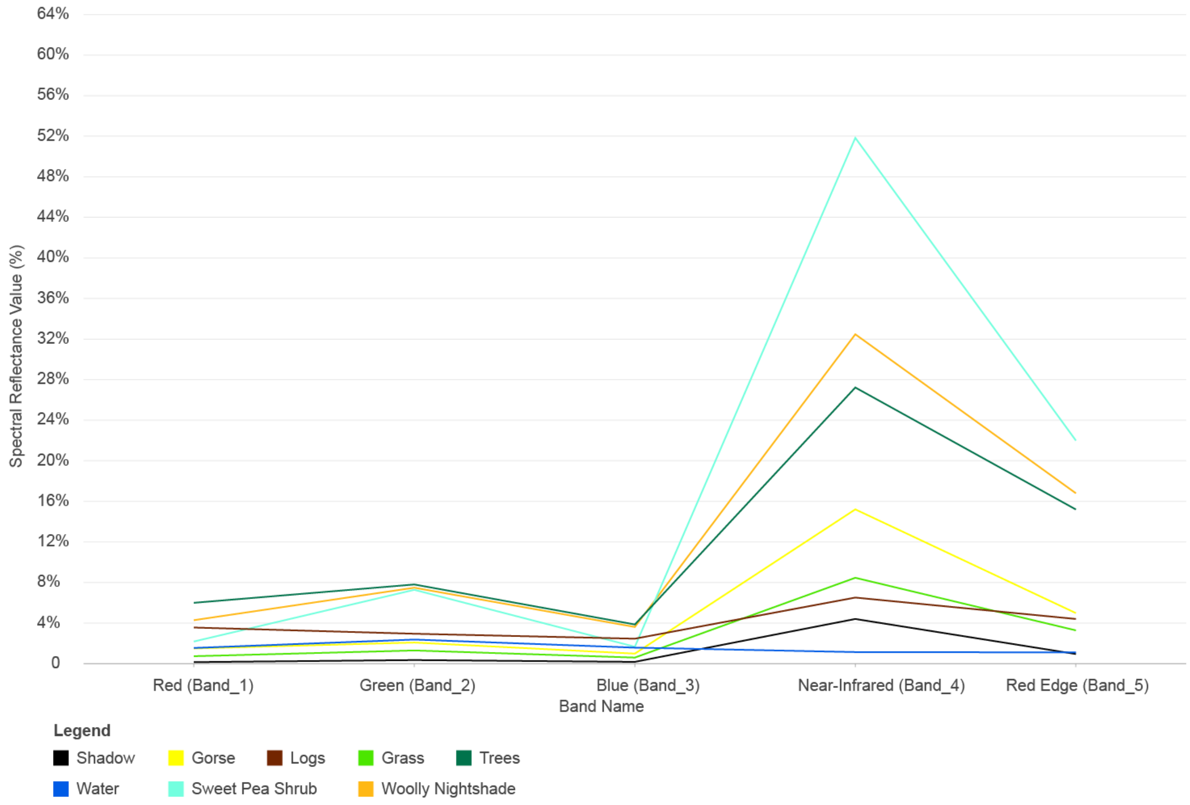

Figure 23: Ponga Hollow Class Spectral reflectance generated using the spectral profile tool on ArcGIS Pro. Each class shows the average spectral profile.

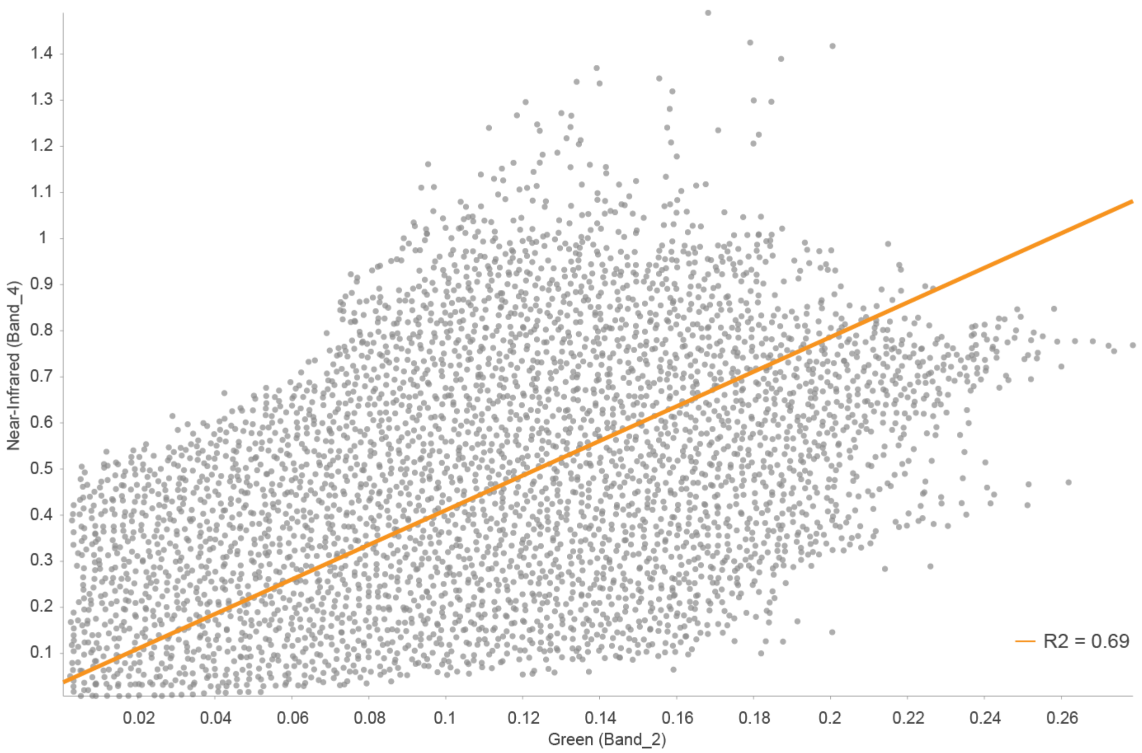

Figure 24: Correlation between green and NIR band.

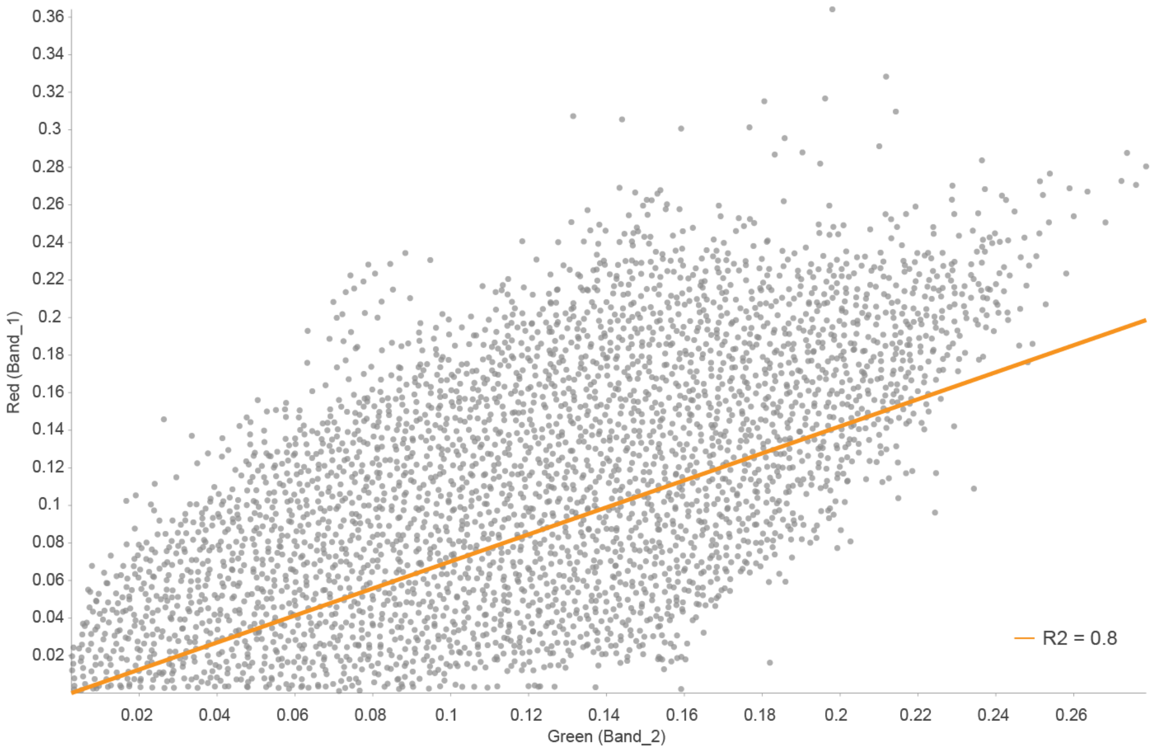

Figure 25: Correlation between green and red band.

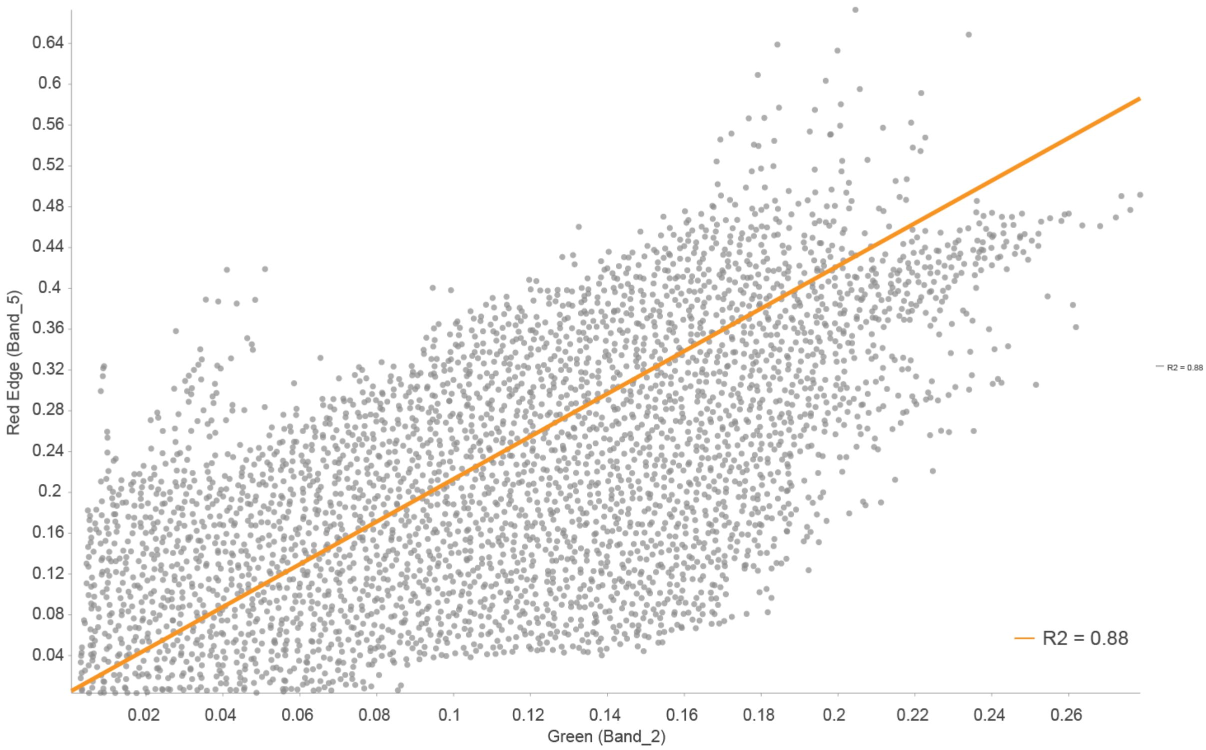

Figure 26: Correlation between green and RE band.

A composite image of NIR, blue, and green was used, as most plants showed high variability in the NIR range. Figure 27 shows the composited image of NIR, blue, and green bands. The highest variation in reflectance values among plant types was in the

NIR band. The reflectance of the classes in Band_3 (Green) was between 1% to 0.5%. Band_4 (NIR), which is NIR, was between 1% to 52%. Plants were between 15% to 52%. Sweet Pea Shrub had the highest reflectance value percentage of 52%, and Gorse had the lowest reflectance value of 15%. Woolly Nightshade had a reflectance value of 32.5%, and native trees had a reflectance value of 26%%. The grass had a reflectance of 8%. Band_2 (Blue) shows that most plants except Gorse had a reflectance value of 7%.

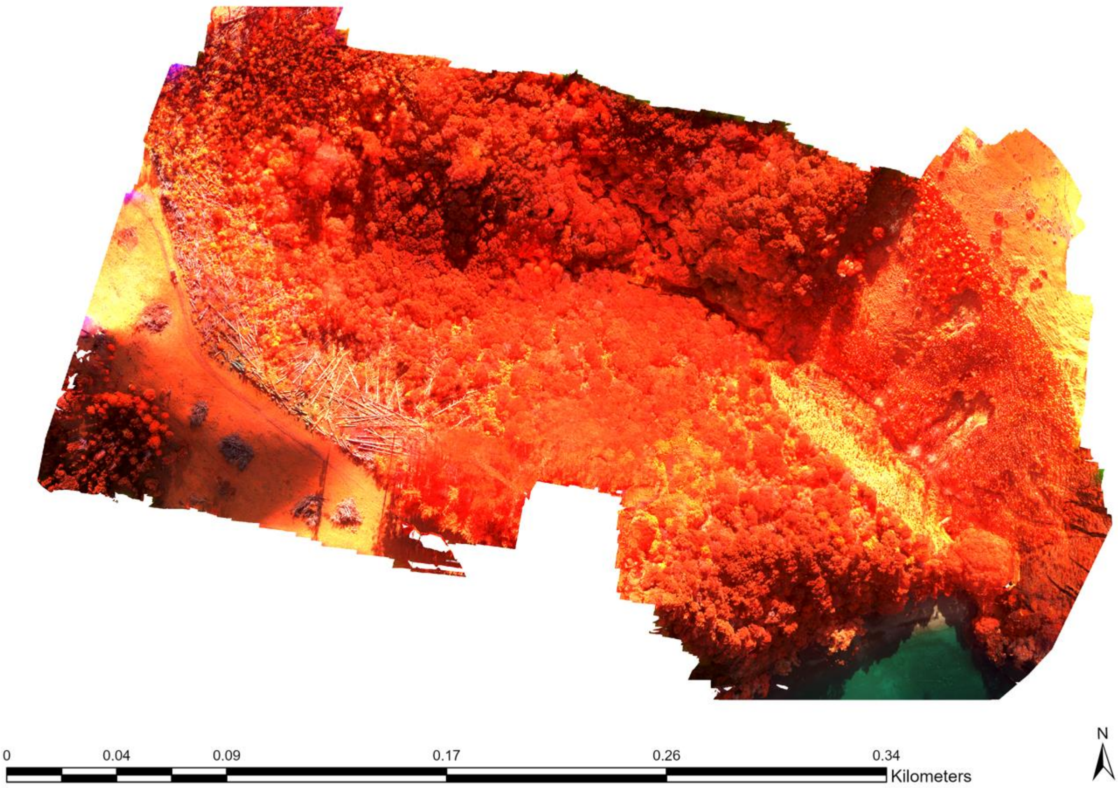

Figure 27 False image composite of NIR, Green and Blue.

4.3 Accuracy assessment by classifier

4.3.1 Maximum Likelihood (ML)

The mosaiced imagery was classified with Supervised ML, a parametric classifier. The mosaiced imagery was classified into eight classes: logs, water, grass, shadow, trees, Woolly Nightshade, Sweet Pea Shrub, and Gorse. The mosaiced imagery was tested with nine segmentation parameters to determine which performed optimally to acquire the invasive plants in the study. Table 11 shows the OA of all classes for each segmentation parameter and the accuracy for each. Parameter setting 9 had the highest accuracy of 56.15%, and parameter setting 4 had the lowest accuracy of

48.71%. Most parameters did not differ significantly. The kappa of this classifier was between 41% and 50%.

Table 11: Plant species user and producer accuracy and overall accuracy for all classes per segmentation parameter setting using ML classifier

	Woolly Nightshade		**Sweet Pea Shrub**		**Gorse**		**OA**	**Kappa**
	User	**Producer**	**User**	**Producer**	**User**	**Producer**		
1	0.00%	0.00%	3.17%	100.00%	0.00%	0.00%	53.97%	47.39%
2	0.00%	0.00%	3.17%	66.67%	1.59%	100.00%	50.10%	42.97%
3	0.00%	0.00%	3.17%	100.00%	1.59%	100.00%	49.01%	41.72%
4	0.00%	0.00%	1.59%	100.00%	3.17%	66.67%	48.71%	41.36%
5	1.59%	100.00%	3.17%	100.00%	3.17%	100.00%	51.39%	44.44%
6	0.00%	0.00%	6.35%	100.00%	1.59%	100.00%	52.38%	45.58%
7	0.00%	0.00%	3.17%	100.00%	0.00%	0.00%	53.37%	46.71%
8	3.17%	100.00%	3.17%	100.00%	1.59%	100.00%	52.98%	46.26%
9	0.00%	0.00%	3.17%	100.00%	3.17%	100.00%	56.15%	49.89%

Parameter 8 had the best results in detecting Woolly Nightshade with a U-accuracy of 3.17%. The rest of the parameters failed to detect Woolly Nightshade. This was not the case with Sweet Pea Shrub and Gorse. The Sweet Pea Shrub parameter setting 6 had the highest U-accuracy of 6.35%. The rest of the parameters had at least some detection of Sweet Pea Shrub. Gorse had similar results to Sweet Pea Shrub. However, the highest U-accuracy was 3.17 for several parameters. Only parameter settings 1 and 7 failed to detect Gorse. All P-accuracy's produced extreme results of either 0% or 100% P-accuracy.

Accuracy assessment classes had 63 stratified random points (Appendix 9). All three plants were misclassified as either trees or grass. Woolly Nightshade had the highest misclassification for the grass class ranging between 3 to 30 points, while Sweet Pea Shrub had the lowest ranging between 0-5. The misclassification of Gorse as grass range was between 0-14. All three invasive plants had high misclassifications as trees. Sweet Pea Shrub had the highest misclassification ranging from 58 to 63. Woolly Nightshade ranged between 33 to 60 while Gorse recorded 49 to 63. Sweet Pea Shrub points ranged from 0-2, while Woolly Nightshade ranged from 0 to 3 and Gorse ranged from 0-4.

4.3.2 Support Vector Machine (SVM)

Table 12 shows the OA for SVM for all classes for each segmentation parameter and accuracy for each plant using the SVM classifier. Parameter setting eight had the highest accuracy of 58.33%, and parameter setting nine had the lowest accuracy of 52.38%. Most parameters did not differ significantly.

Table 12: Plant species user and producer accuracy and overall accuracy for all classes per segmentation parameter setting using SVM classifier.

	Woolly Nightshade		Sweet Pea Shrub		Gorse		OA	Kappa
	User	Producer	User	Producer	User	Producer		
1	7.94%	83.33%	0.00%	0.00%	9.52%	85.71%	56.35%	50.11%
2	4.76%	100.00%	0.00%	0.00%	12.70%	88.89%	59.33%	53.51%
3	6.45%	100.00%	1.59%	100.00%	14.29%	100.00%	56.51%	50.28%
4	3.17%	100.00%	4.76%	100.00%	0.00%	0.00%	56.55%	50.34%
5	3.17%	100.00%	4.76%	100.00%	3.17%	100.00%	52.98%	46.26%
6	3.17%	100.00%	1.59%	100.00%	0.00%	0.00%	56.94%	50.79%
7	1.59%	100.00%	0.00%	0.00%	0.00%	0.00%	53.68%	47.06%
8	11.11%	100.00%	4.76%	100.00%	4.76%	100.00%	59.33%	53.51%
9	1.59%	100.00%	0.00%	0.00%	3.17%	100.00%	52.38%	45.58%

The user and producer accuracy of the invasive plant species for each segmentation parameter are shown for SVM in Table 12. Parameter setting 8 had the best results in detecting Woolly Nightshade with a U-accuracy of 11.11%. The lowest accuracy was 1.59% which was using segment parameter 9. Sweet Pea Shrub parameter setting 4, 5 and 8 had the highest U-accuracy of 4.67%. The other parameters had more than 1.6% U-accuracy. Four parameters did not detect any Sweet Pea Shrubs. Gorse had similar results to Woolly Nightshade, with the highest U-accuracy of 14.29% for parameter 3. The lowest parameter setting was 5 and 9, which has an accuracy of 3.17%. Two parameters did not detect any Gorse plants.

Accuracy assessment classes had 63 stratified random points. The confusion matrix table for SVM is in Appendix 8. All three plants were misclassified as either trees or grass, as seen in appendix 8. Woolly Nightshade had the highest misclassification for the grass class ranging between 0 to 10 points, while Gorse had the lowest ranging between 0-4. The misclassification of Sweet Pea Shrub as grass ranged between 0-2. All three invasive plants had high misclassifications as trees. Sweet Pea Shrub had the highest misclassification ranging from 59 to 63. On the other hand, Woolly Nightshade had a range between 43 to 62, while Gorse had 47 to 62. Sweet Pea Shrub accuracy points ranged from 0-3, while Woolly Nightshade ranged from 1 to 7 and Gorse ranged from 0-9.

4.3.3 Random Trees (RT)

Table 13 shows the OA for RT for all classes for each segmentation parameter and the accuracy for each plant using the RT classifier. From Table 13, we can see that parameter settings 2 and 8 had the highest accuracy of 60.12% and parameter setting 4 had the lowest accuracy of 52.38%. Most parameters did not differ significantly.

Table 13: Overall accuracy for all classes per segmentation parameter setting using RT classifier.

	Woolly Nightshade		**Sweet Pea Shrub**		**Gorse**		**OA**	**Kappa**
	User	**Producer**	**User**	**Producer**	**User**	**Producer**		
1	1.59%	50.00%	7.94%	83.33%	7.94%	100.00%	58.13%	52.15%
2	9.52%	100.00%	7.94%	100.00%	11.11%	70.00%	60.12%	54.42%
3	3.17%	100.00%	4.76%	100.00%	12.70%	57.14%	55.36%	48.98%
4	0.00%	0.00%	4.76%	100.00%	6.35%	40.00%	54.96%	48.53%
5	6.35%	0.00%	4.76%	100.00%	15.87%	66.67%	58.93%	53.06%
6	3.17%	0.00%	1.59%	100.00%	0.00%	0.00%	56.94%	50.79%
7	4.76%	62.50%	3.17%	100.00%	15.87%	62.50%	55.16%	48.75%
8	0.00%	0.00%	3.17%	100.00%	6.35%	80.00%	60.12%	54.42%
9	1.59%	100.00%	3.17%	100.00%	9.52%	50.00%	57.14%	51.02%

The invasive plant species user and producer accuracy for each segmentation parameter is shown for RT. Parameter setting 2 had the best results in detecting Woolly Nightshade with a U-accuracy of 9.52%. The lowest accuracy was 1.59% using segment parameters 1 and 9. Despite OA having the highest results in using parameter eight settings, there was no detection of Woolly Nightshades. Gorse had the lowest detection rate. Sweet Pea Shrub parameter setting 1 and 2 had the highest U-accuracy of 7.94%. Unlike ML and SVM, RT parameters all had some detection of Sweet Pea Shrub. Gorse had the highest U-accuracy of 15.87% for parameters 5 and 7. The lowest U-accuracy was 6.35% for parameter setting eight despite having the highest overall score of approximately—60%.

Appendix 7 to 9 shows the classification results for supervised classification techniques of the three classifiers used in this study. All classifiers were able to identify most of the land cover types. I tested different parameters for all classifiers to determine which produces the most accurate results. From appendix 7 to 9, all three plants were highly misclassified as either trees or grass. Woolly Nightshade had the highest misclassification for the grass class ranging between 0 to 12 points, while Sweet Pea Shrub had the lowest ranging between 0-2. Misclassification of Gorse as the grass was between 0-5. All three invasive plants had high misclassifications as trees. Sweet Pea Shrub had the highest misclassification of points ranging from 55 to 61. Woolly Nightshade ranged between 43 to 63, while Gorse had 50 to 61. Sweet Pea Shrub's accuracy points ranged between 1-6, while Woolly Nightshade ranged between 0 to 6 and Gorse ranged between 0-16.

4.4 Kappa agreement

Okwuashi et al. (2012) and Chen et al. (2015), assigned Kappa values into six categories: values over 0.80 as almost perfect agreement, values between 0.61 and 0.80 as substantial agreement, values between 0.41 and 0.60 as moderate agreement, values between 0.21 and 0.40 as fair agreement and values below 0.20 as slight agreement. Using Okwuashi et al. (2012) and Chen et al. (2015), all three classifiers had a kappa range between 41% to 60%, which is regarded as moderately in agreement. Machine Learning had the lowest kappa range between 41% to 49%. SVM had a range between 45% to 53%. RT had the highest kappa agreement range between 48% to 54%.

Spectral reflectance of each plant species

Figures 23 and 28 show the spectral reflectance of classes. The spectral reflectance of Gorse in Figure 23 is approximately 16% which is the same as seen in Figure 28 non-shaded Gorse, this was not the case for shaded Gorse. Shaded Gorse had a spectral reflectance of 10%, which is similar to grass, which was 8%, and shaded trees which had a spectral reflectance of 9.5% (Figure 23). The spectral reflectance of Trees was 26% (Figure 23). Figure 29 shows that when Gorses were in all classifiers, they were majorly classified as trees and occasionally grass. ML, however, classified more Gorse objects than the other two classifiers.

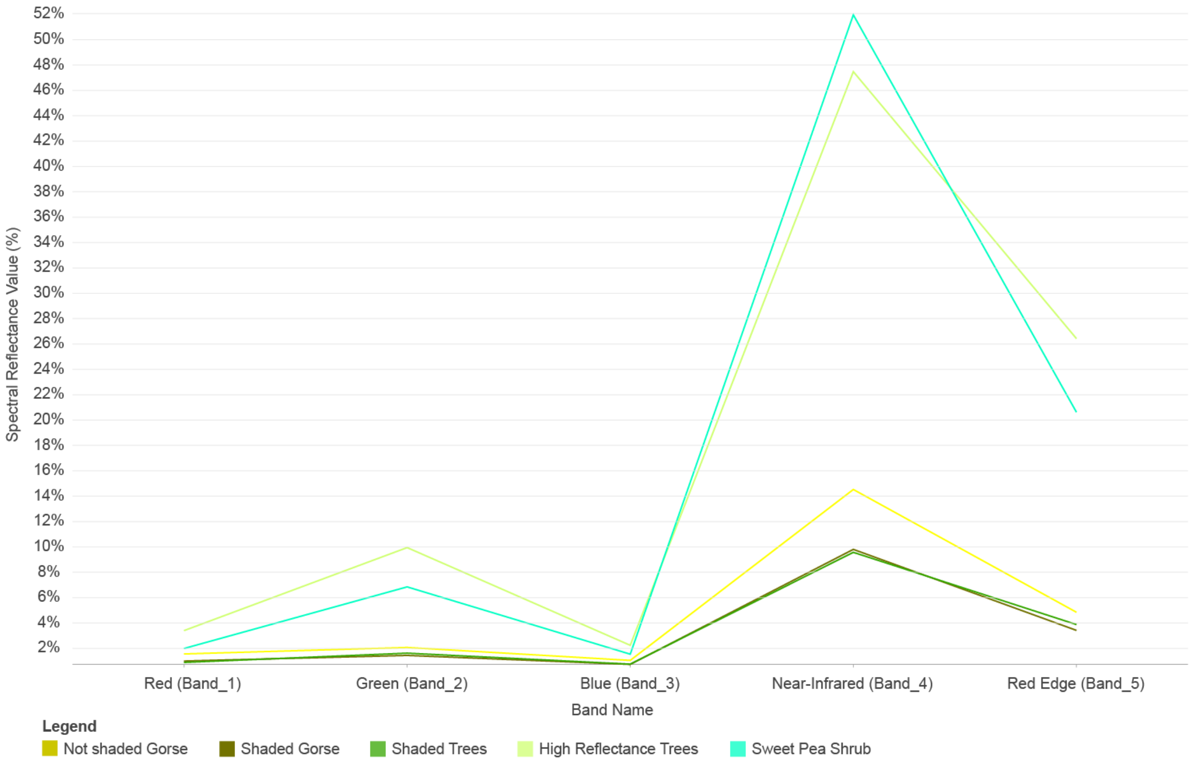

Figure 28: Spectral Reflectance of shaded, non-shaded invasive plants and Trees.

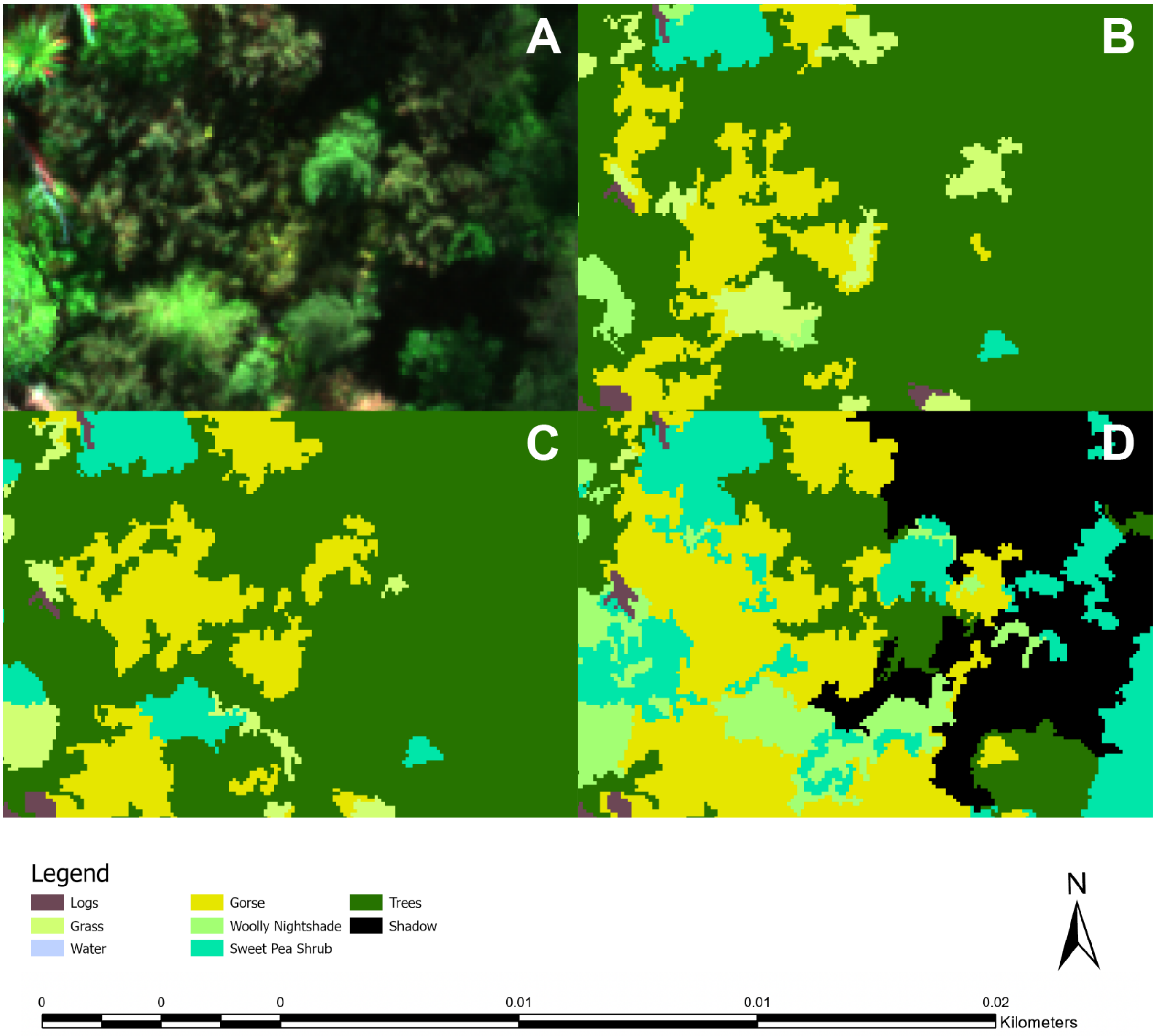

Figure 29: (A) True colour of Gorse, (B) RT, (C) SVM, (D) ML.

Sweet Pea Shrub had the highest spectral reflectance of 52% (Figure 23). Therefore, Sweet Pea Shrub's misclassification appears in areas with high reflectance values. This could be due to what is seen in Figure 30, where visually, Sweet Pea Shrub and trees are similar in higher reflectance areas such as the open region. In open areas, certain native trees had a high spectral reflectance of 47% (Figure 28). This high reflectance can explain the high misclassification of Sweet Pea Shrub as trees in the three classifiers.

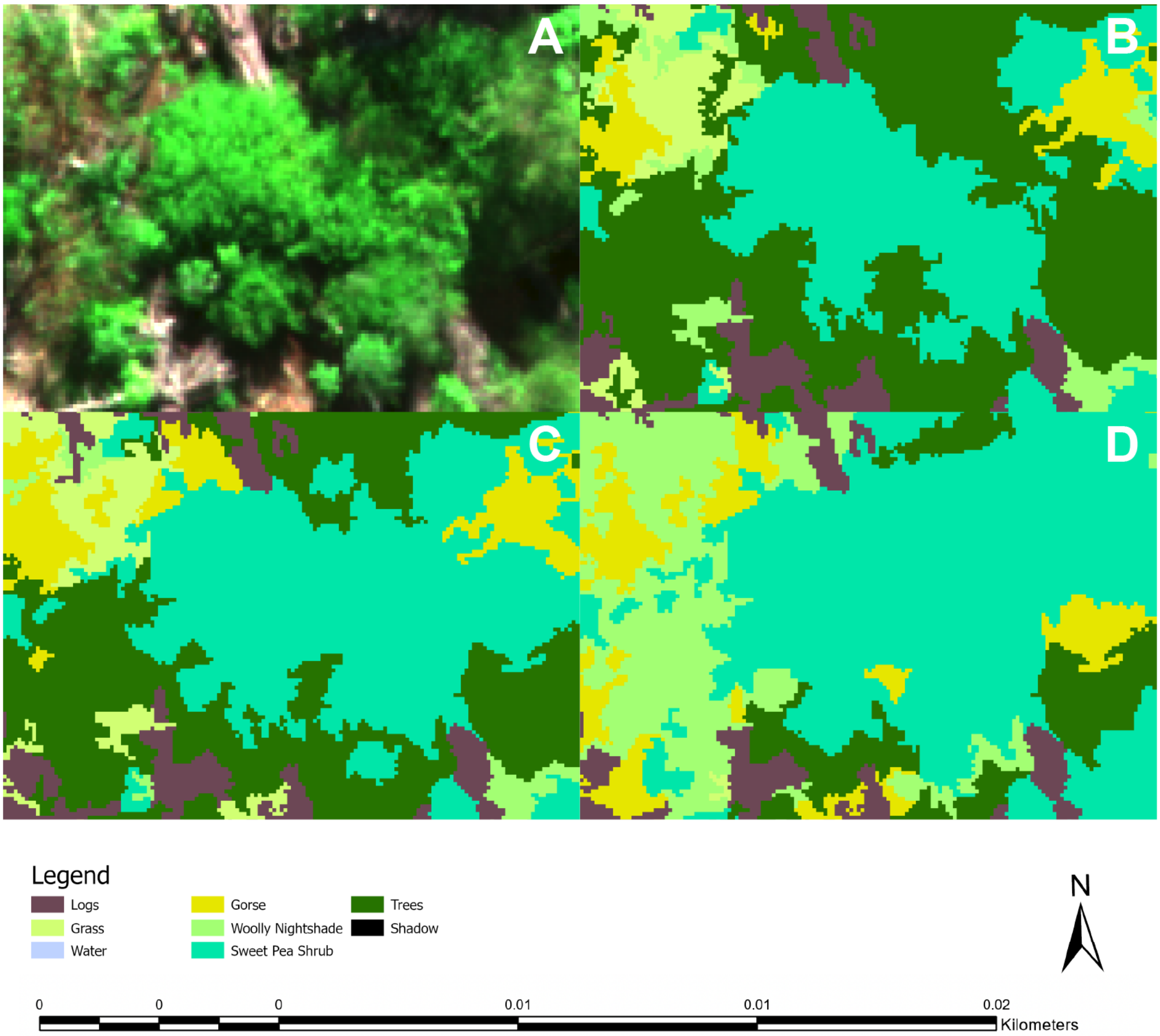

Figure 30: (A) True colour of Sweet Pea Shrub, (B) RT, (C) SVM, (D) ML.

Woolly Nightshade was the least misclassified plant compared to Sweet Pea Shrub and Gorse. In Figure 23, Woolly Nightshade had the second-highest spectral reflectance of 32%, only 4% higher than non-shaded trees. This means misclassified Woolly Nightshades as trees indicate that some trees had a reflectance of approximately 32% (Figure 23). Higher reflectance values were classified as Sweet Pea Shrub, as mentioned previously.

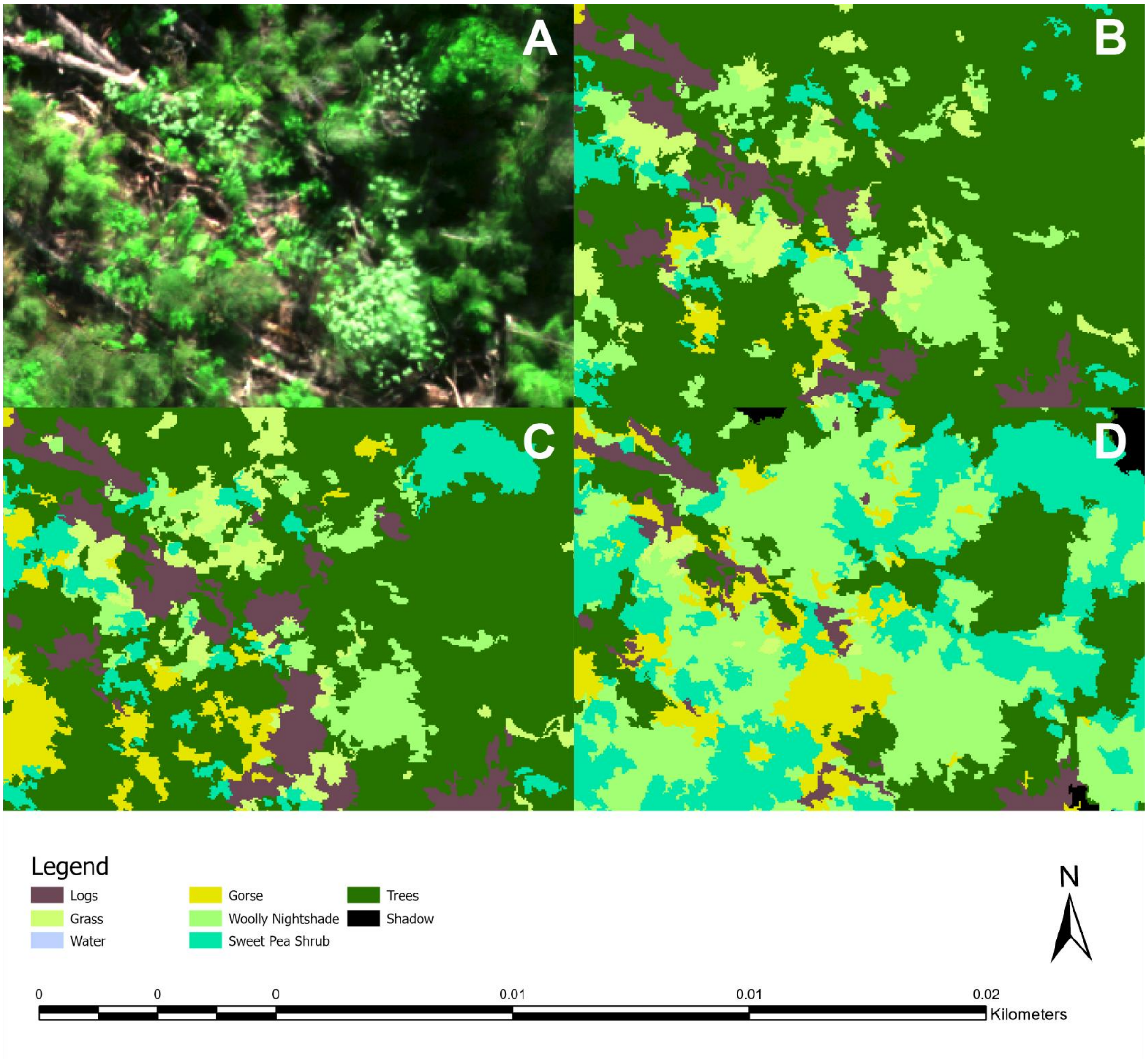

Figure 31: (A) True colour of Woolly Nightshade, (B) RT, (C) SVM, (D) ML.

4.5 Segmentation Parameters

One of the main goals of this research is to determine the best parameter to detect invasive plants. We investigated nine parameters, each with different spectral and spatial detail. Each classifier combined with the nine parameters had different results. Appendix 3 shows all the parameters segmentation with the NIR-G-B band composition. From the appendix, we can see that for the ML classifier, the best performance had a spectral detail of 10 and a spatial detail of 5. However, SVM and RT performed best with parameters two and eight. Parameter two had a spectral detail of 20 and a spatial detail of 15, while parameter one had a spectral detail of 10 and a spatial detail of 10. ML had a low OA with parameter two settings; this was the same for parameter eight. ML classified most trees as Sweet Pea Shrub. The grass class was misclassified as Gorse and Woolly Nightshade. The SVM classifier had much greater spatial detail even with low parameter settings. In comparison, segmentation in RT was much more confined, and thus there were no clusters of objects nearby.

Chapter 5: Discussion

5.1 Spectral reflectance

Spectral information was not enough to distinguish plants from others. The results for each plant differed with each classifier. The overall accuracy (OA) for all classes differed for a number of reasons. The segmenting parameters, spectral and spatial detail of the maps had an impact on the results. While there were no clear correlations, there were instances where some spectral and spatial detail settings worked better for some plants than others. For example, the spectral and spatial detail of 10 and 6 respectively applied to a Maximum Likelihood (ML) classifier had an OA of 56%. However, this setting did not detect any Woolly Nightshade. A spectral and spatial detail of 15 and 5 respectively had a lower accuracy of 51% and detected all three invasive plants. Random Trees (RT) and Support Vector Machine (SVM) had the highest OA with spectral and spatial detail of 20, 15 (parameter 2) and 10, 10 respectively (parameter 8). RT for those settings had an OA of 60% while SVM had 59%. While the maps segmented with those settings had the highest accuracy results, for RT, the spectral and spatial detail of 10 failed to detect Woolly Nightshade and had the lowest detection of Sweet Pea Shrub. Similarly, SVM did not detect any Sweet Pea Shrub with a spectral detail of 20 and a spatial detail of 15. Similar to Machine learning, an OA lower than 60% and spectral and spatial detail of 20 and 10 had the highest detection of Gorse, Sweet Pea Shrub, and Woolly Nightshade.

The difference in accuracy with slight changes to segmenting parameters is possibly due to the spectral reflectance. The spectral reflectance of the objects included important components such as shadow effect and seasonal time adjustments to acquire data. The spectral reflectance often is said to have the highest value variance when using the Near-infrared (NIR) band. In fact, the NIR band is commonly used to detect and distinguish plants from each other (Bannari et al., 1995). I used a scatter plot on ArcGIS to determine the pixel values correlation between the red, green, near-infrared, and red edge bands (Figure 24-26). The R^2 determined the correlation between the bands. On the ArcGIS webpage, it states that the lower the R^2 correlation, the better it is for invasive plant detection (Esri, n.d.-b). The green and NIR bands had a R^2 of 0.69 (Figure 24) while, the red edge and green had R^2 of 0.88 (Figure 26) and green and red had a R^2 of 0.8 (Figure 25). Although the R^2 of the bands compared were still considered high, NIR and green had the lowest R^2 correlation, suggesting weaker correlation and therefore lower pixel value similarities. The NIR band is suggested to present more than 90% of information related to vegetation in comparison to other bands (Bannari et al., 1995). Yet, although NIR combined with the green band had the lowest correlation value, our results were unsuccessful. de Sá et al. (2018) stated that the detection and distinguishability of *Acacia longifolia* compared to other plants was heavily decreased in the NIR band. Instead, they found the blue band was the most valuable in detecting the yellow flowers of the invasive plant. The NIR band failed to distinguish and differentiate the yellow flowers from the background, and thus performed poorly in comparison to the blue band (de Sá et al., 2018). Further, Müllerová, Bartaloš, et al. (2017) argue that while longer wavelengths/ bands such as NIR in low-cost drones are limited, they can still be helpful and provide a satisfactory detection rate in achieving less distinct species such as knotweed. However, Lien (2014) concluded in their study that using spectral information alone is not enough to detect plant species; rather, using texture parameters in combination with spectral information can enhance the accuracy of results. This is because the textural parameters are sensitive to the canopy's shape, height, and size (Abeysinghe et al., 2019; Lien, 2014). The increased detection rate of the plants may have been caused by the alteration of the spectral and spatial detail parameters. Each plant had a different leaf size, shape, colour, and texture, and thus, each plant had a different detection for each classifier.

5.2 Classifier

The study's objective was to find the optimal classifier for detecting invasive plants. Pixel-based ML classifier had the least accurate averages compared to object-based SVM and RT. The classifier failed in differentiating classes from each other even though, all classes in band_4 (NIR range) had different spectral reflectance (Figure 23). The highest overall accuracy (OA) was 56.15% and Kappa value (K) of 49.89%, while the lowest OA for SVM and RT were 52.38% (K- 46.26%) and 54.96% (K- 48.53%), respectively. Regarding accuracy of the invasive plants, SVM and ML also had the lowest detection rate of the invasive plants compared to RT. Each class had 63 accuracy points. ML Sweet Pea accuracy points ranged from 0-2, while Woolly Nightshade ranged from 0 to 3, and Gorse ranged from 0-4, similarly to SVM Sweet Pea accuracy points ranged from 0-3, while Woolly Nightshade ranged from 1 to 7, and Gorse ranged from 0-9. RT, on the other hand, Sweet Pea accurate points ranged from 1-6, while Woolly Nightshade ranged from 0 to 6, and Gorse ranged from 0-16~~. From our analysis, we can confirm that RT is the most suitable classifier compared to SVM and ML.~~

The pixel-based classification was found to cause the salt pepper effect, which produced less accurate results for the detection of the invasive plant Knotweeds

(Müllerová, Bartaloš, et al., 2017). The salt and pepper effect created blurred imagery and combined individual pixels of different classes. ML classification did not work as well as the other classifiers due to the assumption of the normal distribution of each class. ML also calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability. If the highest probability is smaller than the threshold specified, the pixel remains unclassified (Richardson & Hill, 1998). In this study, the data was not normally distributed. These findings were also noticed in G. Zhou & Xiong (2013) where they compared object-oriented and ML classifications of land use in the Karst area. The overall results were 78.94%, and a Kappa coefficient of 0.7633 with ML method compared to the OA of the object-based classification was 93.96% and kappa coefficient of 0.932. These results show a difference of 15.02% between the two methods. This shows that object-based classification is best suited for research studies on invasive plant detection.

As seen in Figure 28, the misclassification seen throughout the classifiers is due to shadows. Shadowing can cause within class spectral variation, negatively affecting classification accuracy (Blaschke, 2010; Kattenborn et al., 2020; Lopatin et al., 2019). Low sun elevation can cause visible shadows, which is unfavourable for data (de Sá et al., 2018; James & Bradshaw, 2020). However, it was misclassified due to the effects of shadows. This further reduced the accuracy of shrub. The shadow effect is a common issue seen in various studies when data acquisition occurs during winter. For example, Yang et al. (2021) detected flowering of leafy spurge (*Euphoria esula* L.). James and Bradshaw (2020) found that flowers of plants in winter seasons can be misclassified due to shadows. Further, Lopatin et al. (2019) compared the influence of shadows have on *Acacia dealbata, Ulex europaeus* and *Pinus radiata*. The results indicated that shadows had significantly affected the accuracy results for all plants. The range of misclassification and inaccuracy was between 65% to 100%. For this thesis, all classes had spectrally different reflectance and some plant species were not detected due to shadowing affect. Shaded trees and shaded Gorse had similar spectral reflectance to (Figure 28), which further reduced the accuracy and distinguishability of the plants. Yet certain classes such as Logs and Grass that had similar reflectance of 6% and 8.5% respectively were not misclassified as each other. These results were similarly found with Kentsch et al. (2021), where the aim was to detect blueberry plants. The plants were misclassified and found to be difficult to distinguish them in shadowed areas. Similarly, in Kattenborn et al. (2020) shadows significantly impacted classification accuracy when detecting *Pinus radiata*.

5.3 Going forward

5.3.1 Vegetation Index

A number of studies such as Bannari et al. (1995), Campbell and Wynne (2011), A. Wang et al. (2019) and W. Yang et al. (2015) used vegetation indices to increase the detectability accuracy of plants. A vegetation index (VI) is an effective and simple algorithm for distinguishing plants apart. The vegetation index results from combining data from two or more spectral bands (Jackson & Huete, 1991). Vegetation indices are sensitive to leaf chlorophyll content, leaf area index (LAI), canopy cover, and soil reflectance (Richardson & Wiegand, 1977; Hunt et al., 2011). They are used to enhance the vegetation signal, while minimising soil background and atmospheric effects (Bannari et al., 1995; J. B. Campbell & Wynne, 2011; Jackson & Huete, 1991). Laporte-Fauret et al. (2020) detected Atlantic coastal dune vegetation using pixel-based Random Forest and the Normalised Difference Vegetation Index (NDVI). The two classification approaches used had OA of 100% and 92.5% for sand and vegetation ground cover types respectively. Similarly, Rupasinghe and Chow-Fraser (2019) had an OA of 88.56% using, Normalised Difference Water Index (NDWI), NIR and NDVI detecting *Phragmites australis* (Cav.) during different seasons. The author stated that using the NDVI and NDWI aided in differencing between Phragmites, cattail (*Typha latifolia* L.), and meadow marsh during the late summer and fall periods. This was found to be the case as the red and NIR are particularly sensitive to the colour green (Meyer & Neto, 2008). The red spectral band correlated with the chlorophyll concentration, while the NIR spectral band correlated to the leaf area index and vegetation density (Bannari et al., 1995; Z. Zhou et al., 2018). As mentioned above, the majority of classes had significantly different spectral reflectance, yet in this thesis, the OA of the invasive plant classes did not exceed 15%. Using vegetation indices can further discriminate vegetation from other plants and soil backgrounds. The possible challenge with this method is that even though RGB-NIR imaging sensors provide sufficient information to discriminate vegetation from the soil, they can hardly discriminate between species, especially in the early growth stage when plants and weeds have similar reflectance characteristics (A. Wang et al., 2019).

5.3.2 Seasonality variance

Plant detection with any classifier often results in misclassification; however, certain aspects, often plant phenological phases, are used as an indicator to decrease the misclassification rate (Marzialetti et al., 2021; Müllerová, Bartaloš, et al., 2017). The flowering of plants and deciduous trees can help increase the accuracy of detection (de Sá et al., 2018; Marzialetti et al., 2021; Müllerová, Bartaloš, et al., 2017). Using their phenological period of flowering can help detect the plants and distinguish them easily from native plants. For example, Marzialetti et al. (2021) compared *Acacia salign* pre-flowering and flowering periods. The accuracy of the random forest classifier using DSM and RGB was 91.17% pre-flowering. During the flowering period, the accuracy increased to 93.5%. The positive aspect is seen in X. Yang et al. (2021) where they measured the land cover spread of *Euphoria esula* L. over a period of two years and as a result, there was a decrease in coverage of 0.2%. For Moturoa Island, this could mean that the changes in community caretakers detection approach of invasive plants, could also measure the landcover of the plants throughout the years.

One of the main issues with detecting invasive plants is that they grow in the understorey or under the shadows of other plants. The invasive plants of this study, such as Woolly Nightshade and Sweet Pea Shrub, can tolerate shade and therefore can be misclassified and undetected using UAVs. de Sá et al. (2018) detected *A. longifolia* understorey of pine canopy due to its yellow flowers. Gränzig et al. (2021) found that Gorse was classified with 78% accuracy while flowering. However, there was misclassification in patches where there was no flowering Gorse as either shrubs or water. In our case, Gorse was more often either classified as grass and trees for SVM and ML, while for RT, it was misclassified as trees and logs. Müllerová, Bartaloš, et al. (2017) used ML, SVM, and RF to detect Knotwood at pre-flowering and flowering periods. When the plants were flowering, the detection accuracy was up to 100%, whereas when the plants were not flowering, the accuracy results were down to 60%. Similarly, de Sa et al. (2018) looked at the impacts of *Trichilogaster acaciaelongifoliae*, a biocontrol agent on *Acacia longifolia* flowering periods. de Sá et al. (2018) like Müllerová, Bartaloš, et al. (2017) used random forest classifier. The results in detecting the plant during flowering periods had an accuracy of 96%.

5.3.3 Limitations

Moth Plant was undetectable with the drone due to the season. Moth Plant flowers from November and produces pods between December and May (R. Hill & Gourlay, 2011; Winks & Fowler, 2000). The imagery was collected in July, and the visibility of Moth Plant was low. Thus, Moth Plant was not selected for the detection process. An attempt to collect imagery in January, the flowering season of Moth Plant, Gorse and Woolly Nightshade, was unsuccessful due to COVID19 restrictions causing the second trip to collect the data for the summer season to be cancelled.

The training samples of this study were inconsistent due to the timing of the flight. The GPS points collected in January 2021 showed new growth in the plants. These new growths were not present during July 2020, and therefore, the majority of GPS points of new growth were not present. Unfortunately, this caused training samples to decrease from 30 to approximately 20 for each invasive plant species. Training sampling is essential, especially for the detection of plants. Ainiwaer et al. (2020) compared training sample quantity and their accuracy in detecting plant communities, of *Populus* and *Tamarix* using various models and algorithms. They found that as the training sampling quantity increased, the OA increased, which resulted in better detectability and distinguishing of the plant communities. Similarly, Pham et al. (2019) compared classifiers performance for plant detection of Pohutukawa (*Metrosideros excelsa* Sol. ex Gaertn). The authors compared Naïve Bayes, Logistic Regression, Random Forest, and SVM as well as compared the sampling size effect on classification. There were six classes of which the classifiers were tested. Each class had training levels of 10, 25, 50, 75, 100 and 125. Similarly, to Ainiwaer et al. (2020), as the sampling size increased, the detectible increased. However, unlike Ainiwaer et al. (2020), the significance of the increase between 50 samples to 125 samples did not differ greatly. At 50 samples, the OA of 82.2% was for SVM, while 126 samples for SVM only had 88.2%, which is a difference of 6% accuracy. It seems that as more than 25 samples were added on, increased accuracy of 2% occurred. However, for conservation communities/ groups, this may be time-consuming.

While we collected our imagery in July, there is a possibility that OA would have increased if the imagery had been taken in January when the invasive plants were flowering. Plant detection of the plants was not successful. The reason behind this is not detecting invasive plants during their unique phenological growth phases and as a result, misclassification occurred (He et al., 2015). Müllerová, Brůna, et al. (2017) argue that the object-based classifier is not suitable for objects that do not have distinct shapes or colours.

Chapter 6: Conclusion

The aims of this research was to:

Find the optimal classifier for the detection of invasive plants using a multispectral camera.

This study used a multispectral UAV to acquire imagery of Ponga Hollow, a site on a private sanctuary island called Moturoa. We attempted to detect four invasive plants in Ponga Hollow: Moth Plant, Sweet Pea Shrub, Woolly Nightshade, and Gorse. The images were acquired on the 12th of July 2020 using Phantom 4 UAV with MicaSense Red Edge Sensor. The data was analysed using Pix4D mapper for the multispectral bands and Esri ArcGIS Pro to analyse the bands. We used a supervised classification method with pixel and object-based techniques. We tested all three classifiers offered by ArcGIS pro, pixel-based classifier Maximum Likelihood (ML) and object-based classifiers Support Vector Machine (SVM), and Random Trees (RT). The ArcGIS image classification wizard tool was used to segmented settings for all three classifiers. We created a total of nine segmentation parameters which were tested on each classifier and as a result, we had 27 classified maps.

The spectral and spatial detail of the segmented images had different results with each classifier. For example, RT and SVM classifiers performed best when spectral detail and spatial detail were either 20 and 15 or 10 and 10, respectively. On the other hand, Maximum Likelihood performed best when spectral detail and spatial detail were at 10 and 5, respectively. The highest accuracy for RT , SVM and Maximum Likelihood was 60%, 59% and 56%, respectively.

The study results showed that a UAV could detect Gorse and Woolly Nightshade to an acceptable level. The limitation of the study included shadowing and high exposure affecting the spectral reflectance of plants, the season to acquire the imagery, and the low number of training samples. The time when the imagery of plants is taken should heavily depend on the phenology flowering stage. Shadowing should also be minimised as much as possible. From the above information, we saw that Gorse spectral reflectance was significantly different in shadowed areas compared to non-shadowed areas. Similarly, certain trees had similar reflectance to Sweet Pea Shrub and shaded trees.

Ultimately, the results from this thesis provide an opportunity for further study based on the critical evaluation of the methods used within this thesis. It has provided the foundations for further research using of low altitude drone imagery in combination with ArcGIS to detect invasive plants.

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Appendices

Appendix 1: Table of studies chosen for the literature review

Authors	Article Title	Year	Invasive Plant	Classifier	Journal	Classification method
Sravanthi, R; Sarma, ASV	Efficient image-based object detection for floating weed collection with low cost unmanned floating vehicles	2021		K-means and Fast Marching	Application of soft computing	Object-Based
Tay, JYL; Erfmeier, A; Kalwij, JM	Reaching new heights: can drones replace current methods to study plant population dynamics?	2018	Ragwort, Senecio jacobae	ANOVA	Plant Ecology	Pixel-based
James, K; Bradshaw, K	Detecting plant species in the field with deep learning and drone technology	2020	Hakea	Deep Learning; U-Net	Methods in Ecology and Evolution	Supervised-based
Kentsch, S; Cabezas, M; Tomhave, L; Gross, J; Burkhard, B; Caceres, MLL; Waki, K; Diez, Y	Analysis of UAV-Acquired Wetland Orthomosaics Using GIS, Computer Vision, Computational Topology and Deep Learning	2021	North American blueberry hybrids (Vaccinium corymbosum x angustifolium)	deep neural network	Satellite and UAV Platforms, Remote Sensing for Geographic Information Systems	Supervised-based
Yang, XH; Smith, AM; Bourchier, RS; Hodge, K; Ostrander, D; Houston, B	Mapping flowering leafy spurge infestations in a heterogeneous landscape using unmanned aerial vehicle Red-Green-Blue images and a hybrid classification method	2021	Leafy spurge (Euphoria esula L.)	eCognition	Remote Sensing	Object-Based
Marzialetti, F; Frate, L; De Simone, W; Frattaroli, AR; Acosta, ATR; Carranza, ML	Unmanned Aerial Vehicle (UAV)-Based Mapping of Acacia saligna Invasion in the Mediterranean Coast	2021	Acacia saligna	Geographic Object-Based Image Analysis techniques (GEOBIA) in combination with Random Forest (RF) classifier, NDVI	Drones for Ecology and Conservation	Object-Based
Hung, C; Xu, Z; Sukkarieh, S	Feature Learning Based Approach for Weed Classification Using High Resolution Aerial Images from a Digital Camera Mounted on aUAV	2014	water hyacinth, tropical soda apple and serrated tussock	K-means	UAV-Based Remote Sensing Methods for Modeling, Mapping, and Monitoring	Object-Based

					Vegetation and Agricultural Crops	
Ahmed, S; Nicholson, CE; Muto, P; Perry, JJ; Dean, JR	The Use of an Unmanned Aerial Vehicle for Tree Phenotyping Studies	2021	black pine, Norway maple, Scots pine, and sycamore, trees -oak and silver birch	K-means	Urban Environment Using Chemical Analysis	Pixel-based
Whiteside, T. G., Boggs, G. S., & Maier, S. W.	Comparing object-based and pixel-based classifications for mapping savannas.	2011	Eucalypt	Maximum likelihood	International Journal of Applied Earth Observation and Geoinformation	Object-Based; Pixel Based
Madurapperuma, B; Lamping, J; McDermott, M; Murphy, B; McFarland, J; Deyoung, K; Smith, C; MacAdam, S; Monroe, S; Corro, L; Magstadt, S; Dellysse, J; Mitchell, S	Factors Influencing Movement of the Manila Dunes and Its Impact on Establishing Non-Native Species	2020	Manila Dunes; buckwheat (Fagopyrum esculentum), coyote brush (Baccharis pilularis), dune goldenrod (Solidago spathulata), European beach grass (Ammophila arenaria), European sea rocket (Cakile maritima), and ice plant (Carpobrotus edulis)	Maximum Likelihood; Agisoft PhotoScan	Remote Sensing	Object-Based; Pixel Based
Mullerova, J; Bruna, J; Bartalos, T; Dvorak, P; Vitkova, M; Pysek, P	Timing Is Important: Unmanned Aircraft vs. Satellite Imagery in Plant Invasion Monitoring	2017	giant hogweed (Heracleum mantegazzianum)	Maximum Likelihood; Random Forest; Support Vector Machine	Plant Science	Object-Based; Pixel Based
Nhamo, L; van Dijk, R; Magidi, J; Wiberg, D; Tshikolomo, K	Improving the Accuracy of Remotely Sensed Irrigated Areas Using Post-Classification Enhancement Through UAV Capability	2018	Crops	Maximum Likelihood: NDVI	Remote Sensing for Crop Water Management	Supervised-based
Abeysinghe, T; Milas, AS; Arend, K; Hohman, B; Reil, P; Gregory, A; Vazquez-Ortega, A	Mapping Invasive Phragmites australis in the Old Woman Creek Estuary Using UAV Remote Sensing and Machine Learning Classifiers	2019	Phragmites australis	Neural network (NN), Support Vector Machine (SVM), and k-nearest neighbor (kNN).	Remote Sensing	
Tang, F; Zhang, DB; Zhao, XH	Efficiently deep learning for monitoring Ipomoea cairica (L.) sweets in the wild	2021	Ipomoea cairica (L.) sweets	R-CNN and Fast R-CNN	Mathmatical Bioscience and Engineering	Deep Leanring
Martin, FM; Mullerova, J; Borgniet, L;	Using Single- and Multi-Date UAV and Satellite Imagery to	2018	Asian knotweeds (Fallopia japonica; Fallopia x bohemica)	Random Forest	Advances in Remote Sensing Applications for the	Object-Based

Dommanget, F; Breton, V; Evette, A	Accurately Monitor Invasive Knotweed Species				Detection of Biological Invasions	
Wijesingha, J; Astor, T; Schulze-Bruninghoff, D; Wachendorf, M	Mapping InvasiveLupinus polyphyllusLindl. in Semi-natural Grasslands Using Object-Based Image Analysis of UAV-borne Images	2020	Lupinus polyphyllusLindl. (Lupine)	Random Forest	Photogrammetry, Remote Sensing and Geoinformation Science	Object-Based
Kedia, AC; Kapos, B; Liao, SM; Draper, J; Eddinger, J; Updike, C; Frazier, AE	An Integrated Spectral-Structural Workflow for Invasive Vegetation Mapping in an Arid Region Using Drones	2021	Giant reed (Arundo donax), stinknet/globe chamomile (Oncosiphon piluliferum), Sahara mustard (Brassica tournefforti), saltcedar (Tamarix spp.), and southern cattail (Typha domingensis).	Random Forest	Drones in Geography	Pixel-based
de Sa, NC; Castro, P; Carvalho, S; Marchante, E; Lopez-Nunez, FA; Marchante, H	Mapping the Flowering of an Invasive Plant Using Unmanned Aerial Vehicles: Is There Potential for Biocontrol Monitoring?	2018	Acacia longifolia	Random Forest	Remote sensing of invasive species	Pixel-based
Hill, DJ; Tarasoff, C; Whitworth, GE; Baron, J; Bradshaw, JL; Church, JS	Utility of unmanned aerial vehicles for mapping invasive plant species: a case study on yellow flag iris (Iris pseudacorus L.)	2017	yellow flag iris (Iris pseudacorus L.),	Random Forest	Unmanned aerial vehicles for environmental applications	Pixel-based
Bolch, EA; Hestir, EL; Khanna, S	Performance and Feasibility of Drone-Mounted Imaging Spectroscopy for Invasive Aquatic Vegetation Detection	2021	Water Hyacinth (Eichohornia crassipes) and Water Primrose (Ludwigia spp.)	Random Forest	Remote Sensing	Supervised using Object Based
Michez, A; Piegay, H; Jonathan, L; Claessens, H; Lejeune, P	Mapping of riparian invasive species with supervised classification of Unmanned Aerial System (UAS) imagery	2016	Impatiens glandulifera Royle, Heracleum mantegazzianum Sommier and Levier, and Japanese knotweed (Fallopia sachalinensis (F. Schmidt Petrop.), Fallopia japonica (Houtt.) and hybrids	Random Forest	Applied Earth Observation and Geoinformation	Supervised-based
Granzig, T; Fassnacht, FE; Kleinschmit, B; Forster, M	Mapping the fractional coverage of the invasive shrub Ulex europaeus with multi-temporal Sentinel-2 imagery utilizing UAV	2021	Ulex europaeus (common Gorse)	Random Forest	International Journal of Applied Earth Observations and Geoinformation	Supervised-based

	orthoimages and a new spatial optimization approach					
Baron, J; Hill, DJ; Elmiligi, H	Combining image processing and machine learning to identify invasive plants in high-resolution images	2018	Yellow Flag Iris	Random Forest	Remote Sensing for Environment Applications	Supervised-based
Elkind, K; Sankey, TT; Munson, SM; Aslan, CE	Invasive buffelgrass detection using high-resolution satellite and UAV imagery on Google Earth Engine	2019	Bufflegrass	Random Forest	Remote Sensing in Ecology and Conservation	
Kattenborn, T; Lopatin, J; Forster, M; Braun, AC; Fassnacht, FE	UAV data as alternative to field sampling to map woody invasive species based on combined Sentinel-1 and Sentinel-2 data	2019	Pinus radiata, Ulex europaeus and Acacia dealbata	Random Forest	Remote Sensing of Environment	Object-Based; Pixel Based
Chabot, D; Dillon, C; Shemrock, A; Weissflog, N; Sager, EPS	An Object-Based Image Analysis Workflow for Monitoring Shallow-Water Aquatic Vegetation in Multispectral Drone Imagery	2018	water soldier (Stratiotes aloides)	Random Forest	Geo-Information	Object-Based
Wang, L; Zhou, YZ; Hu, Q; Tang, ZH; Ge, YF; Smith, A; Awada, T; Shi, YY	Early Detection of Encroaching Woody Juniperus virginiana and Its Classification in Multi-Species Forest Using UAS Imagery and Semantic Segmentation Algorithms	2021	eastern redcedar (Juniperus virginiana), ponderosa pine (Pinus ponderosa), Scots pine (Pinus sylvestris), green ash (Fraxinus pennsylvanica), and hackberry (Celtis occidentalis)	Random Forest, Decision Tree, AlexNet and ResNet; CNN	Applications of Remote Sensing in Invasive Species Assessments	Deep Learning
Laporte-Fauret, Q; Lubac, B; Castelle, B; Michalet, R; Marieu, V; Bombrun, L; Launeau, P; Giraud, M; Normandin, C; Rosebery, D	Classification of Atlantic Coastal Sand Dune Vegetation Using in Situ, UAV, and Airborne Hyperspectral Data	2020	Ammophila arenaria, Galium arenarium, Helychrisum stoechas, Artemisia campestris, Elymus farctus, Otanthus maritimus, Mobile Dune Sand, Grey Dune Sand, Sparse Vegetation, Grey Dune Vegetation, Pinus marimima, Incipient Foredune Sand, Established Foredune Sand	Random Forest, NDVI; End-Member Spectra; Stability Index	Hyperspectral Remote Sensing for Biodiversity Mapping	Pixel-based
Dash, JP; Watt, MS; Paul, TSH; Morgenroth, J; Pearse, GD	Early Detection of Invasive Exotic trees Using UAV and Manned Aircraft Multispectral and LiDAR Data	2019	Pinus sylvestris and P. ponderosa	Random Forest; logistic regression	Environmental Remote Sensing	Pixel-based

Appendix 2: The list of Governments in New Zealand and the classified programs for each invasive plant in this research

Region Council		**Woolly Nightshade (S. mauritianum)**	**Gorse (U. europaeus)**	**Sweet Pea Shrub (P. europaeus)**	**Moth Plant (A. sericifera)**
Auckland Council	Program	Sustained Control - Whole region Eradication	Sustained Control - Whole region Aotea Island- Eradication	Sustained Control Aotea Island-	Sustained Control
	Management	Monitor and weed control at prioritised high biodiversity value areas. Action upon complaints. Landowner control.			
	Finding GNR	Yes	No	No	
Bay of Plenty Regional Council	Program	Absent	Absent	Absent	
	Management	Absent	Absent	Absent	
	Finding	Absent	Absent	Absent	
	GNR	Absent	Absent	Absent	
Chatham Islands Council	Program	Absent	Sustained Control	Absent	
	Management	Absent	No formal procedure	Absent	
	Finding	Absent	No formal procedure	Absent	
	GNR	Absent	Yes	Absent	
Environment Canterbury	Program	Absent	Absent	Absent	
	Management	Absent	Absent	Absent	
	Finding	Absent	Absent	Absent	
	GNR	Absent	Absent	Absent	
Environment Southla nd	Program	Absent	Sustained Control	Absent	
	Management	Absent	No formal procedure	Absent	
	Finding	Absent	No formal procedure	Absent	
	GNR	Absent	No	Absent	
Gisborne District Council	Program	Progressive Containment	Progressive Containment	Absent	Progressive Containment
	Management	Occupier	Occupier	Absent	Occupier
	Finding	No formal procedure	No formal procedure	Absent	No formal procedure

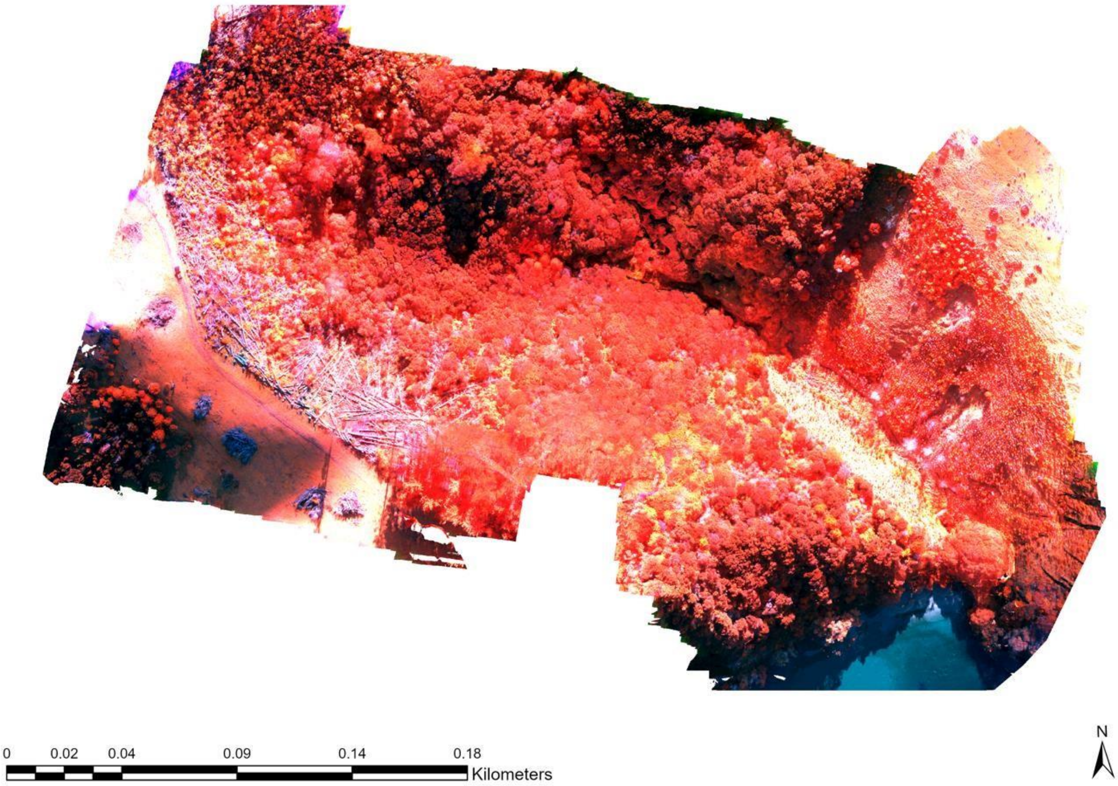
	GNR	Yes	Yes	Absent	Yes
Greater Wellington Regional Council	Program Management	Eradication Monitor known sites until no plants have been found for nine consecutive years.	Harmful organism Controlled within GGWRC's Key Native Ecosystem program (areas of high biodiversity value throughout the region) depending on the site.	Harmful Organism	Eradication Monitoring or surveillance in areas that are vulnerable.
	Finding	Through public and staff. Software and apps used are Collector, ArcMap and Survey123 – to help record new sites and keep data on current sites.			
	GNR	No	No	No	
	Program	Progressive Containment	Sustained Control	Absent	Harmful Organisms
Hawkes Bay Regional Council	Management	Monitor known sites until no plants have been found for five consecutive years.	No Formal Procedure	Absent	
	Finding	Through public and staff. Added to a spreadsheet of sites present		Absent	
	GNR	Yes		Absent	
Horizons Regional Council	Program Management	Eradication Occupier	Progressive Containment Occupier and Council	Absent Absent	Progressive Containment Occupier and Council
	Finding	Through public and staff.	No Formal Procedure	Absent	Public
	GNR	No	Yes	Absent	Yes
Marlborough District Council	Program Management	Sustained Control Monitor and control known sites. Landowner control.	Sustained Control Landowner control. Only monitor containment zones, via aerial surveillance, landowner communications, surveillance, and compliance work in containment areas.	Absent Absent	Sustained Control Landowner Control
	Finding	Monitoring of Inaturalist in Marlborough daily. Through public and staff. Biosecurity officer mark plants in using GPS.		Absent	
	GNR	No	Yes	Absent	No

Northland Regional Council	Program Management	Sustained Control	Sustained Control	Absent Absent	
	Finding			Absent	
	GNR		Yes	Absent	
Otago Regional Council	Program Management	Absent Absent	Sustained Control Landowner control. Property owners clear their boundaries for a distance of 10 metres providing the complainants boundary is already clear. Act only upon complaints.	Absent Absent	Exclusion
	Finding	Absent	Only four sub areas and fly over one sub area each year for surveillance. Infestations are logged on GPS sand then followed up with the landowner.	Absent	
	GNR	Absent	Yes	Absent	No
	Program	Absent	Sustained control	Absent	Eradication
Taranaki Regional Council	Management	Absent	Landowner control. Two site visits per annum for our eradication species and undertake control work if needed. App called pest mapper which records all known infestations of listed pest plants.	Absent	The Council will undertake direct control of Moth plant.
	Finding	This is a complaints-based system so is only recorded if a complaint has come through. Both Gorse and Woolly Nightshade have biocontrol programmes in the region		Absent	Known sites to manage

	GNR	Absent	Yes	Absent	No
Tasman District Council	Program Management	Absent Absent	Sustained Control	Absent Absent	
	Finding	Absent		Absent	
	GNR	Absent	Yes	Absent	
Waikato Regional Council	Program Management	Sustained control Landowner control. Council enforces those rule upon local people complaint. Annual control and monitor of sites visits and delimit a 50-100 meters radius	Sustained Control Council enforces boundary control on a complaint from an adjoining landowner. No formal monitoring program.	Absent Absent	Progressive containment
	Finding	Staff and complaints findings.		Absent	Staff and Public
	GNR	No	Yes	Absent	Yes
West Coast Regional Council	Program	Progressive containment/ eradication	Sustained Control	Absent	
	Management	Landowner control. Action upon request.	No monitoring or control.	Absent	
	Finding	Maps shows pest plants that only need to be controlled within those zones. DOC provided the data for the distribution of pest plants across the coast. No formal procedure to follow to detect new sites of interest.	No formal procedure to follow to detect new sites of interest.	Absent	
	GNR	Yes	Yes	Absent	

Appendix 3: Segmented images

Segment 1



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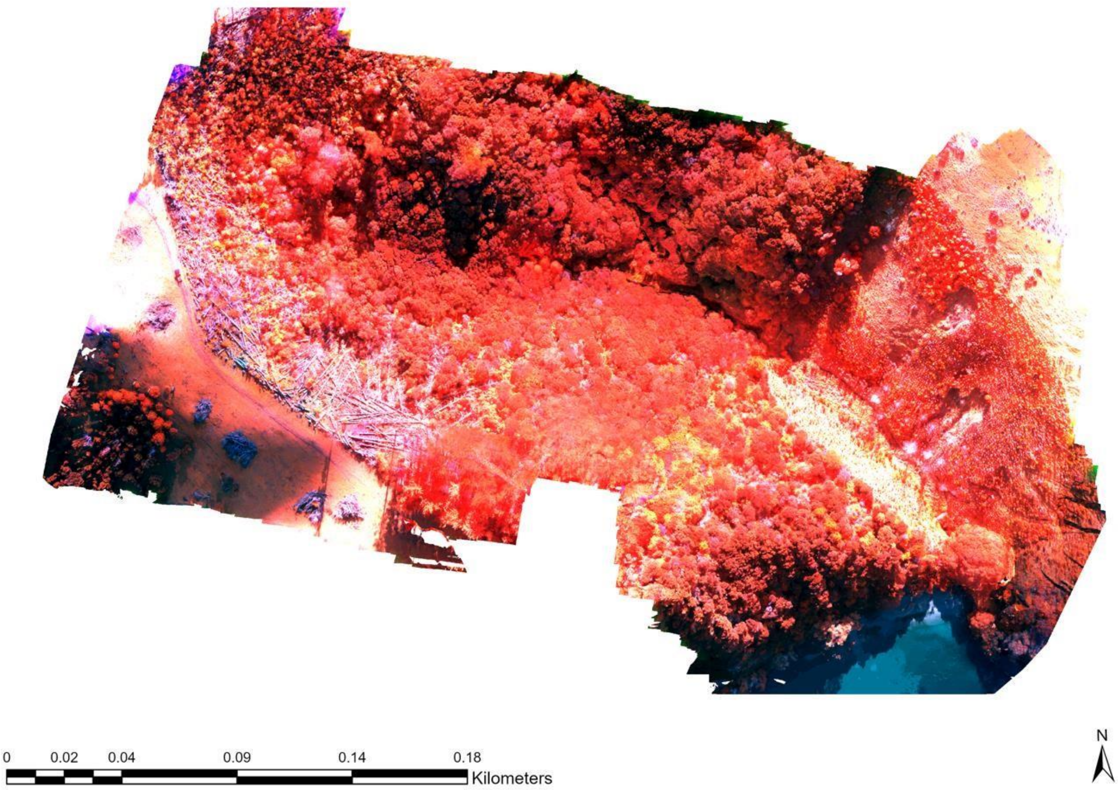

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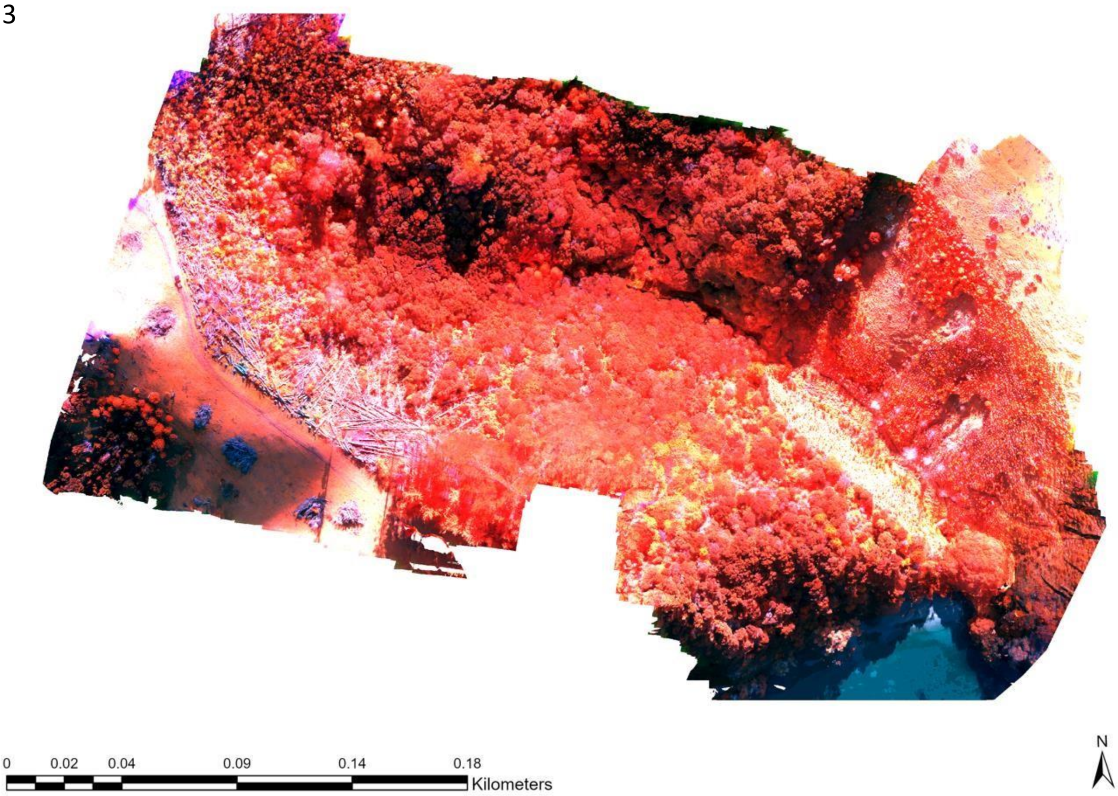

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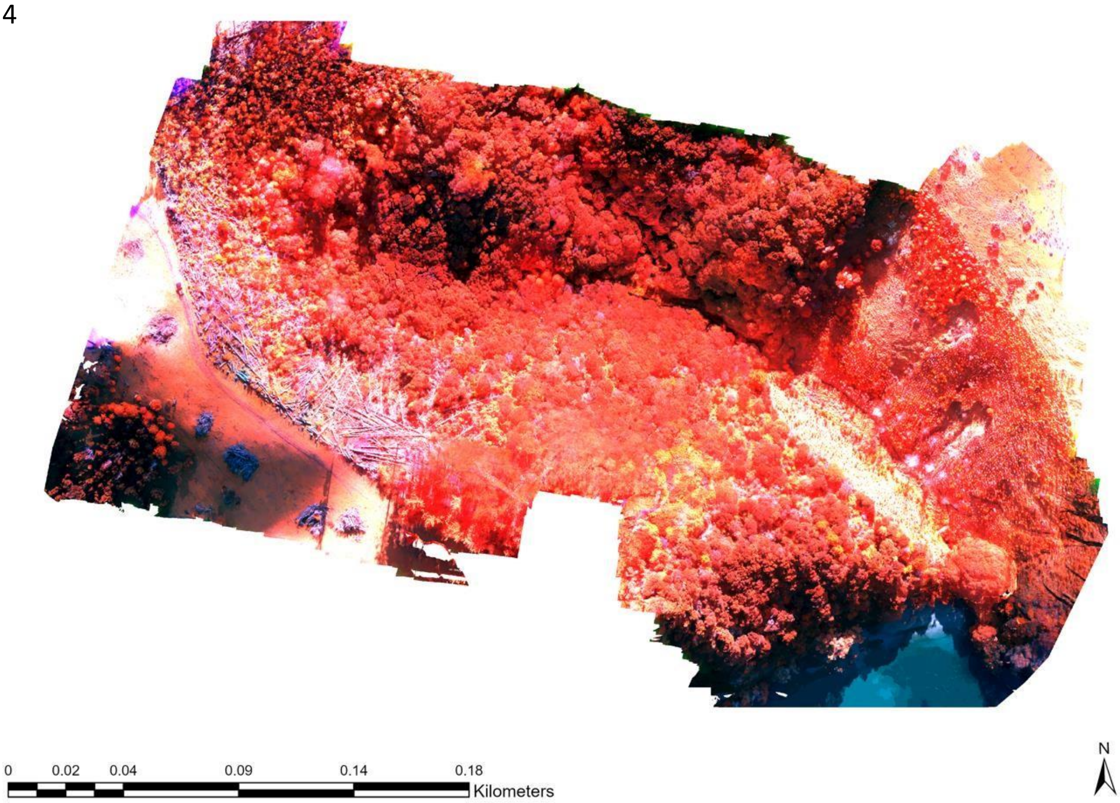

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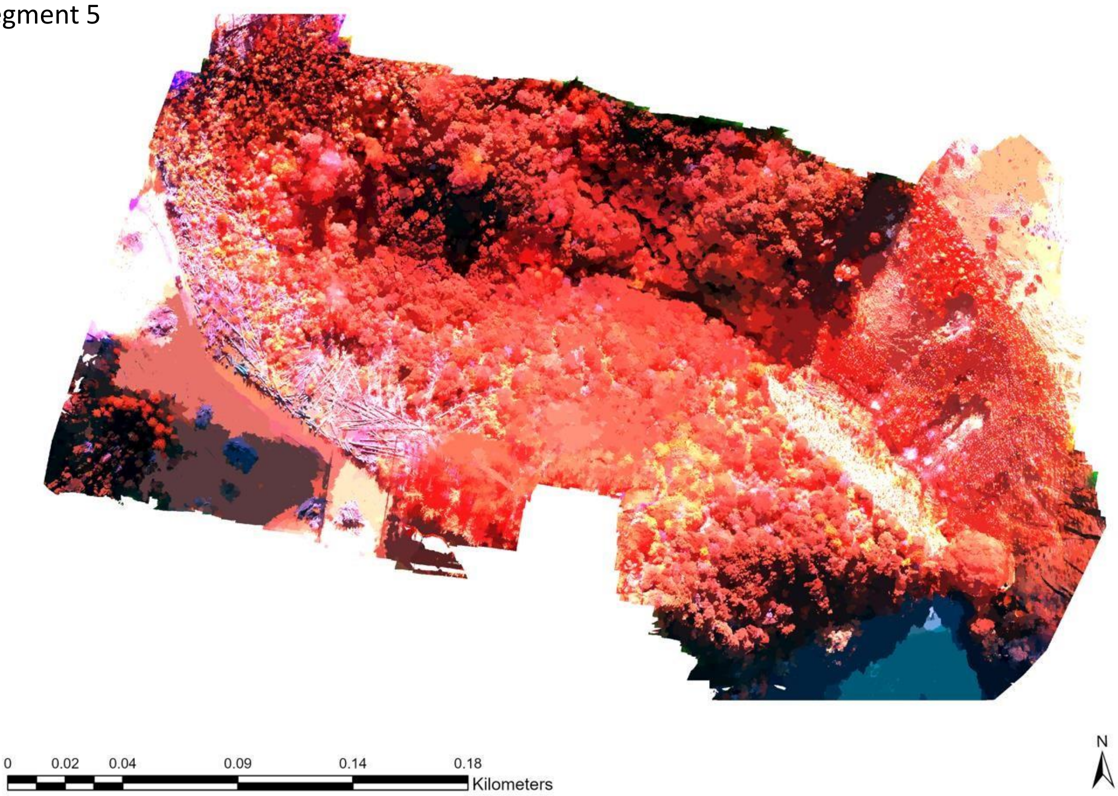

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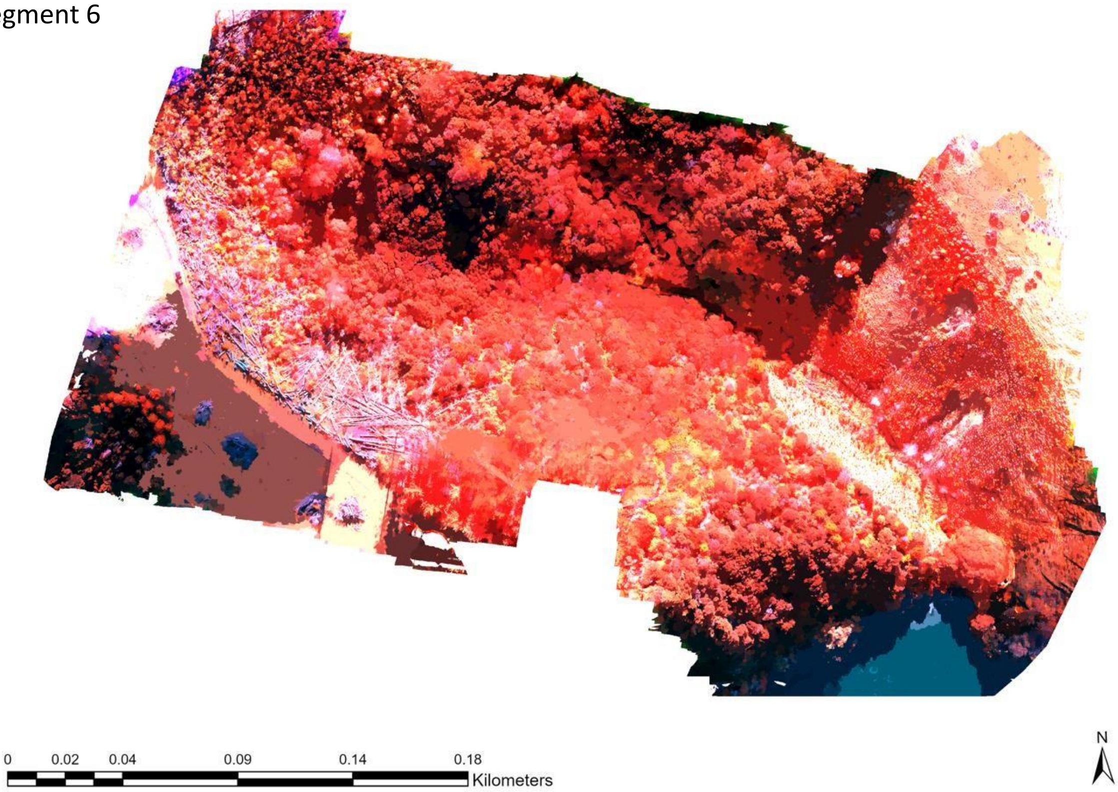

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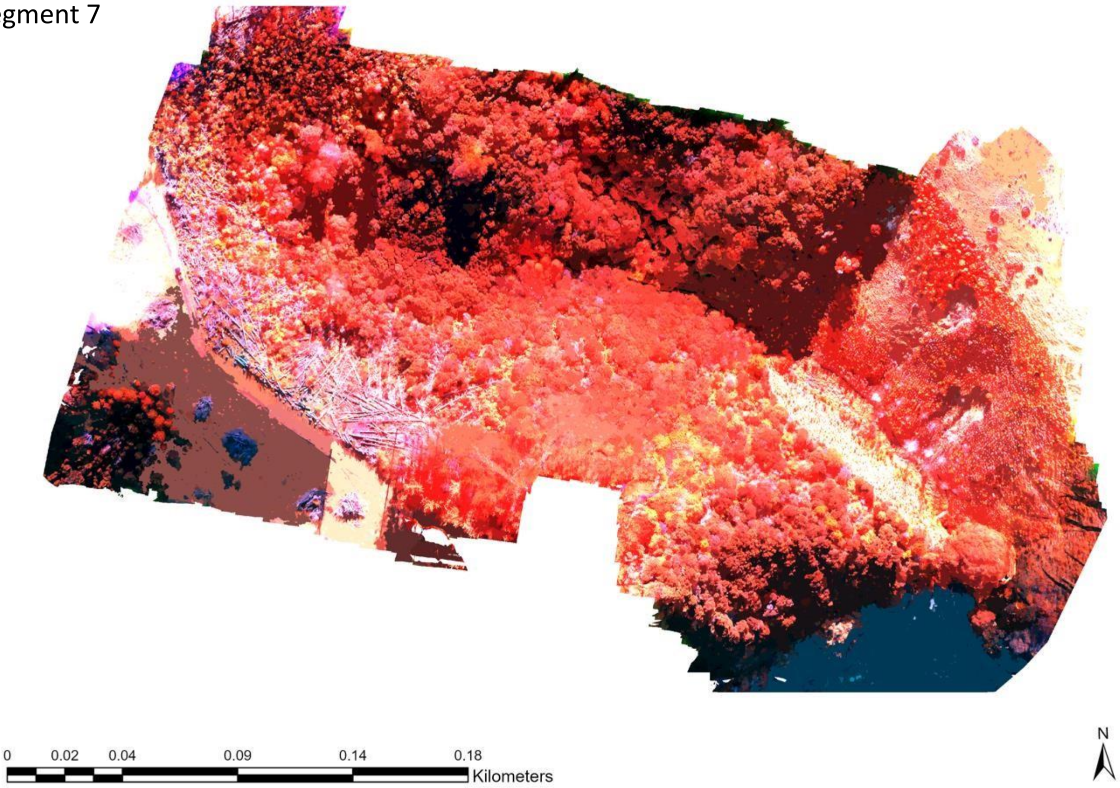

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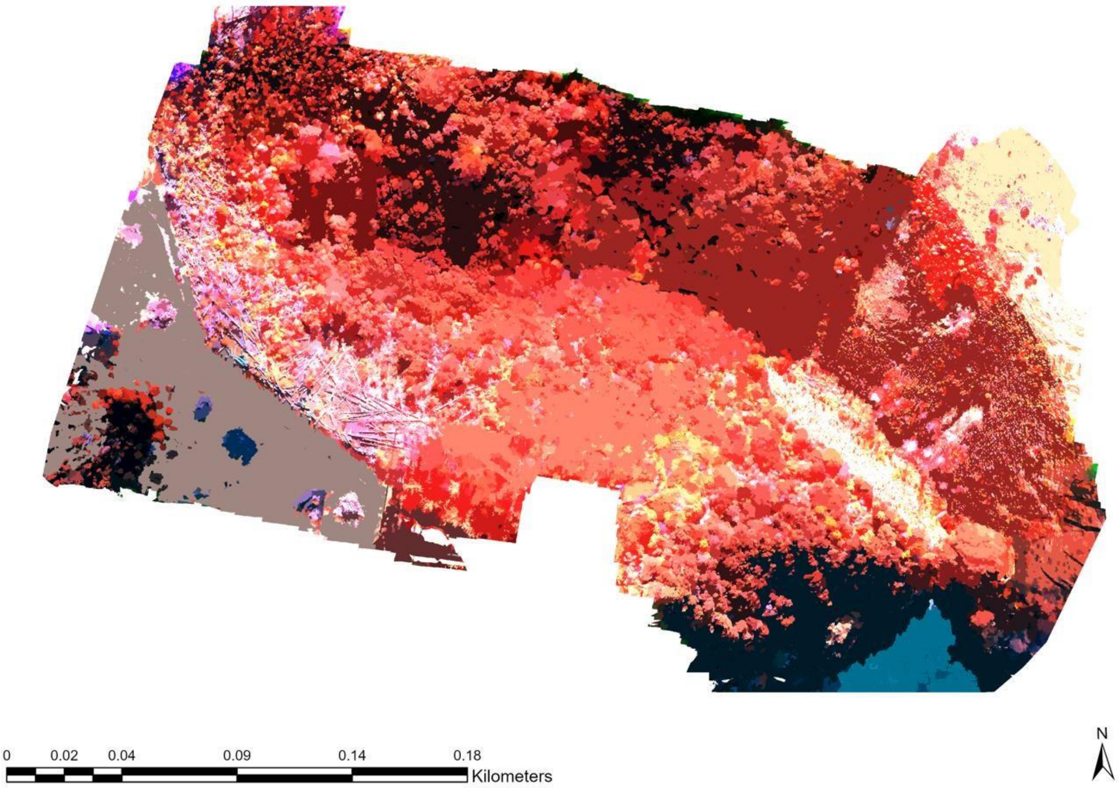

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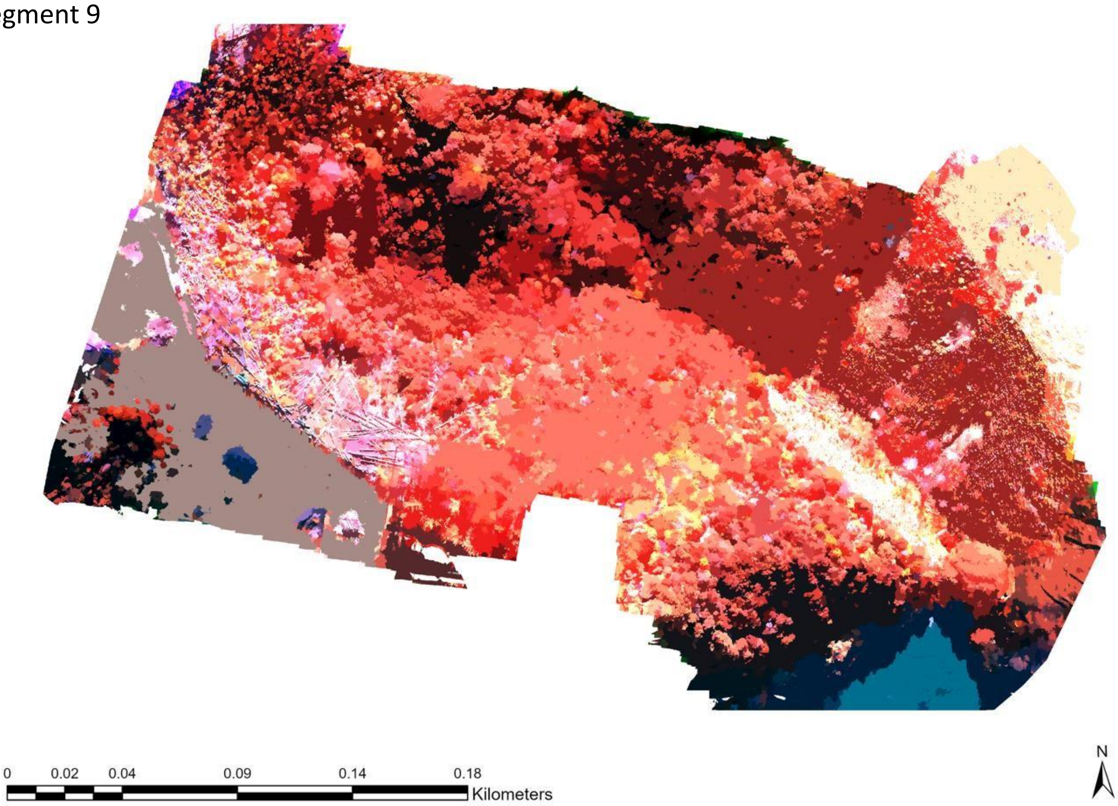
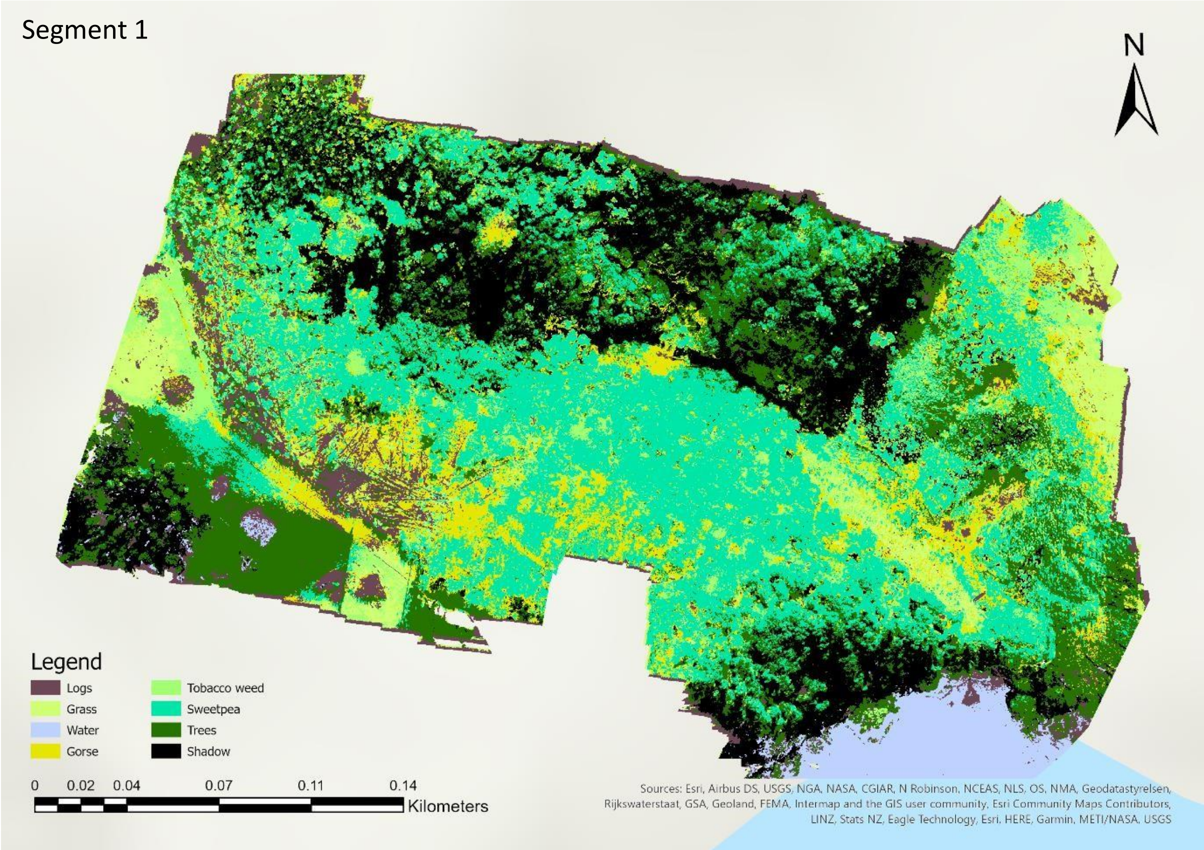
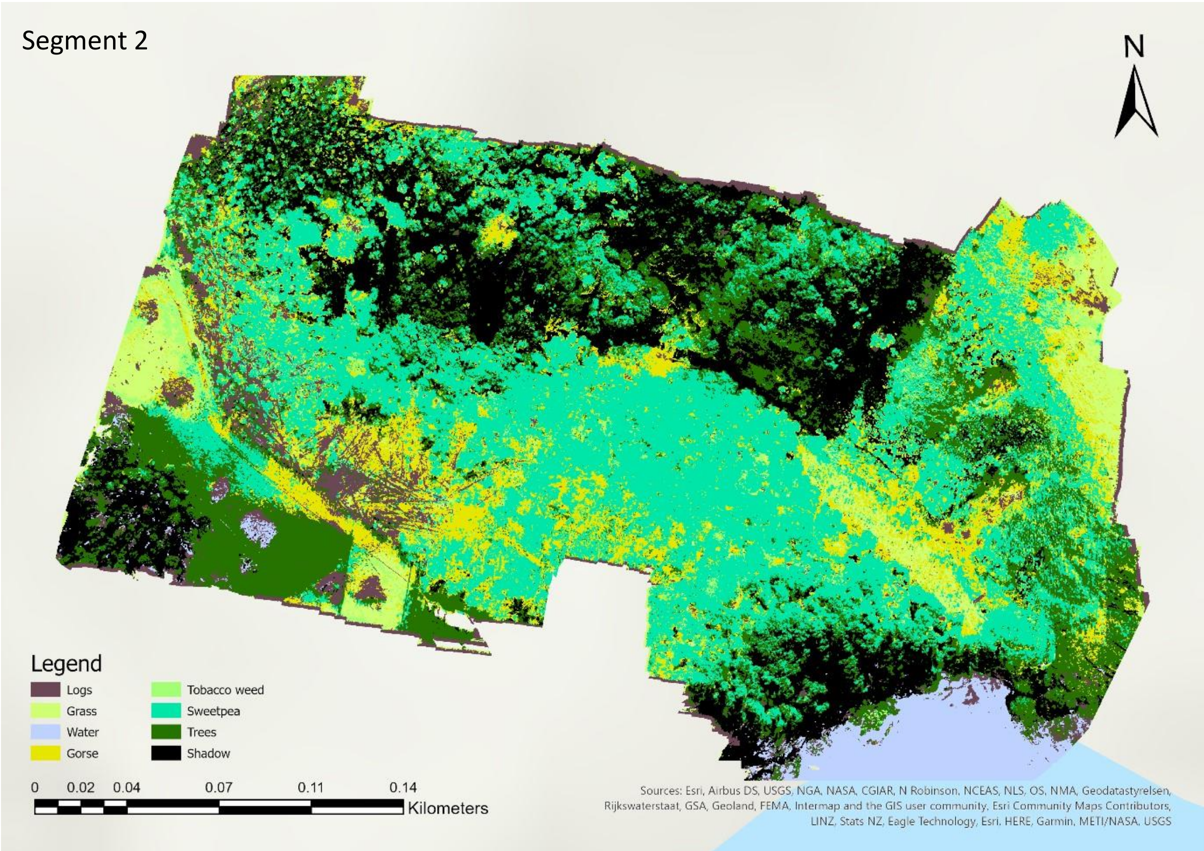
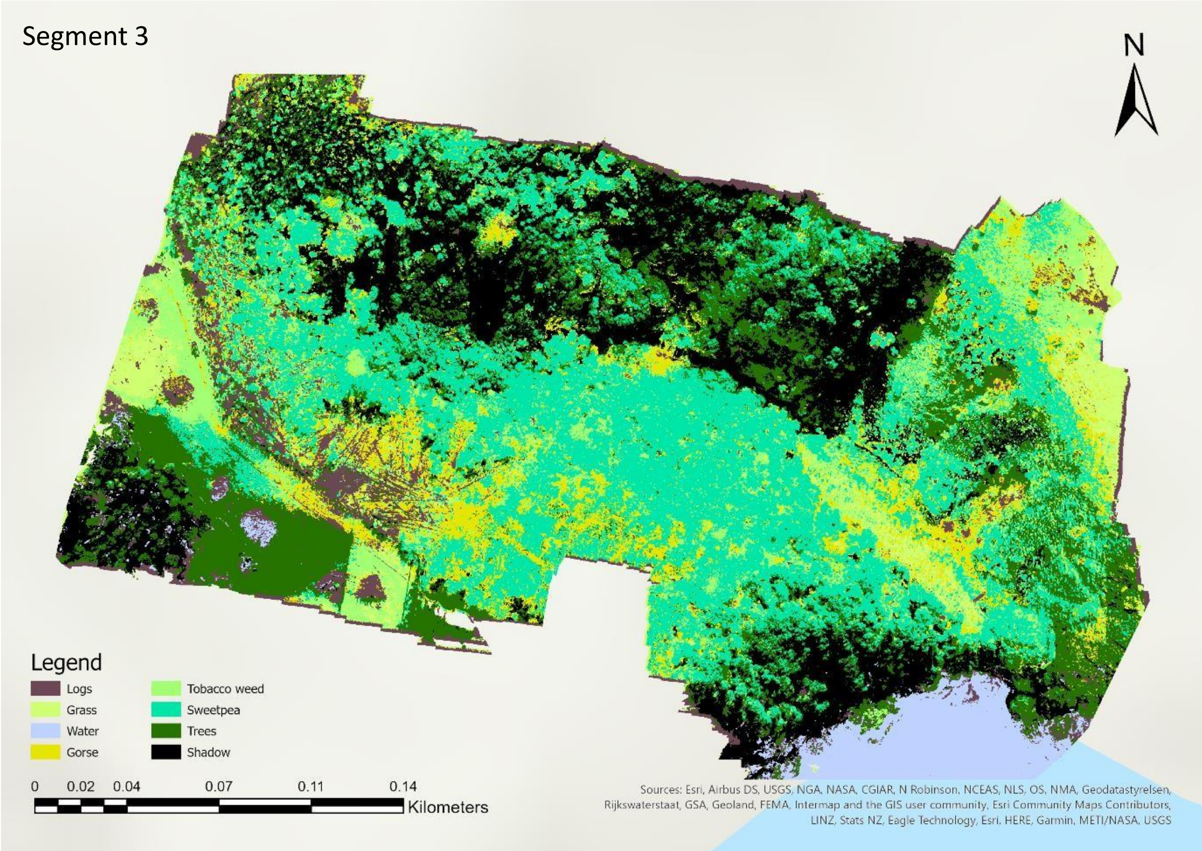


Appendix 4: Maximum Likelihood classified maps



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Water
Gorse
Tobacco weed
Sweetpea
Trees
Shadow
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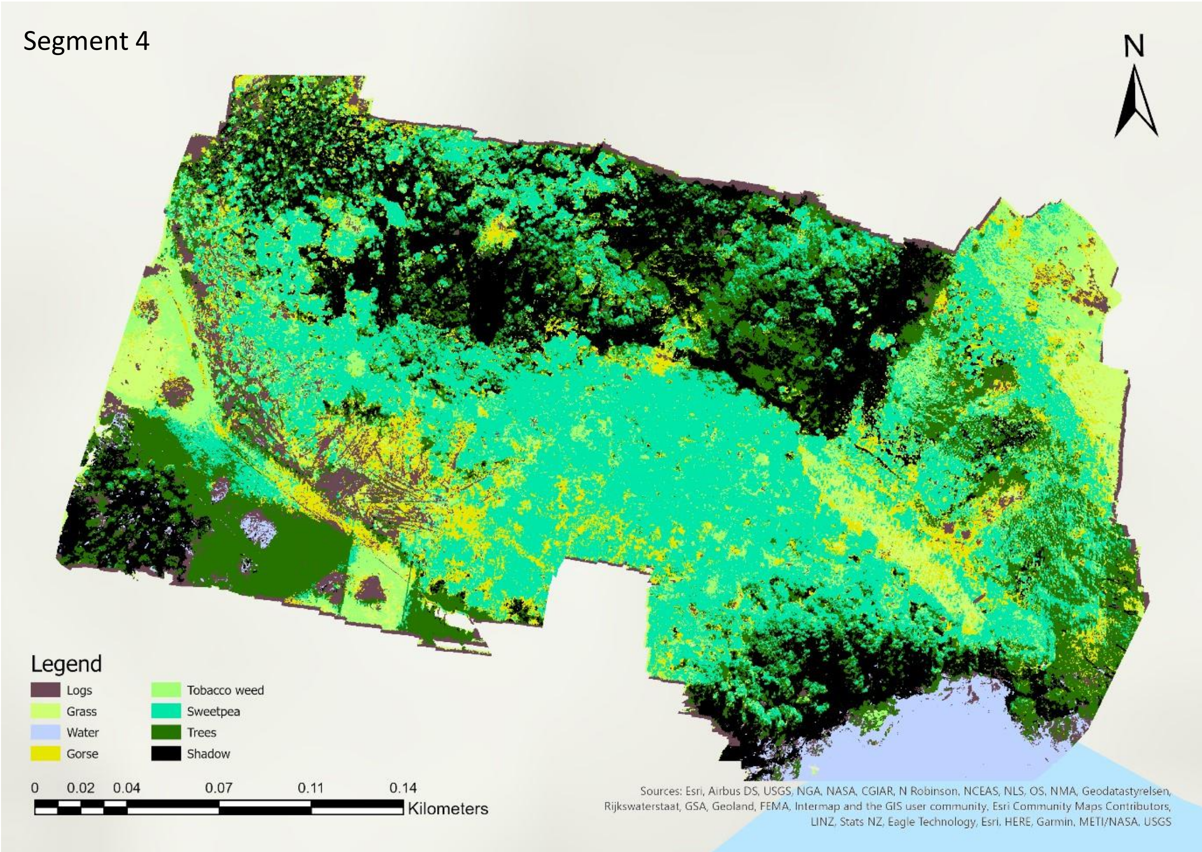
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS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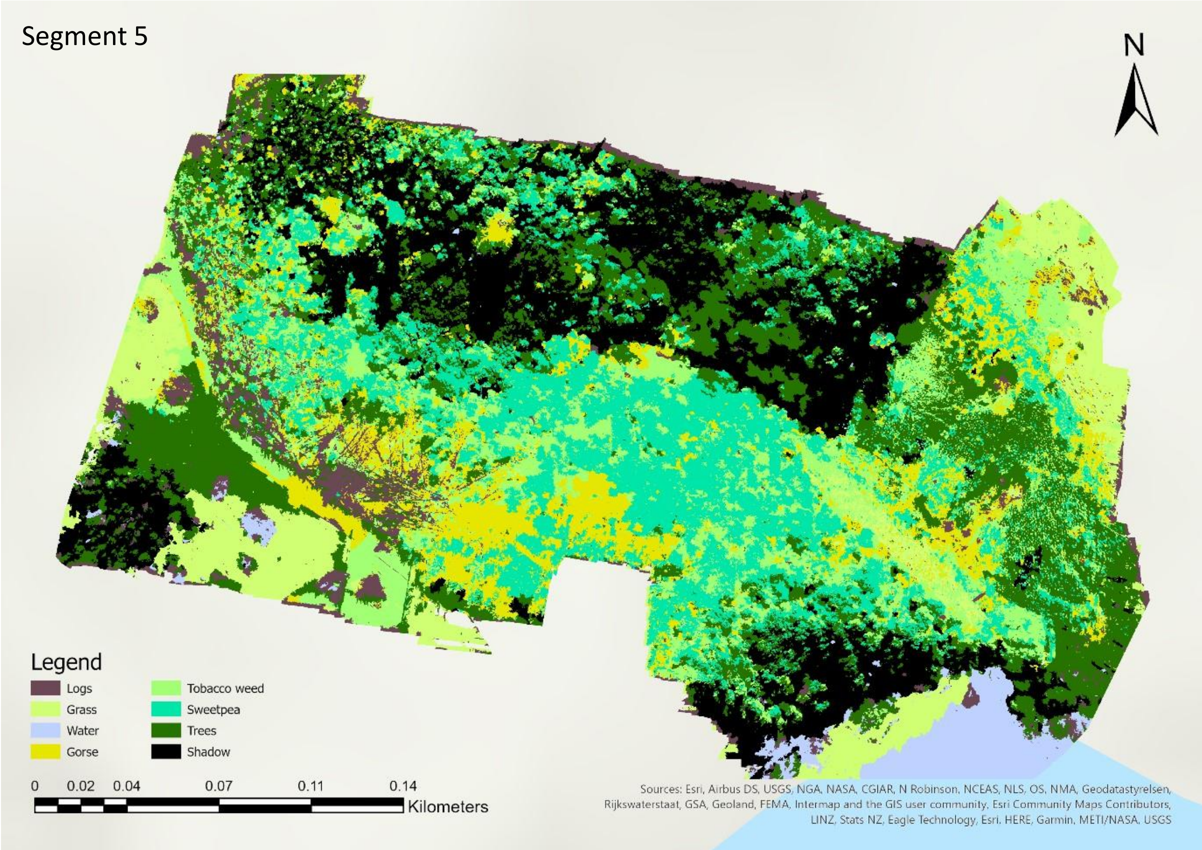
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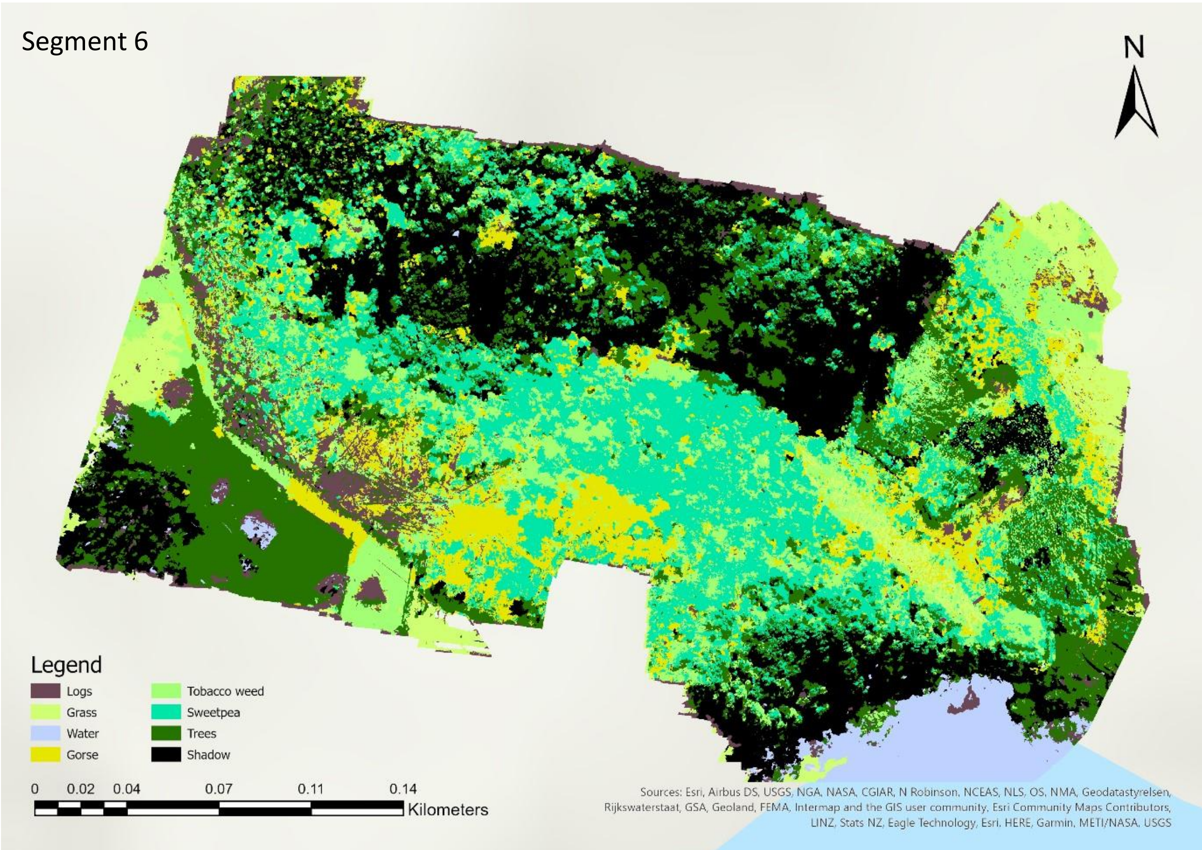
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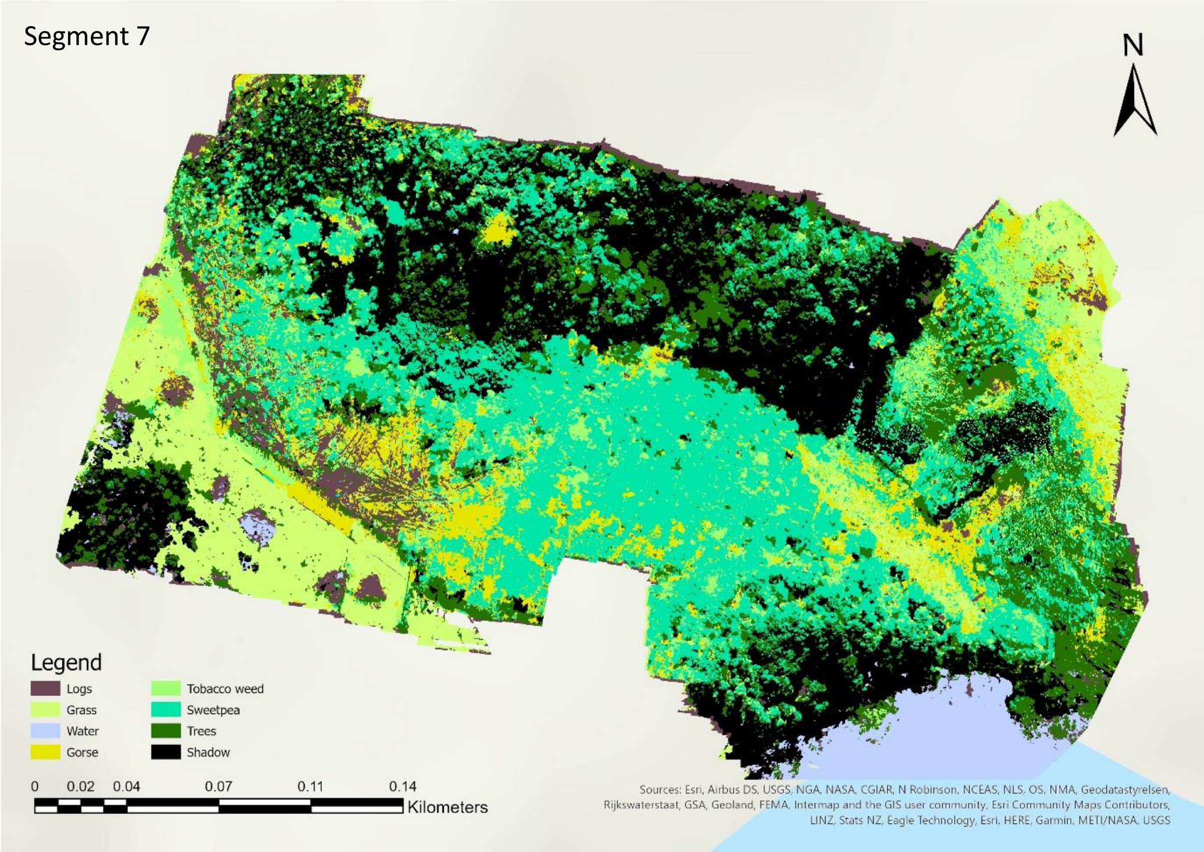
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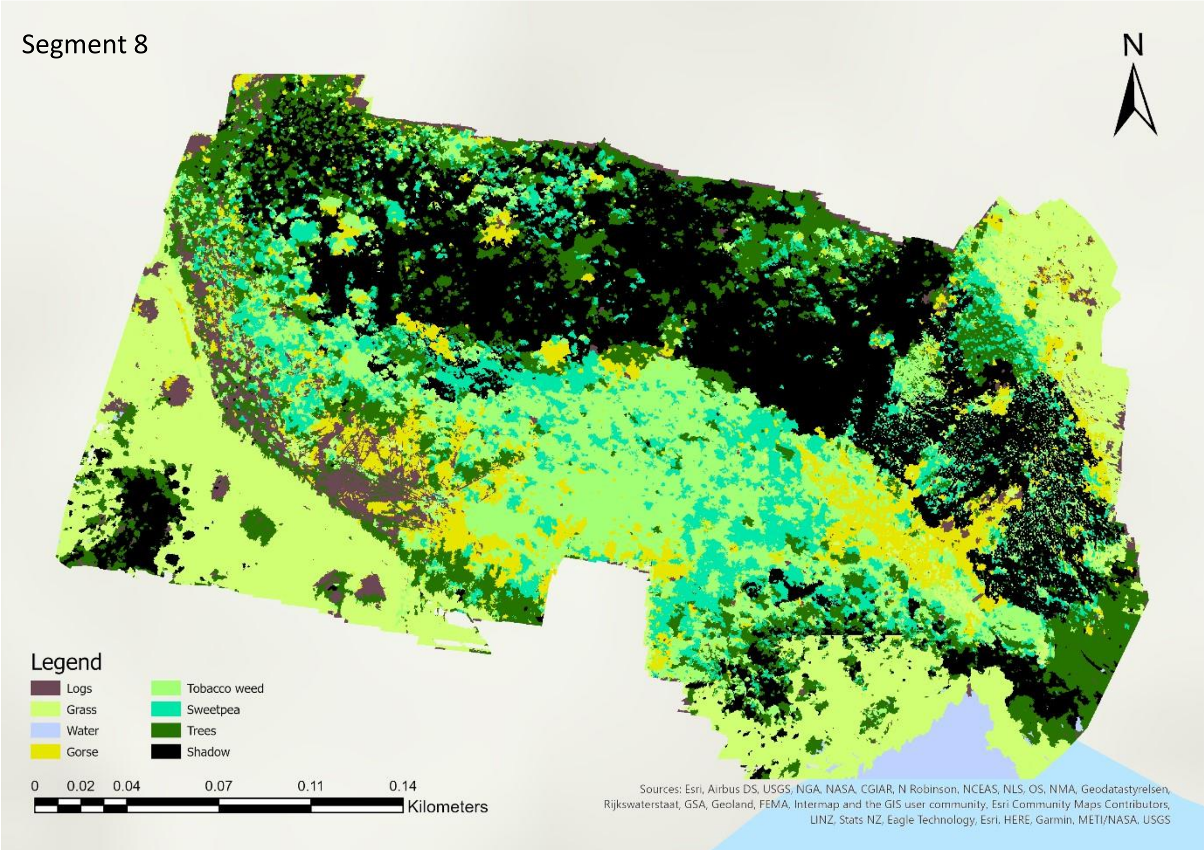
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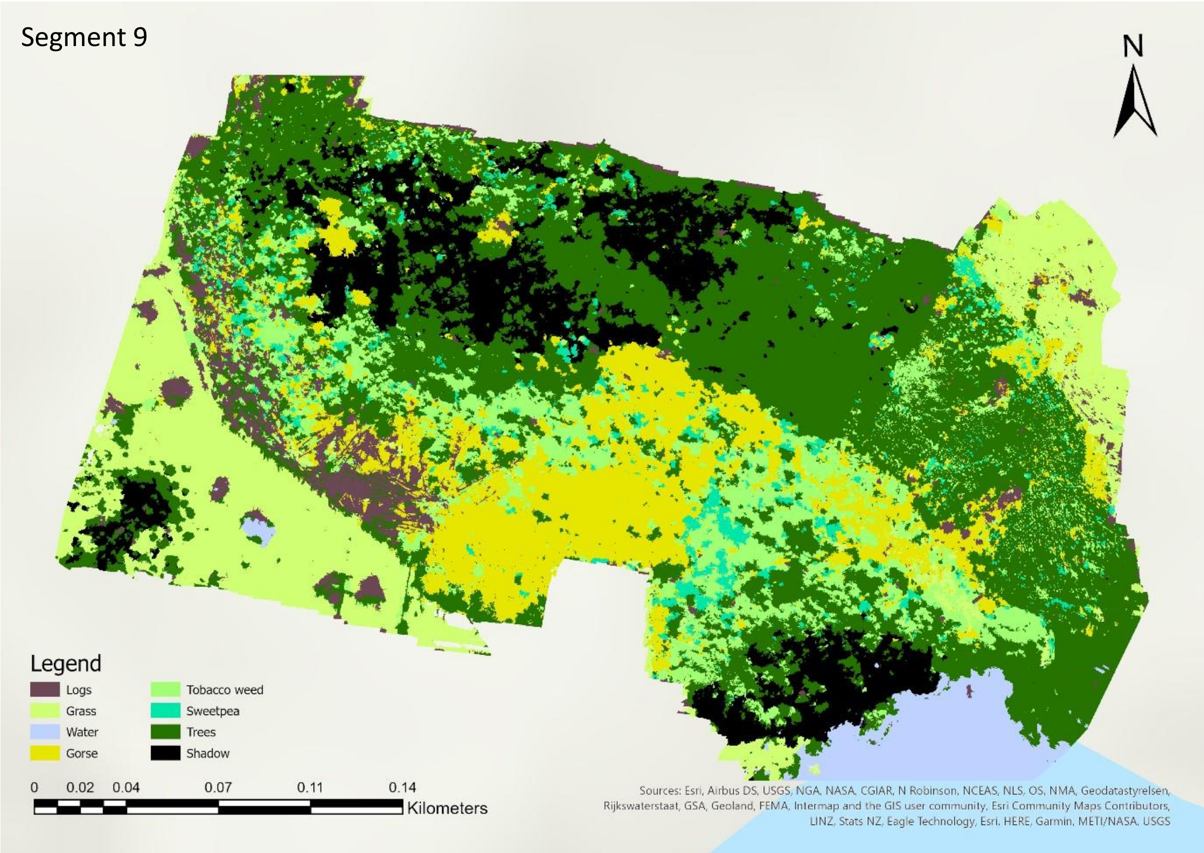
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Kilometers
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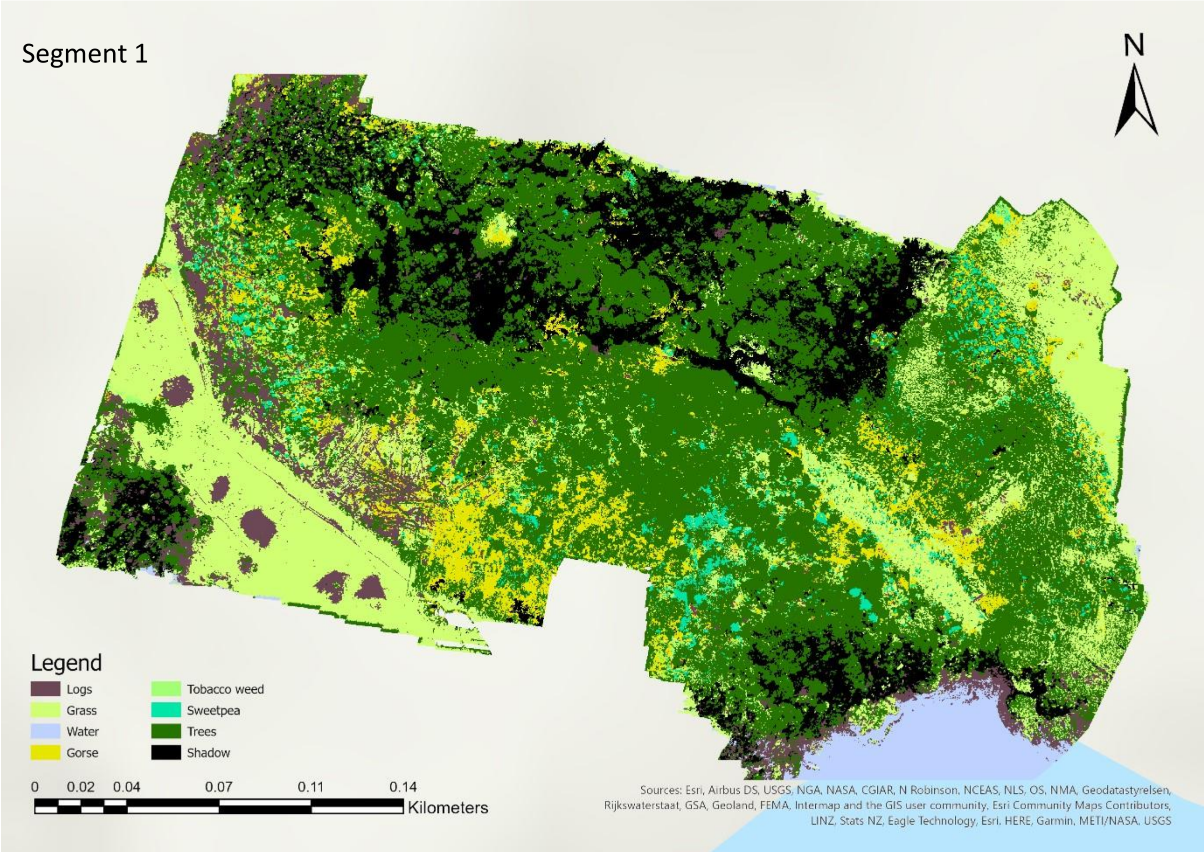
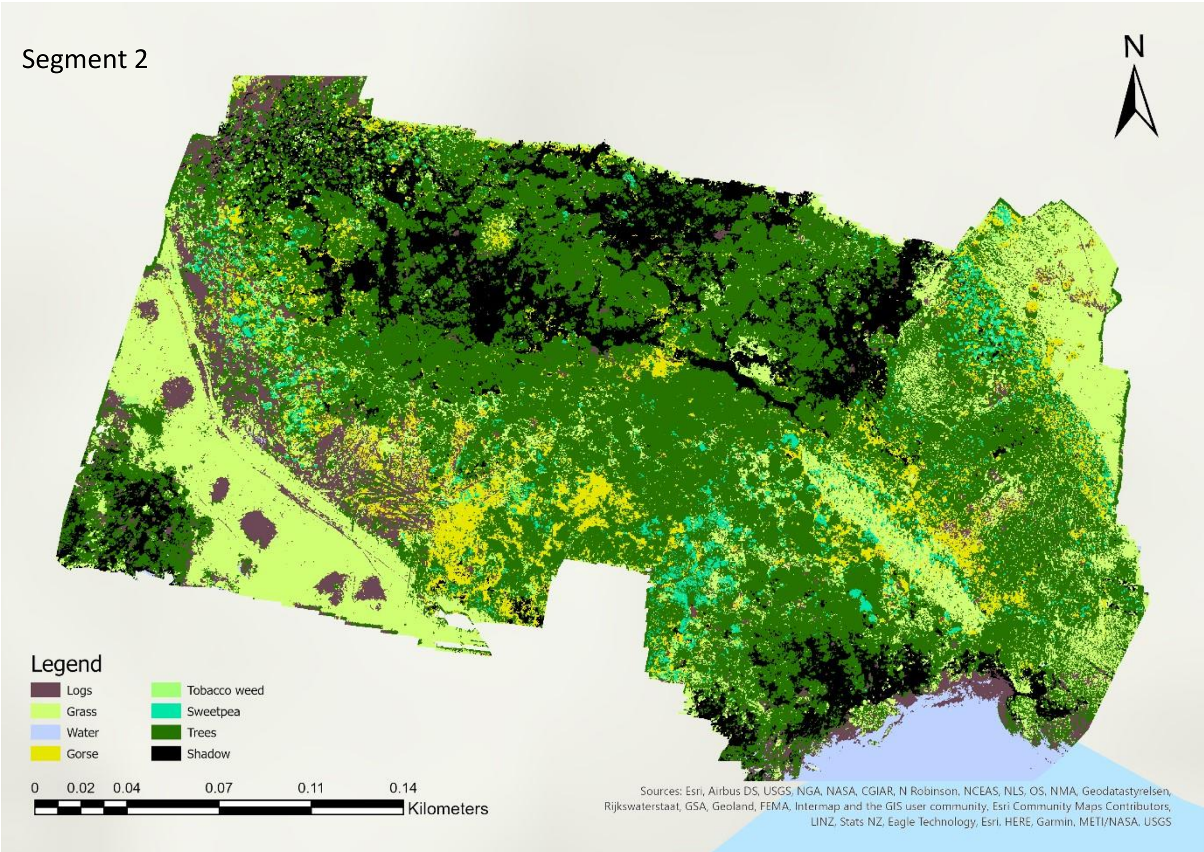
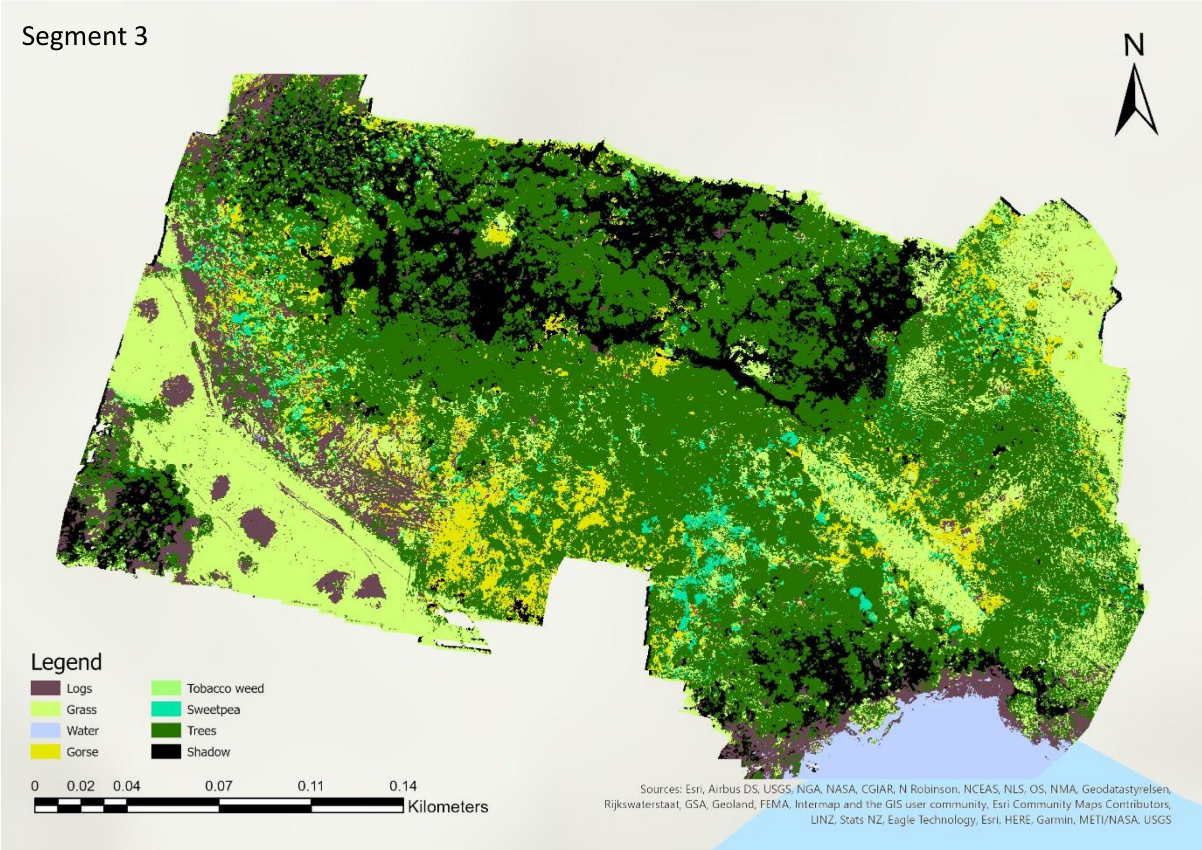
Appendix 5: Support Vector Machine classified maps



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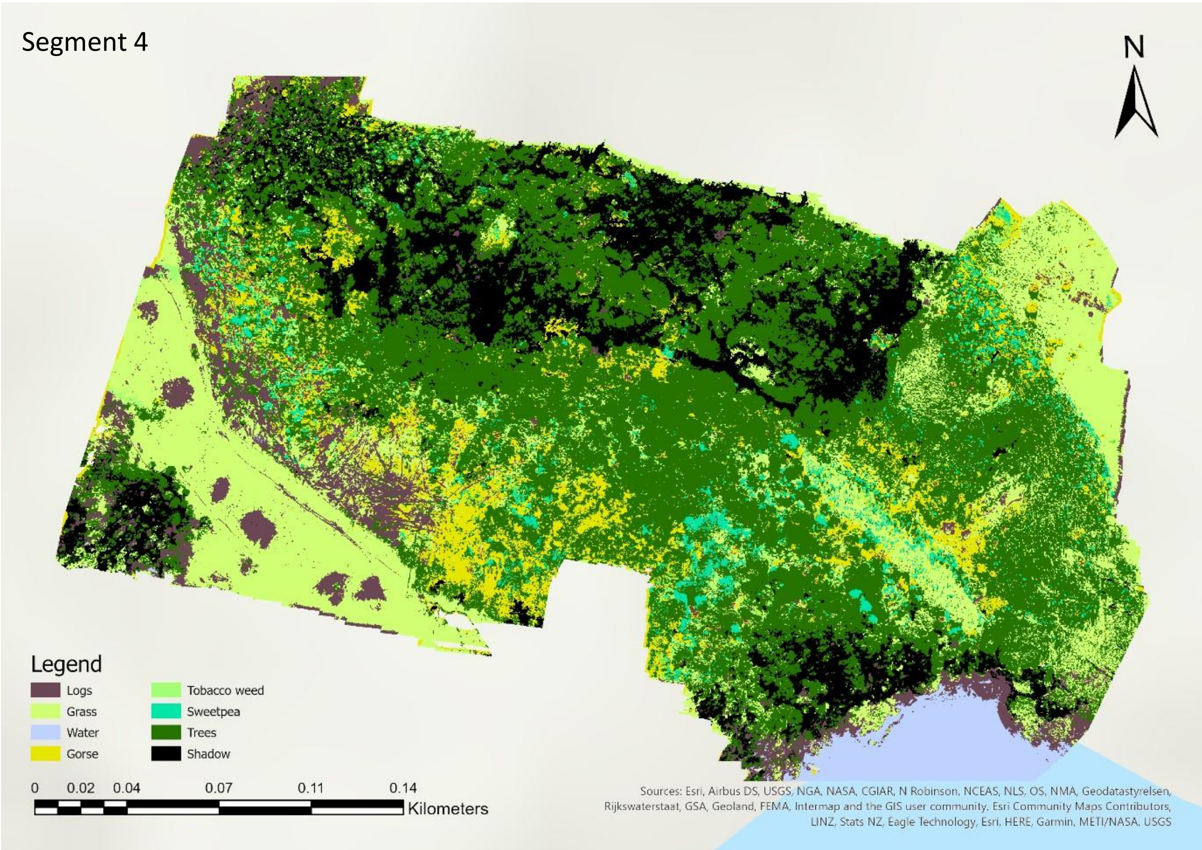
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS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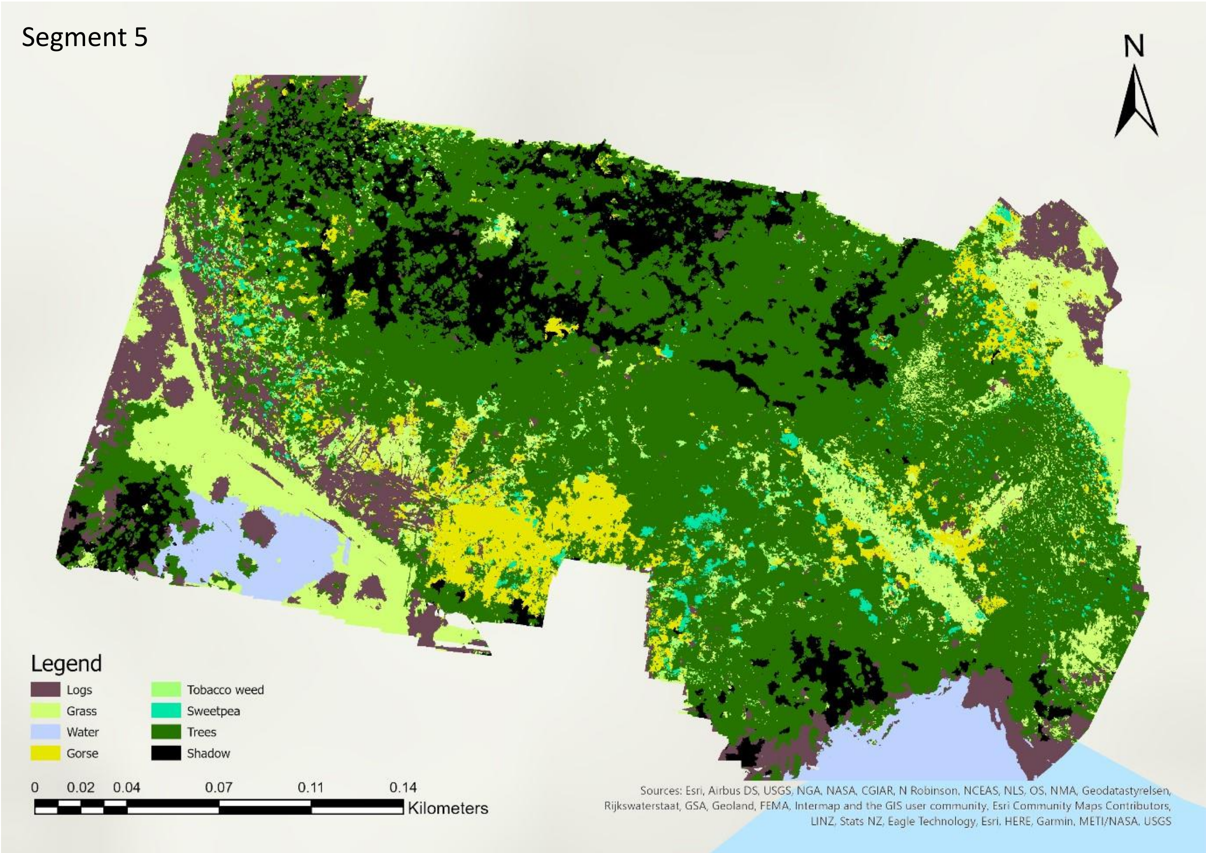
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS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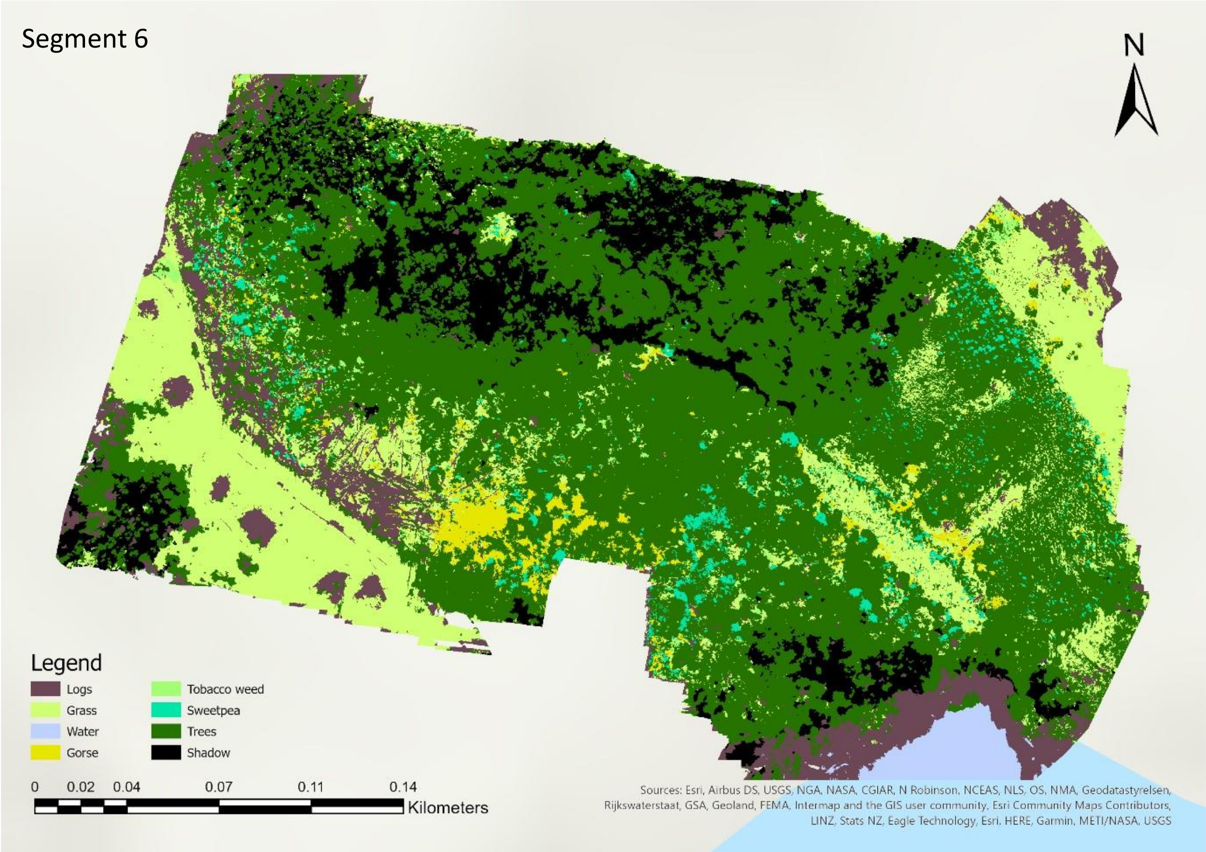
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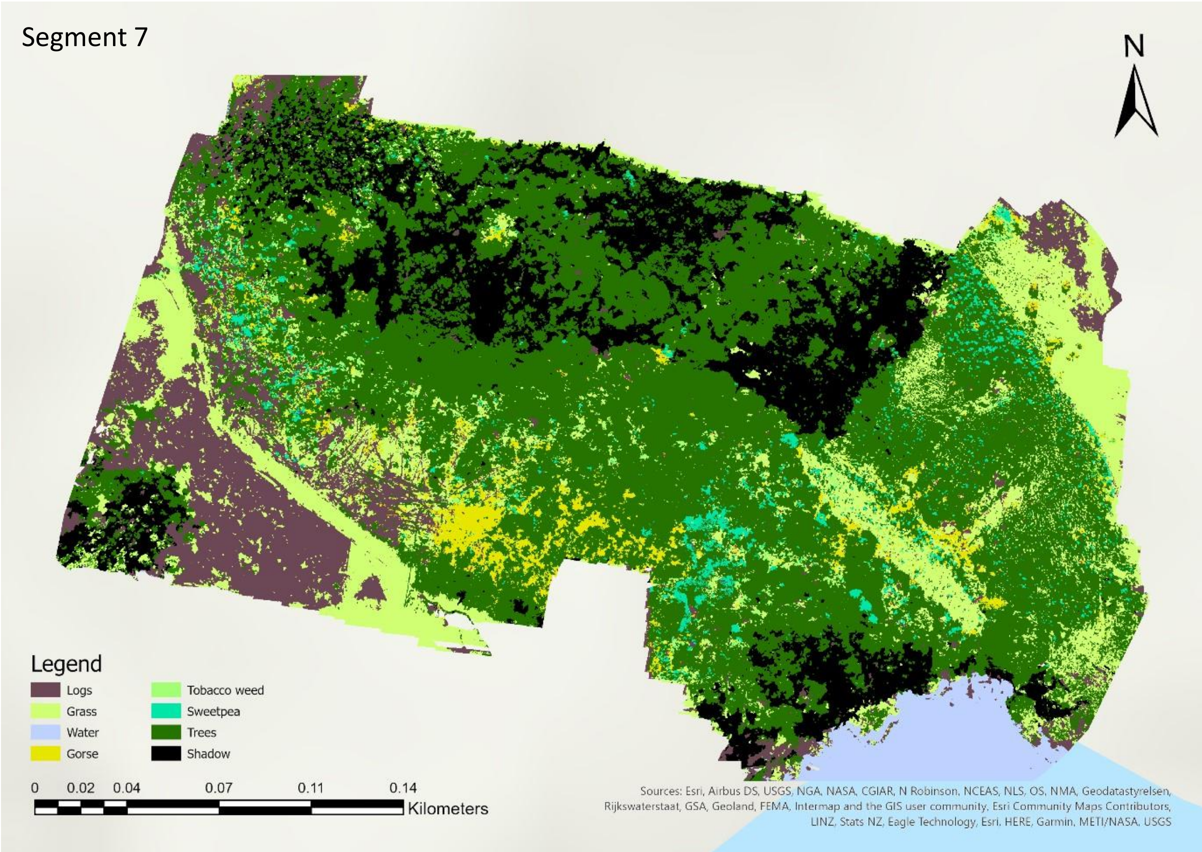
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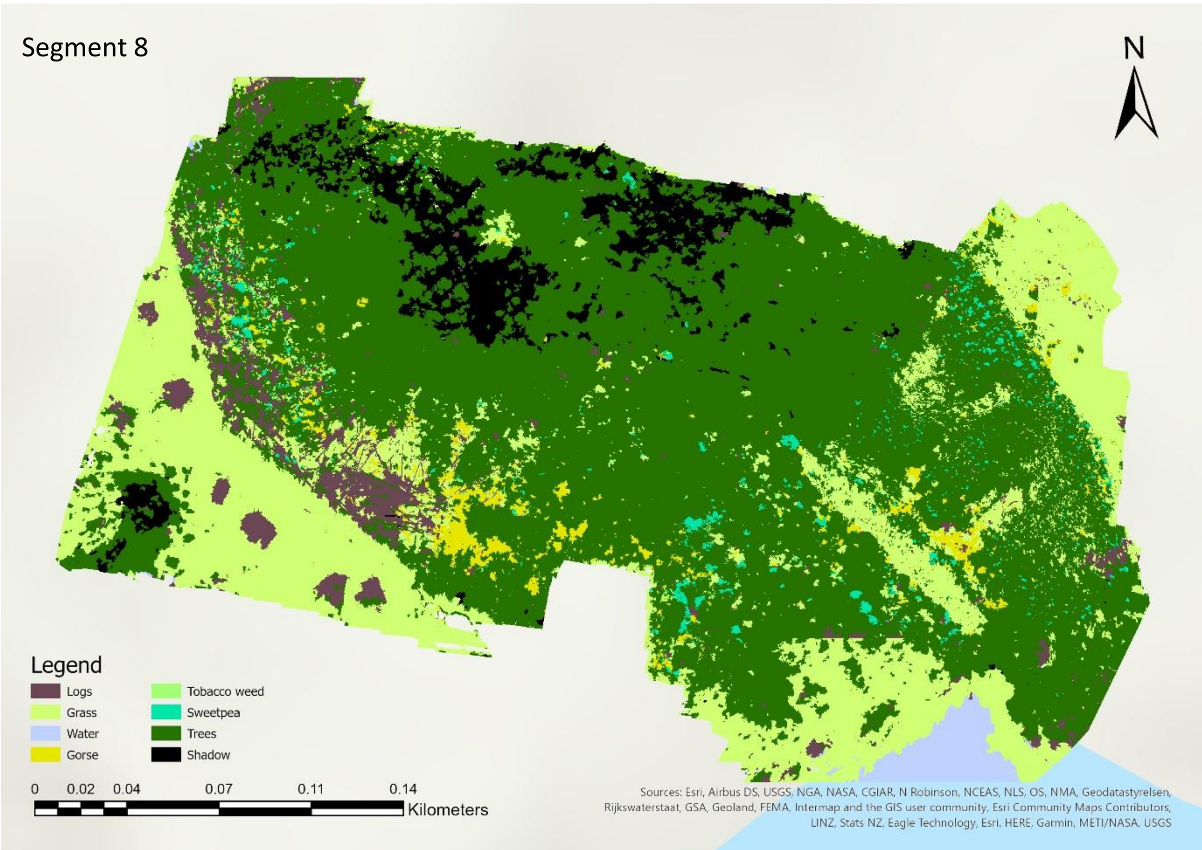
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS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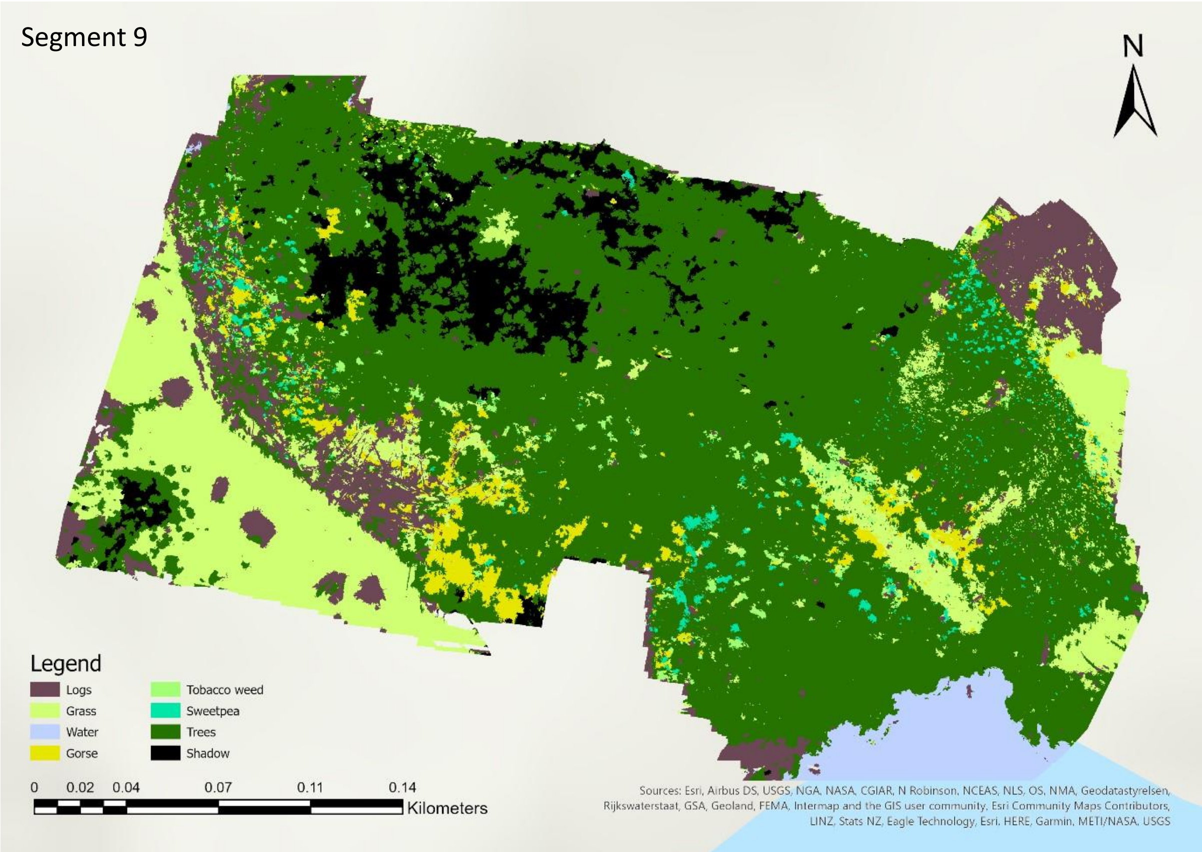
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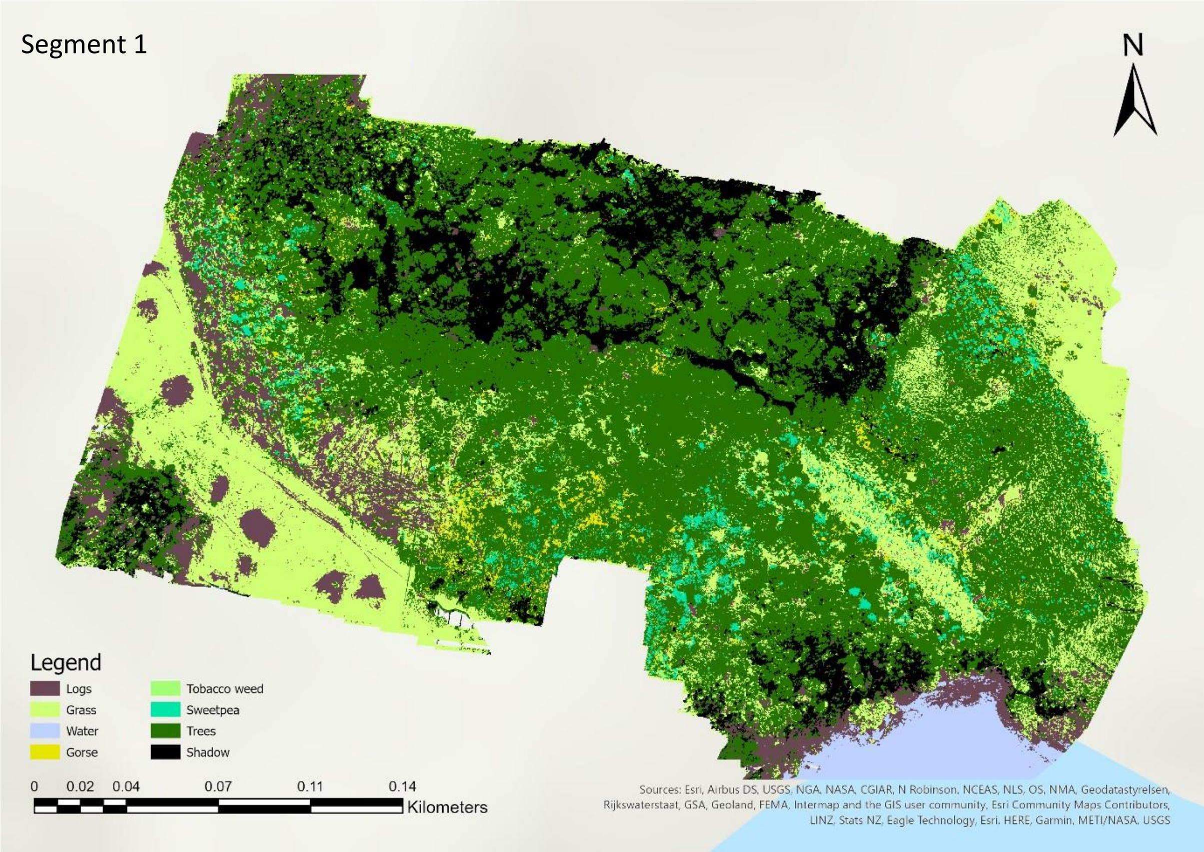
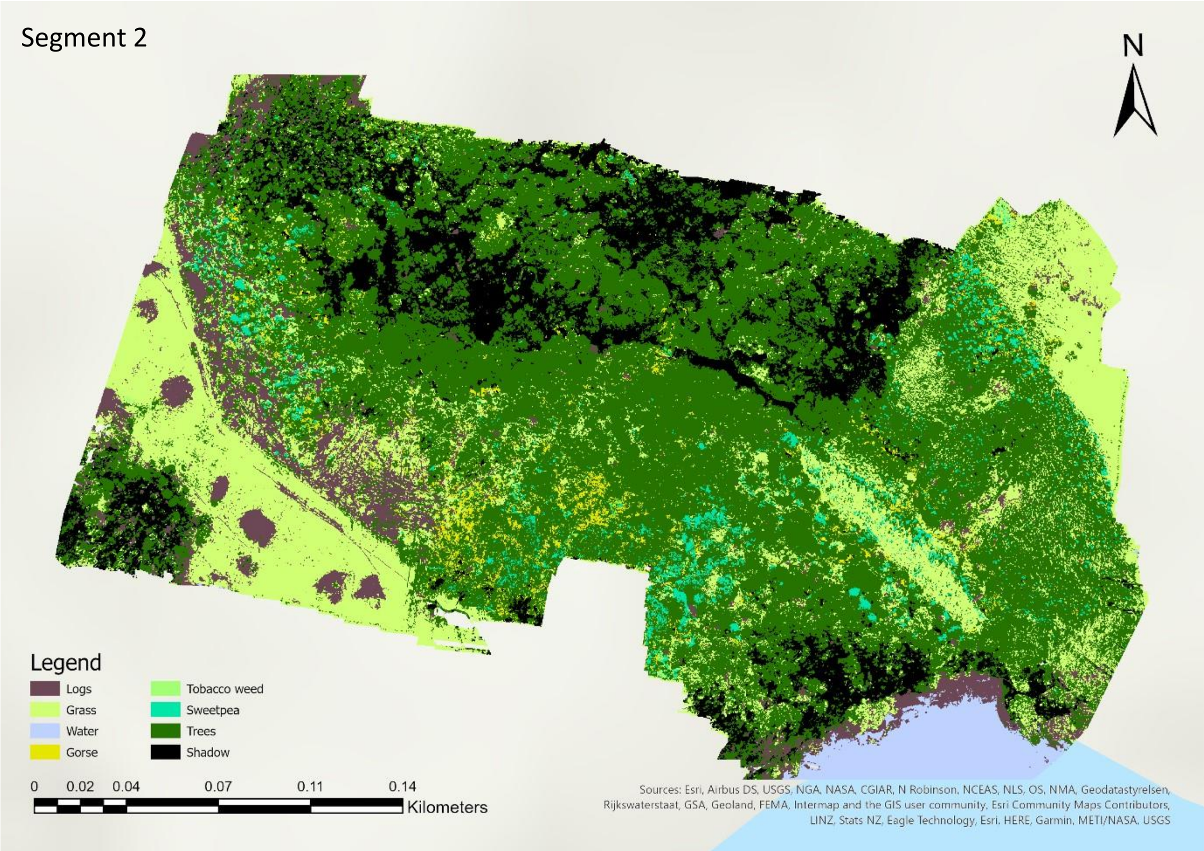
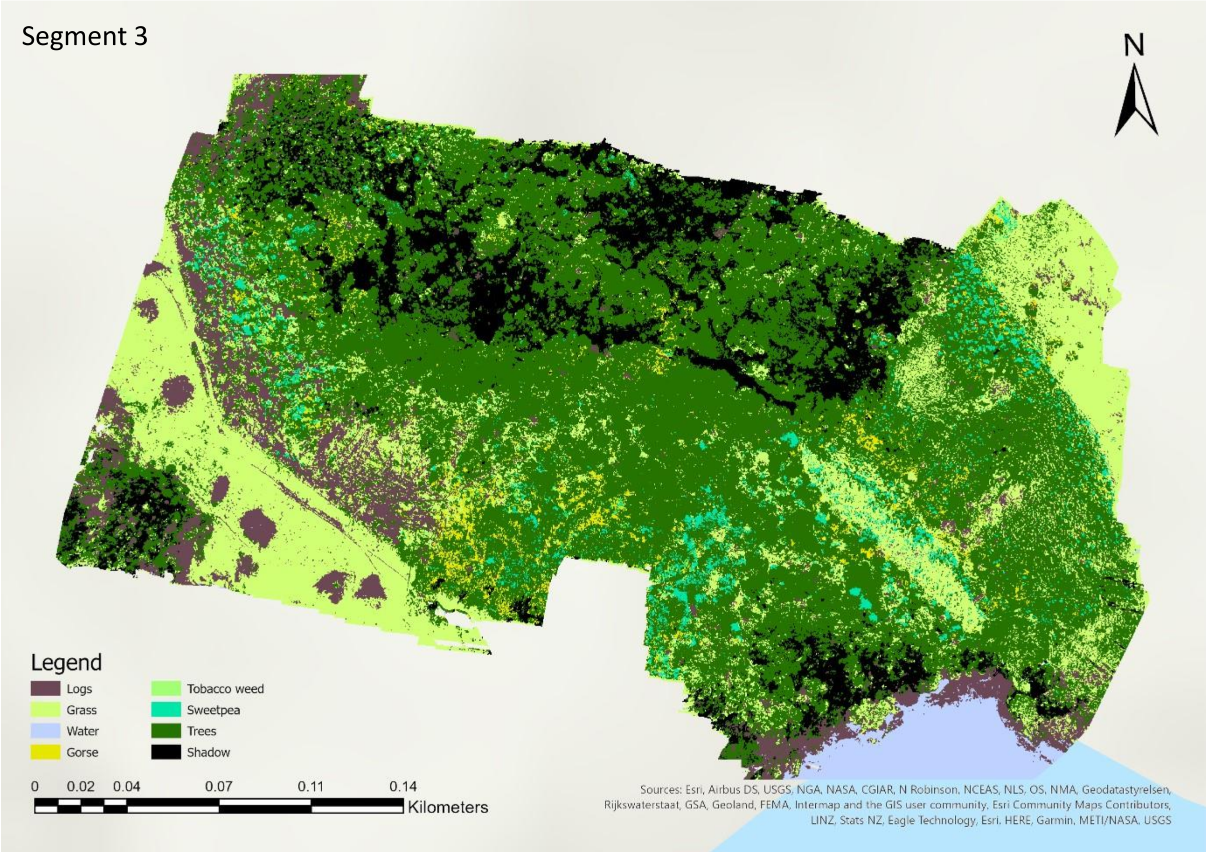
Appendix 6: Random Trees classified maps







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Trees
Shadow
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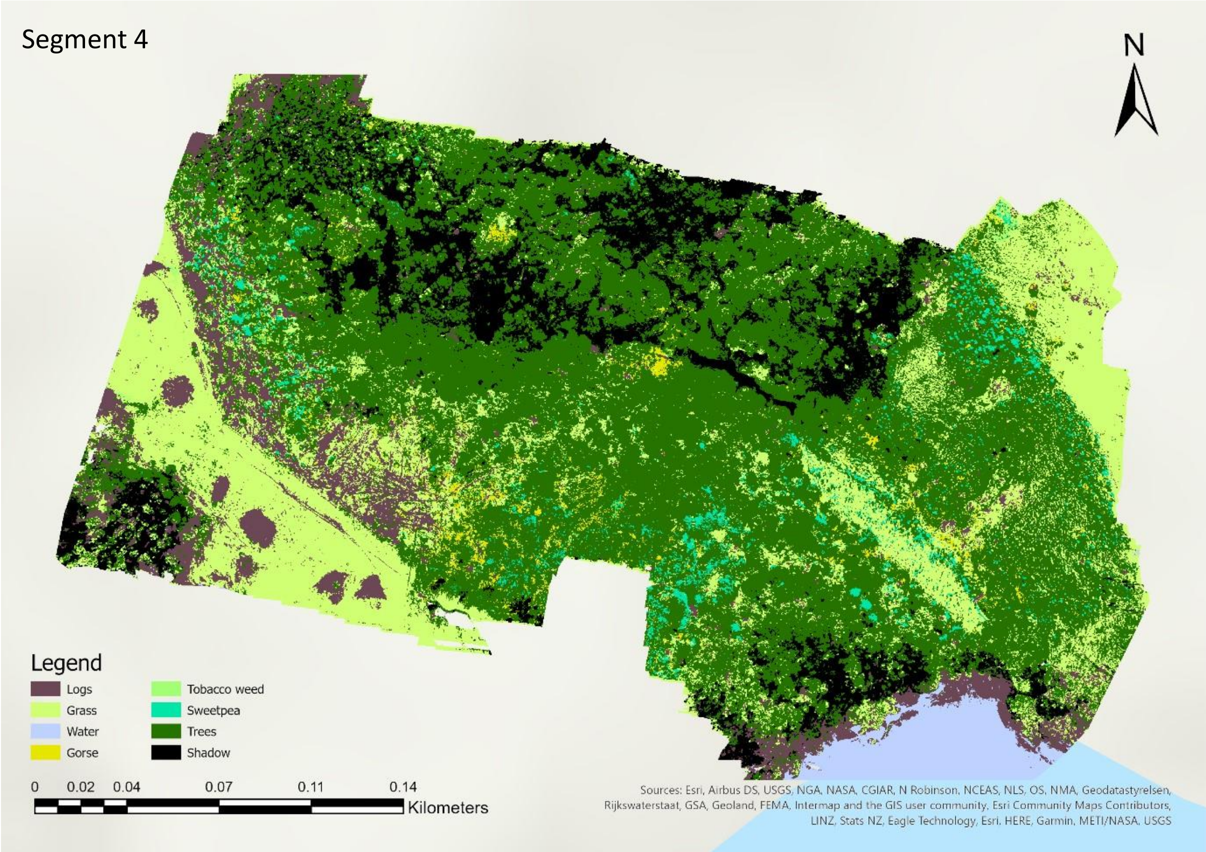
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS



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Trees
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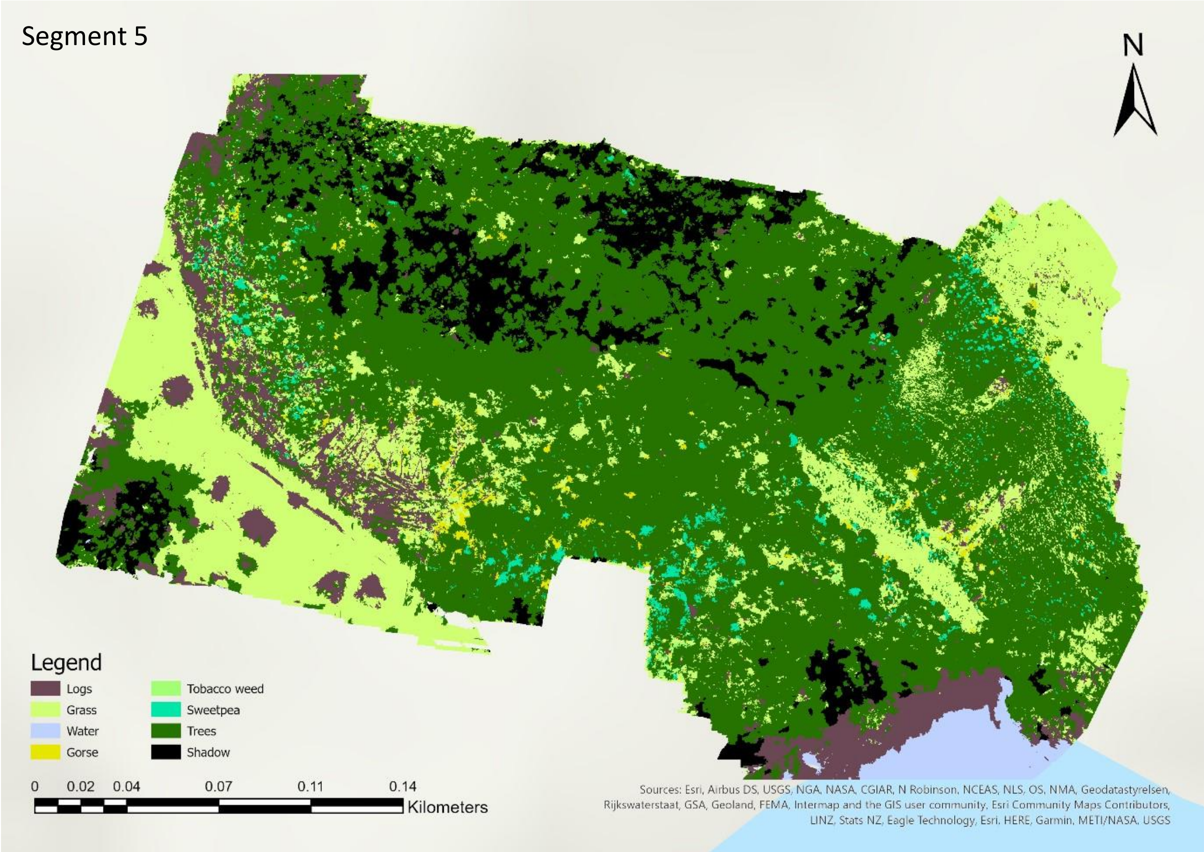
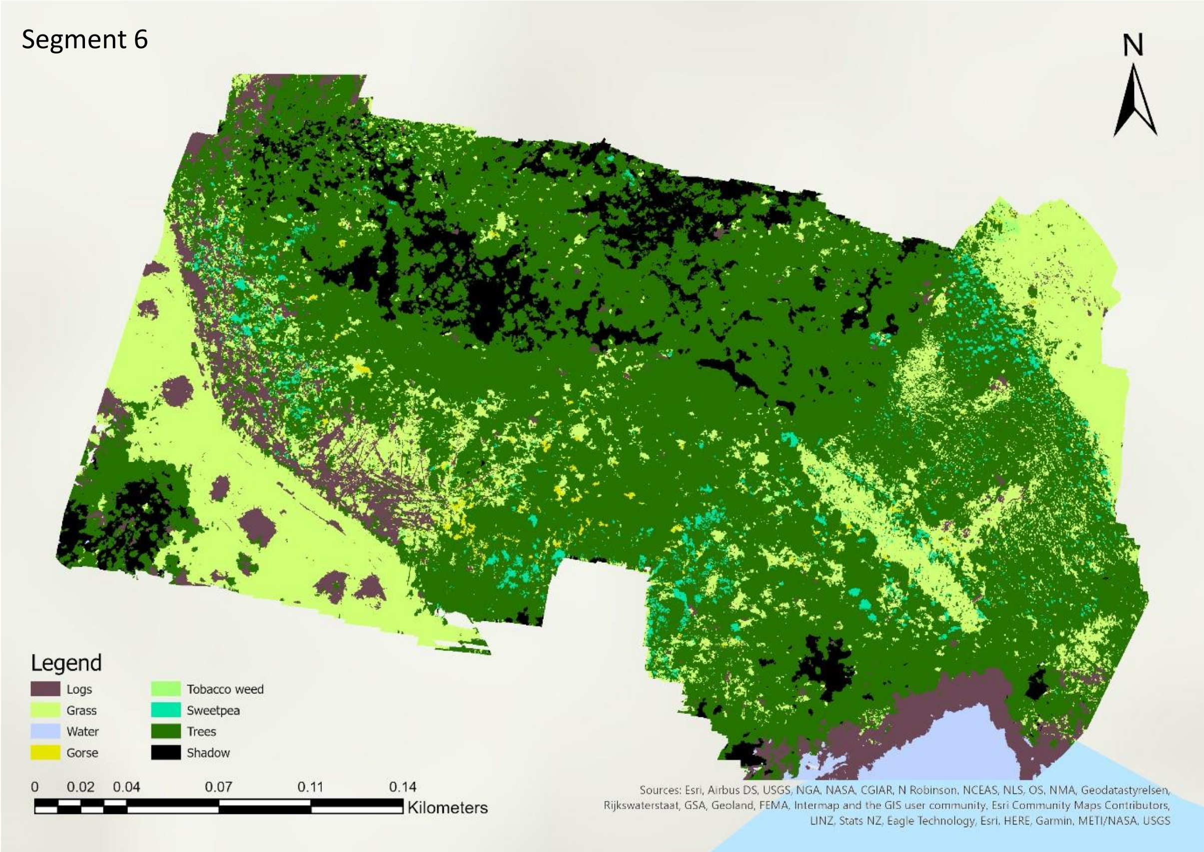
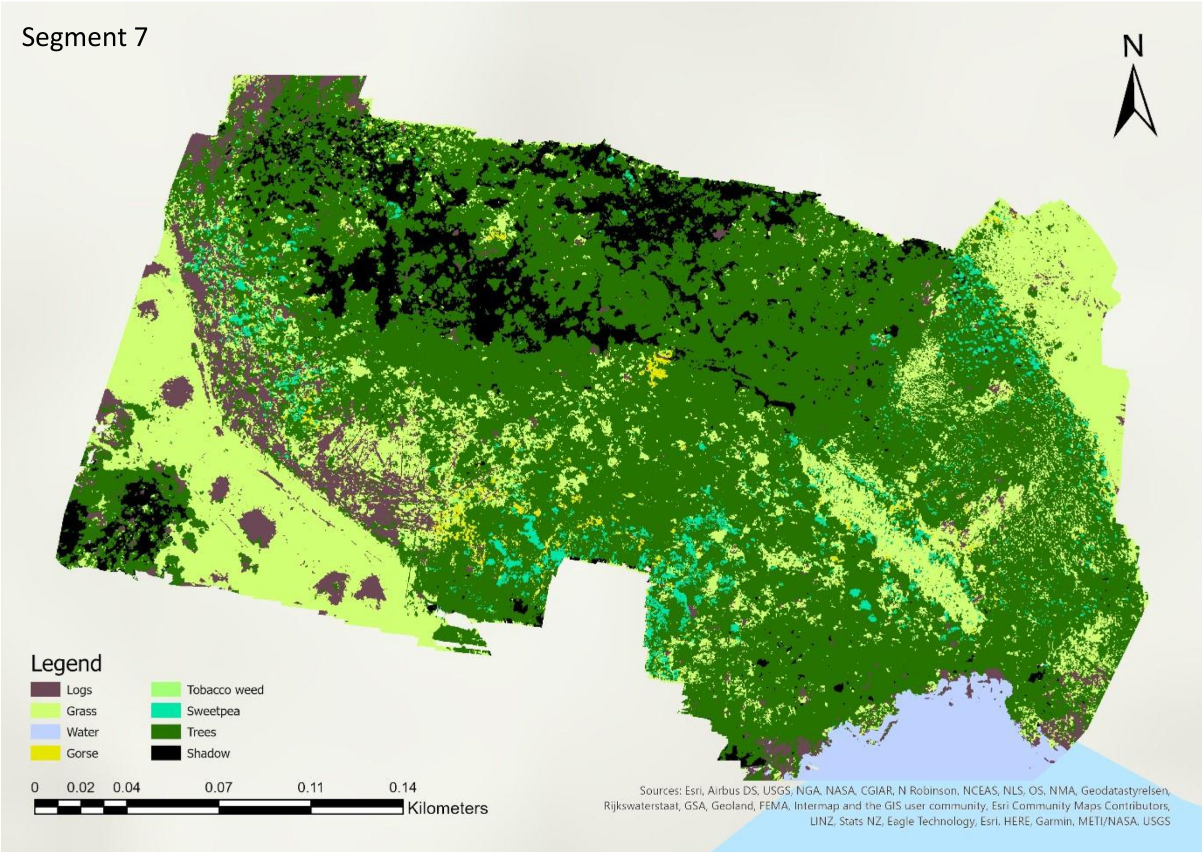
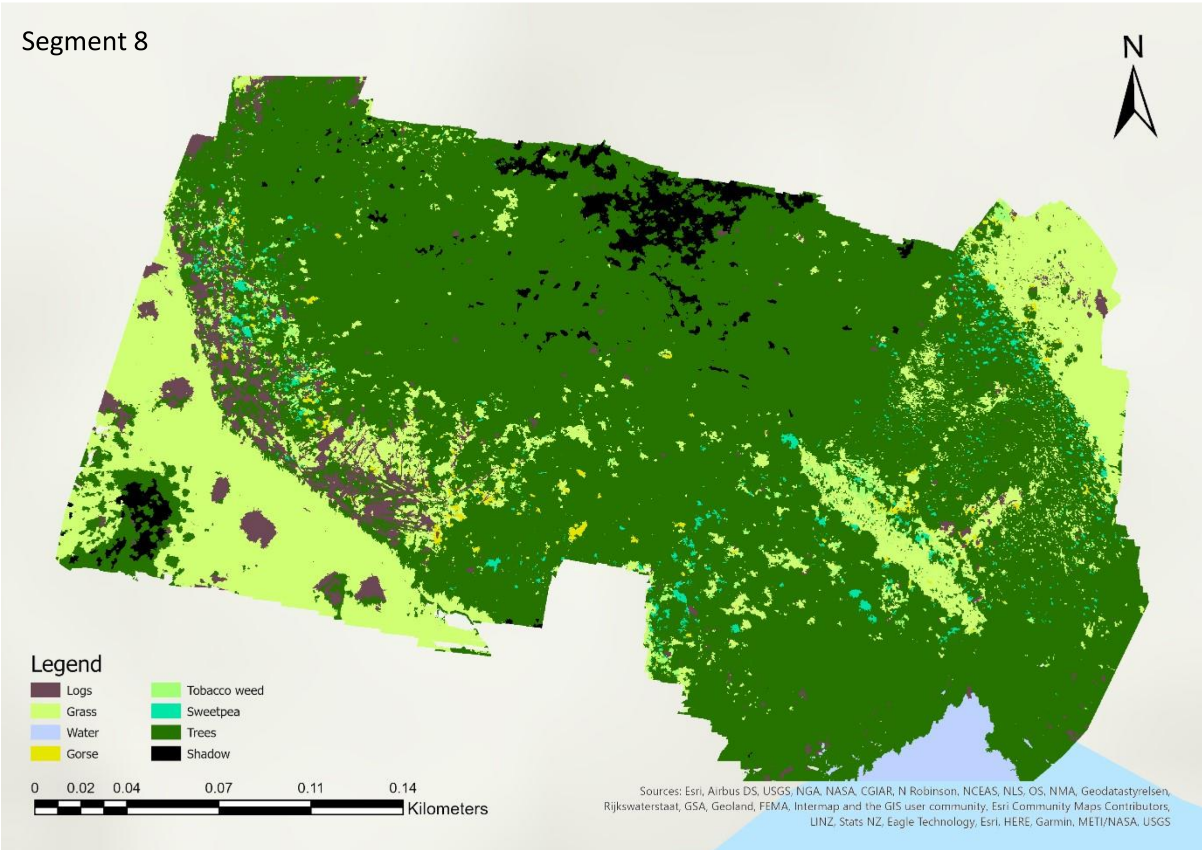
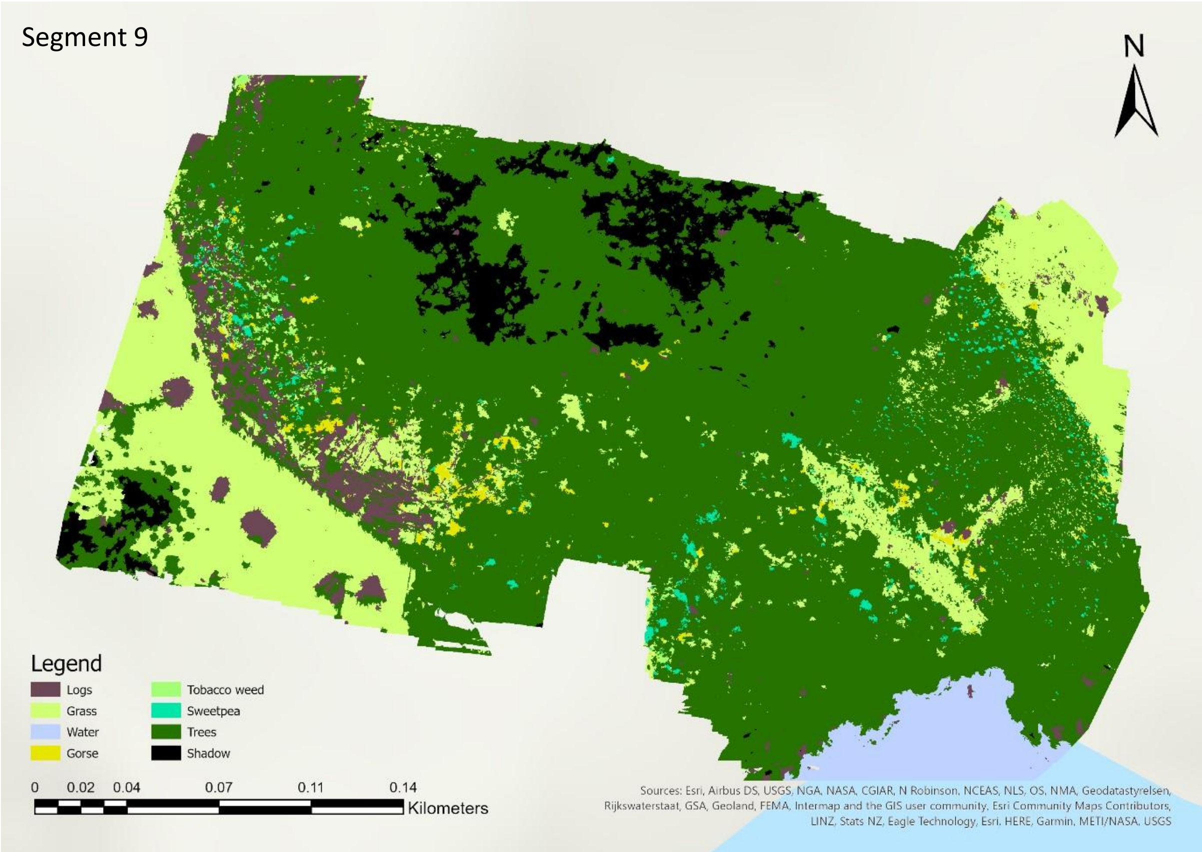
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS


Segment 5
N
Legend
Logs
Grass
Water
Gorse
Tobacco weed
Sweetpea
Trees
Shadow
0 0.02 0.04 0.07 0.11 0.14
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS


Segment 6
N
Legend
Logs
Grass
Water
Gorse
Tobacco weed
Sweetpea
Trees
Shadow
0 0.02 0.04 0.07 0.11 0.14
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS


Segment 7
N
Legend
Logs
Grass
Water
Gorse
Tobacco weed
Sweetpea
Trees
Shadow
0 0.02 0.04 0.07 0.11 0.14
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS


Segment 8
N
Legend
Logs
Grass
Water
Gorse
Tobacco weed
Sweetpea
Trees
Shadow
0 0.02 0.04 0.07 0.11 0.14
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS


Segment 9
N
Legend
Logs
Grass
Water
Gorse
Tobacco weed
Sweetpea
Trees
Shadow
0 0.02 0.04 0.07 0.11 0.14
Kilometers
Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Esri Community Maps Contributors, LINZ, Stats NZ, Eagle Technology, Esri, HERE, Garmin, METI/NASA, USGS

Appendix 7: Maximum Likelihood Confusion Matrix tables results for each segmented parameter

Parameter 1

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	53	9	0	0	0	0	1	0
2	grass	0	59	0	0	0	0	4	0
3	water	10	1	48	0	0	0	4	0
4	Gorse	1	8	0	2	0	0	52	0
5	Tobacco	1	17	0	0	0	0	45	0
6	Sweetpea	0	5	0	0	0	0	58	0
7	trees	5	11	0	0	0	0	47	0
8	shadow	0	0	0	0	0	0	0	63

Parameter 2

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	46	11	0	0	0	0	6	0
2	grass	0	56	0	0	0	0	7	0
3	water	11	2	45	0	0	0	4	0
4	Gorse	6	12	0	2	0	0	43	0
5	Tobacco	1	25	0	0	1	1	35	0
6	Sweetpea	1	2	0	1	0	0	59	0
7	trees	4	16	0	0	0	0	43	0
8	shadow	0	1	0	0	0	0	3	59
9	Total	69	125	45	3	1	1	200	59

Parameter 3

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	31	10	0	0	0	0	22	0
2	grass	0	58	0	0	0	0	5	0
3	water	12	2	45	0	0	0	4	0
4	Gorse	3	9	0	2	0	0	49	0
5	Tobacco	0	25	0	0	1	0	37	0
6	Sweetpea	0	1	0	0	0	0	62	0
7	trees	1	13	0	0	0	0	49	0

8	shadow	0	2	0	0	0	0	0	61
9	Total	47	120	45	2	1	0	228	61

Parameter 4

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	23	18	0	0	0	0	22	0
2	grass	0	58	0	0	0	0	5	0
3	water	0	4	47	0	0	0	12	0
4	Gorse	0	14	0	1	1	0	47	0
5	Tobacco	1	30	0	0	2	0	30	0
6	Sweetpea	0	4	0	0	0	0	58	0
7	trees	3	9	0	0	0	0	51	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	27	137	47	1	3	0	225	63

Parameter 5

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	40	11	2	0	0	0	10	0
2	grass	2	52	5	0	0	0	4	0
3	water	6	1	47	0	0	0	9	0
4	Gorse	0	8	0	2	0	0	53	0
5	Tobacco	1	17	0	0	2	0	43	0
6	Sweetpea	0	0	0	0	0	1	62	0
7	trees	2	8	1	0	0	0	52	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	51	97	55	2	2	1	233	63

Parameter 6

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	45	4	0	0	0	0	14	0
2	grass	3	54	0	0	0	0	6	0
3	water	8	0	52	0	0	0	3	0
4	Gorse	0	5	0	4	0	0	54	0

5	Tobacco	0	21	0	0	1	0	41	0
6	Sweetpea	0	1	0	0	0	0	62	0
7	trees	0	16	0	0	0	0	47	0
8	shadow	0	2	0	0	0	0	0	61
9	Total	56	103	52	4	1	0	227	61

Parameter 7

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	48	3	0	0	0	0	12	0
2	grass	0	63	0	0	0	0	0	0
3	water	14	2	39	0	0	0	8	0
4	Gorse	0	13	0	2	0	0	48	0
5	Tobacco	1	15	0	0	0	0	47	0
6	Sweetpea	0	2	0	0	0	0	61	0
7	trees	0	9	0	0	0	0	54	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	63	107	39	2	0	0	230	63

Parameter 8

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	46	3	0	0	0	0	14	0
2	grass	1	46	2	0	0	0	14	0
3	water	1	1	61	0	0	0	0	0
4	Gorse	2	8	0	2	0	0	51	0
5	Tobacco	0	3	0	0	1	0	59	0
6	Sweetpea	0	2	0	0	0	2	59	0
7	trees	2	8	0	0	0	0	53	0
8	shadow	0	1	0	0	0	0	6	56
9	Total	52	72	63	2	1	2	256	56

Parameter 9

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	51	3	0	0	0	0	9	0
2	grass	1	57	0	0	0	0	5	0
3	water	10	2	48	0	0	0	3	0
4	Gorse	0	0	0	2	0	0	61	0
5	Tobacco	0	3	0	0	2	0	58	0
6	Sweetpea	0	1	0	0	0	0	62	0
7	trees	1	2	0	0	0	0	60	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	63	68	48	2	2	0	258	63

Appendix 8: Support Vector Machine Confusion Matrix tables results for each segmented parameter

Parameter 1

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	50	1	1	0	0	0	10	1
2	grass	3	54	0	0	0	0	6	0
3	water	1	0	55	0	0	0	7	0
4	Gorse	5	4	0	6	0	0	47	1
5	Tobacco	0	7	0	1	5	0	50	0
6	Sweetpea	0	0	0	0	1	0	62	0
7	trees	3	0	0	0	0	0	60	0
8	shadow	0	0	0	0	0	0	9	54
9	Total	62	66	56	7	6	0	251	56

Parameter 2

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	45	0	2	0	0	0	16	0
2	grass	0	58	0	0	0	0	5	0
3	water	0	0	61	0	0	0	2	0
4	Gorse	5	3	0	8	0	0	47	0
5	Tobacco	2	2	0	1	3	0	55	0
6	Sweetpea	0	0	0	0	0	0	63	0
7	trees	0	0	0	0	0	0	63	0
8	shadow	0	1	0	0	0	0	1	61
9	Total	52	64	63	9	3	0	252	61

Parameter 3

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	44	2	2	0	0	0	15	0
2	grass	0	48	0	0	0	0	15	0
3	water	0	0	56	0	0	0	3	0
4	Gorse	1	2	0	9	0	0	51	0
5	Tobacco	5	10	0	0	4	0	43	0
6	Sweetpea	0	0	0	0	0	1	62	0

7	trees	0	1	0	0	0	0	62	0
8	shadow	0	0	0	0	0	0	5	58
9	Total	50	63	58	9	4	1	256	58

Parameter 4

OBJECTID	**ClassValue**	**logs**	**grass**	**water**	**Gorse**	**Tobacco**	**Sweetpea**	**trees**	**shadow**
1	logs	50	4	0	0	0	0	9	0
2	grass	2	49	0	0	0	0	12	0
3	water	5	0	55	0	0	0	3	0
4	Gorse	4	1	0	0	0	0	58	0
5	Tobacco	0	9	0	0	2	0	52	0
6	Sweetpea	0	0	0	0	0	3	60	0
7	trees	0	0	0	0	0	0	63	0
8	shadow	0	0	0	0	0	0	0	63

Parameter 5

OBJECTID	**ClassValue**	**logs**	**grass**	**water**	**Gorse**	**Tobacco**	**Sweetpea**	**trees**	**shadow**
1	logs	41	16	0	0	0	0	6	0
2	grass	0	58	0	0	0	0	5	0
3	water	0	25	38	0	0	0	0	0
4	Gorse	0	3	0	2	0	0	58	0
5	Tobacco	1	7	0	0	2	0	53	0
6	Sweetpea	0	1	0	0	0	3	59	0
7	trees	0	3	0	0	0	0	60	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	42	113	38	2	2	3	241	63

Parameter 6

OBJECTID	**ClassValue**	**logs**	**grass**	**water**	**Gorse**	**Tobacco**	**Sweetpea**	**trees**	**shadow**
1	logs	40	10	8	0	0	0	5	0
2	grass	0	59	0	0	0	0	4	0
3	water	0	0	63	0	0	0	0	0
4	Gorse	0	2	0	0	0	0	61	0

5	Tobacco	2	10	0	0	2	0	49	0
6	Sweetpea	0	2	0	0	0	1	60	0
7	trees	2	1	0	0	0	0	60	0
8	shadow	0	0	0	0	0	0	1	62
9	Total	44	84	71	0	2	1	240	62

Parameter 7

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	37	24	0	0	0	0	2	0
2	grass	0	49	0	0	0	0	13	0
3	water	4	0	58	0	0	0	1	0
4	Gorse	0	4	0	0	0	0	59	0
5	Tobacco	0	0	0	0	1	0	62	0
6	Sweetpea	0	0	0	1	0	0	62	0
7	trees	0	1	0	0	0	0	62	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	41	78	58	1	1	0	261	63

Parameter 8

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	54	2	0	0	0	0	7	0
2	grass	1	48	3	0	0	0	10	1
3	water	0	0	62	0	0	0	1	0
4	Gorse	11	4	0	3	0	0	45	0
5	Tobacco	0	3	0	0	7	0	53	0
6	Sweetpea	0	0	0	0	0	3	60	0
7	trees	0	4	0	0	0	0	59	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	66	61	65	3	7	3	235	64

Parameter 9

OBJECTID	**ClassValue**	**logs**	**grass**	**water**	**Gorse**	**Tobacco**	**Sweetpea**	**trees**	**shadow**
1	logs	38	17	0	0	0	0	8	0
2	grass	1	52	0	0	0	0	10	0
3	water	13	0	46	0	0	0	4	0
4	Gorse	9	3	0	2	0	0	49	0
5	Tobacco	2	1	0	0	1	0	59	0
6	Sweetpea	0	0	0	0	0	0	63	0
7	trees	0	0	0	0	0	1	62	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	63	73	46	2	1	1	255	63

Appendix 9: Random Tree Confusion Matrix tables results for each segmented parameter

Parameter 1

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	50	1	1	0	0	0	11	0
2	grass	2	49	0	0	0	0	12	0
3	water	2	0	61	0	0	0	0	0
4	Gorse	2	0	0	5	0	1	55	0
5	Tobacco	0	3	0	0	1	0	59	0
6	Sweetpea	0	0	0	0	1	5	57	0
7	trees	0	3	0	0	0	0	60	0
8	shadow	0	1	0	0	0	0	0	62
9	Total	56	57	62	5	2	6	254	62

Parameter 2

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	46	8	1	0	0	0	8	0
2	grass	0	52	0	0	0	0	11	0
3	water	0	0	63	0	0	0	0	0
4	Gorse	0	5	0	7	0	0	51	0
5	Tobacco	0	11	0	2	6	0	44	0
6	Sweetpea	0	1	0	1	0	5	56	0
7	trees	0	1	0	0	0	0	62	0
8	shadow	0	1	0	0	0	0	0	62
9	Total	46	79	64	10	6	5	232	62

Parameter 3

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	39	12	0	0	0	0	12	0
2	grass	0	54	0	0	0	0	9	0
3	water	6	0	53	0	0	0	4	0
4	Gorse	1	1	0	8	0	0	53	0
5	Tobacco	1	6	0	3	2	0	51	0
6	Sweetpea	0	0	0	1	0	3	59	0

7	trees	1	2	0	2	0	0	58	0
8	shadow	0	0	0	0	0	0	1	62
9	Total	48	75	53	14	2	3	247	62

Parameter 4

OBJECTID	**ClassValue**	**logs**	**grass**	**water**	**Gorse**	**Tobacco**	**Sweetpea**	**trees**	**shadow**
1	logs	44	6	1	0	0	0	12	0
2	grass	0	51	0	0	0	0	12	0
3	water	1	0	59	0	0	0	3	0
4	Gorse	0	3	0	4	0	0	56	0
5	Tobacco	0	8	0	1	0	0	54	0
6	Sweetpea	0	2	0	3	0	3	55	0
7	trees	0	2	0	2	0	0	59	0
8	shadow	1	0	0	0	0	0	5	57
9	Total	46	72	60	10	0	3	256	57

Parameter 5

OBJECTID	**ClassValue**	**logs**	**grass**	**water**	**Gorse**	**Tobacco**	**Sweetpea**	**trees**	**shadow**
1	logs	52	4	0	1	0	0	6	0
2	grass	0	52	0	0	0	0	11	0
3	water	0	0	56	0	0	0	7	0
4	Gorse	0	3	0	10	0	0	50	0
5	Tobacco	0	0	0	4	4	0	55	0
6	Sweetpea	0	0	0	0	0	3	60	0
7	trees	1	2	0	0	0	0	60	0
8	shadow	0	0	0	0	0	0	3	60
9	Total	53	61	56	15	4	3	252	60

Parameter 6

OBJECTID	**ClassValue**	**logs**	**grass**	**water**	**Gorse**	**Tobacco**	**Sweetpea**	**trees**	**shadow**
1	logs	40	10	8	0	0	0	5	0
2	grass	0	59	0	0	0	0	4	0
3	water	0	0	63	0	0	0	0	0

4	Gorse	0	2	0	0	0	0	61	0
5	Tobacco	2	10	0	0	2	0	49	0
6	Sweetpea	0	2	0	0	0	1	60	0
7	trees	2	1	0	0	0	0	60	0
8	shadow	0	0	0	0	0	0	1	62
9	Total	44	84	71	0	2	1	240	62

Parameter 7

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	50	6	0	0	0	0	7	0
2	grass	0	48	0	0	0	0	15	0
3	water	21	0	41	0	0	0	1	0
4	Gorse	0	1	0	10	0	0	52	0
5	Tobacco	0	1	0	4	3	0	55	0
6	Sweetpea	0	0	0	0	0	2	61	0
7	trees	0	0	0	2	0	0	61	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	71	56	41	16	3	2	252	63

Parameter 8

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	55	3	0	0	0	0	5	0
2	grass	0	56	0	0	0	0	5	2
3	water	0	0	62	0	0	0	1	0
4	Gorse	0	0	0	4	0	0	59	0
5	Tobacco	0	0	0	0	0	0	63	0
6	Sweetpea	0	0	0	1	0	2	60	0
7	trees	0	1	1	0	0	0	61	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	55	60	63	5	0	2	254	65

Parameter 9

OBJECTID	ClassValue	logs	grass	water	Gorse	Tobacco	Sweetpea	trees	shadow
1	logs	60	1	0	0	0	0	2	0
2	grass	0	54	0	0	0	0	9	0
3	water	20	0	43	0	0	0	0	0
4	Gorse	0	4	0	6	0	0	53	0
5	Tobacco	1	12	0	6	1	0	43	0
6	Sweetpea	0	1	0	0	0	2	60	0
7	Trees	0	4	0	0	0	0	59	0
8	shadow	0	0	0	0	0	0	0	63
9	Total	81	76	43	12	1	2	226	63