A MULTI-SENSOR APPROACH
FOR VHR VEGETATION MONITORING

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William O. Weaver

Thesis Committee:

Tomoaki Miura, Chairperson
Creighton Litton
James Jacobi

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Dedication

This thesis is dedicated in loving memory of a champion of Hawaiian mixed-mesic forest restoration and conservation in Hawaii, Daniel K. Sailer. Thank you for your inspirational life's work in service of our imperiled, Hawaiian mixed-mesic forests and the many priceless plants and animals within them.

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Mahalo Nui Loa.

Abstract

The Hawaiian Islands are a showcase of biological diversity. With a myriad of vegetation communities, the tropical forests of Hawaii support a rich assemblage of endemic species, some of which are critically endangered. However, much of the Hawaiian forests are degraded and are subject to disturbance by invasive plants.

Monitoring the response of Hawaiian forests to management efforts and tracking how vegetation changes over time is a key component of conservation and restoration efforts. Traditional "on-the-ground" vegetation monitoring techniques are time consuming and costly, and can vary in accuracy and consistency. Recent advances in remote sensing technology hold potential for providing an accurate and timely assessment of vegetation at a set point in time. Until recently, the available satellite sensors lacked the spatial resolution required to differentiate individual tree crowns, and thus, classification was limited to the stand or community level. Several new very high resolution (VHR) platforms have emerged in the field of remote sensing that can differentiate individual tree crowns and, thus, have the potential to change the paradigm of vegetation monitoring and its efficacy. VHR, sub-meter imaging platforms are now readily available for public use with commercial VHR satellite and aircraft imaging, unmanned aerial system (UAS) digital imaging, and the Gigapan system.

The primary objective of this thesis was to determine the utility of new high spatial resolution remote sensing technologies for vegetation mapping and monitoring in Hawaiian forests. The strengths of the three platforms were evaluated and then combined, to produce an effective synthesis to implement remote sensing-based mapping to the species level and an OBIA procedural workflow was outlined. WV-3 imagery was classified with object based image analysis in eCognition into 7 vegetation classes and validated with UAS and Gigapan imagery.

The dense vegetation of the Hawaiian mixed-mesic forest presents a challenging task to separate vegetation classes to the species level. Validation results yielded an overall user's accuracy of 65% with Sparse Veg representing the highest user's accuracy of 94% and Strawberry guava representing the lowest user's accuracy of 38%. Kukui=75%, Christmas berry=73%, Koa=50% and Native Complex=42%. Grouping native and non-native vegetation classes yielded an overall accuracy of 72% with non-native=94% and native=69%. The high accuracy of mapping sparse veg shows great potential for providing information towards fuel mapping via this method. Further work is needed to accurately separate native vs non-native vegetation to the species level. A stronger computer processer is needed to add additional geometric and textural features into the iterative classification process.

The UAS VHR platform shows the greatest potential for integration of remotely sensed imagery into an operational vegetation monitoring method. UAS allow for low cost, repeatable, high resolution data collection without risk to field personnel. A recommended method could employ a UAS to fly transects in a target area with visual or deep/machine learning analysis of random plots along the transects. Further advancements in multispectral sensors and longer lasting batteries will serve to allow for greater utility in monitoring, and management applications. Vertical takeoff and landing UAS may be of great use in areas without suitable landing area for typical fixed wing UAS.

The costs associated with the implementation of remote sensing based monitoring protocols were determined as compared to traditional ground based monitoring methods. Ultimately, if new imagery was obtained under contract, remote sensing based monitoring serves to be more expensive than traditional ground based methods. However, an operational comparison which factors in either prior acquisition of imagery or capacity to gather data without going out to contract, shows a lower cost associated with remote sensing based monitoring.

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Acronyms

DSM- Digital surface model

GCP- Ground Control Point

GSD- Ground Surface Distance

MUs- Management Units

NDVI- Normalized Difference Vegetation Index

NIR- Near Infrared

OBIA- Object Based Image Analysis

OANRP-Oahu Army Natural Resources Program

USFWS- United States Fish and Wildlife Service

VHR- Very High Resolution

WV-2- WorldView 2

WV-3- WorldView 3

Chapter 1. Introduction

1.1 Background

1.1.1 The Hawaiian Forest

The Hawaiian Islands are a showcase of biological diversity and host an array of unique and rare native species found nowhere else on earth. The native Hawaiian flora is represented by nearly 1,000 species of flowering plants, 89% of which are endemic (Wagner *et al.*, 1999). Hawaii has the highest known degree of endemism for terrestrial plants for any major island group (Juvik and Juvik, 1998). These species are distributed within a myriad of dry, mesic and wet forest vegetation communities across 600,000 forested hectares throughout the Hawaiian Islands (Juvik and Juvik, 1998; Gon, 2003; Sailer, 2003; Wagner *et al.*, 1999).

1.1.2 Disturbance of the Hawaiian Forest

Much of the Hawaiian forest has been severely impacted by disturbance and the subsequent introduction of many non-native species (Juvik and Juvik, 1998; Takahashi *et al.*, 2010; Mair and Fares, 2009). Disturbance of Hawaiian forests began with the early Polynesian settlers about 1,000 years ago, who started clearing leeward and coastal areas for agriculture and introduced a small number of alien species (Kirch, 1982; Kirch, 2011; Juvik and Juvik, 1998; Burny *et al.*, 2001; Staples and Cowie, 2001). However, extensive damage to mesic forests occurred with the arrival of Western settlement and agriculture during the 19th and 20th centuries (Juvik and Juvik, 1998; Friday, 2003). By the late 1800s and early 1900s forest decline was very high due to intentional burning to locate fragrant sandalwood, commercial logging, conversion to agriculture and pastureland, heavy grazing by hoofed mammals and the increased frequency of wildfires (Tomich, 1986; Cuddihy and Stone 1990; Friday, 2003).

Extensive disturbance of these areas has allowed for invasions of non-native plants. Many of the plants and trees that were introduced accidentally or intentionally as ornamentals, or used in agriculture and forestry have naturalized and are serious threats to disturbed, as well as intact, native ecosystems (Staples and Cowie 2001; Friday, 2003; Woodcock, 2003). Invasive species continue to be a major concern for conservation and resource management (D'Antonio and Kark, 2002). Invasive plants often outcompete native plants for resources as they rapidly grow, reach maturity at a relatively young age and excel at dispersal (Vitousek *et al.*, 1987; Mack *et al.*, 2001; Friday, 2003). In addition, they can affect ecosystem processes such as primary productivity, decomposition, hydrology, nutrient cycling and natural disturbance regimes (Vitousek *et al.*, 1987; Vitousek, 1990; Mack *et al.*, 2001).

1.1.3 Conservation and Monitoring of the Hawaiian Forest

Many efforts have been made to conserve native plant species and eradicate invasive plants and animals in Hawaiian forests. State, Federal and non-profit organizations work to control invasive species, propagate native plants and restore plant communities (Juvik and Juvik, 1998; Staples and Cowie 2001; Friday, 2003). The Oahu Army Natural Resources Program (OANRP) leads one of the most comprehensive endangered species mitigation, conservation and restoration efforts in Hawaii. The OANRP is required by the U.S. Fish and Wildlife Service (USFWS) to stabilize a targeted group of endangered species potentially threatened by U.S. Army training. In selected areas, active efforts are underway to manage target rare species and the native forest habitat that supports them. The OANRP has an active vegetation monitoring program that strives to measure change in vegetation over time in designated management units (MUs) (OANRP, 2010). Effective and efficient monitoring methods and tools suited to difficult terrain or sensitive ecosystems are actively evaluated prior to their implementation.

Monitoring the response to resource management and tracking how an area changes over time is a key component of conservation and restoration efforts. Monitoring provides a measure of progress towards the goals of stabilization (MIP, 2003). In addition, monitoring provides the basis for understanding the intricate distribution, composition, structure, and dynamics of the vegetation in an area. The baseline data provided by vegetation monitoring can be especially useful in areas that are being restored (Elzinga *et al.,* 2001; Jacobi, 2008). Monitoring the change in an area over time serves as a status update and allows natural resource managers to make informed adaptive management decisions (Moore *et al.,* 2003).

Vegetation species composition and percent cover are common indicators that are often recorded with vegetation monitoring (Moore *et al.,* 2003; USGS, 2011). These variables may be assessed by many methods, including "on-the-ground" data collection and remote sensing methods. The traditional, on-the-ground vegetation monitoring techniques, which include transects, point intercepts, quadrats, and measured plots, can be time consuming and costly, and may vary in accuracy and consistency depending on observer error and bias (Congalton, 1991; Mueller-Dombois and Ellenberg, 2002; Moore *et al.,* 2003; Milberg *et al.,* 2008; US Geological Survey, 2011; Cho *et al.,* 2015). One of the benefits of ground based monitoring is that all layers of vegetation can be documented from the ground up, including overlapping taxa (Akamine pers. com., 2017). Also, species identification can be better accomplished from the ground. However, on-the-ground monitoring may be damaging to sensitive native ecosystems and difficult or unsafe to accomplish in steep terrain and thick vegetation (Akamine pers. com., 2017).

1.1.4 Remote Sensing for Vegetation Mapping

Remote sensing is the science and art of collecting data about a specific object of interest without actual physical contact with that object (Jensen, 2007). Aerial or space-borne remote sensing has been used by the scientific community as an alternative or to compliment ground based field surveys to quantify vegetation and ecosystem processes (Cabello *et al.,* 2012). Analysis of remotely sensed imagery can provide an accurate and timely assessment of vegetation at a set point in time (Bunting and Lucas, 2006; Jacobi, 2008). This assessment can then be systematically replicated to monitor change in the vegetation communities and species composition of specific areas (Bunting and Lucas, 2006). Until recently, the available satellite sensors such as Landsat (30m spatial resolution) and MODIS (250-500m) lacked the spatial resolution required to differentiate individual tree crowns, and classification was limited to the vegetation stand or community level (Nagendra and Rocchini, 2008; Katoh, 2004).

Very high resolution (VHR) satellite sensors are distinguished by their capability to capture image data with a spatial resolution of less than 1m at nadir (Agrafiotis and Georgopoulos, 2015). Several new VHR imagery platforms have emerged in the field of remote sensing that can provide a different perspective and have the potential to change the paradigm of vegetation monitoring and its efficacy. These sub-meter imaging platforms are now readily available for general use and include commercial VHR satellite imaging, unmanned aerial system (UAS) digital imaging, and the Gigapan system (Adelabu and Dube, 2015; Boyle *et al.*, 2014; Bunting and Lucas, 2006; Carleer and Wolff, 2004; Stock *et al.*, 2010).

WorldView-3 (WV-3) VHR satellite imagery became available to the public in February 2015, by Digital Globe. WV-3 provides the finest spatial resolution data for civilian satellites and is an improvement of spatial resolution from the World View 2 (WV-2) satellite (Table 1) with imagery at a spatial resolution of 0.31m for the panchromatic band and 1.24m for the eight multispectral bands (Satellite imaging corp., 2015). Per the Satellite imaging corp. (2016), Digital Globe is awaiting approval from the US Department of Commerce to sell WV-3 imagery at the highest resolution it can collect, 0.25m panchromatic and 1.0m multispectral.

Table 1. Nominal Resolutions of Select Very High Resolution Satellite Sensors

Satellite Sensor	Spatial Resolution (for Nadir Viewing)		Spectral Resolution (Number of spectral bands)	Temporal Resolution (Revisit Time in days)
	Panchromatic m)	Multispectral (m)		
IKONOS	0.82	3.2	5	3
Quickbird	0.65	2.62	5	1-3.5
WorldView-2	0.46	1.84	9	1.1
WorldView-3	0.31	1.24	9	1

1.1.5 Past work

Multiple challenges exist for researchers seeking to map tree crown and canopy cover or tree density, including understanding gap dynamics, and/or discriminating and classifying species (Bunting and Lucas, 2006). Canopy reflectance can be influenced by shadowing between crowns, contributions from non-photosynthetic material (e.g., primary branches) in the crown and the underlying soils and vegetation, and variations within and between species and growth stages as a function of foliar biochemistry, moisture content, internal structure and age of leaves (Bunting and Lucas, 2006).

Currently, little work has been published on the utility of WV-3 for vegetation classification. The high resolution multispectral sensors of IKONOS, Quickbird and WorldView-2 (WV-2) have shown potential for species mapping in urban areas, plantations, and temperate forests (Cho *et al.*, 2015; Rapinel *et al.*, 2014). However, little work has been done mapping forests to the species level in tropical forests (Cho *et al.*, 2015). In Hawai'i Jacobi and Ambagis (2013) used IKONOS and QuickBird imagery to map vegetation communities in the Hanalei watershed on Kauaʻi and in the Kawela watershed on Molokaʻi. The higher spatial resolution offered by WV-3 may allow for greater accuracy in land cover classification and finer species level mapping.

Traditionally, manned airborne systems such as airplanes, helicopters and balloons have been used to obtain VHR sub-meter spatial resolution imagery (Bourgeois and Meganck, 2005; Eisenbeiss and Sauerbier, 2011). Bunting *et al.,* (2010) used VHR manned-aerial imagery to conduct supervised classification of tree crowns in Queensland, Australia. Recent advancements in camera sensors and aerial platforms have led to new possibilities for acquiring aerial images with unmanned systems (Eisenbeiss and Sauerbier, 2011; Devaney pers. com., 2016). Unmanned aerial system (UAS) photogrammetry, although initially developed for military applications, is increasingly being applied for remote sensing of natural resources (Laliberte *et al.,* 2011, Eisenbeiss and Sauerbier, 2011; Keane and Carr, 2013). Among the available data products are ortho-imagery and 3-D imagery. UAS can fly completely autonomously, guided by GPS, along predetermined flight paths, allowing for precise data acquisition (Devaney pers. com., 2016). A major advantage of a UAS platform is the capability to inexpensively deploy the UAS repeatedly to obtain high temporal resolution data at high spatial resolution without risk to human life (Laliberte *et al.*, 2011).

Another VHR system that holds much potential for monitoring is the ground based Gigapan system. The Gigapan robotic unit allows a user to capture very high resolution digital images (<1cm) with billions of pixels (gigapan.com; Sargent *et al.*, 2010; Stock *et al.* 2010). The Gigapan robotic unit pans through a predetermined scene firing a mounted camera at regular intervals with 60% overlap. The Gigapan software is used in postprocessing to stitch the images together into a single very high resolution, often gigapixel file. The Gigapan company also hosts a website that allows users to upload, store and explore Gigapan images from around the world. The technology utilized by the Gigapan robotic unit was developed by Carnegie Mellon for the Mars Rovers, Spirit and Opportunity, to capture panoramic images of the red planet (gigapan.com, 2014). Gigapan is gaining use by researchers across many other fields of science to capture site information from geology to ecology, and to complement fieldwork (Sargent *et al.*, 2010). However, little work has been done to assess the utility of the Gigapan system for vegetation mapping and monitoring.

1.1.6 Object Based Image Analysis

With the advent of these high-resolution imaging technologies, a shift has also occurred in the approach to image analysis. A pixel based image analysis has been the accepted methodology since the launch of Landsat-1 in 1972 (Blaschke *et al.*, 2014). However, Blaschke *et al.* (2014) point out that once the spatial resolution is finer than the object of interest, it is advantageous to focus on the patterns that are created by the pixels. Research in the 2000s started developing object based image analysis (OBIA) focusing on the color, tone, texture, patterns, shape, shadow and context of groups of pixel objects. Development of these techniques represents a new paradigm in image analysis (Blaschke *et al.*, 2014).

Many different software packages incorporate OBIA. Definiens and Trimble have developed widely used software known as eCognition®. Bunting and Lucas (2006), described a study that focuses on using eCognition® to delimit tree crowns in the mixed forests of Queensland, Australia. Bunting *et al.* (2010) demonstrated a technique that mimics aerial photo interpretation, but eliminates some of the drawbacks of aerial photo interpretation that can be subjective and influenced by the skill of the observer by combining visual with supervised classification. In Hawai'i Jacobi and Ambagis, (2013) mapped vegetation communities in the Hanalei watershed on Kaua‘i and the Kawela and Kamalo watersheds on the island of Moloka‘i, Hawai‘i, using OBIA with eCognition®. Their classification results were validated with high resolution aerial Pictometry® Online imagery.

The OBIA process with eCognition uses a hierarchy of image objects to group and classify pixel groups based on both spectral and shape data characteristics (Hay *et al*., 1996; Jacobi and Ambagis, 2013). Classification with eCognition begins with a segmentation process that separates an image into image objects based on spectral values. A supervised iterative process is then used to classify the image objects starting with broad classes of vegetation vs. non-vegetation, utilizing the normalized difference vegetation index (NDVI). Thresholding levels are used to create the guidelines for classification into finer classes of vegetation (Ambagis pers. com., 2015). Training samples may also be incorporated to guide the supervised classification process with a nearest neighbor classifier (Jacobi and Ambagis, 2013; Ambagis pers. com., 2015). A classified image may then be exported as a shapefile allowing for use with other mapping software such as ArcGIS for a final accuracy assessment.

1.2 Objectives

The primary objective of this thesis is to evaluate the utility of several new very high spatial resolution remote sensing technologies for vegetation mapping and monitoring in a Hawaiian forest. Specific objectives are to:

1. Develop an effective synthesis of the outputs from a VHR satellite platform, UAS and Gigapan using an OBIA procedural workflow to implement remote sensing-based mapping to the species level.
2. Make recommendations for the integration of remote sensing methods into vegetation monitoring.
3. Determine the costs associated with the implementation of remote sensing-based monitoring protocols as compared to traditional monitoring methods, including recommendations on how to scale back to facilitate cost saving.

Chapter 2 VHR Imagery Synthesis with WV-3, UAS and Gigapan

2.1 Introduction

2.1.1 Objectives

New technology is changing the face of vegetation mapping and its efficacy in the form of remote sensing and GIS. Analysis of VHR imagery can provide accurate and timely assessments of vegetation on a large scale at a set point in time (Bunting and Lucas, 2006). Accurate and timely classification of remote sensing imagery is vital to planning resource management efforts, tracking progress, and driving management decisions for restoration and resource management. Little work has been conducted in Hawaiian forests with supervised classification of remotely sensed imagery to the species level.

This chapter investigates the utility of VHR image data from WV-3, UAS, and Gigapan platforms for species-level classification. The objectives were to:

Objective 1. Develop an effective synthesis of the outputs from a VHR satellite platform, UAS and Gigapan using an OBIA procedural workflow to implement remote sensing-based mapping to the species level.

Objective 2. Make recommendations for the integration of remote sensing methods into vegetation monitoring.

The initial project objective was to evaluate each of the three VHR platforms independently with supervised classification via OBIA and eCognition® (Figure 1). Early testing was conducted to determine the effectiveness of classifying Gigapan imagery and VHR ortho-aerial Pictometry® imagery with supervised OBIA classification. Gigapan and ortho-aerial imagery did not serve to pair well with OBIA due to shadowing, differences in lighting during image capture and the limiting number of only three spectral bands. However, past work with OBIA and multispectral

VHR satellite imagery has shown potential for accurately classifying to the species level (Jacobi and Ambagis, 2013).

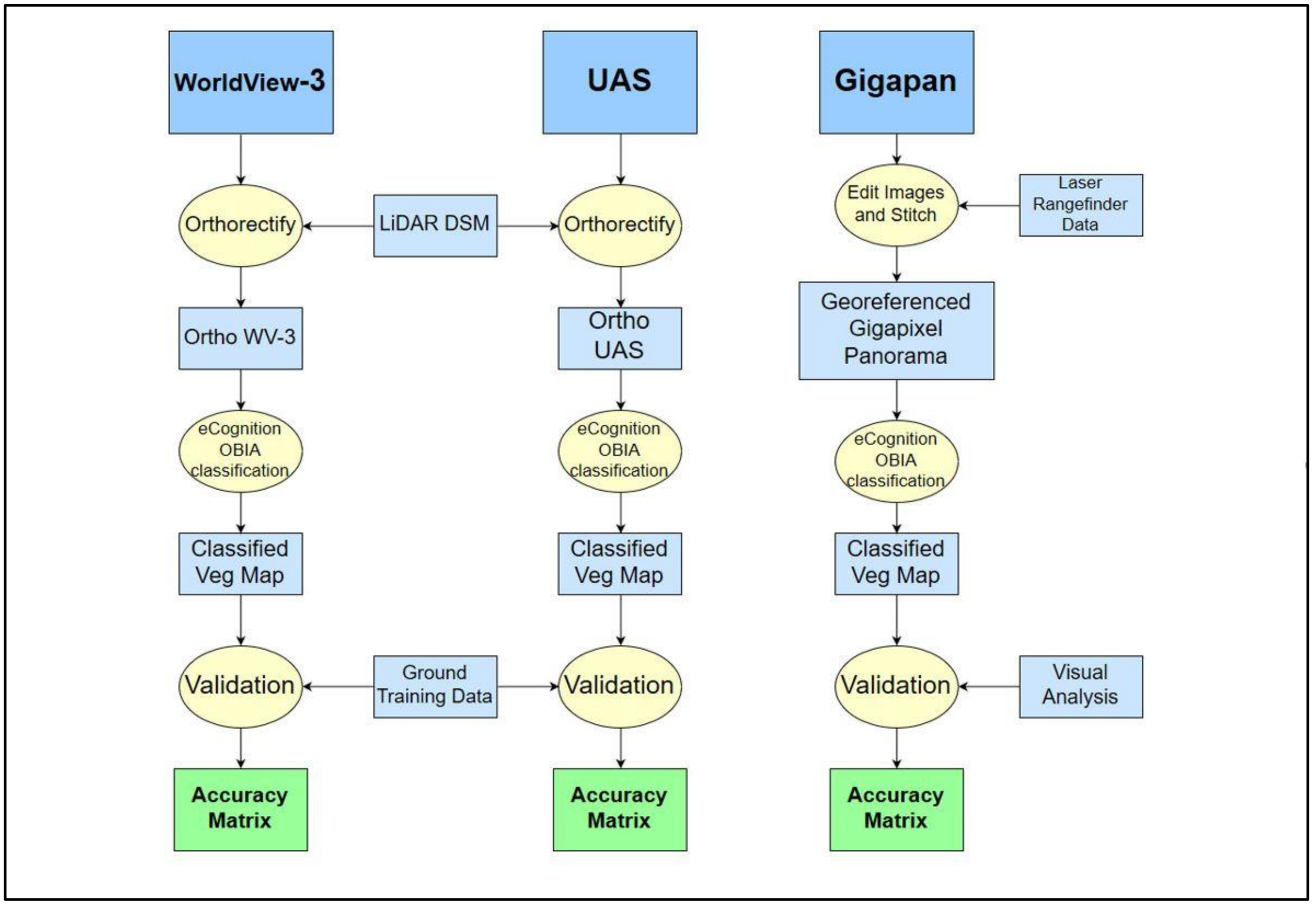


Figure 1. Initial proposed approach for achieving species level classification and an evaluation of each of the three VHR platforms.

High resolution UAS imagery with a spatial resolution of 1-2 cm may allow for visual identification of attributes needed for species identification of imagery of the target area. Preliminary visual analysis of ortho-aerial Pictometry® and Gigapan imagery has demonstrated potential for reliable visual classification of vegetation species. This initial work led to the project shift towards developing a synthesis of the three VHR platforms, in which the strengths of each platform are utilized to produce a validated, classified vegetation map, with WV-3 as the base layer, rather than an independent evaluation of each platform separately (Figure 2).

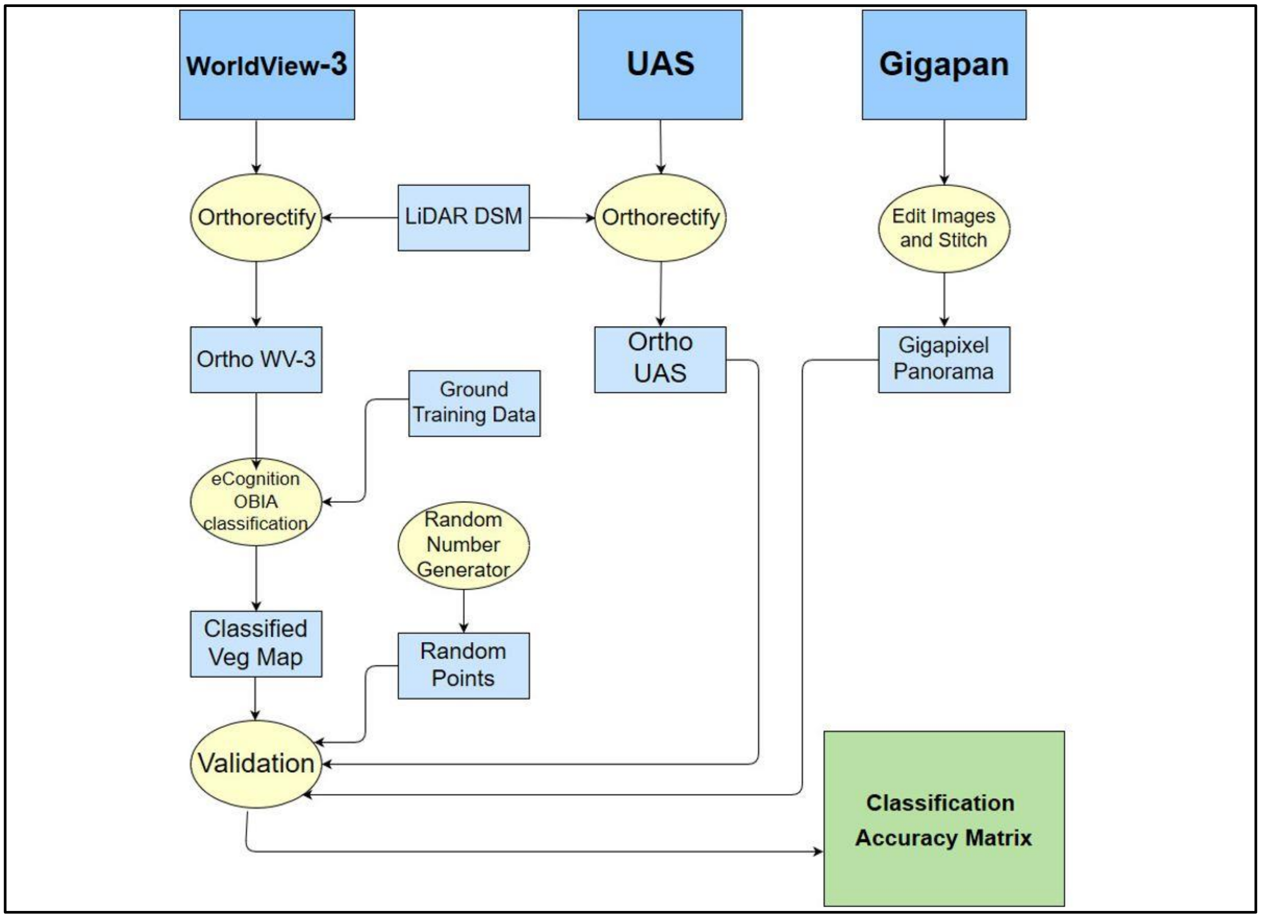


Figure 2. Final approach utilizing a synthesis of the three VHR platforms to produce a validated, classified vegetation map with WV-3 as the base layer.

The following native and non-native canopy species may represent the predominant classes of vegetation that can potentially be separated via OBIA of WV-3 with respect to vegetation canopy size greater than WV-3 spatial resolution (Table 2). Vegetation monitoring by the OANRP in 2015 found these species to have high frequencies in the canopy within the study area described in the next section (i.e., Kahanahaiki Management Unit) (OANRP, 2015). In addition, the canopy diameters are greater than the 1.24 m spatial resolution of WorldView-3. The canopy crowns will be represented by multiple pixels on the satellite image, potentially allowing for classification. Certain species may not be discernable from others due to spectral and textural similarities. Strawberry guava and Christmas berry are the predominant invasive species in the target area.

They also represent the most frequent targets during invasive species control actions in Kahanahaiki by the OANRP. The OANRP database shows that the initial installation of the belt plot monitoring took 294 hours. A remote monitoring procedure may involve less of an investment in time, however this must be weighed with the cost of image acquisition and analysis.

Table 2. Proposed vegetation classes with potential for separation with OBIA of WV-3.

Native tree	**Non-Native tree**	**Others**
Acacia koa (Koa)	*Aleurites moluccana* (Kukui)	Native ferns
Metrosideros polymorpha (Ohia)	*Psidium cattleianum* (Strawberry guava)	Non-native grasses
Diospyros sandwicensis (Lama)	*Schinus terebinthifolius* (Christmas berry)	Barren (bare ground)

2.1.2 Study Site

A key ecosystem within the islands is the Hawaiian mixed mesic forest, an area found in coastal, lowland, and montane areas that receive 1200 mm - 2500 mm rainfall annually (Wagner *et al.*, 1998). Mesic forests support a variety of common native and rare endemic species, significantly supplement groundwater recharge, and buffer wet forested areas from degradation by land use change, ungulate damage, and fires (Sailer, 2003; Juvik and Juvik, 1998; Mair and Fares, 2009). On Oahu, a representative example of a Hawaiian mixed-mesic forest is the valley of Kahanahaiki.

The Kahanahaiki Management Unit (MU), hereafter also referred to as Kahanahaiki, is located within Kahanahaiki valley on the leeward side of the northern Waianae Mountain Range on the island of Oahu. Kahanahaiki is in the Makua Military Reservation on the northeastern border of Makua Valley, at approximate UTM Coordinates: 04Q 583496 2382342 (Figure 3). With a total land area of 36 ha, ranging in elevation from 425 m to 707 m, Kahanahaiki has served as a model research and management site for a wide variety of past and present studies. It is representative of the many native resources and challenges faced for management in the Waianae Mountain Range of Oahu and was chosen as the primary project site.

The mixed-mesic forest of Kahanahaiki is made up of native and non-native flora and fauna. According to the OANRP year-end report (2015), native trees with the highest frequencies (in >10% of plots) were: *Psydrax odorata* (alahe'e), *Acacia koa* (koa), *Metrosideros polymorpha* (ohia), *Coprosma foliosa* (pilo), *Diospyros sandwicensis* (lama), and *Psychotria mariniana* (kopiko). Non-native trees with the highest frequencies (in >10% of plots) were *Psidium cattleianum* (Strawberry guava), *Aleurites moluccana* (kukui), and *Schinus teribenthifolius* (Christmas berry).

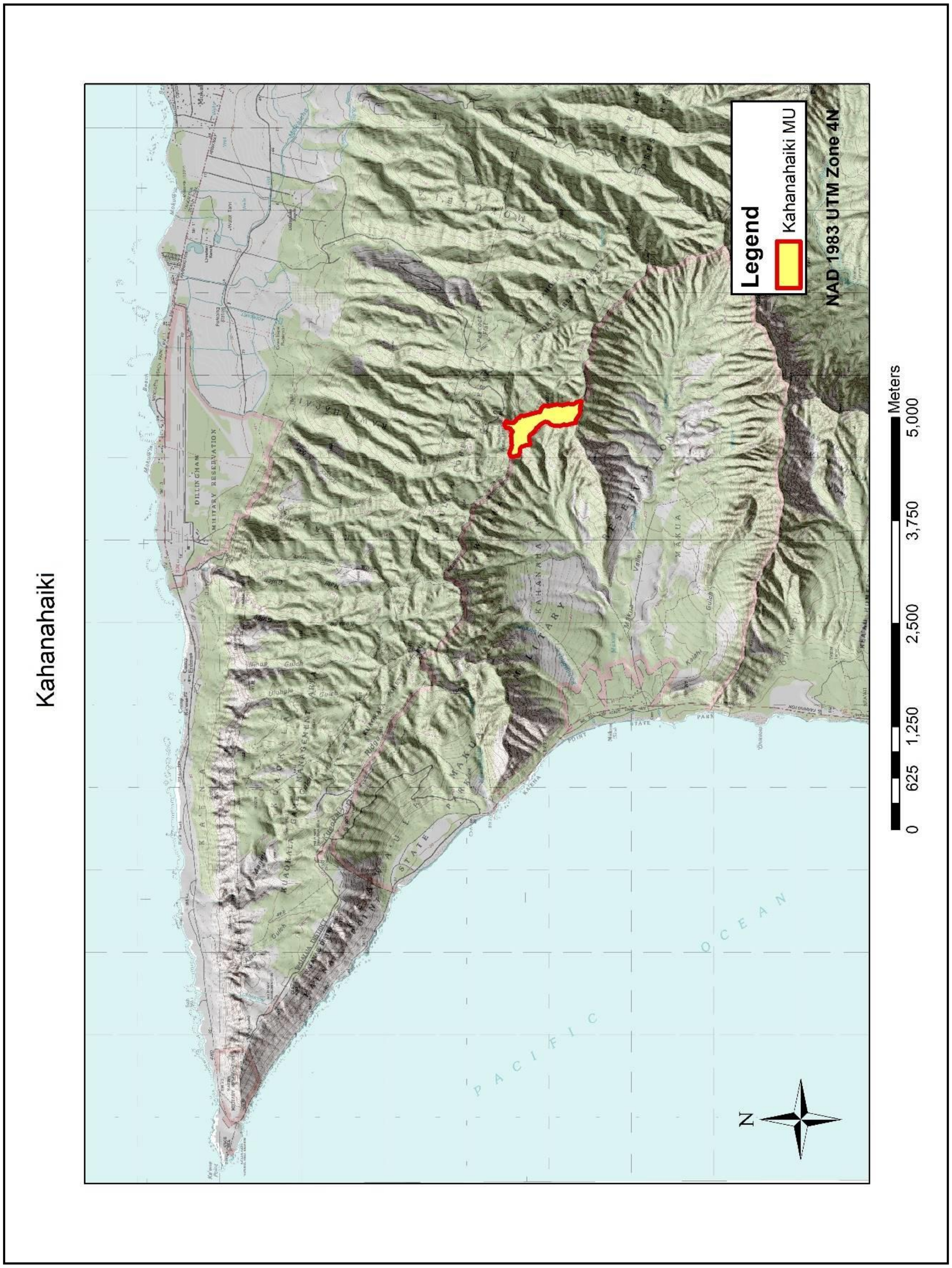


Figure 3. Map of study site location in Kahanahaiki within the Northern Waianae Mountain Range of Oahu, Hawaii.

2.1.3 Management History

The Oahu Army Natural Resources Program (OANRP) fenced the Kahanahaiki MU in 1996 to provide protection to 12 managed endangered taxa (OANRP 2009). Feral pigs were eradicated from Kahanahaiki and weed control was initiated targeting non-native vegetation with known ecosystem level impacts. The OANRP has spent thousands of hours working to restore the mesic forest in Kahanahaiki through a mix of threat management including: small mammal control, invertebrate control, and weed control. Yearly efforts are made to reintroduce common native and endangered plants throughout the MU. Active restoration efforts are underway with ecosystem level weed control conducted annually across the MU.

Vegetation monitoring was initiated with the installation of belt transect plots in 2009 to gather measurable data on how the vegetation composition is changing in Kahanahaiki over time. Objectives were to assess how coverage of native vs. non-native vegetation in the understory and canopy may be changing with response to active management of the Kahanahaiki MU. Transects were established at 100m intervals east to west in the moderate grade southern portion and south to north in the steeper gulch region. Five meter by 10m plots were installed along the transect every 50m (Figure 4). Full vegetation assemblage was recorded and the percent cover of understory and overstory species were estimated within the plots with ranges of 0-1%, 1-5%, 6-10%, 11-20%, 21-30% and so on to 91-100%. The transects were reanalyzed at three year intervals in 2012, and 2015. Ground vegetation monitoring has proven to be time intensive and may be subject to observer bias and inconsistency among observers, notably with canopy cover estimates. In addition, foot traffic may unintentionally impact sensitive areas with repeat visits and terrain in other areas makes ground work unfeasible, necessitating a change in the orientation of the transect.

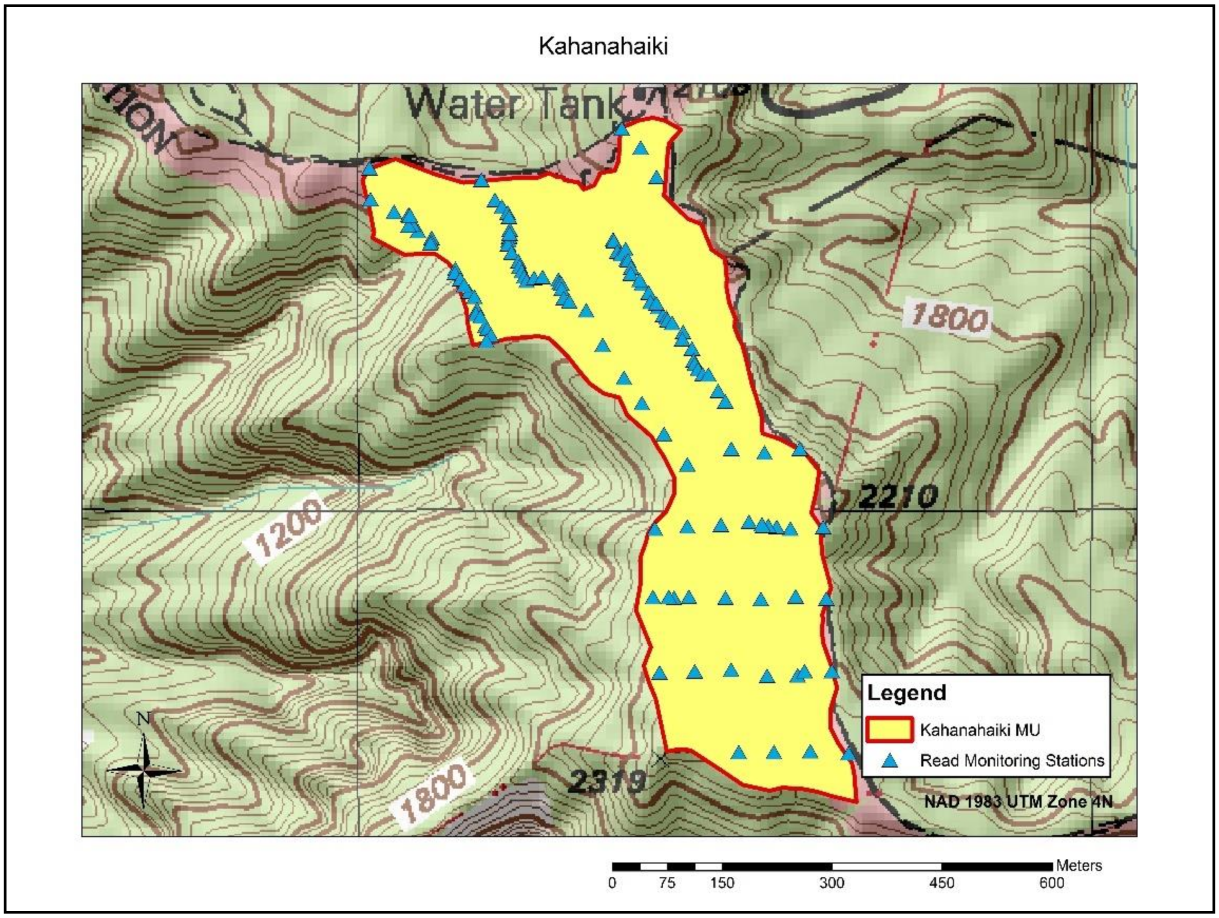


Figure 4. Kahahahaiki MU and ground vegetation monitoring plots installed in 2009 by OANRP.

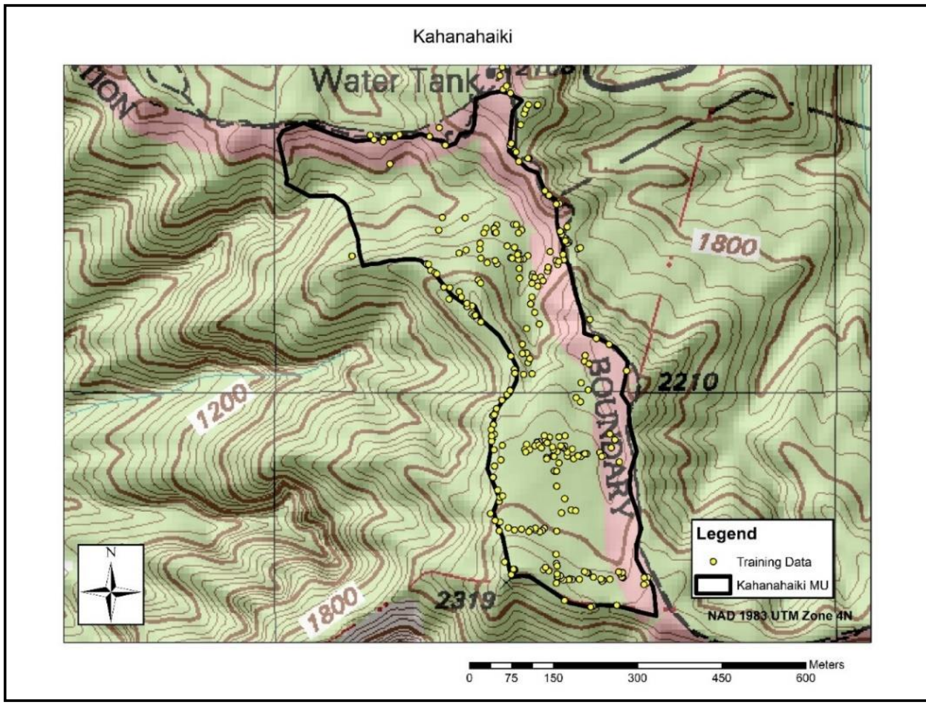
2.2. Materials and Methods

2.2.1 Field Data Collection

A Trimble Geo7XH GPS unit was rented from Pacific GPS for ground control point (GCP) and training data collection. The Geo7XH has the capacity to capture GPS ground locations with a positional accuracy of 50cm. GCPs were installed along the boundary of Kahanahaiki along the ridges and in the interior at open spaces with markers and spraypaint on the ground (Figure 5). These visual markers were installed to assist the orthorectification process of the high resolution aerial imagery. Locations of characteristic vegetation were identified throughout Kahanahaiki in a stratified non-random sampling strategy (Figure 6). These locations, to be used later for the collection of training data, were found on the gulch, flat upper plateau, and bordering ridgelines (Figure 7).

Figure 5. Orthorectification ground marker data collection.

Figure 6. Kapua Kawelo gathering training data locations of characteristic vegetation.



1	Bidtort	2
2	Diosan	9
3	Dodvisc	1
4	Diclin	2
5	Micstr	1
6	Nepexa	2
7	Phichi	1
8	Cibcha	1
9	Grerob	13
10	Acakoa	20
11	Melmin	34
12	Metpol	15
13	Nessan	1
14	Panmax	1
15	Pipalb	1
16	Pissan	1
17	Psicat	42
18	Psicatluc	7
19	Psyodo	9
20	Sanfre	2
21	Schter	33

Figure 7. Kahanahaiki MU with field collected training data of characteristic vegetation.

2.2.2 Gigapan

Scouting was undertaken along the rim of Kahanahaiki to find effective vantage points for Gigapan gigapixel mosaic imagery. Four locations were identified and imagery was taken between 11:00 a.m. and 1:00 p.m. Hawaii Standard Time to minimize variations in shadowing due to the change of the sun's position. The northern portion of Kahanahaiki is composed of a moderate drainage and imagery was taken on both sides of this gulch (Figures 8-10). Equipment included: Canon EOS 60D, Canon 100-400mm F4-5.6L lens, tripod and Gigapan Epic Pro. Different settings were used to find an optimal compromise of manual focus vs. autofocus, aperture and shutterspeed, and manual mode vs. Aperture priority. The most effective panorama was taken with the following settings: full zoom to 400mm, AV priority mode, f8, ISO 400, and image stabilizer off. The camera needed tending as it would not focus on a background of sky or ocean, necessitating a manual switch over to manual focus during these scenes and back to autofocus with a forest background

(Figure 8|). GPS offsets for use with the Gigapan were explored with the integration of a Truepulse® 360R laser rangefinder connected by bluetooth to the Trimble® GPS (Figure 9).

Figure 8. Gigapan data collection at Kahanahaiki facing southwest into the main gulch.

Figure 9. GPS offset exploration with laser rangefinder and Trimble GPS.

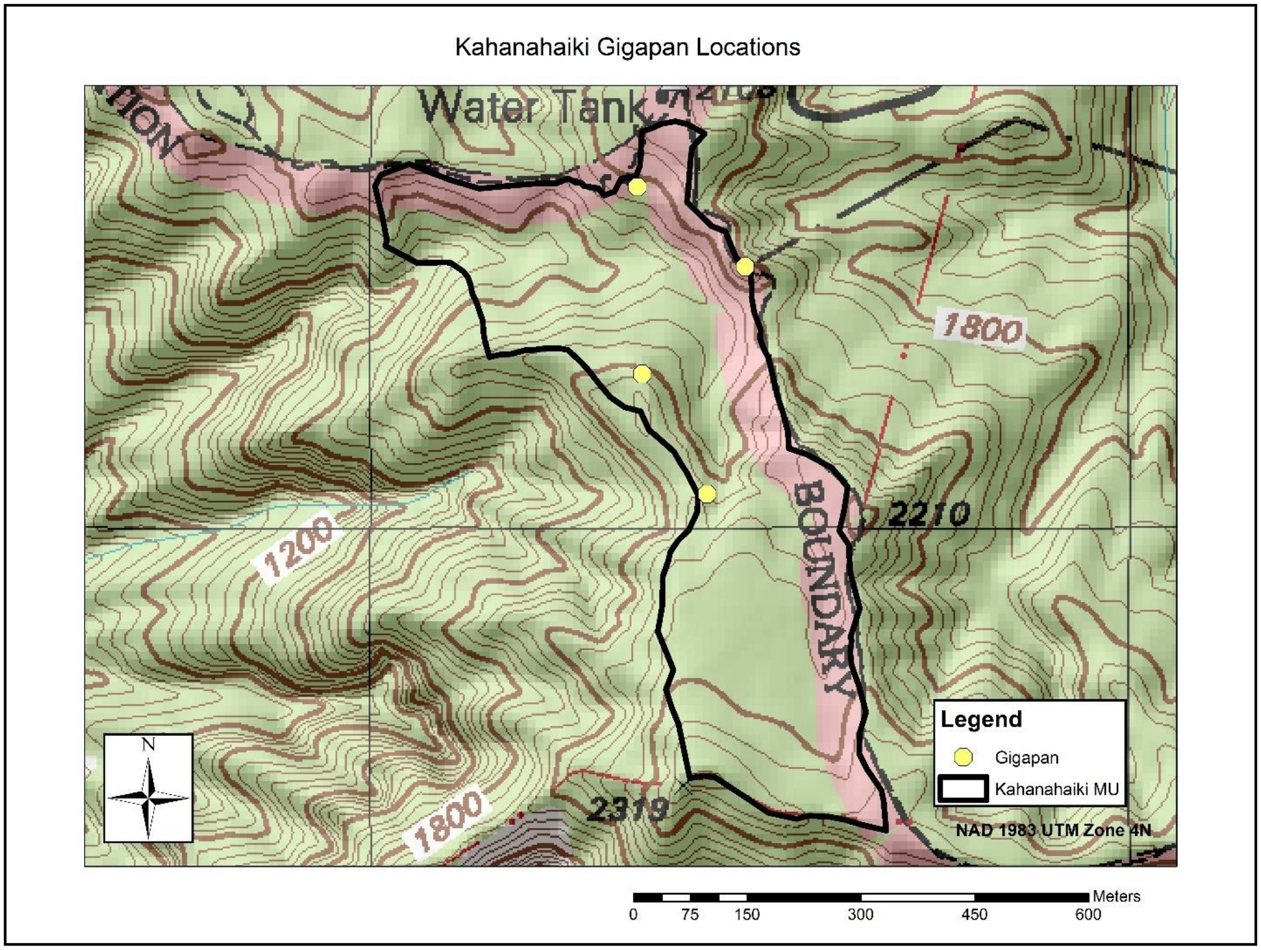


Figure 10. Gigapan image acquisition locations in Kahanahaiki.

2.2.3 High Resolution Aerial

Resource Mapping Hawaii was contracted in the spring of 2015 to collect high resolution orthorectified imagery of Kahanahaiki and Makaha. Four flights were made with a Cessna 206 in an attempt to image the target areas. Flights were made after 10 a.m. to capture imagery when the sun was overhead and casting the least amount of shadowing. Incidentally there were significant low level clouds during the flights and several missions were deemed to be unsafe to the pilot and crew. Partial imagery of upper Makaha was obtained (Figure 11).

Figure 11. Makaha subunit II image sample from a Resource Mapping flight. The Kumaipo LZ and MU fence is discernable with dark green Strawberry guava and light green koa canopy.

After four failed flights, focus switched to an Unmanned Aerial System (UAS) in order to safely collect data flying below the cloud ceiling. UH Manoa Geography graduate, Charles Devaney was brought on for the UAS phase. A test flight was conducted with a DJI Phantom and GoPro Hero 3 camera. Resulting imagery showed potential. The flight mission was preplanned in Mission Planner® by Mr. Devaney to image Kahanahaiki and a flight was coordinated with favorable weather conditions. A Y-6 rotary UAS was prepped and flown by Mr. Devaney. It flew 3 out of 5 preplanned flight segments on Pixhawk® autopilot after the initial launch (Figures 12 and 13). The Y-6 mission was aborted due to significant compass errors and potential firmware issues complicated by possible interference from nearby communication towers.

Figure 12. Y-6 rotary UAS being prepped for launch.

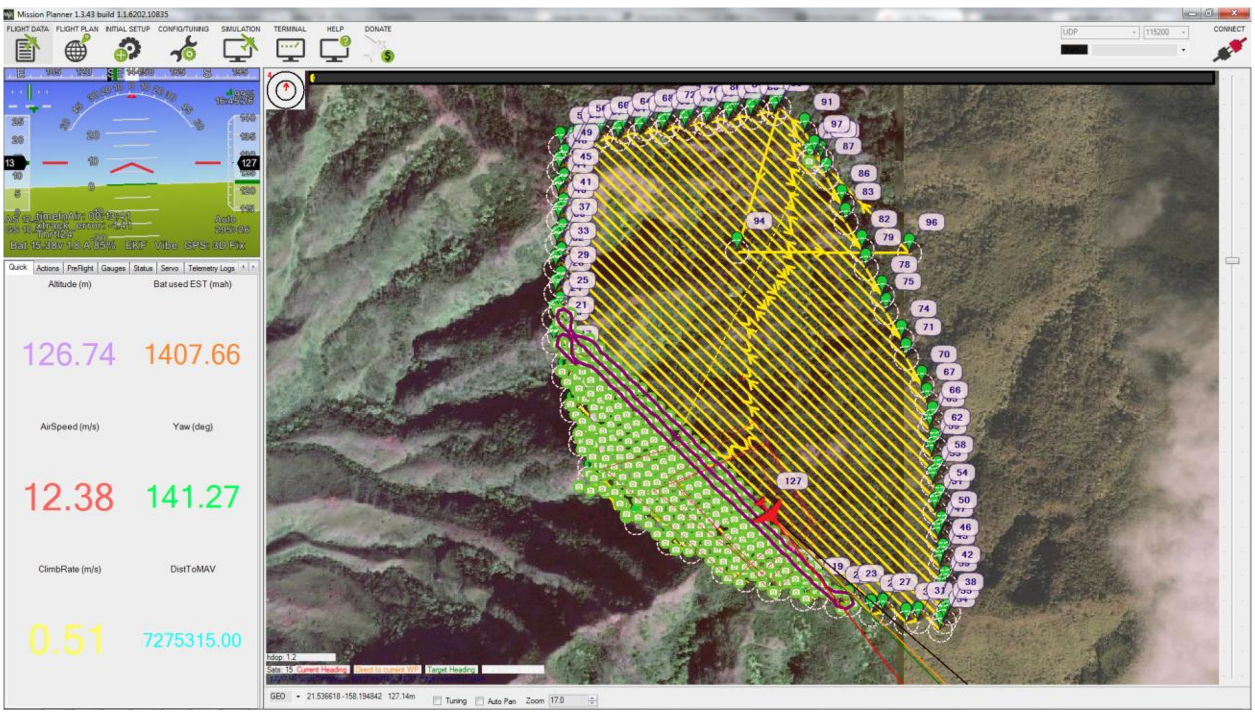


Figure 13. Flight mission planned in Mission Planner®.

A fixed wing, Skywalker 1900 UAS was identified as potentially more suitable for the mission (Figure 14). A launch and land location was identified and troubleshooting and equipment testing were conducted. It was flown under conditions that started optimally with light winds and a high cloud ceiling. Weather moved into Kahanahaiki from the south with a low cloud ceiling. An entire MU dataset was collected and the fixed wing performed well on Pixhawk® autopilot staying true to the planned flight. Line of site was achieved throughout the mission, however approximately 25% of the image dataset of Kahanahaiki was partially obstructed by low clouds.

Figure 14. Skywalker 1900 fixed wing UAS pre-launch for test flight by Charles Devaney.

2.2.4 VHR Satellite Imagery Collection

Apollo mapping was contracted to deliver cloud free, 8-band multispectral, 1.24m spatial resolution WV-3 satellite imagery of 185km^2 of the Waianae mountain range. A cloud free portion of the dataset for the northwestern Waianae mountain range including the target MU Kahanahaiki was collected in May, 2015.

2.2.5 Data Processing

Gigapan

Image post-processing was conducted with a Dell XPS ONE_2710, with processor: Intel ® Core ™ i5-3450S CPU @2.80 GHz, Installed memory (RAM): 6.0GB, and System type: 64-bit operating system. Images were processed in Adobe Light Room® 5.0. A 10% level increase was applied to contrast, vibrance, clarity, saturation, sharpening and noise reduction of each image. The gigapixel panorama of the study site was merged using GigaPan Stitch® 2.3.0307.

UAS

Two image deliverables were obtained from the Skywalker 1900, a 3-D image mosaic of and orthorectified tiles of the cloud free southern portion of the MU. Agisoft Photscan ® was used to mosaic the images and orthorectify both mosaics collected by the two platforms. Ground control points were used to orthorectify the image mosaics. Both image sets were merged in Agisoft Photscan® to create a final image mosaic of Kahanahiki. Spatial resolution (horizontal cell resolution) of uniform grid size was approximately 2cm.

WV-3

Apollo mapping delivered a georeferenced WV-3 dataset with approximately 100m positional horizontal error. Figure 15 shows this error with the Kahanahaiki fence overlain on the WV-3 image. WV-3 Imagery for Kahanahaiki was orthorectified with a LiDAR Digital Surface Model (DSM) with the help of Dr. Qi Chen in the UH Geography department (Figure 15). The

LiDAR data was derived from the 2013 coastal dataset collected by NOAA with a 1m horizontal accuracy with vertical positional accuracy of 10.1cm. ENVI® was used with a rigorous orthorectification procedure to orthorectify the WV-3 imagery with the LiDAR Digital Surface Model (DSM).

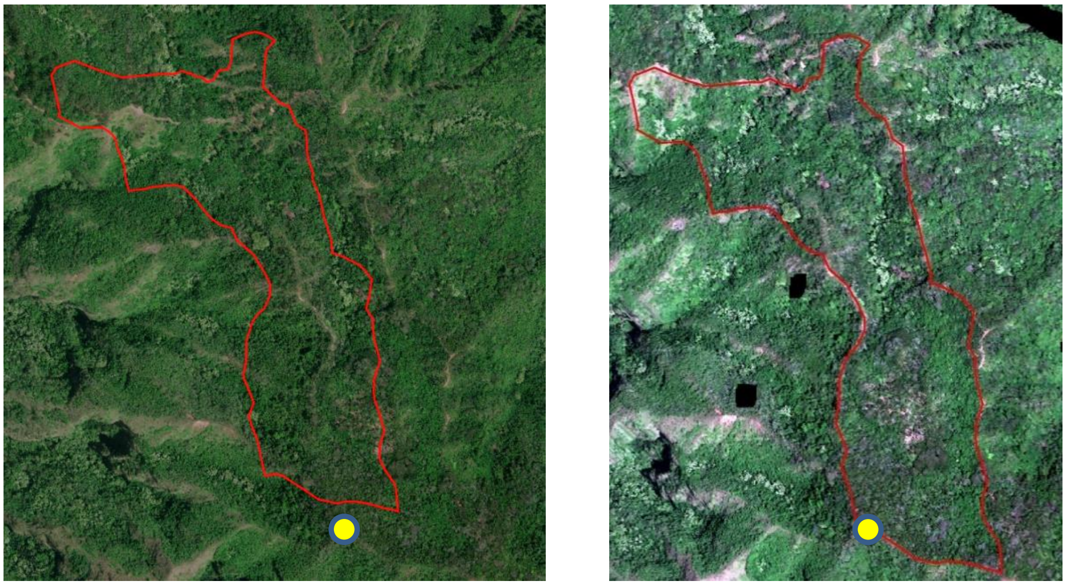


Figure 15. The WV-3 area of interest with Georeference error shown with before and after orthorectification. The red line denotes the MU fence boundary. The reference point on both images shows the location of the southwest corner of the MU fence.

2.2.6 Imagery Classification

The WV-3 satellite image was used as a base image layer classified with eCognition® OBIA and validated with the UAS and Gigapan imagery. Training data collected from the study site were used as representative vegetation samples to develop the eCognition classification algorithm decision ruleset. Image processing was conducted with a Dell™ XPS 8500, Processor: Intel® Core™i7-3770 CPU @ 3.40 GHz, Installed memory (RAM): 16.0GB, System type: 64-bit Operating system. The orthorectified WV-3 imagery was processed in eCognition® Developer 9.1 using an object based approach to classify vegetation classes. The process began with a segmentation algorithm that divides the image up into image objects. The image objects were separated into classes through an iterative process of setting threshold values for the 8 different spectral bands. Training data were obtained from GPS locations of target species to run a nearest neighbor classification algorithm. The classes were: Bare ground, Sparse Vegetation (which included grasses, herbaceous weeds and understory ferns), Kukui (*Aleurites molucanna)*, Psicat (*Psidium cattleianum)*, Schter (*Schinus terebinthifolius)*, Koa (*Acacia koa)*, and Native Complex (which includes a host of native vegetation species). See Figures 16-22 for images taken during the OBIA process. See Appendix B for a complete eCognition® procedural workflow. The Gigapan mosaics were used for cross-referencing ortho-aerial imagery through visual comparison to improve the training dataset and assist with the accuracy assessment. Gigapan imagery was used in instances where the UAS imagery showed distortion from vegetation movement due to wind, insufficient image overlap and terrain, or blur by cloud cover during the data collection (Appendix C).

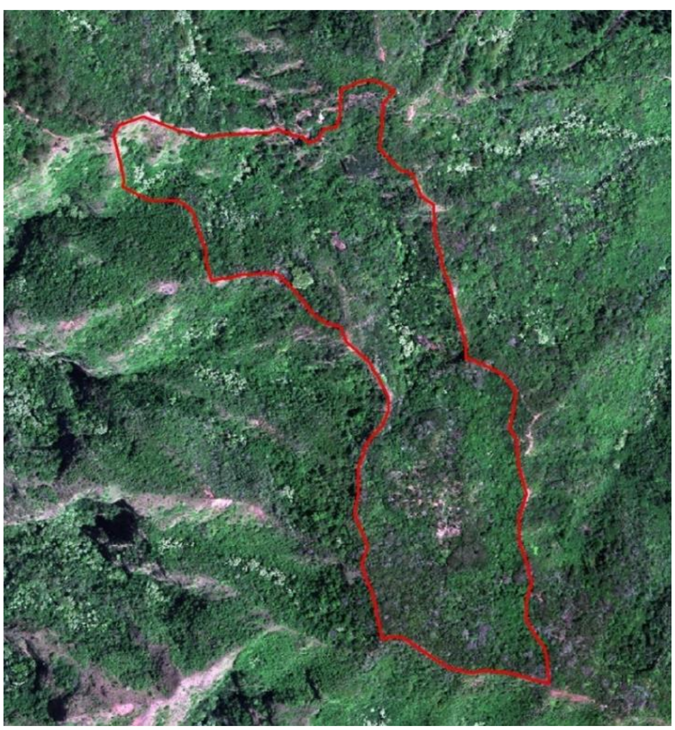


Figure 16. Area of interest for image classification. The red line denotes the MU fence boundary

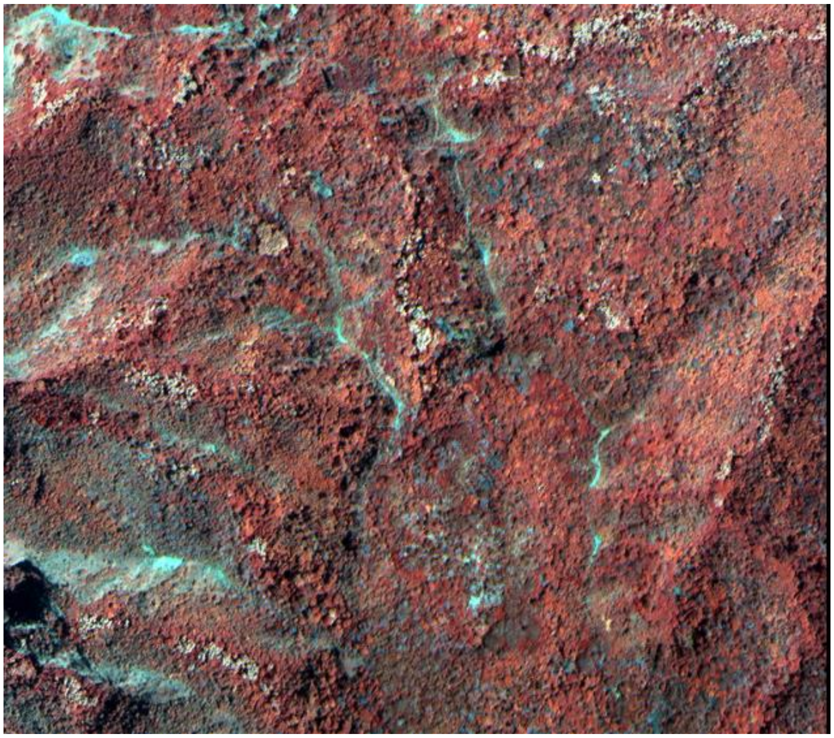


Figure 17. The 6 layer mix false color composite.

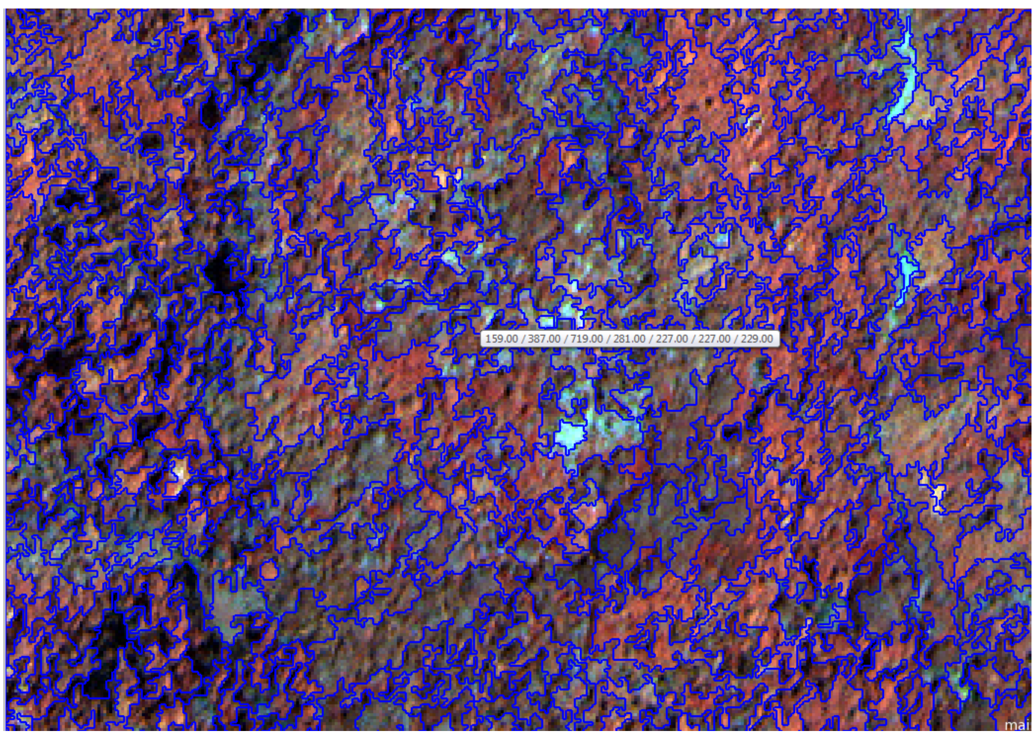


Figure 18. Segmentation algorithm separating tree crowns into image objects by reflectance values.

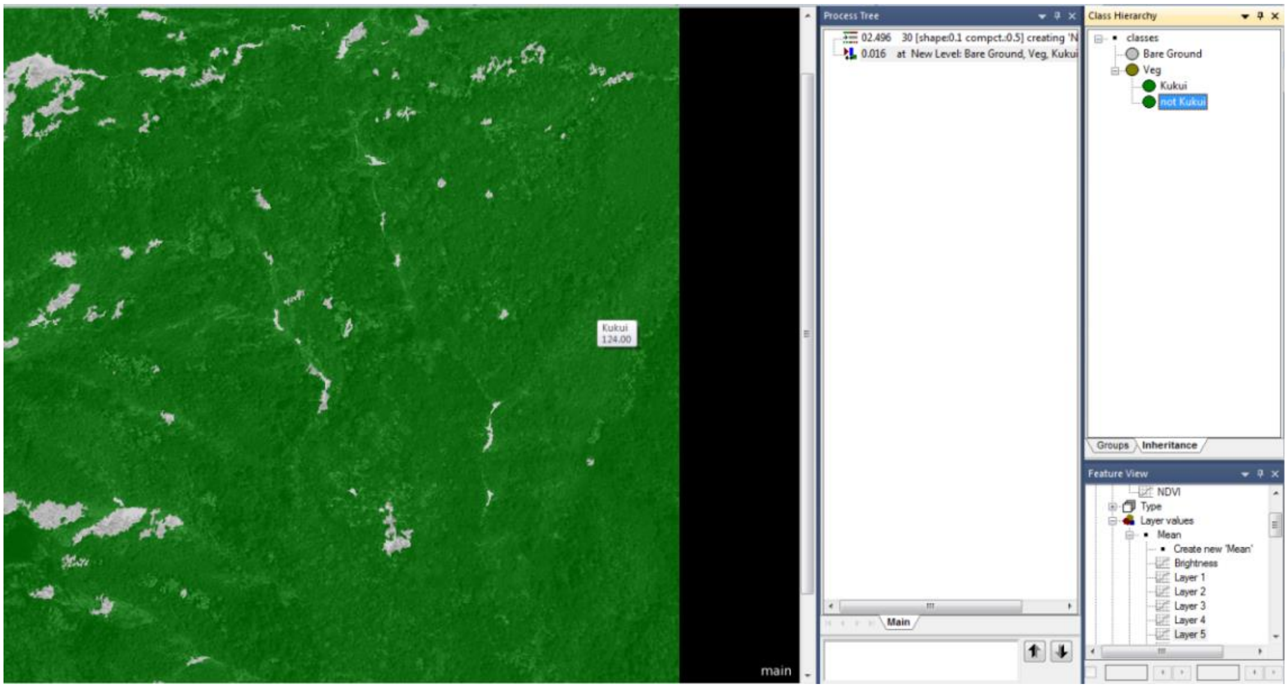


Figure 19. Vegetation vs. non-veg bare ground with vegetation in green and bare ground as grey.

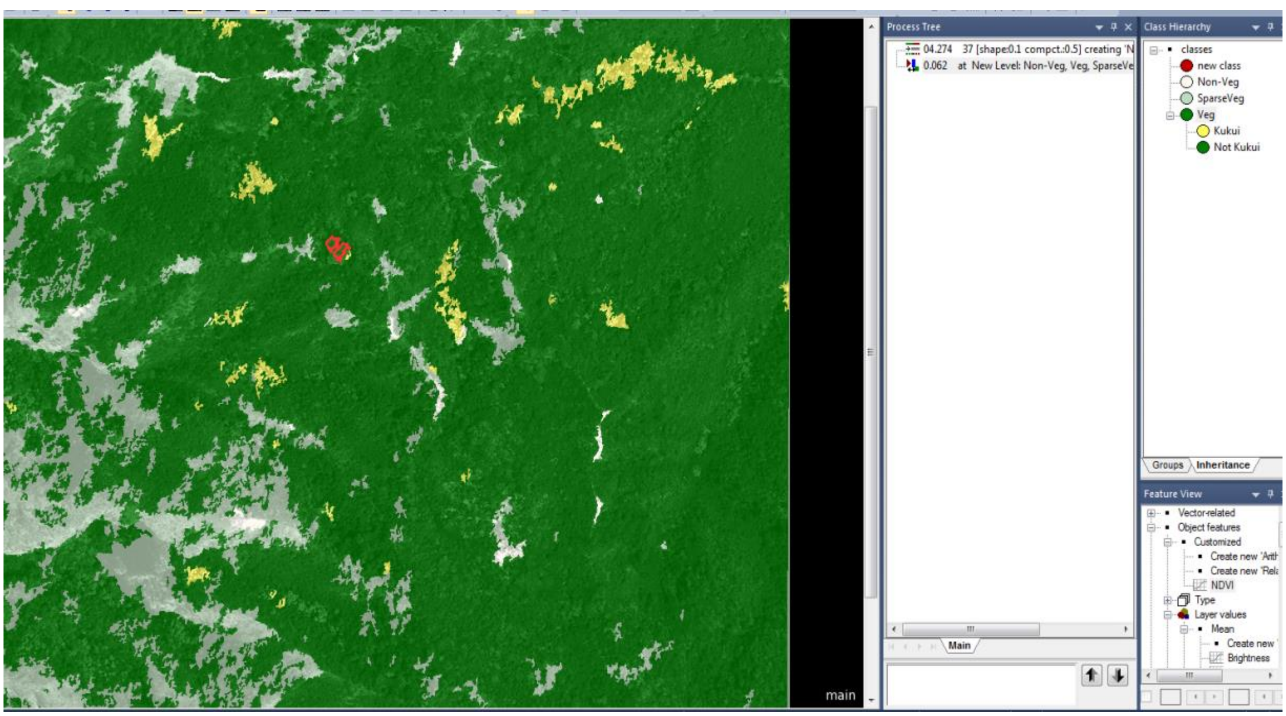


Figure 20. Kukui classification result in yellow.

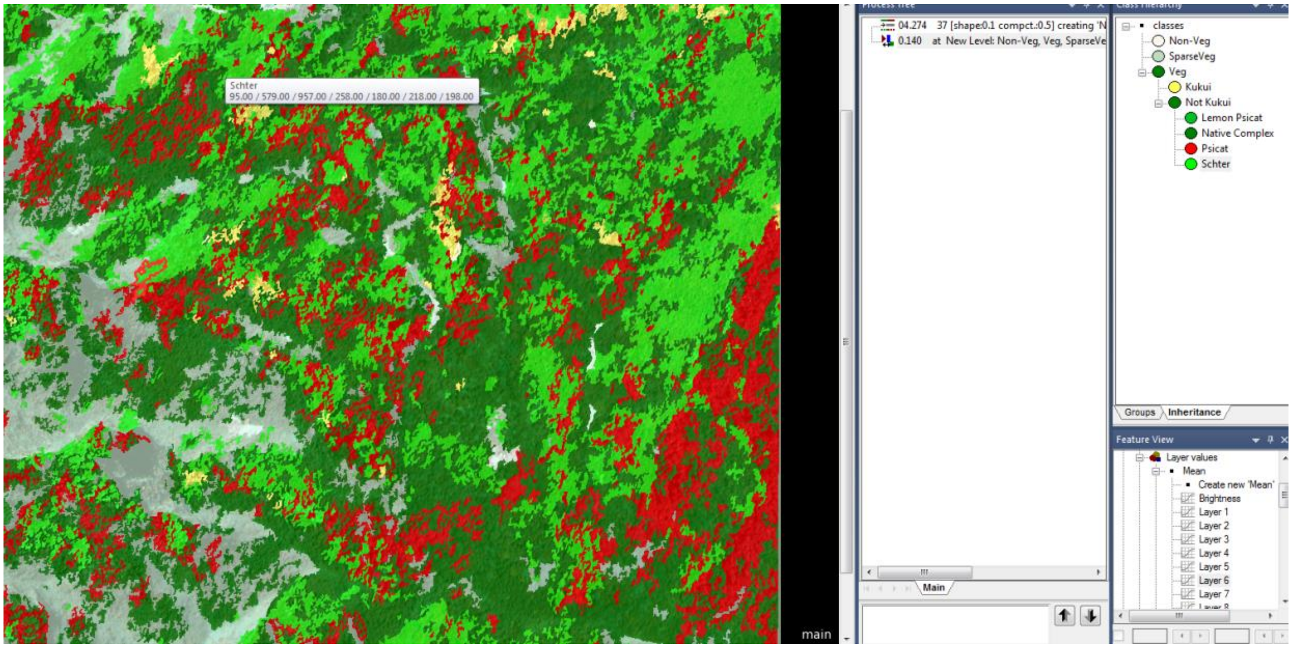


Figure 21. Classification of Bare ground (white), Sparse veg (grey), Kukui (yellow), Strawberry guava (red), Christmas berry (light green), and Native Complex (dark green).

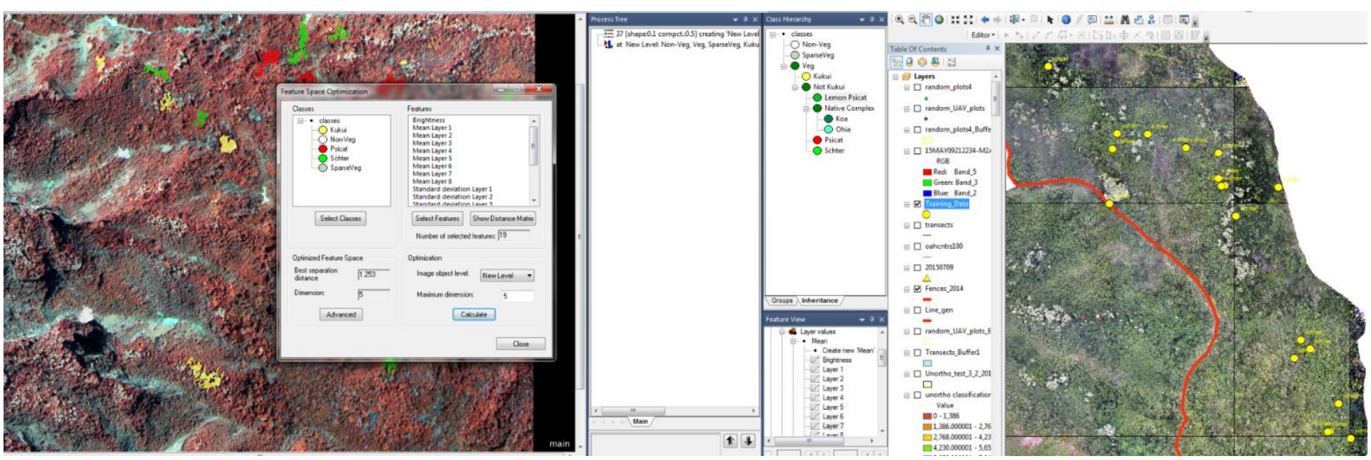


Figure 22. Selecting samples with training data from ground work and running the nearest neighbor algorithm.

2.2.7 Validation

The classified imagery was analyzed using ArcMap® to overlay the various image layers for the study area. A stratified random design was utilized by randomly deploying 50 random points per class or strata in ArcMap® using the Create Random Points tool. In order to achieve an objective validation assessment, the list of points was randomized using a random list generator from www.random.org and the class of each point was determined blindly without referencing the classified map (Figure 23). UAS and Gigapan images were used in a visual assessment of each point to determine the accuracy of the classified vegetation map (Appendix C). The classification of each point was compared to the eCognition® classification results and a confusion matrix was generated to show the "overall accuracy" of the map, or the percentage of correctly classified map units. In addition, a "producer's accuracy" was generated showing how well a classified unit can be mapped, and a "user's accuracy" representing the probability that a pixel classified in the map is actually that unit on the ground (Congalton, 1991; Jacobi and Ambagis, 2013). The Gigapan mosaics were used for cross-referencing ortho-aerial imagery through visual comparison to assist with the accuracy assessment. Gigapan imagery was used in instances where the UAS imagery showed distortion from vegetation movement due to wind, insufficient image overlap and terrain, or blurry cloud cover during the data collection. ArcMap® 10.1 was used to determine the percent cover of each class.

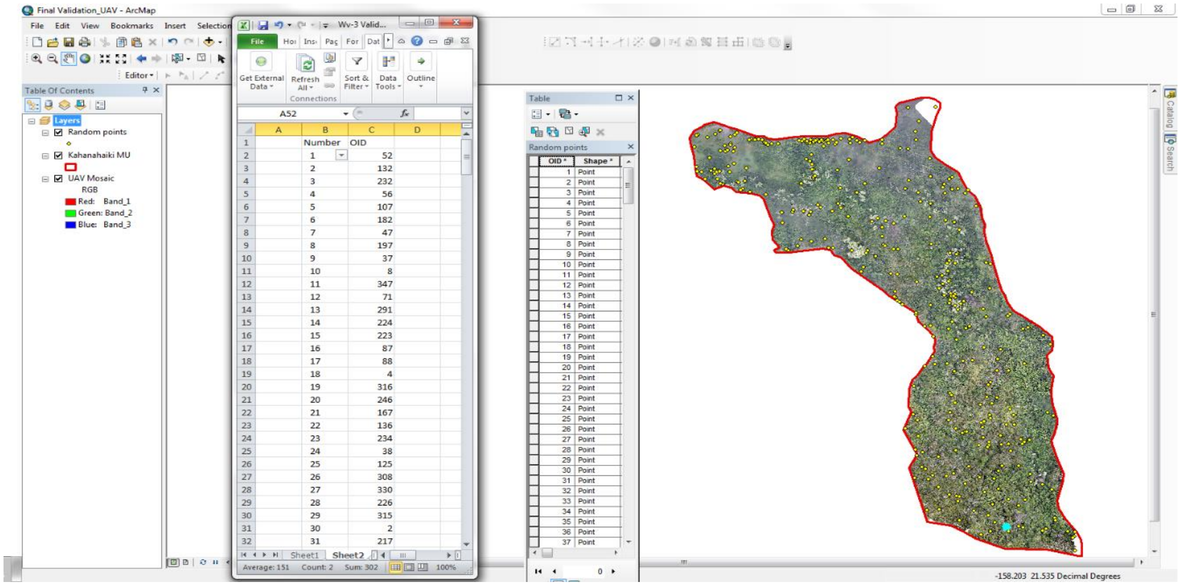


Figure 23. Validation with 50 randomized points per class.

2.3 Results

2.3.1 Comparison of Gigapan, UAS, and WV-3 Images

The WV-3 satellite image covers the greatest area and has consistent exposure and tone. Topography and broad vegetation cover are visually discernable with the 1.24m spatial resolution (Figure 30).

Figure 24. WV-3 satellite image from Apollo Mapping, acquired May 9, 2015.

The UAS imagery extends across the Kahanahaiki MU and shows some inconsistency in lighting and some blurred areas due to clouds. The high spatial resolution of 2cm allows for visual identification of vegetation to the species level (Figure 25).

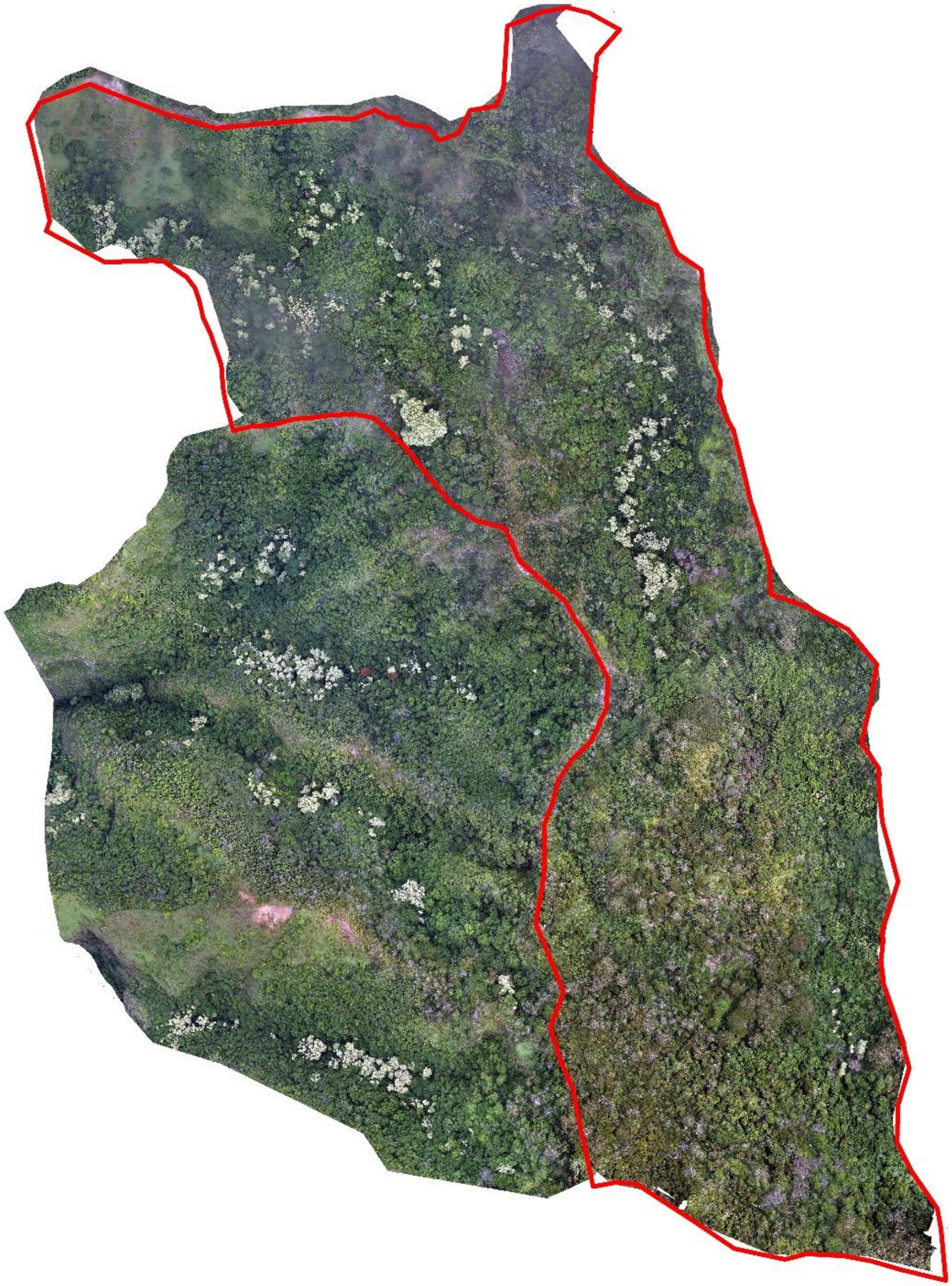


Figure 25. Complete UAS image mosaic with MU fence boundary in red.

The Gigapan imagery extends across parts of the Kahanahaiki MU and shows much inconsistency in exposure due to changes in lighting. The southern portion of the MU was not imaged as terrain is fairly flat and there were no suitable vantage points. The high spatial resolution of 0.5-1cm allows for visual identification of vegetation species and in some instances, vegetation phenology (Figures 26-28).

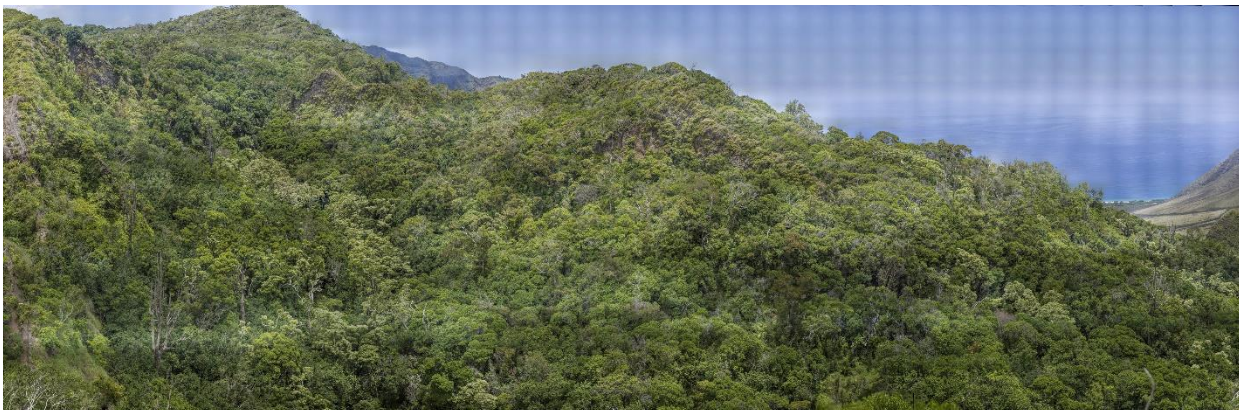


Figure 26. Gigapan 1- 900 image Gigapan mosaic of the northeast facing main gulch.

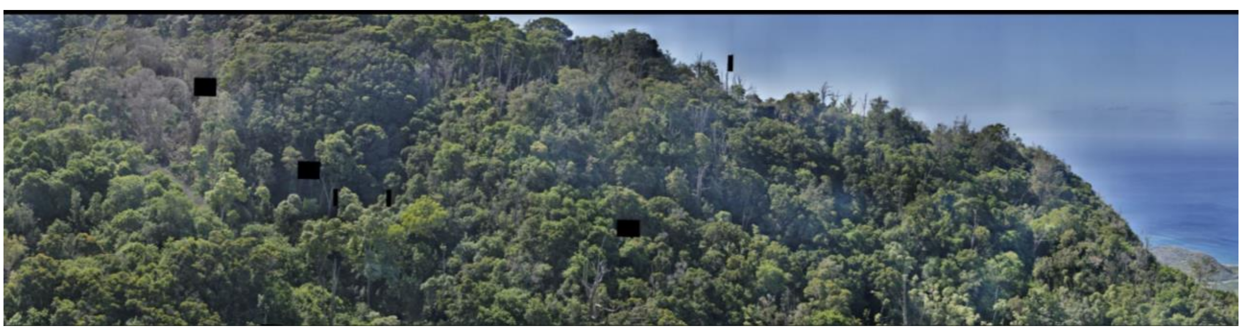


Figure 27. Gigapan 2. 660 image Gigapan mosaic of northwestern portion of gulch

Figure 28. Gigapan 3. 720 image Gigapan mosaic of southwest facing slope of the main gulch.

Figures 29-31 depict approximately the same scene collected by WV-3, UAS and Gigapan. In the WV-3 image (Figure 29) the pixels are prominent but a trained observer can discern different plant species. The light green in the gulch is kukui (*A. moluccana)*, whereas the dark green on the upper slope is strawberry guava (*P. cattleianum*). In Figure 37, the same kukui and strawberry guava prominently stand out, in addition to a host of other plant species. The gigapan image (Figure 31) shows a high oblique perspective. Plant species are easily discernable.

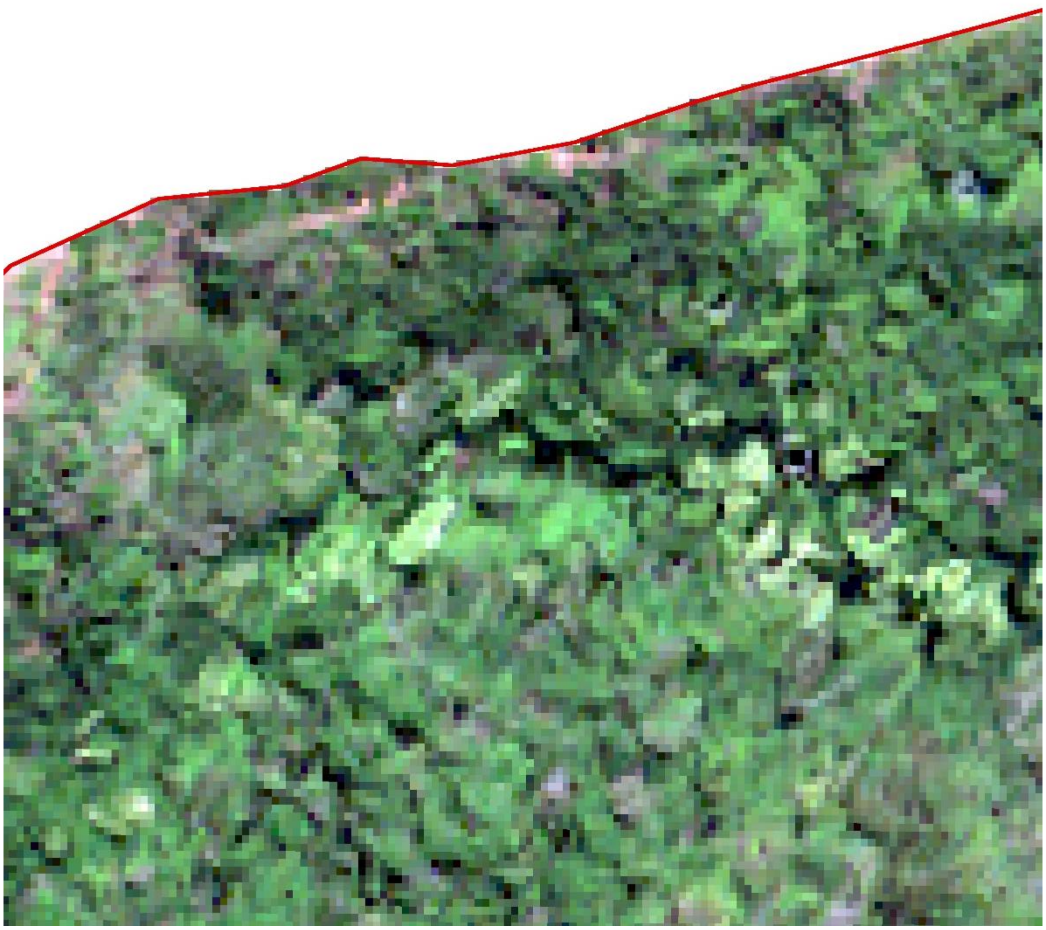


Figure 29. Cropped WV-3 image of a target location for comparison.

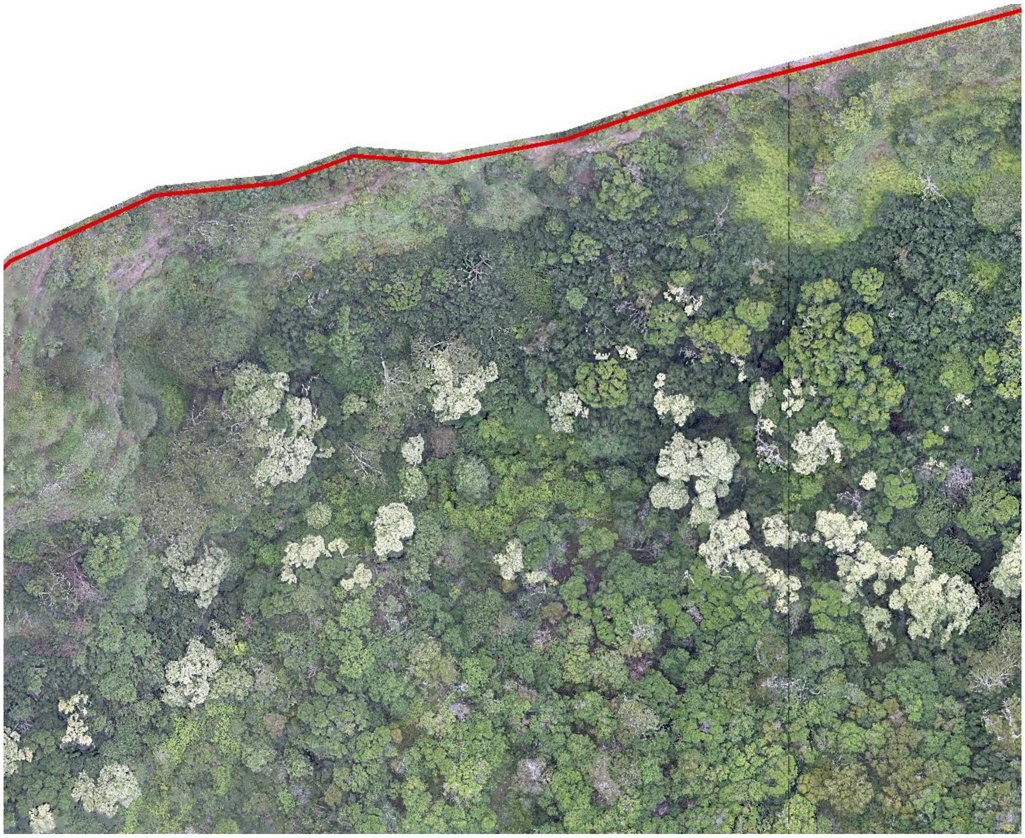


Figure 30. Cropped UAS image of a target location for comparison.

Figure 31. Cropped Gigapan image of a target location for comparison.

Zooming in further on the chosen scene yields the images displayed in Figure 32. The WV-3 image is extremely pixelated and vegetation is undiscernible without comparison to other imagery. The UAS and Gigapan imagery shows a prominent dead tree surrounded by strawberry guava (*P. cattleianum)* with kukui (*A. molucanna)* and koa (*A. koa*) below.

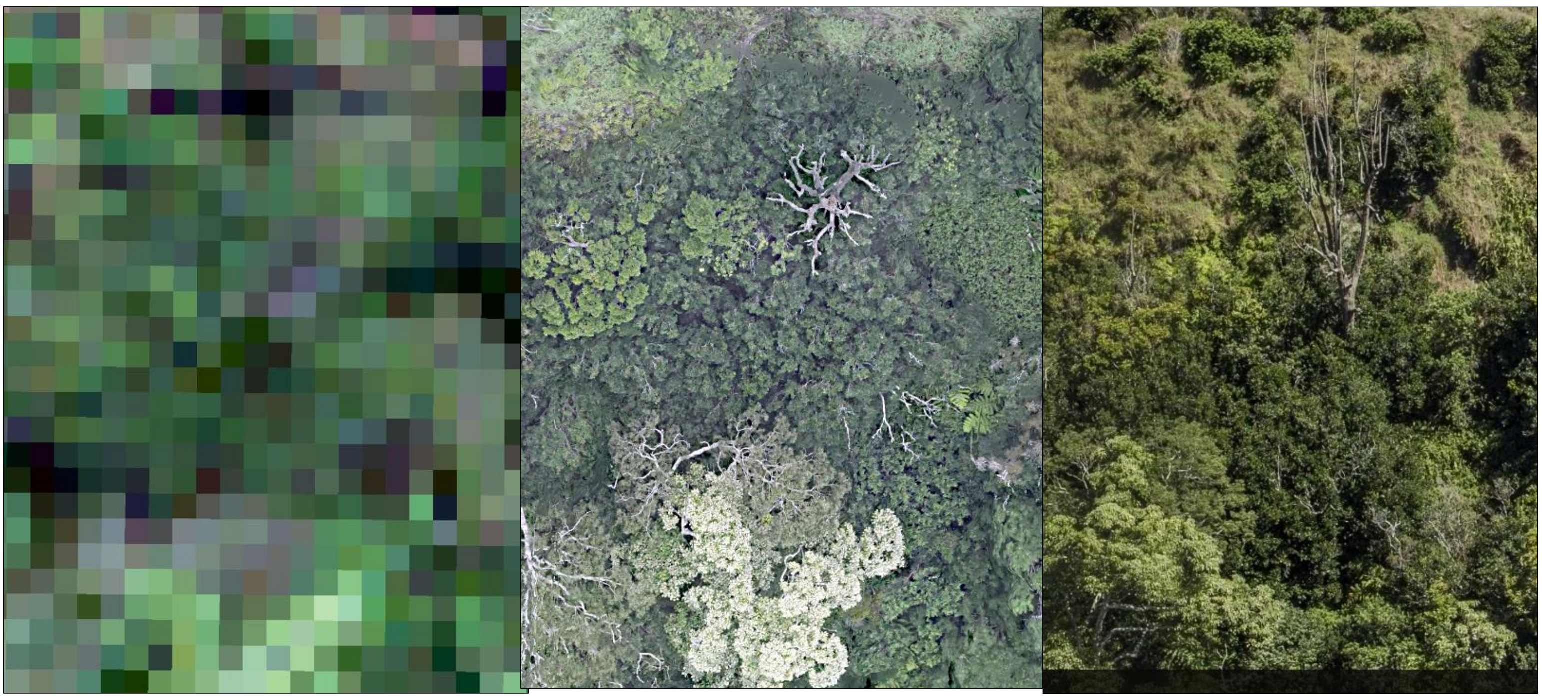


Figure 32. Extreme zoom of the target location with WV-3, UAS and Gigapan imagery.

2.3.2 Vegetation Classification

The result of vegetation classification of the WV-3 imagery is shown in Figure 33. Seven classes were mapped across the Kahanahaiki MU. The Kukui class seems to show a distribution in the lower gulch. Christmas berry is spread dominantly across the MU. Native Complex is distributed across the MU with the highest frequency in the southern portion. Table 5 shows a percent cover analysis with the breakdown of percent cover per class and the overall percentages of Native vs. Non-native cover, Native Cover = 42.99% and Non-native Cover = 53.38%.

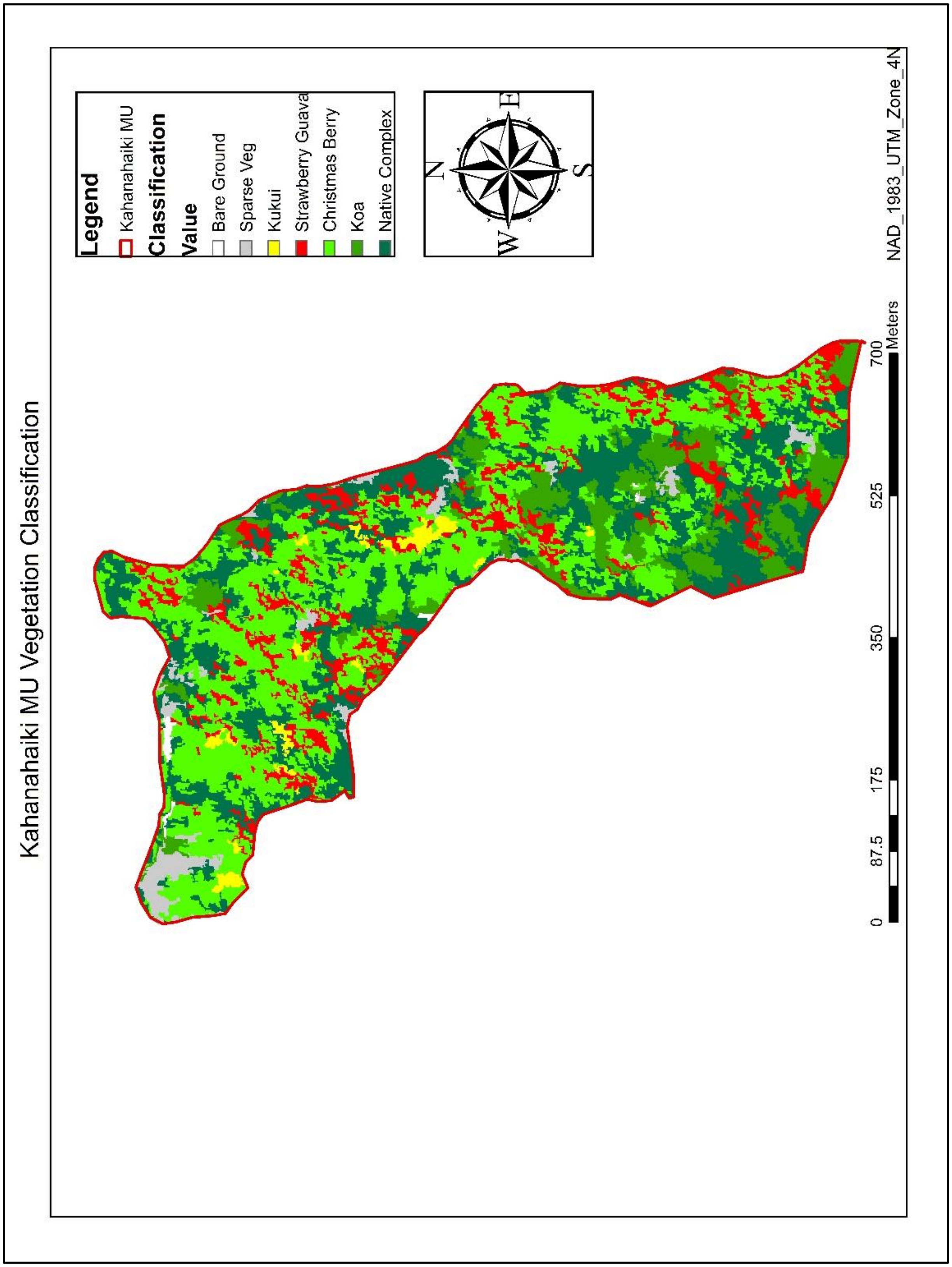


Figure 33. Final Kahanahaiki MU vegetation classification map generated with WV-3 imagery.

Table 3. Percent cover of classes

Class	Description	Pixel Count	%Cover			
1	Bare Ground	580	0.35%			
2	Sparse Veg	5395	3.28%			
3	Kukui	2809	1.71%			
4	Strawberry guava	20398	12.42%			
5	Christmas Berry	64478	39.25%			
6	Koa	21124	12.86%			
7	Native Complex	49481	30.13%		Native Cover	42.99%
		164265	100.00%		Non-native Cover	53.38%

Validation results yielded an overall user's accuracy of 65% with Sparse Veg representing the highest user's accuracy of 94% and Strawberry guava representing the lowest user's accuracy of 38% (Table 5). The user's accuracies of the other classes were: Kukui=75%, Christmas Berry 73%, Koa=50% and Native Complex=42% (Table 5). Grouping native and non-native vegetation classes yielded an overall accuracy of 85% with non-native = 93% and native = 69% (Table 6).

Table 4. Confusion matrix for the validation results of the classification map.

	UAS Reference										User's Accuracy	
eCognition Veg Map		Class	Bare Ground	Sparse Veg	Kukui	Strawberry guava	Christmas Berry	Koa	Native Complex	Total	% Correct	
		Bare Ground	40	10						50	80%	
		Sparse Veg		46			2	1		49	94%	
		Kukui			35	7	7	1		47	75%	
		Strawberry guava	1	5	1	16	13	5	3	42	38%	
		Christmas Berry		1	4	5	33	2		45	73%	
		Koa		3		4	3	22	12	44	50%	
		Native Complex		1		4	10	6	15	36	42%	
		Total	41	66	40	36	68	37	30	318		
	Producer's Accuracy	% Correct	98%	70%	88%	44%	49%	60%	50%		65%	Overall Accuracy

Table 5. Simplified confusion matrix of validation results grouping native and non-native classes.

	UAS Reference						User's Accuracy	
eCognition Veg Map		Class	Bare Ground	Non-Native	Native	Total	% Correct	
		Bare Ground	40	10		50	80%	
		Non-Native	1	175	12	188	93%	
		Native		25	55	80	69%	
		Total	41	210	67	318		
	Producer's Accuracy	% Correct	98%	83%	82%		85%	Overall Accuracy

2.4 Discussion

2.4.1 Data Collection Challenges

Spring of 2015 was chosen as the image collection window as much of the vegetation flushes and blooms during this time, allowing for change in phenology to assist in vegetation classification. However, spring and summer of 2015 were also a period of unstable weather and low clouds, which presented data collection issues. Fortunately, a relatively clear window of weather allowed for a cloud free data collection for WV-3 in May, 2015. June and July were unseasonably wet in the Waianae Mountains. Four missions were attempted with the Cessna 206 but low clouds served to be an issue and this data collection method was abandoned for UAS. The UAS approach was taken to fly below the clouds and four flights were made. Two out of four missions were partially successful and a workable dataset was produced from the merging of two image datasets. On these occasions weather was favorable in the morning; however, during mid-flight the clouds set in. This highlights the difficult nature of capturing cloud free ortho-imagery around the remote, mountainous areas of Oahu. Often conditions are clear in the morning hours and then become cloudy when the collection window at midday nears. It may have been better to collect imagery during the winter months, targeting a window with a change in weather following a cold front when the wind shifts from the north, the trade wind inversion is interrupted, and clear weather persists.

2.4.2 Gigapan Challenges, Utility and Recommendations

Gigapan image collection faced challenges with camera focus and proper exposure of images due to weather changes. The Gigapan occasionally skipped images if proper focus was not found due to a sky background. To avoid this, the operator must switch the camera back and forth between autofocus and manual focus as the Gigapan pans through the scene. Setting the manual focus to infinity for the duration of the scene was tried with poor results. Image stitching was impacted with gaps in data due to skipping. A blank “no data” image was inserted in instances where images were skipped to keep the rest of the row in line. As clouds moved into the scene images were rendered darker in the shadows. Post-processing in LightRoom® was conducted to even out the exposure changes due to clouds. This served to be time consuming. Ultimately, it was best to choose an optimal weather day with consistent cloud cover.

Three different gear configurations were tested. A $6,000 Canon 300mm f2.8 lens was rented and tested in Makaha Valley (Appendix A). A $1,700 Canon 100-400mm F4-5.6 lens was purchased and used for the primary project discussed and shown in Chapter 2. Finally, a $479 Canon SX60 with 60x zoom was evaluated. The least expensive option, the superzoom Canon SX60 showed the most potential and captured the highest resolution imagery with the best autofocus system. The Canon 60D and zoom lens systems would not focus on a blank background such as the sky or ocean, whereas the point and shoot Canon SX60 did not have an issue focusing on the sky. In addition, the Canon SX60 offers a longer zoom reach at 1,360mm than the costly 300mm or 100-400mm lenses. Thus, the Canon SX60 is a recommended camera for Gigapan with better performance at a fraction of the price.

Various classification methods were initially explored to analyze the Gigapan imagery. Supervised and unsupervised methods explored with OBIA and Isodata analysis did not yield acceptable results. The Gigapan system showed highest utility for native and target invasive species detection via visual analysis (Appendix A). It shows great utility for capturing imagery of steep target areas that may be unreachable on-foot. In addition, the method is easily repeatable, allowing for repeat image capture of target areas to show change over time and may serve as a VHR panoramic photopoint in forest monitoring. Visual classification of a subset of the image was undertaken to be used for the classification accuracy assessment using visual cues, such as canopy shape, canopy size, canopy color, texture, and relationship to other objects (Jensen, 2007) (Table

8). The Gigapan image was imported into ArcMap® 10.1 and a subset of the panorama was selected and delineated by a polygon feature class.

Table 6. Examples of visual cues used for visual classification of the imagery

	Visual Attributes					
Species	**Canopy shape**	**Canopy size**	**Canopy color**	**Canopy texture**	**Bark/ stem color**	**Relationship to other canopy objects**
Strawberry guava	Uniform relatively flat canopy surface	small	dark green	uniform texture	dark bark	Large monotypic stands
Ohia	irregular canopy with light dead branches	medium	dark green	irregular texture	grey bark with many dead branches	solitary well-spaced
Koa	Irregular canopy	large	light green	irregular texture	greyish white bark	solitary to clumped

The low accuracy of the object based classification method may be attributed to a host of factors with the first being the nature of the Gigapan image incident view angle coupled with the very fine spatial resolution (0.8 cm). The Gigapan image is a very high oblique and the image may be subject to substantial shadowing that did not allow the segmentation process to form classifiable objects. In contrast, the very high resolution is a benefit for visual identification and classification of plant species and serves to be useful during the object based process. However, this is a result of the combination of hundreds of images that take a while to capture. It took nearly 40 minutes to cover just half of the scene of upper Makaha Valley. The cloud cover was relatively uniform, which was beneficial, however the light levels fluctuated during the data collection and the scene was brighter as the sun emerged from behind the clouds. This complicated and led to errors in classification as much of the preliminary segmentation was based on reflectance values. The file size is also effectively quite large as a gigapixel file making for time consuming post-processing.

Perhaps the greatest drawback to Gigapan imagery and the specific equipment used for this study was the limiting factor of only three available bands: red, green and blue (RGB). The lack of a fourth near infrared (NIR) band was a hindrance in the object based classification process as several of the classification algorithms rely on this NIR band to run a normalized difference vegetation index (NDVI) vegetation index sequence. eCognition offers manual classification techniques that allows for a higher classification accuracy, but this leads to the question, at what point is it simply more effective to conduct visual classification?

Visual classification of the Gigapan image served to be very effective even to the incipient invasive species level. The very high spatial resolution and this researcher's familiarity with the region and its associated species helped to facilitate this. This highlights perhaps the greatest utility of the Gigapan system with vegetation mapping and monitoring for managers to detect target native species and incipient invasive species in management areas and visually track landscape changes over time. Exploration and close examination of Gigapan #1 yielded the identification of the extirpated, critically Endangered *Cyanea superba* subsp. *superba* in Kahanahaiki gulch (Figure 34). The vantage point used had an unobstructed view and was higher in elevation than the target area. It is of note that this suitable vantage point allows for the best utility of Gigapan. The Gigapan system will serve to be a very useful tool if images can be georeferenced with the Truepulse® system incorporated with a Trimble GPS unit to assist in ground location of target plants.

Figure 34. A zoomed in view of Gigapan 1 yields the identification of the critically Endangered *Cyanea superba* subsp. *superba.*

It would be of great value to identify a process or tool that would georeference Gigapan gigapixel imagery allowing for integration with other base layers and target location identification. The Truepulse® 360R laser rangefinder has high potential to allow for key georeference point collection of gps offsets and showed horizontal error of 1-10m from up to 500m from selected targets. Attaching the Truepulse® to the camera introduced significant compass error to the GPS offsets due to the proximity to the metal components of the lens and camera. However, this error could be calibrated as it showed to consistently offset the true GPS location.

2.4.3 UAS Challenges and Recommendations

Benefits of UAS include but are not limited to: cost effectiveness while delivering a quality suite of image data products, reduction of risk, easier mobilization and the capability of flying safely below the cloud ceiling. The rotor and fixed wing UASs were flown with a Sony Mirrorless camera delivering sharp, high resolution images**.** Battery life of rotor UAS was a limiting factor with 10 minute flights. If a safe landing is achievable the fixed wing UAS shows great potential, as battery life is expanded significantly. The Skywalker 1900 flew on a single battery for 67 minutes with approximately 60% usage. A suitable landing area was not available for Kahanahaiki so the fixed wing UAS was flown into low vegetation at a reduced speed. Minimal damage occurred but this method was not optimal. A UAS with the capacity for a vertical takeoff and landing that would transition into a fixed wing mode would have been best for this area and may be the platform of the future as it may stay airborne longer than a typical rotor UAS.

There are many UAS's available. Table 9 shows a recommended starter system suitable for vegetation mapping as per personal communication with Charles Devaney. Mission preplanning and image processing is key component of UAS use in mapping and monitoring. Several software programs exist including Pix4D® and Agisoft Photoscan® among the premium options. Dronedeploy® is a leading freeware application offering much of the same function.

Table 7. Recommended UAS system

1- DJI Inspire 1 PRO	
1- Transmitter for Inspire 1 Quadcopter	
1- Zenmuse X5 Camera and 3-Axis Gimbal	
1- MFT 15mm f/1.7 ASPH Prime Lens	
2- TB47 Intelligent Flight Battery for Inspire 1 (99.9Wh)	
1- Flight Battery Charger	
1- Remote Controller Charging Cable	
1- Power Cord	
2- Micro USB Cable	
1- Gimbal Clamp	
1- DJI Harness	
1- Camera With Gimbal Box	
4- Spare Prop CW/CCW Pairs	
1- DJI Professional Hard Case	
1- Lexar 16GB MicroSD Card	
1- SanDisk 64GB Extreme MicroSD Card	
	$4,400

2.4.4 WV-3 Recommendations

The WV-3 imagery was georeferenced by Apollo mapping but full orthorectification was needed. The LiDAR DSM showed high accuracy of approximately 10.1cm vertical positional error allowing for orthorectification with minimal distortion. Apollo mapping was contracted to obtain current imagery within the same collection window as UAS and Gigapan, however this may not be necessary. Other less recent data sets exist and may be suitable at no cost. The NRCS accepts requests for current imagery acquisition via Tony Kimmet. Datasets are delivered orthorectified at a substantial cost saving.

2.4.5 Image Classification Results Discussion

As described in Section 2.3.3, validation results yielded an overall user's accuracy of 65% with Sparse Veg representing the highest user's accuracy of 94% and Strawberry guava representing the lowest user's accuracy of 38%, whereas Kukui=75%, Christmasberry=73%, Koa=50% and Native Complex=42% (Table 5). Are these acceptable levels? According to the U.S. Department of Agriculture Forest Service (Brohman and Bryant eds. 2005), for a base level classification with a mapping unit less than 5 acres for vegetation map attribute of cover type, the accuracy goal standard is 65-85% (See Table 10). The overall accuracy of 65.1% is acceptable by this standard. The high accuracy of mapping sparse vegetation shows great potential for providing distributions of light fuels for fuel mapping via this method. Mapping of Strawberry guava, Koa and Native Complex classes were not in an acceptable range when mapped separately but combining them brought them to an acceptable level at 72%. However, Kukui and Christmas berry were within the acceptable range.

Table 8. Recommended accuracy assessment standards for vegetation mapping (Brohman and Bryant eds., 2005).

Vegetation map attribute	Map level			
	National goal standard (%)	Broad goal standard (%)	Mid goal standard (%)	Base goal standard (%)
Physiognomic order	80–70	90–80	90–80	90–80
Physiognomic class	80–70	90–80	90–80	90–80
Physiognomic subclass		90–80	90–80	90–80
Alliance		80–65	85–65	85–65
Association		80–65	85–65	85–65
Cover type		80–65	85–65	85–65
Dominance type		80–65	85–65	85–65
Tree canopy closure		80–65	85–65	80–65
Tree diameter class			80–65	80–65

Some of the limitations and challenges of OBIA with eCognition® include the difficulty of mapping a complex, densely vegetated area and capturing the "human cognition," and ecological knowledge (Bunting *et al*, 2015). The dense vegetation of the Hawaiian mixed-mesic forest is among the most difficult forest type to separate classes to the species level (Ambagis pers. com., 2015). The intent in this project was to use more detailed classes for the native complex but the computer used for the analysis could not handle processing the addition of texture and geometry into the hierarchical classification workflow with the nearest neighbor algorithm. A more powerful computer processer and RAM is needed to incorporate additional geometric and textural features into the iterative classification process. The system crashed when these components were integrated into the OBIA workflow. NDVI thresholding showed much potential to separate out sparse vegetation for light fuels for fuel mapping applications.

Future work with deep/machine learning of VHR imagery shows promise. Dr. Ryan Peroy at UH Hilo has been working with deep/machine learning processing to identify target incipient invasive vegetation with UAS imagery. Early research shows much potential with sample UAS images of Miconia to train a deep/machine learning algorithm (Peroy pers. com., 2016).

2.4.6 Recommended VHR Operational Monitoring

The VHR imagery and analysis performed in this thesis show much potential for use in vegetation monitoring and, in particular, UAS shows a wide range of potential applications for incorporation into monitoring. A recommended operational protocol is to fly a rotor UAS at low altitude along preplanned transects in target MUs. Complete coverage may be obtained for smaller target areas, but for large areas transects may serve to be easier to image due to relatively short lived batteries of rotor UAS. Random plots may be generated within the transect-based strips of imagery allowing for a stratified random sampling design (Figures 35 and 36). These plots could then be analyzed by segmentation into image objects to separate vegetation cover (Figure 37). The image segments could then be classified by species for cover analysis using visual classification as visual classification. Deep/machine learning algorithms are worth pursuing in place of visual analysis, especially in instances with large datasets (Peroy pers. com., 2016).

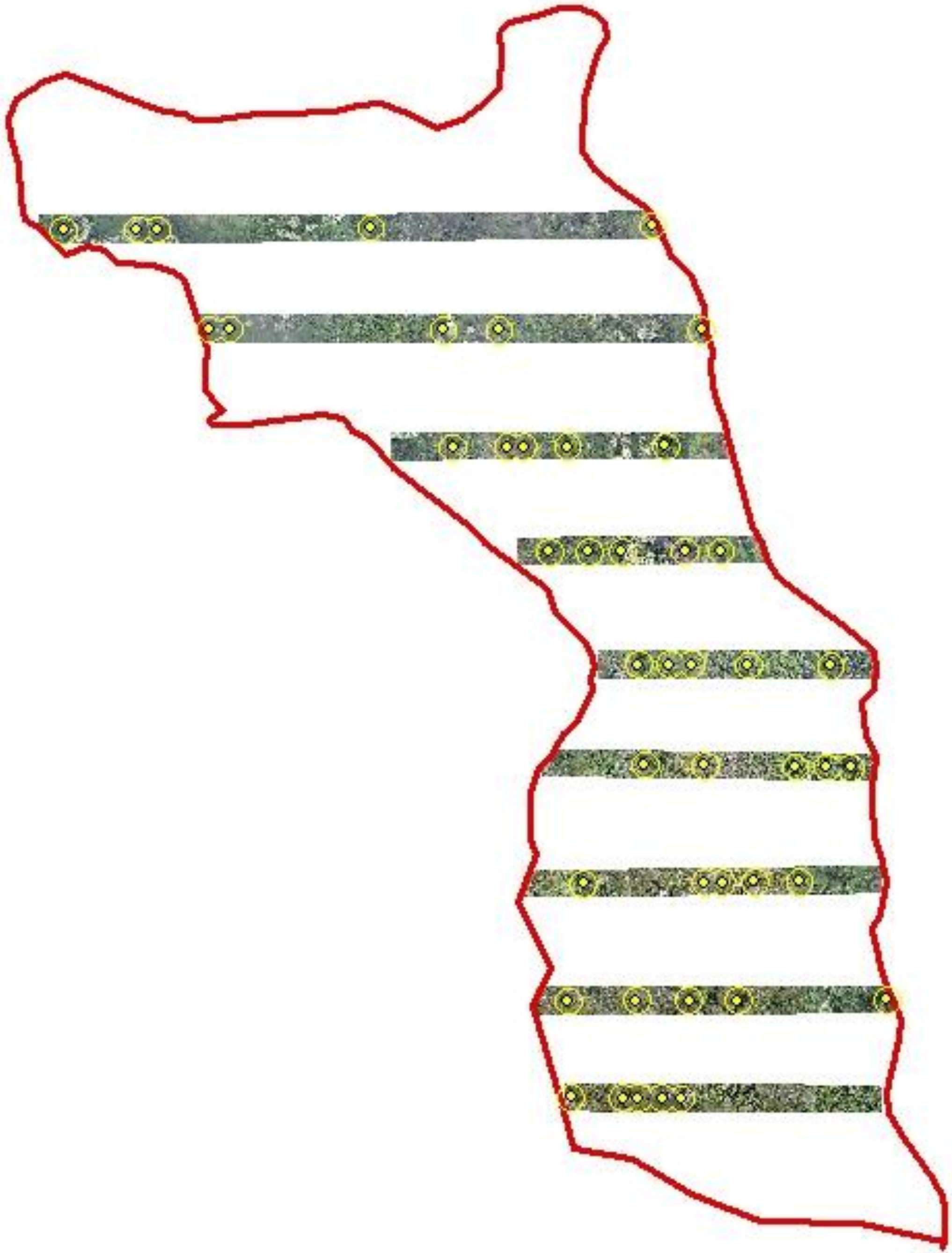


Figure 35. UAS image transect example for Kahanahaiki with random 20 meter diameter plots.

Figure 36. Sample UAS imagery to show a transect method and 20 meter diameter plots.

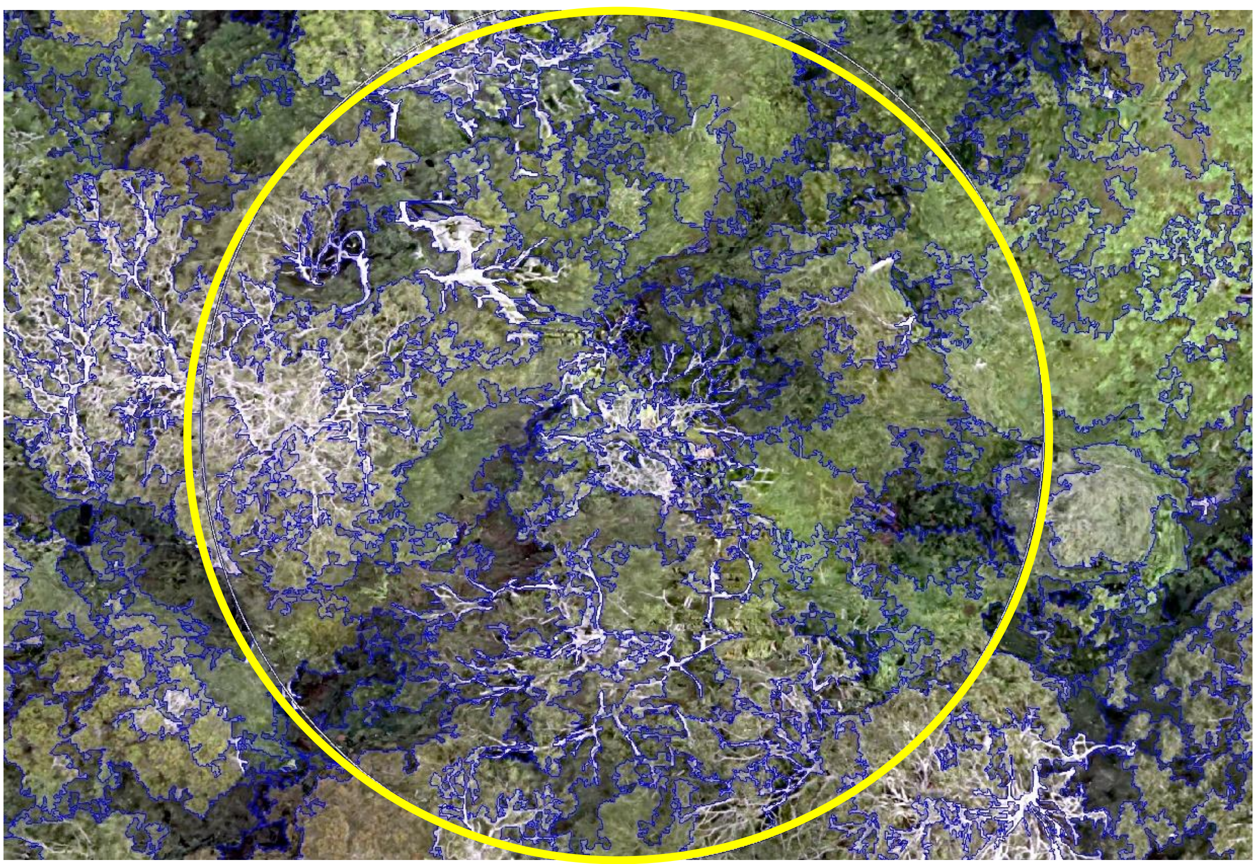


Figure 37. 20meter plot with segmentation of vegetation.

Chapter 3. Cost Analysis

3.1 Rationale

Accurate and timely classification of remote sensing imagery is vital to planning resource management efforts, tracking progress, and driving management decisions for restoration and resource management. As described in Chapter 1, traditional on-the-ground vegetation monitoring techniques can be time consuming and costly. The OANRP database shows that the initial installation of the belt plot monitoring took 294 hours. Analysis of VHR imagery can provide accurate and timely assessments of vegetation on a large scale at a set point in time (Bunting and Lucas, 2006). A remote monitoring procedure may involve less of an investment in time, however this must be weighed with the cost of image acquisition and analysis.

3.2 Objective

Objective 3. Determine the costs associated with the implementation of remote sensing based monitoring protocols as compared to traditional monitoring methods in the same target area.

3.3 Results

A cost analysis was conducted comparing the cost of vegetation classification and validation using the synthesis of WV-3, UAS and Gigapan to that of the current ground-based monitoring in Kahanahaiki. The analysis included data acquisition, field time, and data analysis and processing. Time spent learning to use software was not included. As described in the Study Site section, the OANRP has conducted vegetation monitoring for Kahanahaiki three times on a three-year interval since 2009. Time spent to conduct and analyze the monitoring is kept in the OANRP database and was determined to take 294 hours to conduct in 2009. The remotely sensed vegetation procedure cost $17,073 whereas the ground based method cost $7,350 (Table 11). An operational cost was also determined with estimates once gear is purchased and imagery obtained without contracting. The estimated operational costs is $3,500 (Table 12).

Table 9. Project costs to get up and running

	Rate	Amount	Price	
Equipment				
Gigapan Epic Pro		1	**$960**	
Canon SX60		1	**$479**	
Tripod		1	**$250**	
Batteries		2	**$110**	
Gigapan Image Processing	$21.5/hour	12hours	**$258**	
Trimble Geo7XH		3week rental	**$1,360**	
Contracted Service				
Resource Mapping Hawaii			**$3,900**	
Software Training			**$500**	
WV-3 Satellite Imagery	$50.75/km^2	100km^2 *	**$5,075**	
Software				
eCognition Developer	$90/year (student license)	1 year	**$90**	
Field Time				
GA in the field	$21.5/hour	49hours	**$1,053.50**	
Image Analysis				
GA conducting classification	$21.5/hour	52hours**	**$1,118**	
			$17,073	**TOTAL**
OANRP Plot Monitoring				
Field Time/Data Entry/Analysis	$25/hr	294hours	**$7,350**	**TOTAL**
** 100km^2 is the minimum collection area required for Digital Globe*				
*** Estimate of time spent processing image classification*				

Table 10. Operational costs of remote monitoring once gear is purchased and imagery obtained without contracting to private companies.

	Rate	Amount	Price	
Gigapan image collection	$25/hr	15hours	**$375**	
Gigapan image processing	$25/hr	20hours	**$500**	
UAS image collection	$25/hr	40hours	**$1,000**	
UAS image processing	$25/hr	20hours	**$500**	
WV-3 image Collection			**0***	
Image classification	$25/hr	30hours	**$750**	
Analysis of Data	$25/hr	15hours	**$375**	
			$3,500	**TOTAL**
*Current WV-3 can be obtained from the NRCS at no additional cost				

3.4 Discussion

Ultimately, if new imagery was obtained under contract, remote sensing based monitoring serves to be more expensive than traditional ground based methods. However, an operational comparison that factors in either prior acquisition of imagery or capacity to gather data without going out to contract, shows a lower cost associated with remote sensing based monitoring. Although it is of great merit to look to the experts, it would be advantageous for conservation organizations with active monitoring to look to build capacity to collect UAS imagery or collaborate with universities with active UAS programs.

Chapter 4. Conclusion

The primary project goal was to evaluate the utility of new high spatial resolution remote sensing technologies for vegetation mapping and monitoring in Hawaiian mixed-mesic forests. Three specific objectives were addressed:

Objective 1: Develop an effective synthesis of the outputs from a VHR satellite platform, Gigapan, and ortho-aerial to implement remote sensing-based mapping to the species level and outline an OBIA procedural workflow.

The strengths of the three platforms were evaluated and then combined with the goal of producing a useful and accurate vegetation map for the Kahanahaiki study area. The WV-3 satellite image served as a base layer image to be classified with eCognition OBIA and validated with the UAS and Gigapan imagery. Training data collected from the study site were used as representative vegetation samples to develop the eCognition classification algorithm decision ruleset. The Gigapan mosaics were used for cross-referencing ortho-aerial imagery through visual comparison to help train the classification process and assist with the accuracy assessment. An effective synthesis of the outputs from WV-3, Gigapan, and UAS was determined to implement remote sensing-based mapping to the species level and an OBIA procedural workflow was outlined. WV-3 imagery was classified in eCognition into 7 vegetation classes and validated with UAS and Gigapan imagery.

The dense vegetation of the Hawaiian mixed-mesic forest presents a challenging task to separate vegetation classes to the species level. Validation results yielded an overall user's accuracy of 65% with Sparse Veg representing the highest user's accuracy of 94% and Strawberry guava representing the lowest user's accuracy of 38%, while Kukui=75%, Christmas berry=73%, Koa=50% and Native Complex=42%. Grouping native and non-native vegetation classes yielded an overall accuracy of 72% with non-native=94% and native=69%. The high accuracy of mapping sparse veg shows great potential for providing information towards fuel mapping via this method. Further work is needed to accurately separate native vs non-native vegetation to the species level. A stronger computer processer is needed to add additional geometric and textural features into the iterative classification process.

Objective 2: Make recommendations for the integration of remote sensing methods into vegetation monitoring.

The UAS VHR imagery shows the greatest potential for integration of remotely sensed imagery into an operational vegetation monitoring method. UAS allow for low cost, repeatable, high resolution data collection without risk to field personnel. A recommended method could employ a UAS to fly transects in a target area with visual or deep/machine learning analysis of random plots along the transects. Further advancements in multispectral sensors and longer lasting batteries will serve to allow for greater utility in monitoring, and management applications. Vertical takeoff and landing UAS may be of great use in areas without suitable landing area for typical fixed wing UAS.

Objective 3: Determine the costs associated with the implementation of remote sensing-based monitoring protocols as compared to traditional monitoring methods, including recommendations to facilitate cost saving.

The costs associated with the implementation of remote sensing based monitoring protocols were determined and compared to traditional ground based monitoring methods. Ultimately, if new base imagery was obtained under contract, remote sensing based monitoring serves to be more expensive than traditional ground based methods. However, an operational comparison which factors in either prior acquisition of imagery or capacity to gather data without going out to contract, shows a lower cost associated with remote sensing based monitoring.

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Appendix A. Gigapan Exploration in Makaha

Plate 1. Tested Gigapan®, camera and lens configuration with Truepulse® laser rangefinder.

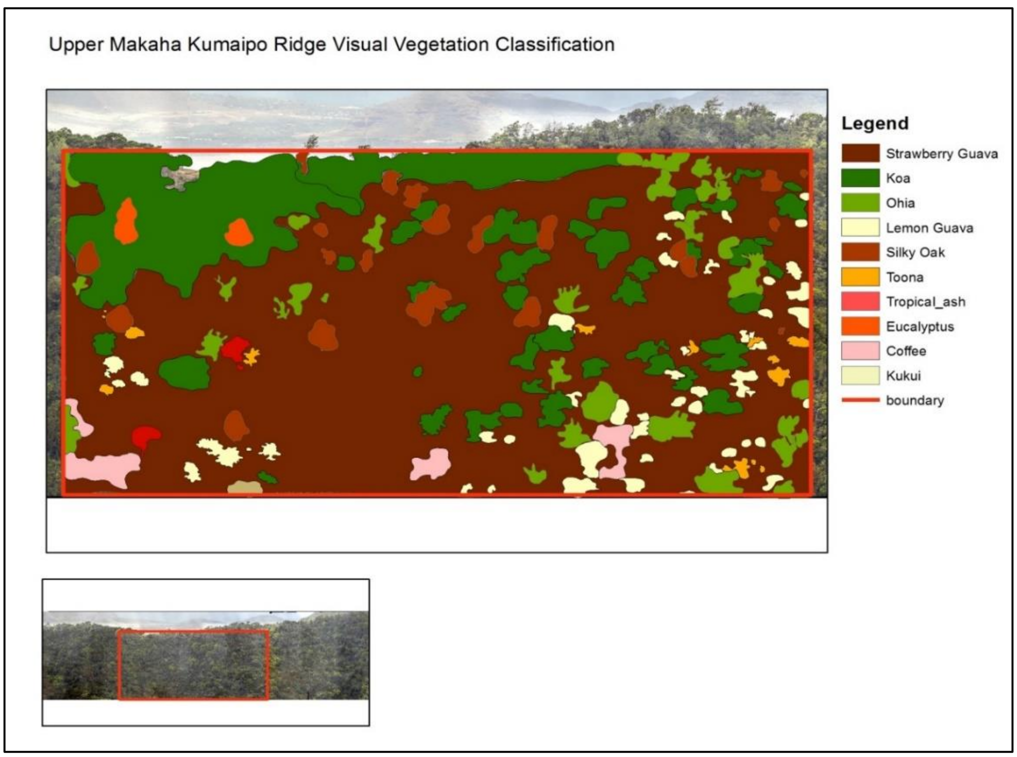

Plate 2. Species level classification map of a target area in Makaha Valley with visual classification methods.

Appendix B. eCognition procedural workflow

>Open eCognition® Developer 9.1
>Load orthorectified WV-3 data
>Select the area of interest
>Select the 6 layer mix false color composite
>Open process tree, class hierarchy, feature view windows as splitscreens
>Insert process- Image segmentation
>Edit process- Algorithm- multiresolution segmentation
>Domain- pixel level
>Image layer weights: 0,1,2,2,2,2,1,0
>Scale parameter- 30
>Compactness- 0.43
>Insert class into Class hierarchy-Non Veg, Veg
>Non Veg- Mean layer 1≥238
Mean layer 5≥158
Standard Deviation Layer 5 ≥33
>Veg- NDVI≥0.62
>Veg- Not Non Veg
>Run Classification- Algorithm- Hierarchical classification
- Domain- Image object level
>Insert class- Sparse Veg- Not Non-Veg
- Not Veg
>Run Classification- Algorithm- Hierarchical classification
- Domain- Image object level
>Insert class- Kukui- Not Sparse Veg
- Standard deviation layer 3 ≥ 34
- Standard deviation layer 4 ≥ 40
>Insert class- Not Kukui- Not Kukui
>Insert class- Native Complex- Not Kukui
- Not Psicat
>Insert class- Psicat- Mean Layer 4 ≤ 157
- Not Schter
>Insert class- Schter- Mean Layer 6 ≥ 395
- Mean Layer 7 ≥ 680
>Run Classification- Algorithm- Hierarchical classification
- Domain- Image object level
>Insert class- Koa- Geometry feature- GLCM Homogeneity (all dir) ≥ 0.052
>Insert class- Other Native- Not Koa
>Run Classification- Algorithm- Hierarchical classification
- Domain- Image object level
>Select Samples-Using training data locations for cross reference
>Run Nearest Neighbor algorithm
>Run Classification- Algorithm- Hierarchical classification
- Domain- Image object level
>Export classified image as a shapefile
>Import into ArcMap® 10.1 and create feature classes for each vegetation class.

Appendix C. Sample UAS images used for validation of vegetation classes

Plate 3. Characteristic depiction of bare ground class (outlined).

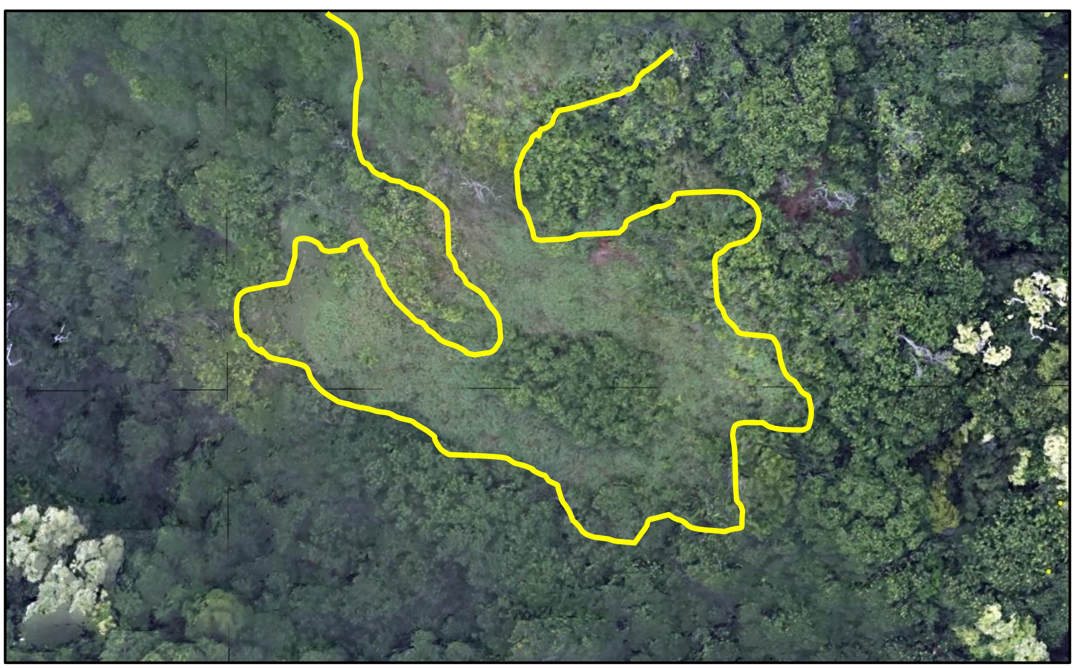

Plate 4. Characteristic Sparse veg class made up of herbaceous weeds, ferns, or grass (outlined).

Plate 5. Characteristic bright, light colored Kukui class (outlined).


Plate 6. Characteristic Christmas berry Schter class (outlined).

Plate 7. Dark green characteristic Strawberry guava Psicat class (outlined).

Plate 8. Characteristic large canopy of Koa class (outlined).

Plate 9. Characteristic mixed vegetation of Native Complex class.

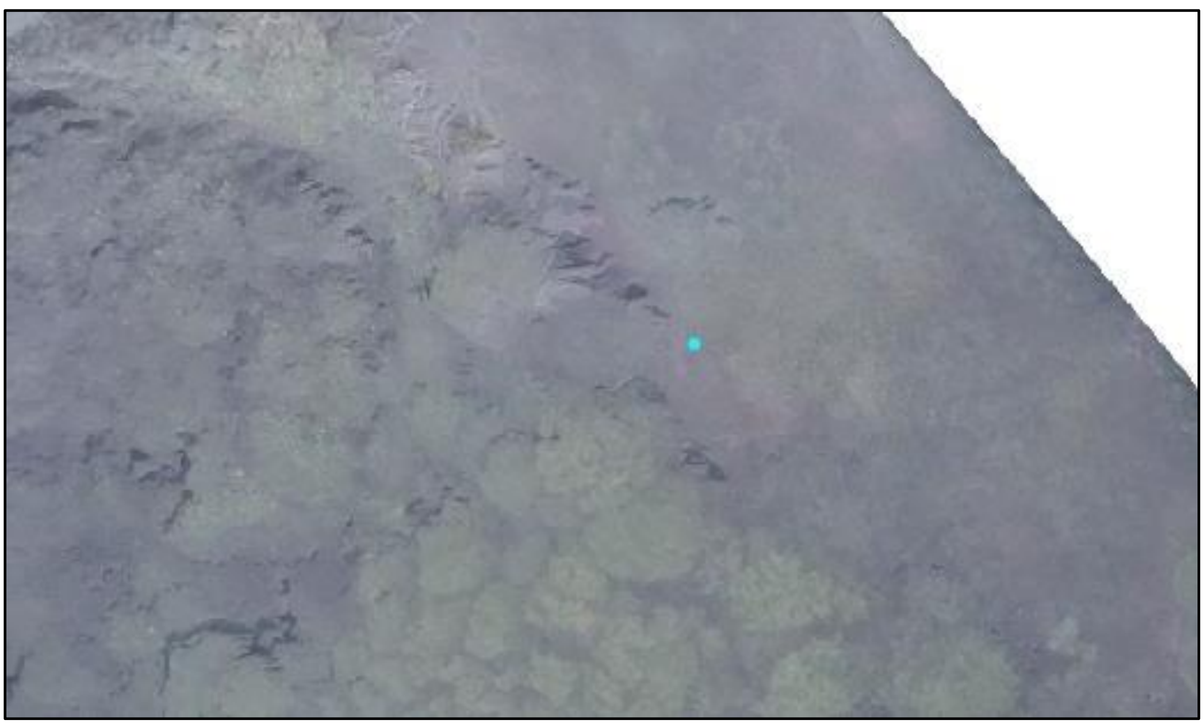

Plate 10. Cloudy, blurred UAS imagery.