

EVALUATION OF ENVIRONMENTAL IMPACTS PRODUCED BY GOLD MINING
AREAS ON THE SURROUNDING FOREST IN SOUTHWESTERN ECUADOR USING
MULTISPECTRAL SATELLITE AND UAS IMAGERY

A Thesis

by

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BS, Pontificia Universidad Católica del Ecuador, Ecuador, 2015

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This thesis meets the standards for scope and quality of
Texas A&M University-Corpus Christi and is hereby approved.

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ABSTRACT

Mining is a dangerous activity that can cause environmental damage to flora and fauna due to the utilization of heavy metals. Ecuador has a long history of mineral extractions and nowadays the activity is increasing in many parts of the country. Environmentalists state that chemicals, such as cyanide and mercury, could cause alterations in vegetation health. This study utilizes satellite and Unmanned Aircraft System (UAS) based remote sensing to analyze impacts to vegetation health around a mining area located in Bella Rica within the El Oro province of the southwestern zone of Ecuador.

Vegetation can be analyzed and identified through many remote sensing techniques, one of them is the Normalized Difference Vegetation Index (NDVI). This band ratio index ranges from +1 to -1 and uses red and near-infrared (NIR) bands to identify the presence of healthy or stressed vegetation. In this study, a small rotary UAS equipped with a two-band sensor recording red and NIR reflectance and a separate red-green-blue (RGB) digital camera was used to gather data and determine if vegetation closer to the mine exhibited different NDVI patterns compared to vegetation located farther away. Spatial differences in NDVI patterns may indicate potential impacts of waste from mining operations. To provide a time series assessment of vegetation changes around the mine, satellite imagery from PlanetScope was acquired and analyzed to measure changes in NDVI throughout the years 2017, 2018, and 2019. PlanetScope uses an array of miniaturized satellites, called CubeSats, equipped with four-band multispectral sensors providing imagery at a resolution of 3 m ground sample distance (GSD). In comparison, spatial resolution of the UAS products, which is dependent on flying height, range from 2.97 cm GSD for the RGB camera to 11.4 cm GSD for the multispectral sensor. Satellite derived NDVI was

statistically compared to UAS derived NDVI values to assess the impact of spatial resolution and sensor quality on NDVI measurement. Furthermore, the UAS acquired RGB imagery was processed using Structure from Motion (SfM) photogrammetry to derive a 3D reconstruction of the scene, referred to as a point cloud. Properties of the point cloud data were analyzed to determine if relationships exist between land cover structure and NDVI patterns captured in the UAS multispectral imagery.

From UAS based multispectral data, significant differences in NDVI values were found between vegetation close to the mining area and vegetation at longer distances ($p < 0.05$), indicating that mining waste could be altering NDVI values in the region. Satellite imagery analysis suggests that changes in NDVI are related to different human activities that have been developed inside the study area. UAS derived NDVI shows a strong linear relationship with PlanetScope derived NDVI ($R = 0.91$), suggesting that the low cost and light-weight sensor onboard the UAS was able to capture similar reflectance information but at much higher resolution. UAS-SfM point cloud data was applied to measure spatial variation in point density and canopy height, and determine if these measures could serve as a proxy for NDVI to assess vegetation health impacts from the mining operation. Results varied with NDVI and point cloud density exhibiting a weak relationship ($R = 0.04$). This relationship held at multiple resolutions suggesting that scene texture and uniformity in the densification stage of SfM does not correlate well with variation in NDVI due to differences in canopy cover. Interestingly, point cloud density changes did show a connection to the type of vegetation with high values of point density occurring over the more densely canopied forest areas. In contrast to point cloud density, UAS-SfM derived canopy height measures exhibited much stronger correlation to the UAS multispectral NDVI values ($R = 0.69$).

Based on the available data and the examined time frame, this study has shown that mining activities have altered NDVI values in the surrounding vegetation at the study site. Moreover, this study has shown that a small UAS platform equipped with a low-cost multispectral sensor can provide similar NDVI values to satellite imagery, but at much higher resolution. The ability to fuse detailed UAS information at a local scale with high repeat frequency CubeSat remote sensing data provides an effective means for monitoring impacts of mining operations at local to regional scales. Finally, results suggest that 3D point cloud data generated from UAS-SfM photogrammetry can enable effective characterization of vegetation structure and canopy height around mining operations providing another tool beyond NDVI to monitor impacts on vegetation growth and health.

DEDICATION

I would like to dedicate this thesis and this degree to my parents. Father, you have been my role model and my support. Everything that I know, everything that I am is because of you. Thanks for being my best friend and for every giving me advise every day that I will use my entire life. Mother, you are my inspiration and my smile, thank you for teaching me how to be a better person. Thank you for your devotion, for your hugs and your kisses, your love makes me stronger. Thanks both of you for your daily support and for everything you have made for me. Everything for you, I love you.

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CHAPTER I: INTRODUCTION AND STUDY PURPOSE

1.1. Introduction

Ecuador, a small country in South America, is one of the seventeen most biodiverse countries in the world and is recognized as one of the favored places to research diversity and evolution (Sánchez & Reyes, 2015). Geographically, Ecuador is comprised of four climate regions, including the coastal region, highlands, Amazon forest, and the island region. This climatic variety has created huge biodiversity in flora and fauna all around the country.

Worldwide, Ecuador also has one of the highest number of species per square kilometer, which have been threatened for centuries by extractive activities such as extraction of oil and minerals like gold, silver, and copper, among others.

Ecuador has a long history of extraction and mining, dating back to the pre-colonial era when millenary cultures started mineral extraction activities around the year 500 BC (Osorio et al., 2018). One of the main minerals extracted from Ecuador is gold. From ancient ancestral cultures to modernity, gold has been one of the most sought-after minerals in Ecuador. Mining is a dangerous activity that can produce environmental impacts on flora and fauna, and in general, around the environment.

There are many types of mining in Ecuador, and all the companies and individual people who are involved in this activity cause damage to the environment to some degree, at least in a minimal way. One of the biggest impacts caused by mining is produced by the utilization of mercury and cyanide in the process of gold recovery. Once these minerals are released into the environment, they can cascade through the processes of biomagnification and bioaccumulation. Amazonian countries are threatened to this type of environmental contamination due to the utilization of mercury in many activities such as gold mining, hydroelectric damming, among

others (Grotto et al., 2010). The consequences of releasing these types of chemicals can cause to vegetation can be devastating; however, it is not easy to investigate the real effects of the contaminations process in forests, this is where technology such as remote sensing plays an important role (Schmid et al., 2013).

Remote sensing techniques and the ability of getting affordable satellite images have given new possibilities of monitoring the earth and its natural resources (Ghauri & Zaidi, 2011). The authors stated that it has been proven that in conjunction with geographic information systems (GIS), and allied technologies, remote sensing techniques are more cost-effective compared to traditional methods. Due to the expansive areas that forests occupy around the world, especially in the tropics, remote sensing has been employed as an alternative to monitoring and making observations of these vast areas (Baldauf & Jimenez, 2016). Peña-Arancibia et al. (2019) stated that tropical forests have been threatened for activities such as agriculture the last decades and many satellite-based methodologies have been used for studying these activities and its impacts. Remote sensors have become an information gathering tool to estimate deforestation and rapid disappearance of forests due to activities such as agriculture and pasture, among others; where it estimated that 5000 km² felled each year just on the Brazilian Amazon, while in Ecuador the deforestation rate exceeds 125 km² per year (Food and Agriculture Organization of the United Nations [FAO], 2013; Tristsch & Le Tourneau, 2016).

Remote sensing techniques such as analyses based on satellite imagery have been used successfully to assess and quantify the impact of mining on the environment, especially in terms of land use changes since one of the biggest impacts of mining is the deforestation processes (Islam et., 2020). Many types of sensors and satellites have been evolving, these new technologies have helped to facilitate space science and exploration; for instance, CubeSat, is a

miniaturized satellite with a mass of 1.33 kg that is used in educational and scientific space research programs (Wu et al., 2020). Unmanned Aircraft Systems (UAS), another remote sensing technique has also been utilized for exploring human activities, vegetation health status, animal distribution, among others (Wang et al., 2020). This low-cost, small, lightweight, and user friendly tool has been used for monitoring activities such as mining due to the ease of exploring difficult to access places and the high utility of high-resolution aerial images (Malpeli & Chirico, 2015).

This study utilizes these two sources, CubeSat satellite imagery and UAS-based imagery, in order to obtain multispectral imagery. Each acquisition method has its own best-fit application and there are many considerations to make in order to analyze data through these two different sources. For instance, satellite imagery can be costly as compared with UAS-based imagery, but they can cover larger areas, on the other hand, imagery from UAS have the capacity of obtaining high resolution products with a temporal resolution determined by the researcher (Broussard et al., 2018).

1.2. Study Purpose and Objectives

The overall purpose of this study is to understand the relationship between mining activities and vegetation health using UAS and satellite images. With the objective of assessing environmental impacts on the forest surrounding a gold mine that uses chemicals such as mercury and cyanide in its processes, this study analyzes some forest health parameters by using and processing multispectral remote sensing imagery and 3D point cloud data generated from a UAS. The differences in spatial and temporal resolution between UAS and satellite imagery and their impacts on the Normalized Difference Vegetation Index (NDVI) values are taken into account.

The specific objectives of this study are:

1. Analyze NDVI values of the area surrounding a gold mine in the Piedmont Seasonal Evergreen Forest of the Western Andes Mountains measured with a UAS equipped with a multispectral (near-infrared and red channel) to determine if vegetation closest to the tailing pond is different from vegetation located at further distances.
2. Examine a three year time series of multispectral remote sensing imagery acquired from PlanetScope sensor of the study site and analyze the NDVI index to determine if the surrounding forest of the mining area has experienced changes in its index over the last three years. Moreover, this study makes a comparison between a PlanetScope satellite image and the multispectral images obtained from UAS data in order to establish differences between these two sources. This comparison is made by examining differences in NDVI at different levels of spatial resolution and geographic scale, using very high resolution at localized scales with the UAS versus lower resolution at larger areas with the satellite image.

3. Apply UAS Structure-from-Motion (SfM) photogrammetry to derive densified 3D point cloud data of the forest structure within the areas of interest and apply these measurements to determine if there is a correlation between point cloud metrics and NDVI values. These point cloud metrics may provide an alternative means to monitor the impacts of mining in the region in addition to NDVI values derived from UAS or satellite imagery.

1.3. Intellectual Merit and Broader Impacts

This study uses UAS and satellite multispectral imagery to determine if there is an influence from mining activities in the area to the local forest ecosystem. The assumption is that the results of the study will suggest the utilization of UAS to identify different NDVI values according to the human activities that are being performed in the area of interest. Also, in Ecuador and many parts of the world, for activities such as mining or oil extraction, it is mandatory to develop reforestation and vegetal restoration after the extraction activities. This study could suggest the utilization of low-cost UAS to monitor these activities and ensure that NDVI levels are in line with what is expected for this type of forest.

Multispectral data obtained from UAS could be coupled with UAS-SfM to improve monitoring of vegetation growth and changes stemming from mining operations. Moreover, this study uses CubeSat imagery in order to compare NDVI changes with NDVI changes identified by multispectral data obtained from the UAS. In this study, UAS information is used for obtaining multispectral imagery as well as for getting 3D measurements of canopy structure obtained from SfM.

The novelty of this study is that the research was conducted in an area that has not been studied deeply and the consequences of mining activities to forest health have not yet been evaluated through the use of remote sensing. The real consequences of different chemicals used in mining are still unknown for the south-west zone of Ecuador and the Piedmont Seasonal Evergreen Forest of the Western Andes Mountains. This study uses techniques that are not well developed in Ecuador, such as obtaining NDVI through multispectral sensors mounted on a UAS.

In particular, the impacts of mining on vegetation in the zone of Bella Rica, have not been studied in-depth as studies in the region have focused on the impacts of the chemical quality of water. In contrast, the results obtained in this study have focused on the impacts in forest health, showing how NDVI values for the studied forest structure can change in accordance with the varying spatial resolution of sensors. Moreover, multitemporal satellite images indicate how the area of interest has been altered by mining activities. Another contribution of the study is the analysis of the relationship between NDVI and point cloud metrics. Both NDVI and point cloud metrics have been studied in-depth and they are considered to be useful parameters to evaluate forest and vegetation health; however, this study investigates a possible relationship between these two factors and how they can work together to give more in depth evaluation of forest health.

CHAPTER II: BACKGROUND AND LITERATURE REVIEW

2.1. Foundations of remote sensing

Remote sensing can be defined as a series of techniques where a recording device that is not in physical contact with an object, gets information or measurements about a certain property of that object (Jensen, 2015). The electromagnetic spectrum is composed of all types of electromagnetic radiation. There are different types of electromagnetic radiation: the gamma-rays, X-rays, ultraviolet light, visible light, infrared light, microwaves, and radio waves are portions of the electromagnetic spectrum (National Aeronautics and Space Administration [NASA], 2013).

A specific wavelength interval in the electromagnetic spectrum is commonly referred to as a band or a channel; for instance, the visible part of the spectrum is what human eyes can perceive and is composed of wavelengths that go from 380 to 700 nanometers (NASA, 2019). However, not all the electromagnetic spectrum can touch the Earth's surface; the atmosphere diverts a big portion of the electromagnetic radiation. Generally, and in this study, in particular, the research in this field is conducted to analyze the object's reflectance of the electromagnetic radiation that reaches the Earth's surface.

Every object, even elements, and molecules have a unique reflectance characteristic that is received by the sensor. Any type of camera that can be mounted on a satellite, or a UAS, or cellular phones camera, or even human eyesight can be considered a sensor. The difference is how each sensor receives this electromagnetic response from the objects. For instance, as mentioned above, human eyes are capable of seeing one part of the spectrum, but other sensors can perceive other parts of the spectrum. Multispectral Scanner (MSS) sensors can capture

multiple spectral bands. An example of an MSS is Landsat Multispectral Scanner System, in 1972 it was the first sensor used by NASA to explore the Earth's surface (NASA, 2000).

Nowadays, remote sensing faces new challenges and applications. For instance, the new trends in remote sensing investigation are the matching between sensors and platforms, reaching a more extensive range of performance, and new applications in relatively low-cost equipment (Pajares, 2015).

2.2. Normalized Difference Vegetation Index.

One part of this study is the analysis of the Normalized Difference Vegetation Index (NDVI), the index that is the result of a combination of the visible and near-infrared part of the spectrum that is reflected by the vegetation (NASA, 2000)

The formula to determine the NDVI is the following:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \quad (1)$$

The near infrared band (NIR) and the red band are the two channels of the spectrum that are used to calculate NDVI; the value that is taken into account in Equation 1 is the digital number of each band (Anderson et al., 2016). As shown in (1), the NDVI is based on the reflectance of objects produced in the red (R) band and the near infrared band (NIR). The range where the index can be located goes from -1 to 1. The results of the equation determine how 'green' the vegetation is in a certain place; negative results indicate that the surface is not covered by vegetation. Surfaces such as barren land, water, ice, snow, or clouds can result in negative NDVI values, while positives values indicate vegetation surfaces. Values close to 1 indicate increasing green vegetation (Jensen J. R., 2015).

In nature there are some things that human eyes cannot see; the Normalized Difference Vegetation Index (NDVI) exemplifies this concept. Currently NDVI has many applications, for

instance, NDVI has been used to detect deforestation, because this index is a very reliable indicator and gives accurate measurements allowing for identification of small patches of deforestation (Koli et al., 2011).

NDVI also is used for identifying photosynthetic capacity, net primary productivity, and evapotranspiration, among other plant health indicators, where the NDVI has been shown to have a high level of correlation (Reid & Walker, 2016). Wang et al. (2019) proposed a method to estimate photosynthetic vegetation (fPV), non-photosynthetic vegetation (fNPV), and bare soil (fBS), based on NDVI. The proposed NDVI model was consistent with the phenological characteristics of that type of vegetation, and also, that the index can be used to determine other types of parameters such as soil wind erosion and fires in vegetation. Also, NDVI can be considered as a vegetation variable through time. Wang et al. (2019) utilized satellite imagery captured by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor to analyze phenological metrics based on NDVI collected from 2001 to 2015, and with the help of classification maps they concluded that some changes occurred in the area of study; however, not enough to consider them significant changes.

Other studies have demonstrated that the accuracy in multispectral data, between satellite imagery and UAS-based imagery depends on the type of land use analyzed. Tian et al. (2017) demonstrated that while estimating leaf area index (LAI) with multispectral imagery, UAS showed higher accuracy than satellite imagery derived LAI in plots covered with homogeneous mangrove. This is because UAS can eliminate the influence of the background and the different species due to its higher spatial resolution. In contrast, satellite imagery depicted higher accuracy in plots that were mainly covered by a variety of mangrove species (Tian, et al., 2017).

Currently, UAS have been used in many other areas; Corti et al. (2018) state that in forestry, multispectral sensors mounted on UAS have been used in different ways. The authors mention that these sensors are ideal to determine stress in crowns. For example, in *Pinus radiata* through the utilization of red, green, blue, red edge, and NIR bands, the crown stress can be easily detectable if a proper camera is used. The last mentioned study analyzed satellite imagery as well where properties from the area of interest were obtained. Fischer et al. (2008) used multispectral imagery attached to a UAS to identify damaged agricultural areas. Through the usage of training samples to extract damaged areas, they found that the classification process depicts more reliable results when the NDVI layer and visible information are analyzed. The results show that visible information without near-infrared data tends to underestimate the damage.

2.2.1 Satellite Derived NDVI

There are many considerations when satellite imagery is analyzed. Among the most important is the different types of resolutions of each image. The reflectance of vegetation can be influenced by the health conditions of the plant; for instance, Bandaru et al. (2016) showed that the same type of plant has different reflectance responses depending on the amount of arsenic in each sample. The authors determined that at the NIR wavelengths ($>750\text{nm}$), plants with a higher arsenic contamination show decreases in their reflectance response; however, at the visible part of the spectrum, the reflectance of contaminated plants increases. It is important to note that some parts of the spectrum are better than others for obtaining biophysical parameters, which is the reason that spectral resolution plays an important role in satellite imagery analysis.

Long term NDVI analysis and land cover change analysis are usually made with satellite imagery. Panek and Gozdowski (2020) analyzed the relationship between cereal-grain yield and

NDVI in four European countries between 2012 and 2016 by using multispectral imagery from MODIS sensor. They found that an increase in NDVI of 0.1 units in early spring indicates an increase of 1.1 - 2.6 t/ha in the grain yield of cereals. The results lead them to conclude that these types of studies are useful for planning food policies.

As important as the spectral resolution and temporal resolution are, the spatial resolution of the satellite imagery also plays a fundamental role in the analysis. This type of resolution can be defined as the measure or the linear dimension that each pixel represents on the ground. Also, it can be defined as the area that the instantaneous field of view (IFOV) of the sensor can image on the ground (Liang et al., 2012). Even though the spatial resolution is always important for an analysis, it becomes more important in certain applications, for example the characterization of multifaceted environments such as dense urban areas. In addition, the recognition of different types of targets largely depends on the spatial resolution of the image. In contrast, sensors with low spatial resolution can be utilized to observe phenomena in studies that are focused on the characterization of large areas, for example projects about ocean dynamics or small-scale deforestation areas (Baghadi & Zribi, 2017).

Jiang et al. (2006) determined that NDVI is a scale dependent index in heterogeneous surfaces. The results of the study suggest that the spatial resolution of the imagery has an important impact on NDVI values. Pax-Lenney and Woodcock (1997) analyzed the effect of spatial resolution to monitor and identify agricultural lands through the usage of NDVI. the study used satellite imagery at spatial resolution of 120 m, 240 m, 480 m, and 960 m. The results of the study show that the error in old agriculture lands goes from 1.9% at 120 m of spatial resolution to 7.5% with 960 m data, and the error in cultivated lands goes from 4.3% to 9.4% at the same spatial resolution respectively.

2.2.2. UAS Derived NDVI.

Another way to collect geospatial information is through Unmanned Aircraft Systems (UAS), a relatively new technology that offers many types of services. UAS include many types of aircraft that vary in size and shape, ranging from handheld aircraft to some as large as airplanes. Also, they may vary in the way they are constructed, some of them can be mainly composed by a fixed wing design or by a rotary winged (Civil Aviation Authority [CAA], 2015).

Although UAS have some limitations, the usage of this relatively new technology can contribute valuable data that can be used to make better decisions and develop new policies in military, security, research, environmental protection, disaster management, agriculture, among other issues (FAO, 2018). UAS represent an alternative to some limitations of traditional techniques of collecting geospatial data from heights (i.e. satellite imagery and aerial photography), such as the improvement of spatial resolution. For instance, the level of detail of dataset products obtained from UAS are extremely high; final results of this type of imagery let the user identify characteristics of the landscape that are not distinguishable from manned aircraft (spatial resolution ~10-100cm) or satellite systems (spatial resolution >50 cm) (Hrwin & Lucieer, 2012).

As mentioned, satellite imagery and UAS are used to monitor changes especially in vegetated and agricultural areas. Many studies have proved some disadvantages of satellite imagery analysis for this method of gathering geospatial data. For instance, Lu et al. (2019) mention that one limitation of satellite imagery is the difficulty of obtaining reliable images that can be used in agriculture, specifically in the monitoring of multiple growth stages in vegetation or crops. The principal complications of satellite imagery for this type of application are the cloud obstacles and the relatively low spatial resolution to analyze small field sizes. On the other

hand, UAS are capable of improving spatial resolution in small areas, and currently, they are broadly used due to their potential in affordability, operation, and relative simplicity in imaging processing.

As mentioned above, multispectral sensors can be mounted on low-cost UAS and satellites. NDVI can be calculated from the outputs of these two different techniques. Broussard et al. (2016) analyzed UAS and satellite technology to assess ecosystem service metrics and species composition in a coastal intermediate marsh. The authors found that the mean for vegetation pixels (NDVI greater than 0) was 0.464 and 0.254 for satellite-derived data and UAS derived data respectively; thus concluding that the mean absolute forecast error (MAE) and RMSE to be relatively large between these two sources. One explanation for the low values for UAS data is that the utilized camera was not designed originally to capture data in the NIR channel (Broussard et al., 2018).

2.3. Photogrammetry principles and applications

SfM is a relatively new method that can be defined as a low-cost photogrammetry technique. It allows the user to make high resolution topographic reconstruction, based on the basic principles of stereoscopic photogrammetry with the main difference that SfM can solve the geometry of the scene, camera position, and camera orientation in an automatic way (Westoby et al. 2012). These parameters are solved through the usage of a bundle adjustment procedure based on features automatically extracted from a set of multiple overlapping images (Starek et al. 2014). The SfM method is based on obtaining multiple overlapping photographs of the same place or area of interest from different spatial positions (Verma & Mary, 2019).

The workflow of SfM starts with the image acquisition and keypoints extraction. In this part of the process it is necessary to find a way of matching features in different photographs, so

an image correspondence is made based on an identification of features. Keypoints are identified in multiple photographs, then these features are described allowing them to be matched. It is important to note that the number of keypoints detected depends fundamentally on resolution of the images. Factors such as the density, sharpness or the distance between the camera and the feature of interest are also taken into account. A critical step in the process is the overlap between photographs; a high percentage of this parameter is necessary to get good outputs. There are many opinions about the right percentage of overlap that should be used. For instance, Nada et al. (2018) mention that in order to ensure the photogrammetric process, it is necessary to have an average overlap of 90% between photographs. Other sources such as PIX 4D (n.d.) software, state that the minimum overlap between photographs in general cases should be 75% frontal and 60% side. In cases where forest, dense vegetation, and fields are predominant the minimum overlap should be 85% frontal and 70% side. Regardless of the percentage of overlap that is used, it is a fact that photogrammetry bases its best results on the match of objects from different photographs, and this process can be vital in the improvement of the geometric accuracy and in the reduction of occlusions such as shadowed or invisible areas in the final products (Corti et al., 2018).

With the objective of finding keypoints and extracting features, a keypoint detection algorithm is used by the photogrammetric software where the overlapping images are analyzed. To minimize the possible errors in the correspondences, a “bundle block” adjustment is developed by solving for camera interior and exterior orientation. Then, the previously matching points are verified, and their 3D coordinates are calculated producing a sparse point cloud. To convert point coordinates to a real-world coordinate system, or from relative to absolute coordinates system there are two options: the onboard global navigation satellite system (GNSS)

of the UAS or ground control points (GCPs) (Starek et al., 2019). Even though, SfM can be performed without the usage of GCPs, the absolute accuracy of the process can be increased significantly with GCPs, which also can be useful to determine check points to verify the accuracy of the final outputs (Pix4D, n.d.). Lastly, the Multi-View Stereo (MVS) algorithm densifies the point cloud throughout the utilization of interior and exterior orientation of each image. The principal output of this process is a RGB densified 3D point cloud that can be used to create a Digital Surface Model (DSM) and a orthomosaic (Starek et al., 2019).

Much research has demonstrated that point cloud density is a parameter that can be used in the determination of vegetation health or agricultural metrics. For instance, Wijesingha et al. (2018) evaluated 3D point clouds for the prediction of grassland biomass. The authors discovered that the point density varied substantially among different harvest days and among different types of grasslands. Grasslands were in different spatial positions and used different types and amounts of fertilizing. The results of the last-mentioned research lead to a conclusion that different stages and health conditions of vegetation can result in different point cloud densities.

Moreover, photogrammetric point clouds have been used for identifying vegetation in non-conventional and extreme environments such as the Antarctic. Lucieer et al. (2011) used SfM point cloud to identify moss beds in the Antarctic. The study generated a detailed 3D point cloud with a point spacing of ~ 1 cm where moss beds are identified; these results were the base to explore moss die-back produced by water stress and terrain characteristic. Another point cloud metric that is usually considered in order to obtain phenologic information is maximum height. Chang et al. (2017) analyzed crop height of sorghum using UAS and SfM photogrammetry obtaining a Crop Height Model (CHM). The authors compared the results of the CHM with

manual crop height measurements and found a Root Mean Square Error (RMSE) of 0.33 m, where the principal source of error may not be the generation of the digital terrain model (DTM), because it was generated before planting (i.e. bare earth). On the contrary, the error may be produced by the unstable data acquisition conditions, in this case, high winds produced positional error and impacts in image quality. Despite the presence of errors, the study concludes that photogrammetric point clouds may replace field-based crop height techniques due to the reliable crop height measurements.

Currently, point clouds derived from UAS-SfM have been used for diverse types of environmental research. Gonçalves et al. (2020) used photogrammetric products to detect marine litter on dune areas and beaches. The study used a pixel-level classification to detect Maximum Likelihood (ML) items based on a Random Forest classifier which has shown to be a robust classifier for this type of environment. The study determined that the location of marine litter was associated to water level dynamics on the beach profiles and beach slope.

One of the principal limitations to this study is the lack of general information related to the type of forest that predominates the zone of the study. The Piedmont Seasonal Evergreen Forest of the Western Andes Mountains is not vast, and information about floristic composition, altitudinal changes, climate changes, contamination degree, among other important information is limited. Even though many mines and human activities are within the Piedmont Forest, much of the research on the environmental impacts and the consequences of the human footprint in primary forests of Ecuador has been focused the Amazon rainforest due to the high biodiversity of the ecosystem. Another limitation of literature is an understanding of the impact that mines cause to vegetation, especially in Ecuador. Ecuador has a historical tradition of developing mines

from a long time ago; however, research is not enough to determine the relationship between health forest and mines, and the distance that can be affected by mining activity.

There are few studies in Ecuador that employ NDVI and explore the value of this index in regard to the forests and damages associated with mining. This study uses state-of-the-art technology; NDVI taken from multispectral sensors mounted on UAS to assess the effects of mining activities in the Ecuadorian Seasonal Evergreen Piedmont. Moreover, the research will further develop our understanding of the relationship between point cloud and NDVI. Previously these two metrics have been studied separately, but few studies investigate the relationship between SfM point cloud density and NDVI data obtained from the same UAS.

CHAPTER III: STUDY AREA AND DATA SETS

3.1. Study Area

The Area of Interest (AOI) is located in Ecuador, South America. Ecuador is divided politically into 24 provinces distributed in four geographical regions, and each province is divided into cantons. Finally, each canton is composed of different ‘parishes’ that are small administrative districts. The AOI is located in a zone called ‘Bella Rica’. This zone is historically a gold mining region located in some cantons of Azuay and El Oro provinces.

The specific area of interest is located in El Oro province, near the border of the province of Azuay. The provinces are divided by the Margarita river. The canton where the mine is located is ‘El Guabo’ and the parish is ‘Rio Bonito’. The area of interest (yellow polygon in Figure 1) that was considered for this study encloses a polygon where one tailing pond is located; moreover, this land is owned by ‘PRODUMINSA S.A.’ the company that operates the mine and its processes. It was necessary to obtain easy and guided access to the areas in order to conduct the research. Permissions to access these areas were obtained from the owners and operators of the gold mining concession. Bella Rica is a zone with almost 3000 inhabitants; even though people from Bella Rica live in a zone rich in gold, many of them lack principal services such as pure water, continuous electric energy, or sewage systems (El Telégrafo, 2013). The research also points that the poor conditions of the inhabitants of Bella Rica are also transferred to their working conditions and the technical procedures that they use working in the mines. Since large scale mining is not being developed in Bella Rica, the Ecuadorian government has granted mining concessions for small scale mining and artisanal mining in that zone. Consequently, most of the time these concessions do not meet the minimum environmental requirements to develop mineral extraction safely.

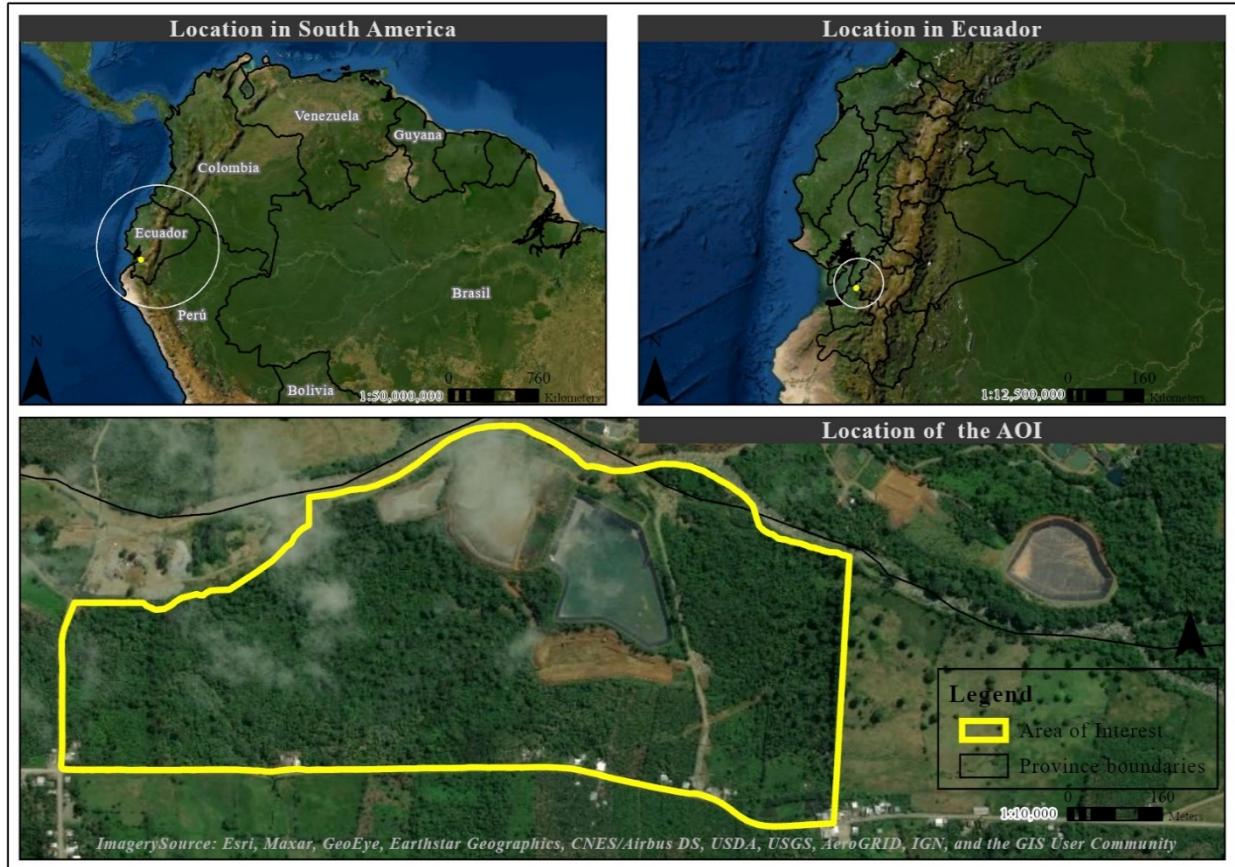


Figure 1: Location of the Area of Interest related to South America and Ecuador.

Mercury, cyanide, arsenic, cadmium, and lead are chemicals that are used in mining procedures where minerals, especially gold, are separated from the rocks that contain them; in majority of the cases these chemicals, in particular, cyanide and mercury (the most commonly used), are not eliminated safely and are released into the environment (Hidayati et al., 2009). In the best-case scenario, the chemicals are put in tailings ponds; however, these ponds are exposed to landslides since Bella Rica is located in an area with a large amount of rainfall per year (Zorrilla, 2013). The combined effects of these conditions have resulted in extreme environmental damage.

According to the Ministry of the Environment of Ecuador and as mentioned previously, the type of ecosystem that predominates the area is the Piedmont Seasonal Evergreen Forest of

the Western Andes Mountains (Ministerio del Ambiente [MAE], 2015). This type of forest goes from 300 meters above sea level to 1400 meters and occupies steep slopes on the sides of the Andes Mountains (MAE, 2013). The canopy of the forest is categorized as ‘moderately dense forest’ the tallest trees reach 20 to 25 meters in height (MAE, 2013). Table 1 below shows the most common canopy layer flora species are the following.

Table 1: Common flora species in the zone.

Scientific Name	Common Name
<i>Cordia alliodora</i>	Laurel
<i>Dussia lehmannii</i> ,	Fruta de sábalo, embagado*
<i>Poulsenia armata</i>	Mastate*
<i>Inga carinata</i>	Guaba*
<i>Inga oerstediana</i>	Ice cream bean
<i>Triplaris cumingiana</i>	Ant Tree
<i>Erythrochiton giganteus</i> ,	Hueso de mono*
<i>Inga silanchensis</i>	Guaba de monte, guaba poroto*
<i>Allophylus incanus</i>	Amarillo*
<i>Matisia soegengii</i>	South American Sapote

Note: Data are from Ministerio del Ambiente (2013).

*Some common names are in Spanish since they lack accurate translation to English

Temperatures in this ecosystem can fluctuate from 15.3 to 25.7 °C. The region has four dry months (May, June, July, and August) where the level of precipitations ranges from 18 mm to 42 mm; the rainiest months can reach 300 mm (MAE, 2013).

3.2. Data Sets and Data Collection

3.2.1. Multispectral and RGB imagery from UAS.

The first set of data was based on the multispectral and the RGB imagery taken from the UAS. The UAS utilized was a DJI Phantom 3 Professional (see Figure 2). The weight of the aircraft is 1280 g and it can reach a speed in ATTI mode of 16 m/s or 57.6 kph (DJI, n.d.). The UAS comes equipped with a Global Navigation Satellite System (GNSS) receiver that has access to broadcast signals from two satellite positioning systems, Global Positioning System (GPS) by the United States and Global Navigation Satellite System (GLONASS) by Russia (Kalacska et al., 2020; Lim et al., 2019). It can fly at an altitude of up to 6000 meters above sea level (DJI, n.d.).



Figure 2: An example of a DJI Phantom 3 Professional (DJI, n.d.).

The RGB camera utilized to obtain the imagery was the original camera that comes with the UAS Phantom 3 Professional. The sensor is equipped with a Complementary Metal Oxide Semiconductor (CMOS) sensor of 1/2.3" and a resolution of 12MP with a GSD of 5cm at an altitude of 120 meters; it can produce photos in JPEG and RAW format (DJI, 2016; Hughes et

al., 2018). For the objective of generating image-based point clouds, it is vital to have images with a high spatial resolution and a high percentage of overlap (Corti et al. 2018).

The multispectral sensor attached to the UAS used to obtain the multispectral imagery is the Sentera High Precision NDVI Single Sensor, distributed and installed by Sentera Company. The sensor captures the precise bands needed for obtaining NDVI. Even though, the company distributes sensors that are able to capture different channels, this sensor consists of just two bands, the red band at 625 nm x 100 nm width and the NIR band at 850 nm x 40 nm width (Sentera LLC, 2018) (Figure 3 and 4). The sensor has a resolution of 1.2 MP with a GSD of 5.5 cm at an altitude of 60.96 meters and 11.0 cm at 121.92 meters with a focal length of 414 mm; the total weight of the sensor is 30 grams and its size is 25.4mm x 33.8mm x 37.3mm (Sentera LLC, 2018).



Figure 3: An example of a Sentera NDVI single sensor (Sentera, n.d.).

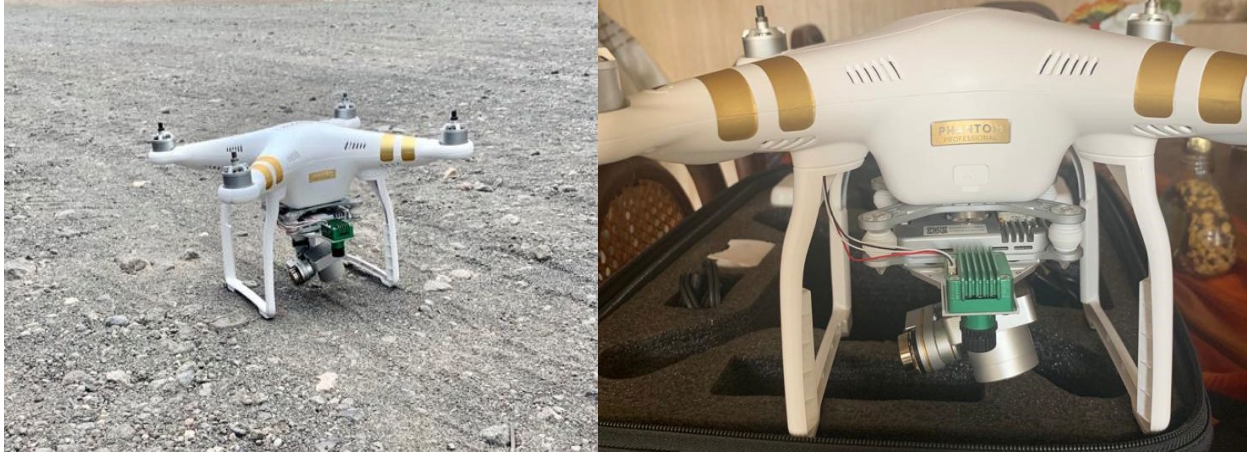


Figure 4: Sentera sensor mounted on the UAS that was used in this study.

The RGB images and the multispectral images were taken together, that is, in the same flight for several reasons. The reflectance of vegetations and other objects in nature can vary depending on the amount of light received by the object. Consequently, the values of the index can vary day to day and even flight to flight. More reliable results are obtained if the two types of images are taken simultaneously.

The Federal Aviation Administration (FAA, 2018) of the United States claims in the Small Unmanned Aircraft regulations that “The maximum allowable altitude is 400 feet above the ground,” which is around 121.92 meters. The height of cables and transmissions towers close to the AOI was between 55 to 60 meters. In order to avoid obstacles and due to safety reasons, two different flights were performed in the AOI on July 15th, 2019 (see Figure 5 and 6). The first flight was completed at an altitude above ground of 120 meters (medium resolution in this study) and the second flight was completed at an altitude above ground of 66 meters (high resolution in this study). Both flights covered an area of 81.84 hectares (202.23 acres); however, the AOI has an area of 59.65 hectares (147.4 acres). The principal objective of flying at two different altitudes

is to examine variability in NDVI values on sensor resolution and the different impacts that different GSD could have in the analysis.



Figure 5: Flights development on the AOI on July 15th, 2019.



Figure 6: Flights development on the AOI on July 15th, 2019.

In UAS photogrammetry, photographs are taken in such way that the area covered by each successive photograph along a flight strip overlaps part of the previous photo. This is called end or front lap; on the other hand, lateral overlapping between flight strips is called side lap (Wolf et al., 2014), see Figure 7.

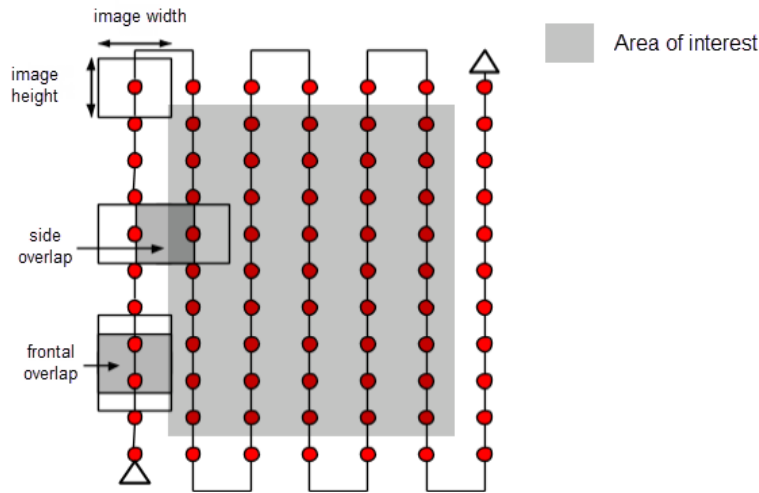


Figure 7: Side and frontal overlap scheme (PIX4D, 2020).

The mobile and desktop application DroneDeploy was used in order to perform the flights. DroneDeploy lets the user interact with some important parameters such as flight altitude, front and side overlap, flight direction, flight speed, and others. Once these parameters are entered, the application automatically states the flight time, the images that are going to be taken, the total area to be photographed, and the number of batteries that the user will need (depending on the UAS). In Table 2, some of the previously mentioned parameters are shown, including the GSD for RGB and multispectral camera. In order to analyze differences in NDVI based on different resolution imagery, imagery were taken at two different altitudes, and as mentioned before, the minimum overlap between photographs in general cases should be 75% frontal and 60% side (Pix4D, 2020).

Table 2: Flights specifications according to DroneDeploy application and Sentera literature.

Flight Altitude	Camera type	GSD	Front Overlap	Side Overlap
120 meters	RGB (Phantom 3 pro)	5.1 cm/pixel	80%	70%
120 meters	Multispectral (Sentera)	10.9 cm/pixel	80%	70%
66 meters	RGB (Phantom 3 pro)	2.8 cm/pixel	75%	60%
66 meters	Multispectral (Sentera)	5.95 cm/pixel	75%	60%

As mentioned previously, the UAS has a GNSS receiver that can record signals from GPS and GLONASS. UAS are integrated with GNSS receivers that allow imagery to be positioned with respective latitude and longitude coordinates; however, the accuracy of UAS onboard GNSS receivers is low and can vary from several to tens of meters (Starek et al., 2019). For this project, relative accuracy is more important than absolute accuracy. Since the lack of equipment and considering that this study intends to show that the utilization of low-cost platforms are useful to analyze health vegetation, ground control points (GCPs) were not used. Relative accuracy is considered as the difference in distance between points represented on the map; consequently, in order to ensure high relative accuracy, it does not matter where the map is located in an absolute sense considering geodetic locations (Forbes et al., 1983). The process to ensure high relative accuracy between all products used in this study is described in Section 4.1.1.

3.2.2. Multispectral satellite imagery.

Planet is a company that operates two Earth-imaging constellations: PlanetScope and RapidEye. For PlanetScope imagery, three products are offered: a Basic Scene product, an Ortho Scene product, and an Ortho Tile product (Planet, 2016). For this study, Ortho Scene products were used. The entire PlanetScope constellation consists of approximately 120 satellites. Each

satellite of the constellation is a miniaturized satellite, which is used for space research and called CubeSat (Planet, 2016). The dimensions are 10 cm by 10 cm by 30 cm; the complete PlanetScope constellation is capable of imaging the entire world every day, which is equal to 150 million km² per day (Planet, 2016).

The multispectral satellite imagery was downloaded from the web page ‘www.planet.com’. After some requests, *Planet* granted to the developer of this study free access to the satellite imagery since the purpose of this study was completely academic. Some PlanetScope constellation and sensor specifications are detailed in Tables 3 and 4. The sensor captures images in four bands at the following bandwidth:

Table 3: Spectral bandwidth of PlanetScope imagery.

Spectral Band	Bandwidth (nm)
Blue	455-515
Green	500-590
Red	590-670
NIR	780-860

Note: Data are from Planet (2016)

The CubeSat satellites count with a four-band frame imager sensor and a split-frame VIS+NIR filter. The sensor frame size is 24 km x 8 km with a GSD for the images of 3.7 m at a reference altitude of 475 km, while the imagery has a daily revisit time since early 2017 (Planet, 2018). The radiometric resolution of the product is 16-bit, and radiometric corrections include the conversion to absolute radiometric values based on calibration coefficients, among others (Planet, 2018). Moreover, geometric corrections have been applied where effects related to the

sensor are corrected using a sensor model and telemetry. Also, the images are orthorectified by using GCPs, reaching less than 10 m RMSE positional accuracy. Finally, regarding atmospheric corrections, the reflectance values are converted to Top of Atmosphere (TOA) and Surface Reflectance (SR) (Planet, 2018). To summarize this information, it can be stated that the processing level of the imagery is the Level 3B (see Table 4). Level 3B are orthorectified products, scaled to TOA and SR; the images are suitable for visual and analytic applications and they are projected to a cartographic projection, in this case, Universal Transversal Mercator (UTM) (Planet, 2016). The imagery uses the horizontal datum World Geodetic System 1984 (WGS 84).

To find annual changes, the satellite imagery had to be captured during the same window every year because images from different windows of the year can result in erroneous results. Even though Ecuador has no seasons, there are ‘rainy’ and ‘sunny’ stages in the year. Consequently, it was necessary to search for images that were taken at least in the same climatic stage. The rainy season in the Coastal region of Ecuador starts on December and ends in April or May; however, normally April presents low levels of rain due to the presence of the warm current of ‘El Niño’ and the ‘Intertropical Convergence Zone’ (Varela & Ron, 2019).

Since one of the objectives of this study was to examine a series of satellite images of different years, the images were searched in a period of time that corresponded to the ‘dry’ season of the Coastal region of Ecuador. Even though the dry months are between May and August, the window period where the imagery was searched was between the months of April and September to increase the possibilities of obtaining suitable imagery. Moreover, the images were downloaded based on the last three years due to the following reasons. First, after some investigations and interviews with the owner and operator of the mine, it was concluded that the

mining activities began in 2017 after many years of abandonment of the area. In the last years the mining activities and internal constructions such as internal roads, warehouses, camps, dining rooms, and heavy machinery inspection center have increased significantly. The real mining activities' impact to the environment should be analyzed in the period of time where these activities were being developed. Table 4 presents the images that were downloaded from the website and some of the previously mentioned technical characteristics.

Table 4: Information about satellite imagery datasets downloaded from www.planet.com (Planet, 2018).

Year	Date	Source	Cloud percentage	Ground Sample Distance	Processing Level	Number of bands
2019	07/11/2019	4-band Planet Scope Scene	28%	3.0 m	L3B	4 (blue, green, red, near infrared)
2019	06/28/2019/	4-band Planet Scope Scene	32%	3.0 m	L3B	4 (blue, green, red, near infrared)
2019	04/14/2019	4-band Planet Scope Scene	14%	3.0 m	L3B	4 (blue, green, red, near infrared)
2019	04/14/2019	4-band Planet Scope Scene	18%	3.0 m	L3B	4 (blue, green, red, near infrared)
2018	07/09/2018	4-band Planet Scope Scene	5%	3.5 m	L3B	4 (blue, green, red, near infrared)
2018	06/30/2018	4-band Planet Scope Scene	17%	3.9 m	L3B	4 (blue, green, red, near infrared)
2018	04/22/2018	4-band Planet Scope Scene	20%	3.9 m	L3B	4 (blue, green, red, near infrared)

2017	08/08/2017	4-band Planet Scope Scene	15%	4 m	L3B	4 (blue, green, red, near infrared)
2017	07/02/2017	4-band Planet Scope Scene	25%	3.9 m	L3B	4 (blue, green, red, near infrared)
2017	04/25/2017	4-band Planet Scope Scene	3%	3.9 m	L3B	4 (blue, green, red, near infrared)

The cloud percentage presented in the previous table does not refer to the cloud percentage of the area of interest but to the entire image, which means it may not affect the AOI directly.

CHAPTER IV: METHODOLOGY

4.1. UAS Data Processing

Once the images were collected, they were processed by commercial SfM photogrammetry software PIX4Dmapper (Pix4D SA, Lausanne, Switzerland). Even though there are many SfM photogrammetry software that can vary in terms of interfaces, processing, or even price, in this study Pix4Dmapper - Educational software was used. The educational license type was used that is owned by The Measurement Analytics Lab (MANTIS) of the Conrad Blucher Institute (CBI) for Surveying and Science at Texas A&M University-Corpus Christi (TAMU-CC).

Four different processes were performed. Even though two flights were made at varying spatial resolutions, two different cameras were used per flight and each was processed separately. Table 5 describes the number of images per flight that were uploaded to the software, the median number of keypoints per image identified by the software, GSD, altitude above ground, and other technical parameters that were obtained after the photogrammetric process.

RGB images were taken with the original camera of the UAS (DJI Phantom 3 Professional). Multispectral images were acquired with the camera attached to the UAS (Sentra High Precision Single Sensor). Once the images are uploaded to the photogrammetry software, it recognizes automatically the initial geolocation of the images based on the geotagged location information assigned to the imagery via the UAS's onboard GNSS system. This information is stored in the images Exchangeable Image File Format (EXIF) data. The images are initially referenced to geographic coordinates in World Geodetic System 1984 (WGS 84) datum and then projected using the cartographic projection Universal Transversal Mercator (UTM). The total area mapped in each flight can be seen in Table 5.

Table 5: Some resulting parameters of the UAS data processing.

Parameters	First Set of Images – Flight number 1	Second Set of Images – Flight number 2	Third Set of Images – Flight number 3	Fourth Set of Images – Flight number 4
Type of camera	RGB - DJI Phantom 3 Professional	Multispectral - Sentra High Precision Single Sensor	RGB - DJI Phantom 3 Professional	Multispectral - Sentra High Precision Single Sensor
Altitude above ground	120 meters	120 meters	66 meters	66 meters
Number of images	670 images	591 images	1168 images	1692 images
Front overlap	80%	80%	75%	75%
Side overlap	70%	70%	60%	60%
Median of keypoints	55033	21199	52947	8943
Ground Sample Distance	5.32 cm	11.41 cm	2.97 cm	6.47 cm
Number of 3D Densified Points	49767057	5088621	295681193	54616360
Total area mapped (acres)	248.25	222.86	202.12	197.16
Acquired date	July 15th, 2019			

4.1.1. Georectification and positional errors

Phantom 3 Professional is equipped with an onboard GNSS system that measures GPS and GLONASS signals. Due to the lack of field surveying equipment, indirect georeferencing methods such as GCPs to ensure absolute accuracy were not used for this study; however, because this study is based on comparisons among photogrammetry products and between satellite and UAS-based imagery, relative accuracy on these rasters is what matters. High relative accuracy can be ensured by using image to image georectification or registration techniques. The registration process is an alternative approach when GCPs are not available, and where the objective to perform change detection analyses across time. Moreover, this technique is useful when in the analysis there is more than one sensor and multitemporal scenes are taken into account (Lin & Tsai, 2017). Image registration is a process where one or multiple images are aligned to a single image that can be considered the base image; this is done with common control points in both images (Gan et al., 2018). Lin and Tsai (2017) propose a scheme based on control points for image registration, part of the workflow used by the authors is used in this study as well. The image registration process was developed internally in Pix4Dmapper software during the SfM workflow.

The image that served as a base was the first UAS-based orthophoto produced by SfM photogrammetry. As Lin and Tsai (2017) did in the previously mentioned study, the input image was elaborated without GCPs and considering the direct georeferencing of the UAS which was in this case the direct georeferencing of the Phantom 3 Professional. The flight that served as a base is flight number 1 with a total of 670 photographs, taken on July 15th, 2019. The overlapping rates for front and side lap were 80% and 70% respectively, the altitude above ground of the flight was 120 meters and the GSD of the resulting orthoimage was 5.32 cm (See

Table 5). After taking this photogrammetry process as a base, the other 3 flights were processed in the photogrammetry software considering control points of the first flight.

Oniga et al. (2018) determined the optimum number of control points in order to obtain a minimum RMSE in UAS-based imagery using Pix4Dmapper software. The results demonstrated that the RMSE significantly decreases when 6 control points are used instead of 5. Moreover, PIX 4D (n.d.) documentation states that it is recommended a minimum of 5 control points and a maximum of 10, even in large projects. It is also recommended that the control points should be placed evenly on the AOI but not in the edges (Figure 8). Taking into account all these recommendations, 6 control points were considered in the base orthoimage (Figure 9). The coordinates of the different control points were extracted from ArcMap 10.6 (ESRI, Redlands, CA), then these coordinates were used in Pix4Dmapper as input GCPs. The features chosen as control points were static elements that were easy identifiable in all images.

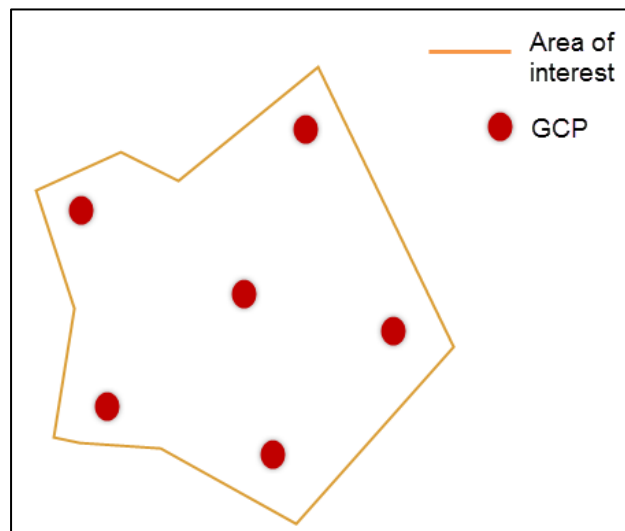


Figure 8: Recommendation of distributions of control points (PIX 4D, n.d.).

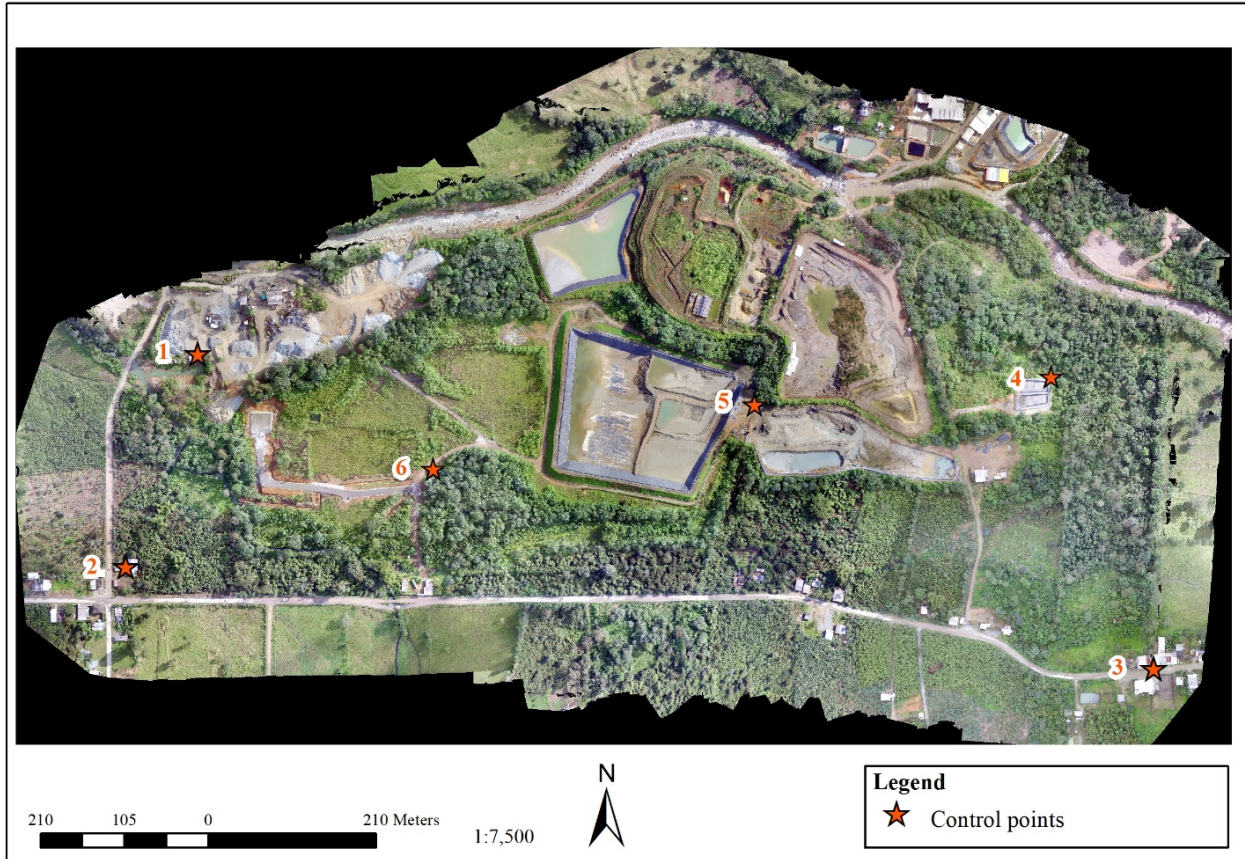


Figure 9: Location of the control points on the base orthophoto.

Positional errors were quantified through the usage of 10 check points, that worked independently of control points. In order to ensure relative accuracy, the RMSE method was used. The objective was to measure the average distance between each check point on all data sources, so a measurement of how well they fit together can be obtained. After the photogrammetry processes were completed for all the data, the quality report of each flight depicted co-registrations errors of the control points and the errors of the check point, these are summarized in Table 6.

Table 6: Horizontal positional errors using flight number 1 as a base.

Flight	Camera type	Altitude above ground	Control points RMSE (6) [m]	Check points RMSE (10) [m]
Flight number 2	Multispectral - Sentra High Precision Single Sensor	120 meters	0.025	0.037
Flight number 3	RGB - DJI Phantom 3 Professional	66 meters	0.013	0.022
Flight number 4	Multispectral - Sentra High Precision Single Sensor	66 meters	0.013	0.023

4.1.2. NDVI Computation of UAS data

As with many multispectral cameras, the processing of the data to obtain NDVI or other vegetation indices can be unique due to sensor characteristics and may be required to be calculated following the recommendations given for that specific camera. The Sentra's Precision NDVI Single Sensor has its own spectral response (see Figure 10) and documentation provided by the company outlines a process to derive more radiometrically correct NDVI values.

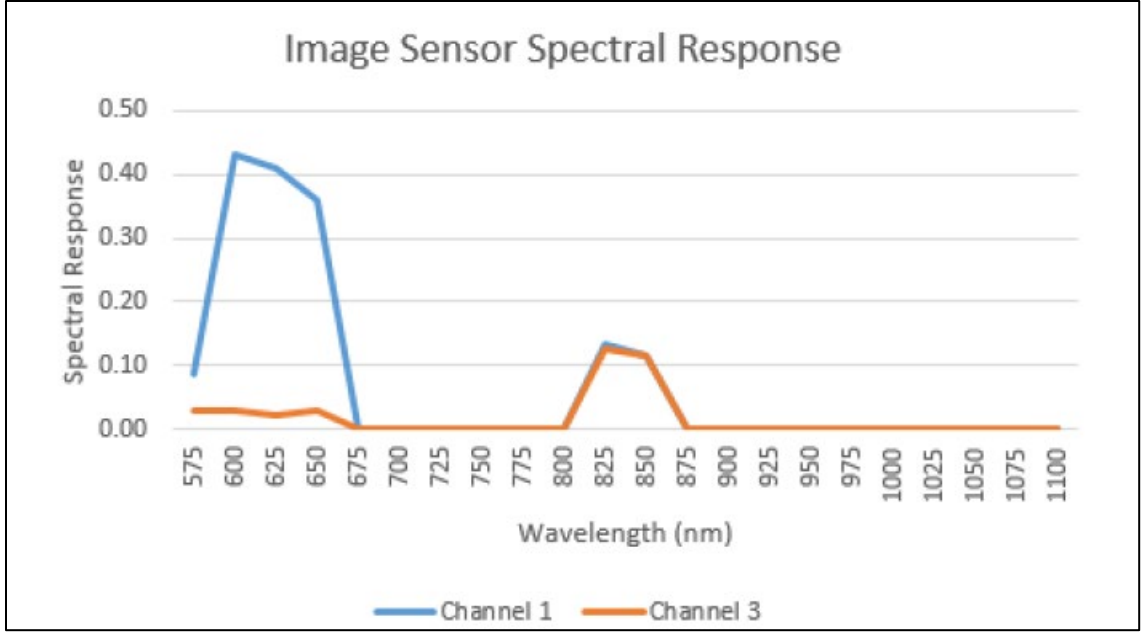


Figure 10: Spectral response of Sentera’s Precision NDVI Single Sensor (Sentera, 2017).

Sentera’s sensor sometimes are referred to as NDVI sensors; however, the sensor is measuring the bands shown in Figure 10, from these measurements it is possible to obtain NDVI and other values (Sentera, 2017). As it is shown in Equation (1), NDVI formula starts with the equation that takes into account NIR and RED; however, in Equation (2) a unique formula developed for this specific sensor is given for deriving NDVI (Sentera, 2017).

$$NDVI = \frac{5.316 * ch3 - 1.286 * ch1}{3.384 * ch3 + 0.714 * ch1} \quad (2)$$

The document provided by the company states that Equation (2) can be used to calculate NDVI from the images obtained by the sensor. Channel 3 (ch3) from Equation (2) and Figure 10 refers to “blue” channel, which actually contains NIR light, whereas Channel 1 (ch1) refers to “red” channel, which contains both red and NIR light. As mentioned above, the utilized camera is a two-band sensor. Consequently, the “green” channel is unused (Sentera, 2017). The equation

can be used in any GIS software that can perform band calculations. In Pix4Dmapper software in the section ‘Index calculator’ the formula was introduced and the index map with NDVI values was generated based on the reflectance information gathered from reflectance maps.

4.2. NDVI – UAS Analysis (Objective 1 of the study)

After getting the processing outputs from the photogrammetry software and after ensuring the correct horizontal alignment between the orthophotos and index rasters, the first objective of this study was analyzed. The following spatial analysis methodology was developed and applied using GIS software ESRI ArcMap 10.6 and ArcGIS Pro 2.5.0 (Esri, Redlands, CA). The first step was to ‘cut’ the original orthomosaics and index maps in one small area due to legal and access reasons which is the AOI. The boundaries of the AOI were delimited following the area that the mine company owns. Even though the flights covered a bigger area, the original outputs were reduced. Thus, the final AOI was drawn using the orthomosaic produced by flight number 1 and then the orthomosaic and the index maps were reduced to the AOI (see Figure 11). The final AOI has an area of 59.65 hectares (147.41 acres) using WGS84 datum.

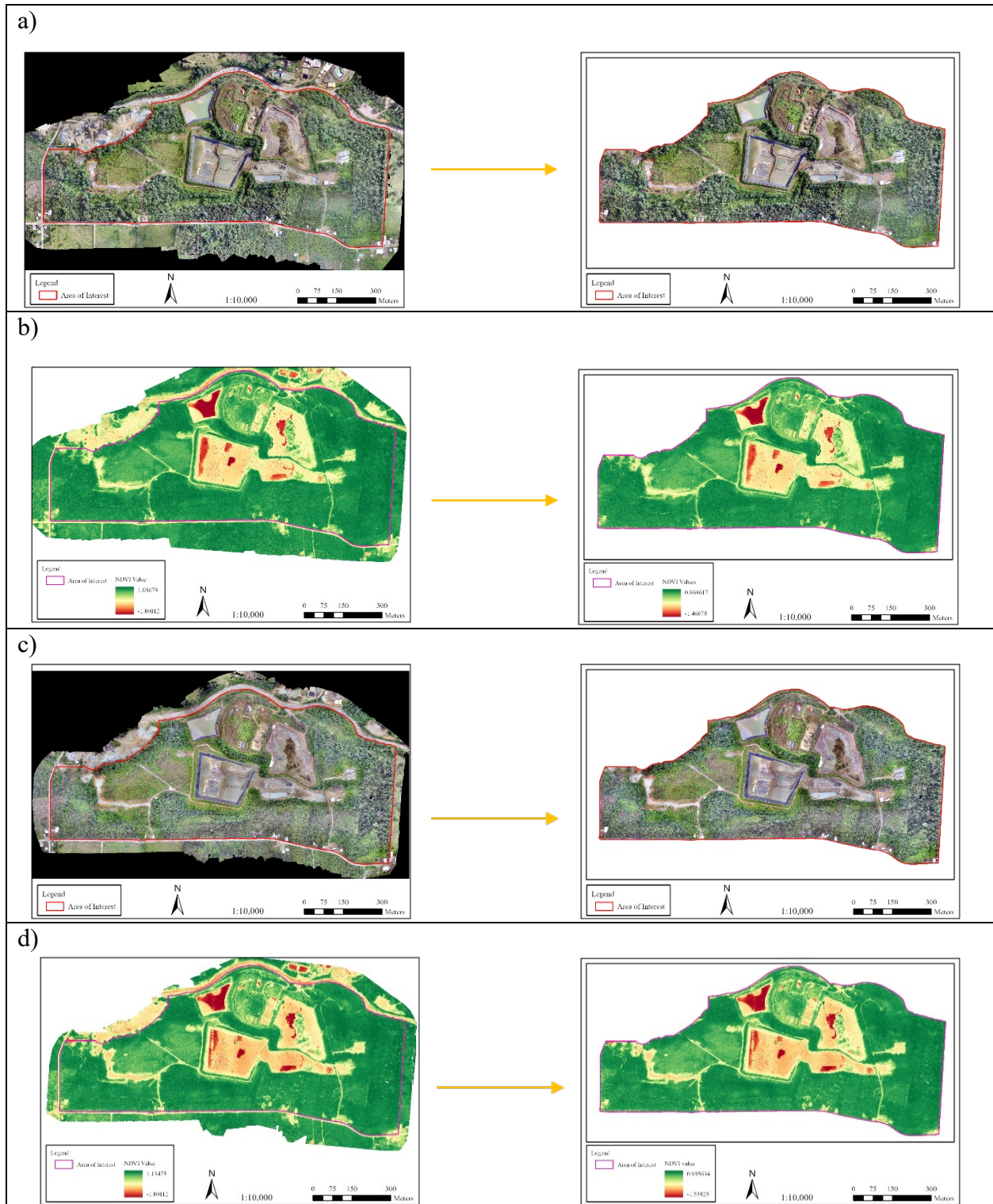


Figure 11: Final AOI of each flight. a) Flight number 1 RGB camera, GSD = 5.32 cm. b) Flight number 2 Multispectral camera, GSD = 11.41 cm. c) Flight number 3 RGB camera, GSD = 2.97 cm. d) Flight number 4 Multispectral camera, GSD = 6.47 cm.

4.2.1. NDVI comparisons based on different landcover categories

Because the principal objective of this study is to analyze the impact of mining activities in vegetation, it is necessary to classify different landcover inside the AOI. Historically, in geospatial analysis, image classification relies on per-pixel based processing with the objective of classifying and extracting objects of interest, usually using unsupervised and supervised algorithms and spectral information (Lu & Weng, 2007). Supervised classification methods require a certain knowledge of the different landcover classes on the AOI. Additionally, most of the times these methods require an interpretation of aerial photography or satellite imagery to locate sites that represent homogenous data of the landcover classes. These sites are known as training sites where multivariate statistical parameters are calculated for each training site and every pixel of the image is then evaluated and assigned to a certain class (Jensen J. R., 2015). Pixel and object-based strategies for landcover classification take advantage of a variety of unsupervised or supervised machine learning algorithms (Pashaei et al., 2020). There are different types of supervised classification, such as Maximum Likelihood (ML), Decision Tree (DT), and Support Vector Machines (SVM), among others (Khatami et al., 2016). One of the most and widely used classification algorithms is ML, which is based on the calculation of the probability of a pixel of belonging to a certain class, then the pixel is assigned to the class with the highest probability (Jensen J. R., 2015).

Many land classification algorithms have been used for analyzing environmental problems. For instance, Fischer et al. (2019) used multispectral aerial imagery taken from UAS to extract areas where wild pigs have caused damage in agricultural crops. The areas were obtained through an object-based classification method. Ying and Erfmeier (2018) analyzed the usage of UAS to capture heterogeneously distributed plant populations using ML classifier. The

authors created training polygons in an orthomosaic by grouping similar areas with visual analysis and assigning them a category.

In this study, the ML algorithm was chosen as the classification method and was developed with ArcGIS Pro software. ML algorithm assumes that each class has an equal probability of occurring in the scene; this classification algorithm is considered one of the most accurate classification techniques and it is recognized as a stable classifier that can be used as a high precision pixel-based method (Sun et al., 2013). Flight 1 RGB orthomosaic was used to locate the training polygons. Four classes of training polygons were created by grouping similar colored pixels and making a visual inspection. The different classes were defined by the user and these were: forest, grass, water, and bare soil and human construction. For instance, in the zones where dense vegetation was found, some ‘forest’ training polygons were drawn. On the other hand, in places where short plants were located, ‘grass’ training polygons were drawn. These steps were repeated for ‘water’ and ‘bare soil and human constructions’ categories. The training polygons were used to create a signature file that was then used to perform the supervised classification by using ML algorithm in the multispectral orthomosaics. Every pixel was assigned in one of the user-defined categories. Two different landcover classification rasters were obtained (Figure 12 and Figure 13). One was produced by classifying the high-resolution reflectance map and the second one was produced by classifying the medium-resolution reflectance map. In this study, products where original imagery were taken at 120 meters above ground level (AGL) were considered as ‘medium-resolution’ outputs, and products where original imagery was taken at 66 meters AGL were considered as ‘high resolution’ outputs (see Table 5).

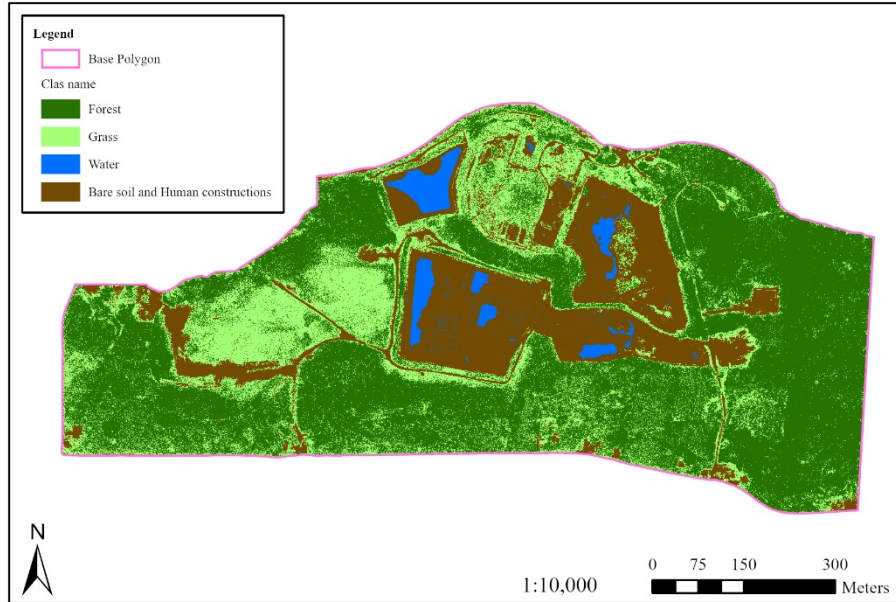


Figure 12: Medium resolution land-cover classification.

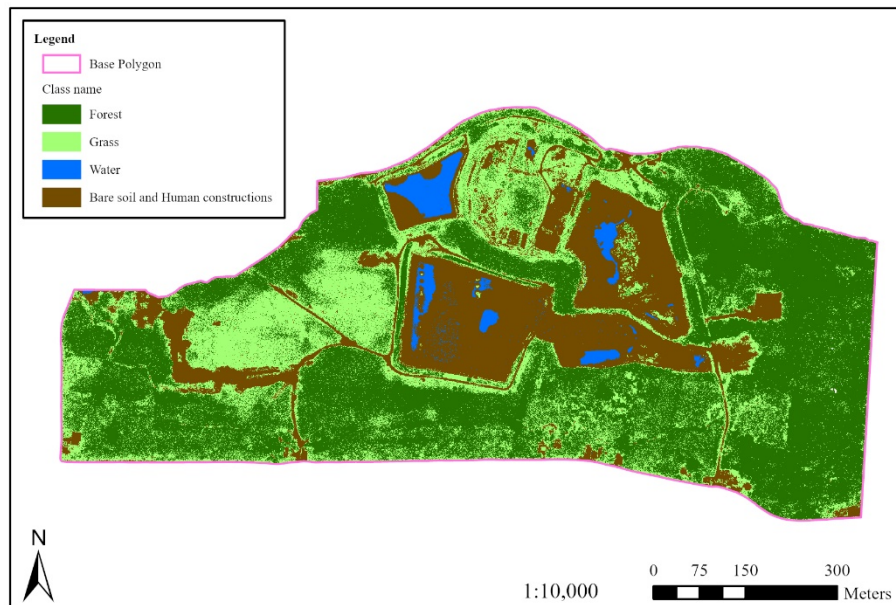


Figure 13: High resolution land-cover classification.

With the objective of assessing the accuracy of the landcover classification, a random point sampling approach with 100 points across each landcover raster (medium resolution and high resolution) was performed and a reference dataset to perform accuracy assessment (i.e.

confusion matrix) was created (Czaplewski, 2003). Two columns were recorded for each landcover raster: assigned class provided by the supervised classification and assigned class according to a visual interpretation of the original orthomosaic (Ying & Erfmeier, 2018). Based on this reference dataset, ArcGIS Pro performs the accuracy assessment and the confusion matrices are created, where the user's accuracy and the producer's accuracy are shown, also, an overall kappa statistic index of agreement is included. Kappa index for medium-resolution landcover classification was 0.83, while for high-resolution land cover classification it was 0.88. The kappa index gives an overall assessment of the accuracy of the classification, and according to the scale developed by Landis and Koch (1977), a kappa coefficient from 0.81 – 1.00 indicates an 'almost perfect' agreement between the visual interpretation of the orthomosaic and the supervised classification. The classification process and the accuracy assessments were done for each flight because NDVI values are very sensitive to change between flights. These changes are produced for many reasons such as differences in GSD, altitude above ground, amount of light received by the sensor, among others; and with the objective of showing differences in NDVI values provided by the different resolutions, in Section 5.1 statistics and classification result differences are shown. The tool 'Zonal Statistics as a table' was used to extract statistic information of NDVI maps based on the landcover classification raster (Figure 14). The output is a table that shows the statistical values of each category; the statistic values that are calculated are the following: majority, maximum, mean, median, minimum, minority, range, standard deviation, sum, and variety (ESRI, 2016).

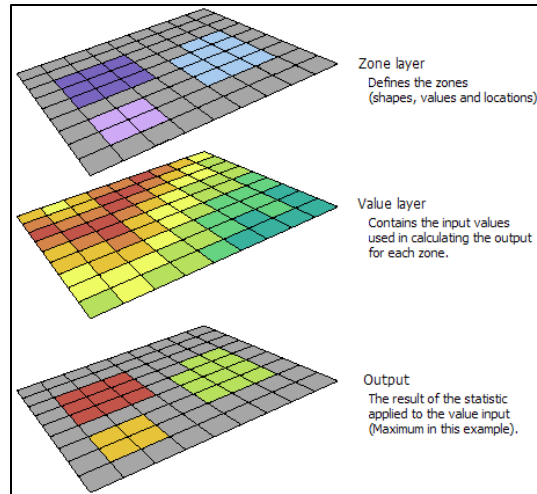


Figure 14: Example of inputs and output of 'Zonal Statistic' tool (ESRI, 2016).

4.2.2. Vegetation NDVI differences based on distances from the contamination source

In order to establish NDVI differences in vegetation, it was necessary to extract vegetation pixels from the reflectance maps. First, the vegetation pixels (i.e. forest and grass categories) were extracted from the landcover classification of high resolution and medium resolution rasters. The tool 'Extract by attributes' was performed by using with the following ArcGIS expression:

Class_name = 'Forest' Or Class_name = 'Grass'

Then, the vegetation pixels were used to extract NDVI pixels from the high and medium resolution reflectances maps by using the tool 'Extract by mask' where the feature mask was the raster with the vegetation pixels (see Figure 15).

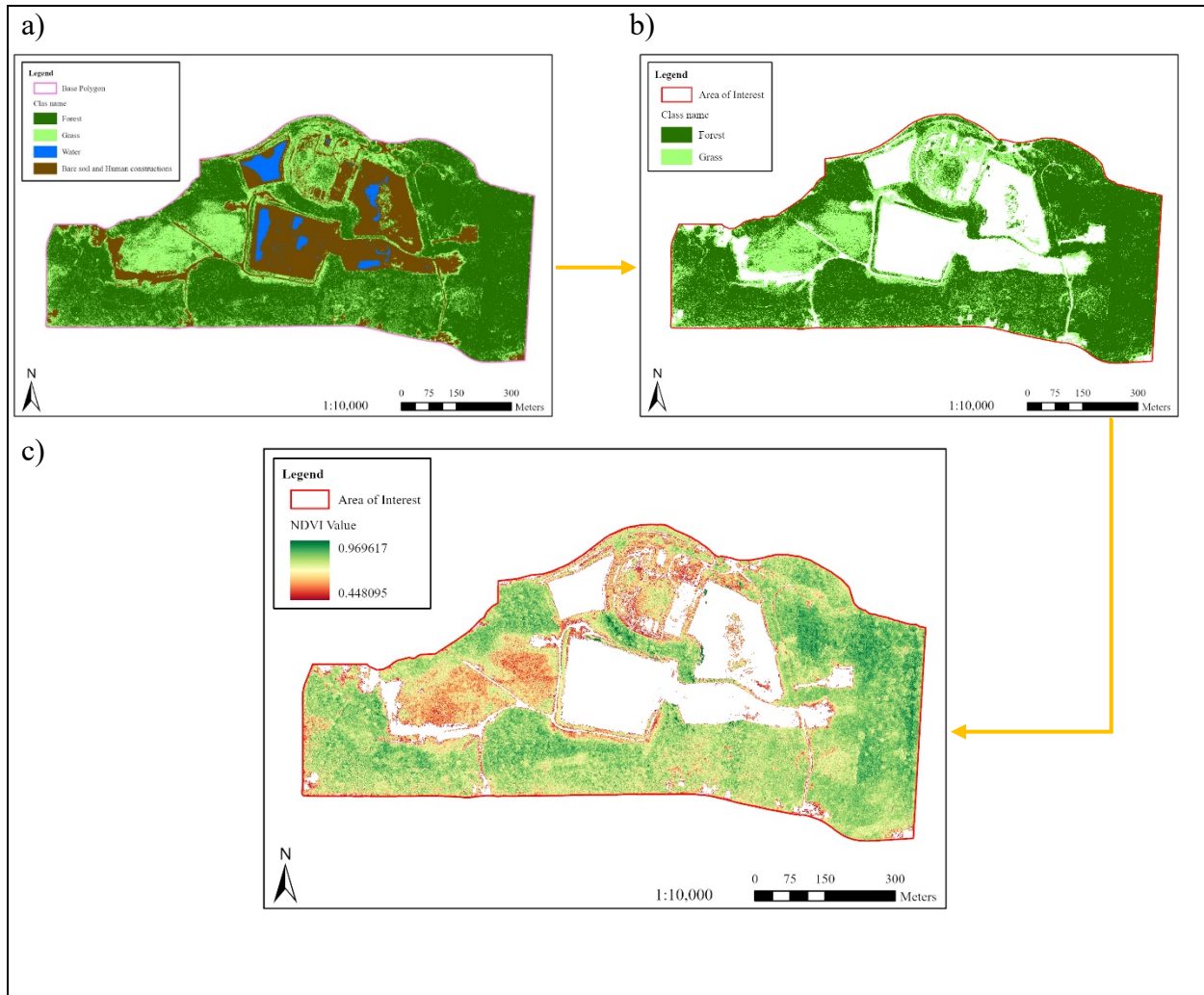


Figure 15: a) Medium resolution landcover classification. b) Medium resolution vegetation pixels from landcover classification. c) Vegetation NDVI pixels from medium resolution map, Flight 2 taken at 120 meters AGL.

The same process of Figure 15 was developed for high resolution products. To accomplish the objective of analyzing if the tailing pond is causing some alteration in NDVI statistics, it is essential to determine the possible contamination source. All the demolished rocks that are the result of the ‘separation’ process, between the minerals and the rocks are placed in a ‘pool’ that is known as ‘tailing pond’. The demolished rocks which are mixed with mercury and cyanide are considered as the possible principal contamination source. The tailing pond was

drawn in each RGB orthomosaic, medium and high resolution (Figure 16). This polygon was drawn with the objective of locating a possible contamination source and then, starting from this polygon, establish radial distances to verify if NDVI statistics have a relationship with the distances of vegetation from the tailing pond.

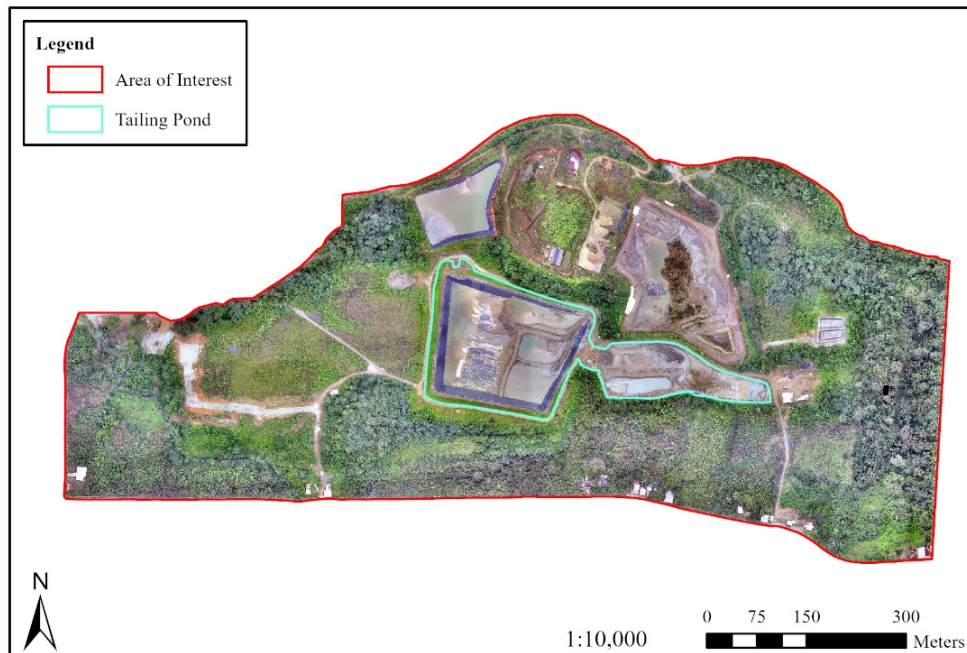


Figure 16: Tailing pond in RGB orthomosaic from Flight 3 – medium resolution.

The tailing pond has a total size of 5.95 hectares (14.69 acres) which represents 9.97% of the total AOI. The first assumption was that the tailing pond could be causing NDVI values alteration depending on the proximity of the pools to the vegetation. To analyze vegetation NDVI values and its relationship with the tailing pond, radial distances away from the pond were constructed through the utilization of ‘buffer’ tool (Chandra et al., 2019). Chandra et al. (2019) mention that one of the purposes of buffers distances is to evaluate the differences in NDVI statistics based on distance factors, moreover, radial buffers allow the assessment of scale

effects. Radial buffers with a linear growth of 100 meters were constructed around the tailing pond (Figure 17). Rhew et al. (2011) analyzed human constructions and NDVI mean values. The authors mention that 100 meters radial buffers is an acceptable distance in order to avoid proximal effects from the source; moreover, at smaller scales spatial resolution effects could be more prominent. A total of six zones were established for further statistical analysis.

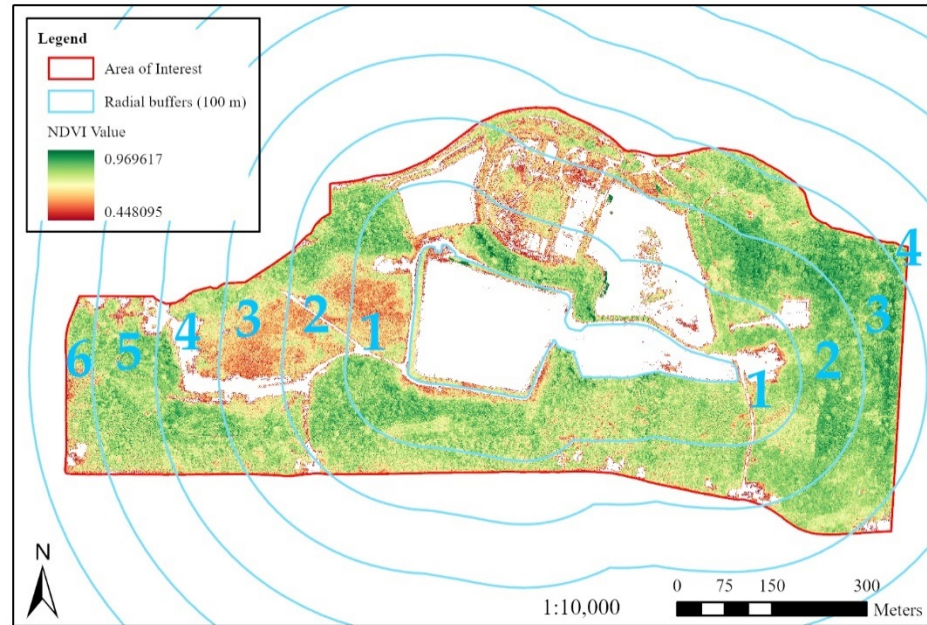


Figure 17: Buffer zones around the tailing pond. As a base, NDVI map from Flight 2 (taken at 120 meters AGL).

4.3. Satellite Imagery Processing (Objective 2 of the study)

The images were downloaded, and the analysis process began (see Table 4). The area that was examined is the same AOI of objective one. The first and one of the most important considerations for this part of the study is that only one sensor was used. Sometimes, it is necessary to integrate data from different sensors in order to obtain enough information to develop long-term NDVI change detection analysis. However, many complications in working with different sensor data can appear such as: the differences in sensor designs, sensor failure, GSD, and radiometric corrections. These problems could be solved with the normalization of the values from different sensors; nevertheless, this process could result in complicated procedures and could affect the consistency of NDVI results (Wenxia et al., 2014). Consequently, in this study, this part of the analysis was made with PlanetScope imagery acquired from CubeSat satellite where Ortho Scene products were used. The sensor of CubeSat satellite constellation captures images in four bands: Blue, green, red, and NIR at a GSD of 3.7 m (Planet, 2018). NDVI values of the AOI were calculated for each image by using Equation (1) in ArcGIS Pro software. Even though the AOI is located in a zone covered by clouds most of the time, the high temporal resolution of PlanetScope allows us to use suitable imagery.

For this part, the software ArcGIS Pro was used due to the new options that the software presents compared to ArcMap. For instance, some analysis functions are easier and friendly-user in this new software, and it is important to take advantage and to be familiarized with these new resources. The first step was to divide the AOI into 6 radial buffers polygons. The buffer zones have a linear growth of 100 meters and they were drawn around the tailing pond to analyze the impact of the tailing pond in closer and more distant vegetation. The radial buffer distances were the same that were used in the objective one of this study (see Figure 17). Due to the irregularity

of the terrain in terms of land use cover and soil properties, it is a good option to characterize the AOI by zones (Khaliq, et al., 2019). The entire AOI of interest can be analyzed at once; however, the high heterogeneity could cause strong variations and difficulties in the analysis of NDVI over time (Jiang, et al., 2006).

4.3.1. PlanetScope imagery analysis.

As mentioned before, some rasters and metadata files come included in each download. The rasters that were analyzed were the ones that had an ‘SR’ ending in the name. These two letters refer to ‘Surface Reflectance’ characteristics. The SR product is “derived from the Standard Planet Analytic (Radiance) product, and is processed to top of atmosphere reflectance and then atmospherically corrected to (bottom of atmosphere or) surface reflectance” (Planet, 2018). According to the information from Planet, this is the product suitable for analytic applications.

One of the new advantages of ArcGIS Pro is the ability to automate processes and make some procedures easier to implement. The NDVI index tool is one example of this functionality. As opposed to having to use a raster calculator directly to make calculations between bands, ArcGIS Pro offers some tools to obtain some indices automatically. The software uses the different characteristics of the red and NIR bands captured in a multispectral raster dataset, where the red band is the chlorophyll absorption band and, NIR captures high or low reflectivity of plant material, to compute NDVI using the standard band ratio formula. As mentioned in Table 4, the infrared band of PlanetScope imagery was band 4, while the red band was band 3. Figure 18 shows an example of the process in ArcGIS Pro software to derive NDVI values from a satellite image.

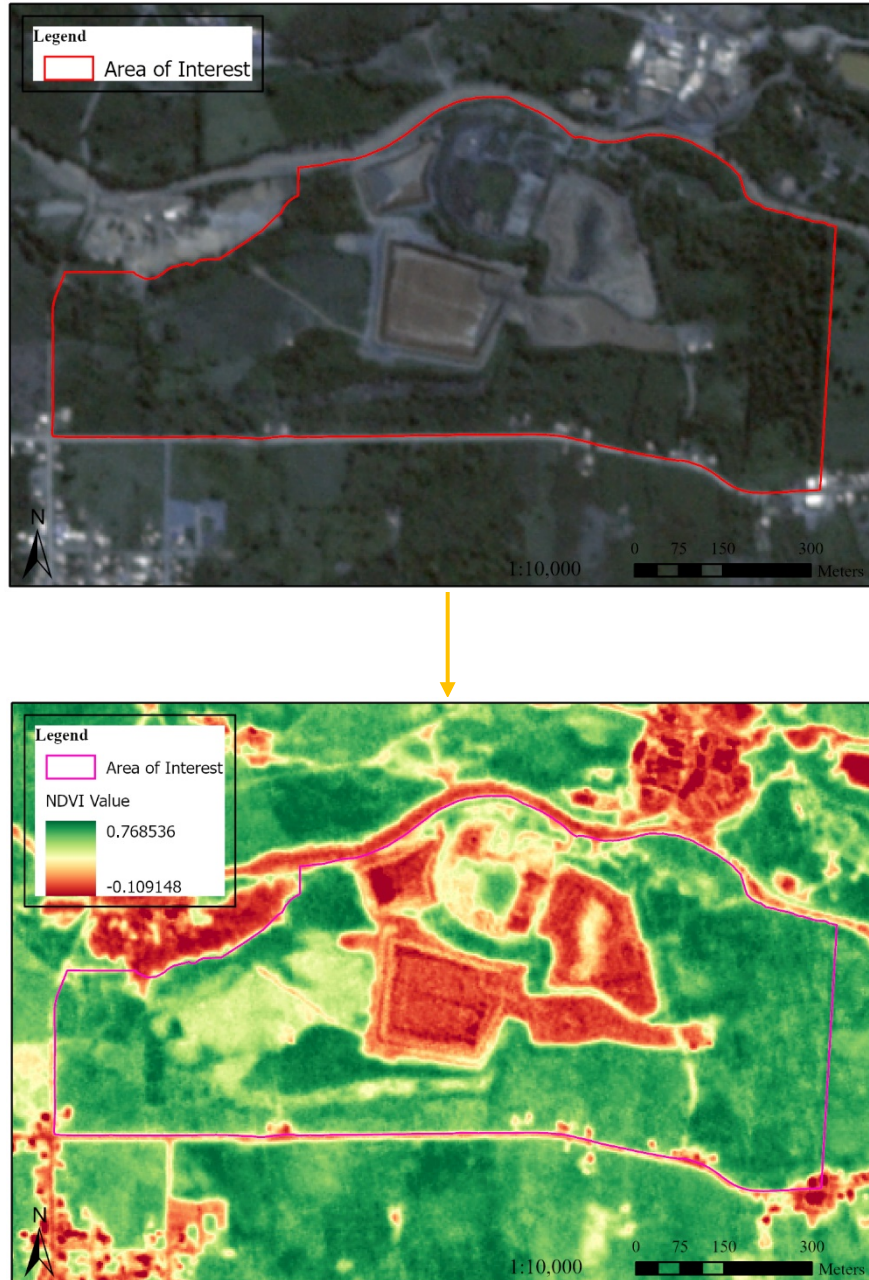


Figure 18: NDVI raster result, obtained from PlanetScope imagery taken on July 9th, 2018.

Radiometric accuracy of PlanetScope products count with an on-orbit calibration and they have been measured at 5% uncertainty (Planet, 2018). Vegetation indices can be affected by many factors, such as atmospheric effects, illumination angles, sensor calibration, among others;

because of these factors NDVI values are not perfect measurements but they can be considered as reasonable proximities for vegetation amount (Horning & Russell, 2009). Cooley, et al. (2017) mentioned that PlanetScope imagery is calibrated to a radiometric uncertainty of 5-6%, which is reasonable compared to other sensors. It is important to take into account that in this study, NDVI values were not normalized among satellite imagery datasets due to the suggestion of the PlanetScope program, where it is recommended to normalize values when NDVI is compared from different sensors due to small differences in the relative spectral response between them (Planet, 2018). As a result of the process for obtaining NDVI values in ArcGIS Pro software by using the standard band ratio formula, 10 different rasters were obtained from the years 2017, 2018, and 2019. The next step was the detection of any kind of change that the NDVI could present over the years.

Some authors have analyzed impacts on forest of development projects by constructing buffer zones around project sites. Choi et al. (2016) extracted landscape metrics for each buffer zone and their statistical similarities were assessed using a one-way analysis of variance (ANOVA) test. Gizachew et al. (2020) analyzed impacts on forested protected areas produced by deforestation using satellite imagery. The authors used ANOVA in order to analyze statistic differences in the protected areas and their buffers zones. After NDVI values were obtained, a one way ANOVA test was performed to investigate significant differences between buffer radial distances based on different years (Gizachew et al., 2020). The analysis also took into account the area where the tailing pond is located.

4.3.2. Comparison between Satellite Image NDVI and UAS-based NDVI

For this step, three different rasters were used. First, one of the satellite images from PlanetScope that was used in Section 4.3.1 of this study was used for this step as well. This image was taken on July 7th, 2019. The date on which the satellite image was taken was the closest one to the date in which the UAS-based images were taken. UAS-based NDVI maps derived from reflectance imagery taken at 120 meters above ground and 66 meters above ground were used to make comparisons. As mentioned in Section 4.1. the spatial resolution of the last two mentioned rasters was 11.4 cm/pixel and 6 cm/pixel respectively. The images obtained with the UAS were taken on July 15th, 2019.

In order to compare two different rasters, it was necessary to match their spatial resolution. The spatial resolution of the PlanetScope image was 3 meters; therefore, the two NDVI UAS-based maps were resampled with the ‘Resample’ tool in ArcGIS Pro to a cell size of 3 meters/pixel, taking account the mean values for each pixel. Matese et al. (2015) compared UAS and satellite remote products to perform precision viticulture, the authors resampled UAS images to match satellite product resolution. Müllerová et al. (2017) monitored plant invasion through the usage of UAS and satellite imagery. With the objective of analyzing the actual role of spatial resolution, the authors resampled UAS products of 5 to 50 cm to match Pleiades satellite resolution.

Another important issue to take into account is the alignment between UAS and satellite imagery products. PlanetScope imagery was georectified taken as a base the reflectance map of Flight 4 taken at an altitude of 66 meters above ground. The alignment process of satellite imagery was similar to the georectification process of UAS-based products (see Section 4.1.1). Similar features identified in all images were chosen and the PlanetScope image was

georeferenced by using the adjust transformation (Moses & Devadas, 2012). When combining and analyzing remote sensing products from different sources it is necessary to develop a geometric registration and the output should have an RMSE less than 1 pixel (Ozyavuz, 2012). The resulting RMSE for the PlanetScope georectification process in this study is 0.424, which is less than one pixel.

The area to be compared in each NDVI map (i.e. UAS Flight 2 taken at 120 meters AGL with Sentera Single Sensor, UAS Flight 4 taken at 66 meters AGL with Sentera Single Sensor, and PlanetScope) was the same. As mentioned above the three rasters had the same downsampled spatial resolution. In order to obtain the correlation coefficient between the three NDVI products, the ‘Band Collection Statistics’ tool was used. Moreover, the ‘Composite Bands’ tool was used among these three rasters.

4.4. Structural comparisons to NDVI with UAS-SfM 3D point cloud data (Objective 3 of the study)

Once the SfM photogrammetry of the RGB imagery was completed, and after the verification of the matched keypoints, a densified 3D point cloud was created. This is the root product of the SfM photogrammetry, and from this product, other outputs are created such as DSMs. The resulting point clouds were analyzed in specific software able to read and process point clouds.

For this study, ArcGIS Pro software and LAStools package were used. The latter is a group of applications that are widely used to analyze, visualize, and filtering LiDAR point clouds; however, it supports data taken from UAS – SfM (Gomes et., 2019). Some metrics from

the point clouds were extracted. Density and heights were obtained and rasterized to make comparisons.

4.4.1. Point cloud density and NDVI

After the extraction of the point clouds from the SfM algorithm developed in PIX 4D software, it was post-processed using LAStools packages. Mlambo et al. (2017) mentioned that, unlike LiDAR data, SfM point clouds have a relatively high-density nature, so, “processing the point cloud as a single file can be memory-demanding for LAStools algorithms.” UAS RGB Flight 1, taken at an altitude of 120 meters, had an average density of 17.5 per m^3 , while Flight 3, taken at an altitude of 66 meters, had an average density of 318 per m^3 . The difference in average density is produced by the different GSD due to the difference in flying height. Figure 19, Figure 20, and Figure 21 show the densified 3D point cloud of Flight 1 and Flight 3 respectively. Some metrics from the point clouds were extracted. Density and heights from vegetation were obtained and these were rasterized to make comparisons.

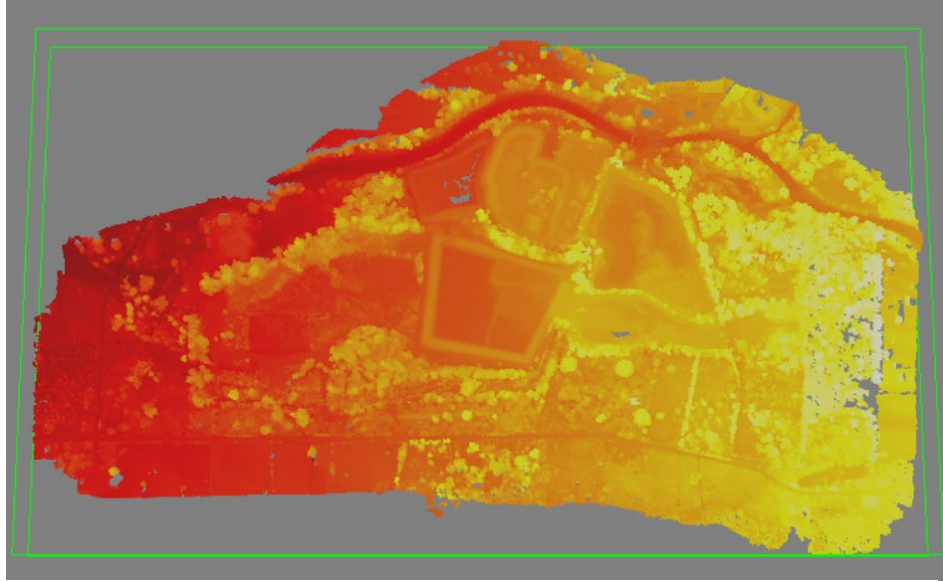


Figure 19: Densified point cloud of Flight 1 (from RGB imagery taken at 120 meters AGL) – Colored by ellipsoid height.

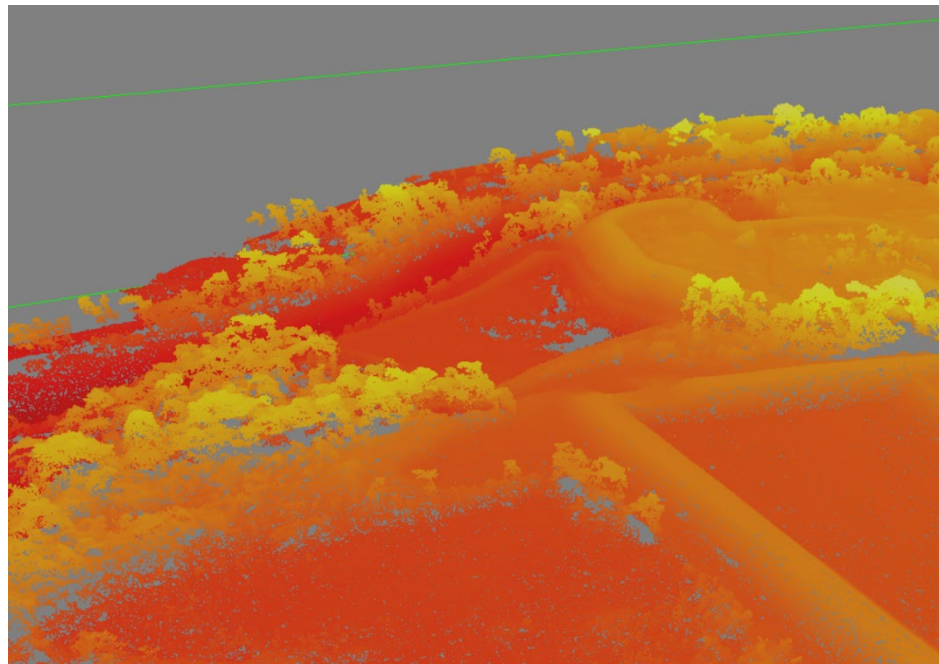


Figure 20: Densified point cloud of Flight 1 (from RGB imagery taken at 120 meters AGL) – Colored by ellipsoid height.

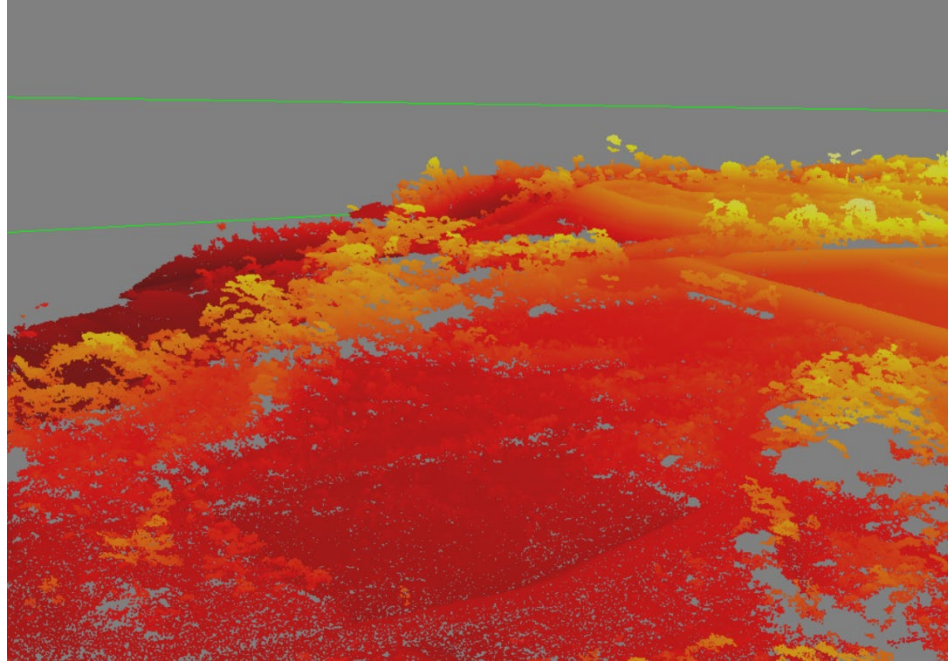


Figure 21: Densified point cloud of Flight 3 (from RGB imagery taken at 66 meters AGL) – Colored by ellipsoid height.

Point cloud density can be considered one of the main parameters of aerial laser scanning. Although this term is used for photogrammetric point cloud as well, it is defined as the number of points per square meter (Kodors & Illmars, 2016). After the point cloud was rasterized using ArcGIS Pro application, a raster of a GSD = 11.4 cm/pixel was obtained where points in this level were computed. The previously mentioned raster had the same spatial resolution as the UAS-based reflectance map produced in Flight 2 taken at 120 meters AGL; consequently, comparisons between rasters with an equal spatial resolution could be developed.

Additionally, the point cloud produced by Flight 1 (RGB camera taken at 120 meters AGL) was computed and rasterized at two more different spatial resolution levels: 50 cm/pixel and 1 m/pixel. NDVI reflectance produced in Flight 2 (originally with a GSD of 11.4 cm/pixel) was resampled at 50 cm/pixel and 1 m/pixel as well (see Figure 22). For point cloud produced by Flight 3 (RGB camera taken at 66 meters AGL), the same process was developed, computing

point density at three different resolutions, obtaining three rasters of 6 cm/pixel, 50 cm/pixel, and 1 m/pixel. NDVI reflectance map produced by Flight 4 (originally with a GSD of 6 cm/pixel), was resampled to a spatial resolution of 50 cm/pixel and 1 m/pixel to match point cloud density rasters resolution (see Figure 23). Cubic resample technique was used to resample NDVI rasters due to this technique is suitable for continuous data. Table 7 summarizes the different spatial resolutions.

Table 7: Different spatial resolutions used to make comparisons between point cloud density and NDVI

	Comparisons for medium resolution (120 meters AGL) – Flight 1 and 2		Comparisons for high resolution (66 meters AGL) – Flight 3 and 4	
	Point density	NDVI	Point density	NDVI
GSD	11.4 cm/pixel	11.4 cm pixel – original GSD	6 cm/pixel	6 cm pixel – original GSD
	50 cm/pixel	50 cm/pixel	50 cm/pixel	50 cm/pixel
	1 m/pixel	1 m/pixel	1 m/pixel	1 m/pixel

Scatterplots show the coefficient of determination between two variables; that is, the amount of one variable that is explained by the second variable and it is represented by R^2 which is also known as the square of the correlation coefficient. Scatterplots were made for each pair of rasters (i.e. point density vs. NDVI) that had the same spatial resolution. Figure 22 and Figure 23 show each pair of rasters that were compared.

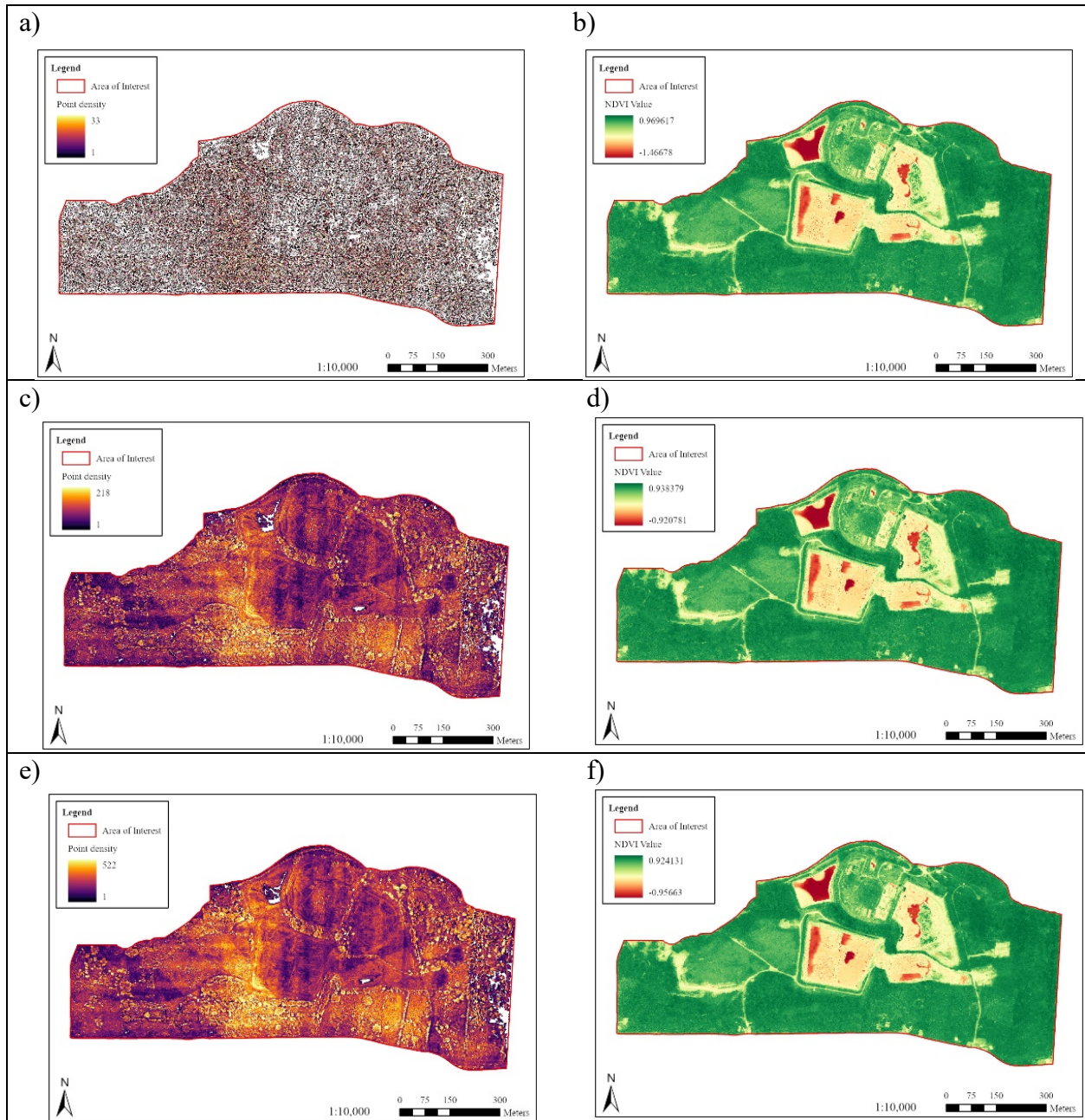


Figure 22: a) Point cloud density from Flight 1 – rasterized at 11.4 cm/pixel. b) NDVI raster from Flight 2 – GSD = 11.4 cm/pixel. c) Point cloud density from Flight 1 – rasterized at 50 cm/pixel. d) NDVI raster from Flight 2 – GSD = 50 cm/pixel. e) Point cloud density from Flight 1 – rasterized at 1 m/pixel. f) NDVI raster from Flight 2 – GSD = 1 m/pixel.

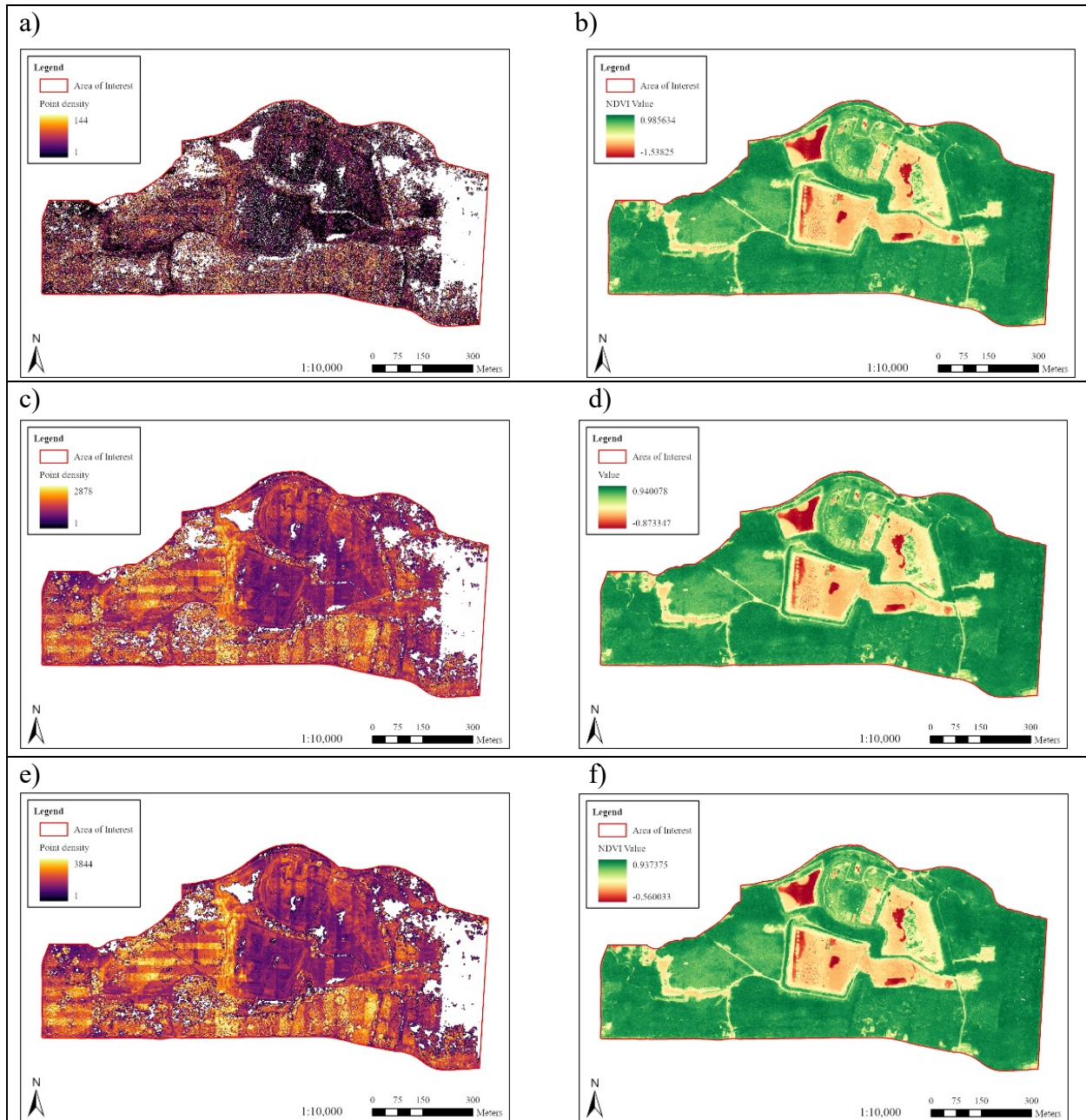


Figure 23: a) Point cloud density from Flight 3 – rasterized at 6 cm/pixel. b) NDVI raster from Flight 4 – GSD = 6 cm/pixel. c) Point cloud density from Flight 3 – rasterized at 50 cm/pixel. d) NDVI raster from Flight 4 – GSD = 50 cm/pixel. e) Point cloud density from Flight 3 – rasterized at 1 m/pixel. f) NDVI raster from Flight 4 – GSD = 1 m/pixel.

Finally, the same process was developed for vegetation landcover. That is scatterplots where point density and NDVI values are compared just in pixels that were classified as vegetation (see Section 4.2.1). This process was made for 6 pairs of rasters (Point Density vs. NDVI) for medium and high resolution flights in three different GSD for each one.

4.4.2. Vegetation heights and NDVI

Another product extracted from the point clouds were the heights of landcover features in the area of interest. The point clouds were rasterized taking into account the spatial resolution of NDVI reflectance maps (i.e. 11.4 cm/pixel and 6 cm/pixel). Height is a phenotypic aspect of plants that can be used as an indicator of yield and as an essential parameter for assessing growth and health conditions (Holman, et al., 2016). Ampatzidis et al. (2019) evaluated citrus rootstock phenotypic aspects throughout the utilization of UAS, the authors measured the relationship between height and NDVI. For this study, this relationship was analyzed as well.

Many studies have analyzed a common forest metric, Canopy Height Model (CHM). CHM indicates the real height of trees and other elements by taking into account the influence of ground elevation (EarthLab, 2019). However, in order to obtain CHM, it is necessary to obtain a Digital Terrain Model (DTM). Even though it is possible to obtain a DTM from post-processing of UAS-SfM point cloud data, the results are not reliable if there are many elements in the ground such as trees, vegetation, houses, and others; on the other hand, other methodologies like LiDAR could provide accurate DTM that could be used in applications where elevation model is needed (Jakovljevic et al., 2019; Kasprzak et al., 2018). DTM generation process is affected by vegetation cover and dense vegetation canopies limit the possibilities of acquiring accurate DTMs (Moudrý et al., 2019). The generation of DTM through SfM photogrammetry is challenging in forested areas due to the incapability of recording ground points. On the other

hand, LiDAR has the advantage of the pulses to penetrate through vegetation canopies and register multiple returns obtaining canopy and terrain data (Moudrý et al., 2019).

Due to the limitation to obtain an accurate DTM from SfM, an alternative is to analyze maximum heights over flat areas. To find these flat areas over the AOI, a reliable and accurate DTM is necessary; for this study, an official DTM produced by the Department of Agriculture of Ecuador was used. The DTM has a spatial resolution of 4 meters and it covers 88% of the Ecuadorian surface (Ministerio de Agricultura [MAG], 2019). The file was required directly to MAG since it is not completely available on the internet.

The Food and Agriculture Organization of the United Nations (FAO) states that terrains with less than 10% of slope can be considered as ‘flat’ and ‘very flat’ areas (FAO, 1985). The slope was calculated by using ArcGIS Pro tool ‘slope’ (see Figure 24); after a categorization of the slope, every area with less than 10% of slope was considered as suitable for the analysis.

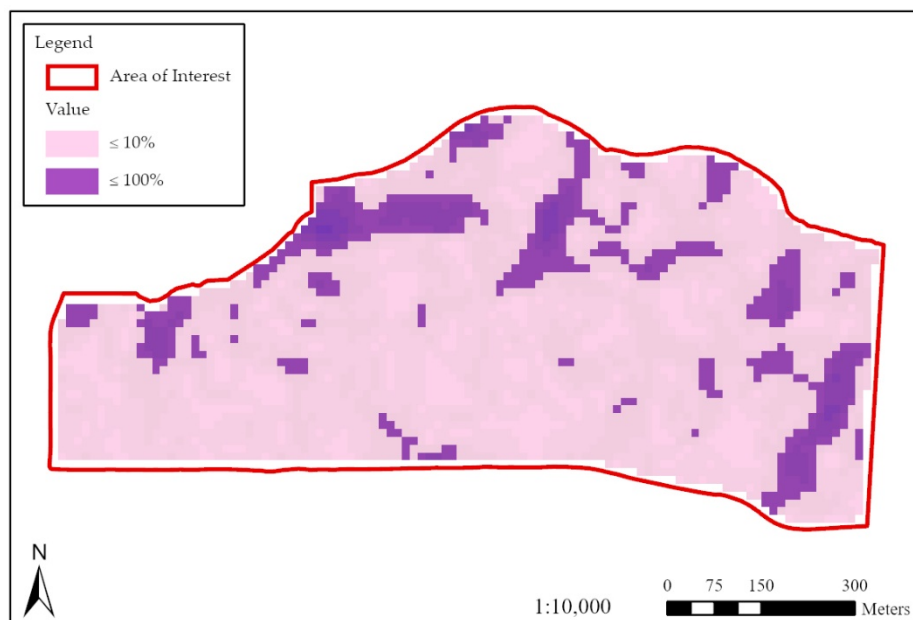


Figure 24: Slopes in the AOI.

In order to compare heights of vegetation and NDVI values, 19 plots were evenly distributed across the AOI in areas where there is a slope of less than 10%. It is important to mention that reflectance maps were georectified taking as base the RGB orthomosaic produced by Flight 1 taken at 120 meters AGL. The NDVI maps (Flight 2 taken at 120 meters AGL and Flight 4 taken at 66 meters AGL) were compared with the height rasters; however, NDVI values just for vegetation were selected for comparisons, according to the results obtaining in the image classification process (see Section 4.2.1). To calculate the correlation trend between these two values, ‘Scatter Plot’ tool in ArcGIS Pro software was used. Moreover, with the objective of taking into account possible resolution effects, the two original NDVI rasters (Flight 2 – GSD = 11.4 cm/pixel and Flight 4 – GSD 6 cm/pixel) were resampled to 50 cm/pixel and 1 m/pixel. Height rasters were resampled as well, resulting in six pair of rasters, three for high resolution and three for medium resolution.

CHAPTER V: RESULTS

5.1. NDVI – UAS Analysis (Objective 1 of the study)

After getting the multispectral NDVI rasters, a supervised landcover classification was completed through the utilization of ML algorithm to find if there is a significant difference between NDVI values based on the classes in each of the different UAS- based imagery resolutions. Then, an analysis of differences in vegetation populations based on distances from the tailing pond was developed.

5.1.1. NDVI comparisons based on different landcover categories

The data of the landcover classifications was grouped by category (Table 8). It is important to note that the classification accuracies can impact the analysis; Kappa index for medium-resolution landcover classification was 0.83, while for high-resolution land cover classification it was 0.88. The results show that the predominant category in the AOI is forest.

Table 8: Categories area on the AOI.

Category	Medium resolution (Flight 2)		High resolution (Flight 4)	
	Pixels	Area (ha)	Pixels	Area (ha)
Forest	24371329	32.01	73755705	30.70
Grass	10173084	13.36	34504563	14.36
Water	1102849	1.45	3085895	1.28
Bare soil and human constructions	9766593	12.83	31921763	13.29
Total	45413855	59.65	143267926	59.64

As it can be seen in Table 8, the categories' areas changed according to the different resolution from where the original multispectral imagery came. Table 9 shows the differences on each category.

Table 9: Area differences of each category taking account of different resolutions multispectral.

Category	Difference (ha)
Forest	1.31
Grass	1.00
Water	0.16
Bare soil and human constructions	0.46

A total of 2.93 hectares were classified in as a different category taking account of the two different resolutions. Thus, for this multispectral sensor, and following the classification parameters specified in Section 4.2.1, a total of 4.9% of the area is classified differently when taking account, the medium and high-resolution multispectral imagery (i.e. 0.11 and 0.06 cm/pixel respectively).

Once the data was obtained from the supervised classification process, it was grouped by different categories, and NDVI statistics were computed (see Table 10). The Kappa index of accuracy is 0.83 and 0.88. Consequently, it can be stated that the overall assessment of the accuracy classification for both resolutions is high (Landis & Koch, 1977). The table shows the NDVI of different land cover types for each of the six indicators in the two NDVI map resolutions.

Table 10: Statistics for NDVI of different land cover categories for each resolution (Medium resolution Flight 2 and high resolution Flight 4).

Land Cover	MIN		MAX		RANGE		MEAN		MEDIAN		STD	
	Med. Res. Fl. 2	High Res. Fl. 4	Med. Res. Fl. 2	High Res. Fl. 4	Med. Res. Fl. 2	High Res. Fl. 4	Med. Res. Fl. 2	High Res. Fl. 4	Med. Res. Fl. 2	High Res. Fl. 4	Med. Res. Fl. 2	High Res. Fl. 4
Forest	0.60	0.61	0.97	0.99	0.37	0.38	0.66	0.65	0.65	0.65	0.03	0.03
Grass	0.45	0.44	0.60	0.61	0.16	0.17	0.55	0.55	0.56	0.56	0.04	0.04
Water	-1.47	-1.35	-0.03	0.00	1.43	1.35	-0.22	-0.13	-0.20	-0.14	0.11	0.07
Bare soil / human constr.	-0.03	-1.54	0.45	0.44	0.48	1.98	0.24	0.24	0.23	0.22	0.11	0.10

The variance and a measure of relative variability such as the coefficient of variation (CV) of each category were calculated as well (Table 11). The CV is also known as the relative standard deviation and is calculated from the ratio of the standard deviation to the mean value; it has been used for analyzing an index over different landcover areas based on different sensors (Tian et al., 2017).

Table 11: NDVI Variance and CV of different land cover categories for each resolution (Medium resolution Flight 2 and high resolution Flight 4).

	VARIANCE		COEFFICIENT OF VARIATION (CV)	
	Medium Resolution Flight 2	High Resolution Flight 4	Medium Resolution Flight 2	High Resolution Flight 4
Forest	0.0009375	0.0006814	4.66%	3.99%
Grass	0.0017105	0.0018897	7.53%	7.84%
Water	0.0117526	0.0052096	50.16%	55.8%
Bare soil and Human constructions	0.0124603	0.0099831	46.41%	41.94%

As can be seen in Table 11, the highest coefficients of variation are associated with the water and bare soil/human constructions categories. Forest and grass show a low CV compared with the other two categories. Moreover, the coefficients of variation of the different resolution imagery datasets are similar. Figure 25 shows a correlation plot of the different coefficients of variation of each category to observe the relationship between them. As can be seen in Figure 25, the correlation coefficient is 0.974 indicating a high correlation between these two variables.

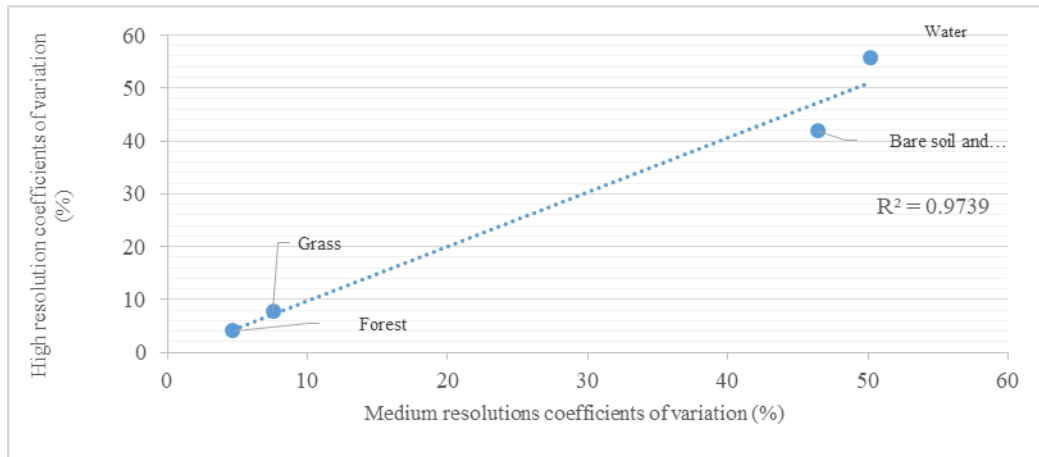


Figure 25: Correlation between coefficients of variations of different categories in NDVI high resolution imagery vs. NDVI medium resolution imagery.

Student's t-test, also known as two-sample-t-test, is one of the most commonly used tools for statistical analysis when two independent groups are compared. The test compares the means of the different samples in order to determine significant differences between groups, and it has been used in numerous applications (Gauthier & Hawley, 2007). For instance, it has been used for comparing vegetation indexes of different landcover areas in order to observe significant differences (Lian et al., 2017; Mancino et al., 2020). In this study, the t-test was used to determine if there were differences between different resolution imagery for each landcover category (see Table 12). The data was analyzed at a 5% level of significance (Svotwa, 2013).

Table 12: Student's t-test for significant differences between different image resolutions (* Significant differences, $p < 0.05$).

Land cover category	p-value
Forest	0.44992034
Grass	0.84563125
Water	0.000*
Bare soil and Human constructions	0.69940647

As was expected, most of the categories do not show a significant difference.

Statistically, NDVI values for three of the landcover categories between high and medium

resolution imagery show high similarity; however, water is the only category that shows a significant difference, the possible reasons for this result are discussed in section 6.1.1.

5.1.2. Vegetation NDVI differences based on contamination source

In order to determine significant differences between sample populations in high resolution imagery and medium resolution imagery of vegetation landcover based on distances from the tailing pond, an ANOVA and post-hoc analysis using Tukey's Honestly Significant Difference (HSD) was employed (Ampatzidis et al., 2019; Dumago et al., 2018; Walker et al., 2015). When ANOVA provides a significant result, it means that at least one sample differs from the other samples. However, the result does not inform differences between means; HSD analysis computes significant differences between two means (Abdi & Williams, 2010). For this part of the study, six radial buffers in each image were used (see Figure 17) and HSD analysis was used in order to find significant differences among radial buffers.

The NDVI values were extracted from the pixels that indicated grass and forest in each radial buffer zone and the analysis of variance was developed for each category and each resolution separately. The results of the one way ANOVA test that analyzed the significant differences between radial buffers distances in each category are depicted in Table 13.

Table 13: Results of the one way ANOVA test of six radial buffer zones for different vegetation categories in medium and high resolution imagery (* Significant differences, $p < 0.05$).

Category	Medium resolution (Flight 2)		High resolution (Flight 4)	
	Mean	p-value	Mean	p-value
Forest	0.66	0.018*	0.65	0.001*
Grass	0.55	0.149	0.55	0.317

The results of Table 13 indicate that in medium and high resolution imagery, the forest category shows a significant difference ($p < 0.05$) between buffer distances; however, for grass

category, there are no significant differences between groups (radial buffer based on distance). The medium and high-resolution imagery show similar results. It is important to mention that ANOVA results indicated that not all the groups' means are equal; however, in this study, it is critical to determine which groups (radial buffer distances) are different from each other, this can be done with the post-hoc analysis using Tukey's Honestly Significant Difference. The results for comparison between each category and each resolution imagery (i.e. significance level for all individual comparisons) are shown in Table 14.

Table 14: Post-hoc analysis with Tukey's Honestly test for different radial buffer distances in forest category (*Significant differences, $p < 0.05$).

Distance (m) radial buffer comparison		Medium resolution (Flight 2)	High resolution (Flight 4)
Buffer 100	Buffer 200	0.288796965	0.980548555
Buffer 100	Buffer 300	0.584617373	0.99965957
Buffer 100	Buffer 400	0.999475923	0.99234244
Buffer 100	Buffer 500	0.999986294	0.790073664
Buffer 100	Buffer 600	0.911315131	0.929405048
Buffer 200	Buffer 300	0.996896291	0.998534385
Buffer 200	Buffer 400	0.486707385	0.789898597
Buffer 200	Buffer 500	0.213328326	0.342097529
Buffer 200	Buffer 600	0.023248897*	0.001920969*
Buffer 300	Buffer 400	0.790127242	0.950666918
Buffer 300	Buffer 500	0.479834888	0.603111243
Buffer 300	Buffer 600	0.089157264	0.008534609*
Buffer 400	Buffer 500	0.996559379	0.980587596
Buffer 400	Buffer 600	0.756516024	0.113220163
Buffer 500	Buffer 600	0.95534328	0.445325079

The results indicate that there is a significant difference between buffer 200 and buffer 600, and between buffer 300 and buffer 600. The rest of the 13 combinations do not show a significant difference. The analysis of the reasons for these results is shown in section 6.1.2.

5.2. NDVI from Satellite Imagery (Objective 2 of the study)

NDVI maps were obtained from multispectral satellite imagery from PlanetScope. NDVI values were obtained from each image. Mean values of each sector were calculated in each NDVI map and the ANOVA was used. Changes through time are identified through charts that display different NDVI values.

5.2.1. PlanetScope imagery results

Images from years 2019, 2018, and 2017 were analyzed. The images were grouped per month due to the possible changes that NDVI could show in different months. These are June and July. Table 15 shows the mean NDVI values of each buffer radial distance and the tailing pond in the last three years considering all landcover categories.

Table 15: Mean NDVI values of the last three years.

Buffer zone	June 2017	July 2017	June 2018	July 2018	June 2019	July 2019
Tailing pond	0.363	0.342	0.198	0.229	0.199	0.248
Buffer 100	0.489	0.470	0.529	0.488	0.413	0.479
Buffer 200	0.453	0.480	0.539	0.499	0.302	0.44
Buffer 300	0.476	0.538	0.630	0.574	0.300	0.471
Buffer 400	0.531	0.556	0.646	0.582	0.433	0.494
Buffer 500	0.577	0.514	0.685	0.624	0.530	0.560
Buffer 600	0.505	0.482	0.601	0.553	0.433	0.464

Two charts are displayed: Figure 26 contains NDVI mean values of each buffer zone, from images taken in June (years 2017, 2018, and 2019). Figure 27 contains NDVI mean values of images taken in July (years 2017, 2018, and 2019). A one way ANOVA and HSD analysis was performed to find significant differences between buffer radial distances based on different years (see Table 16).

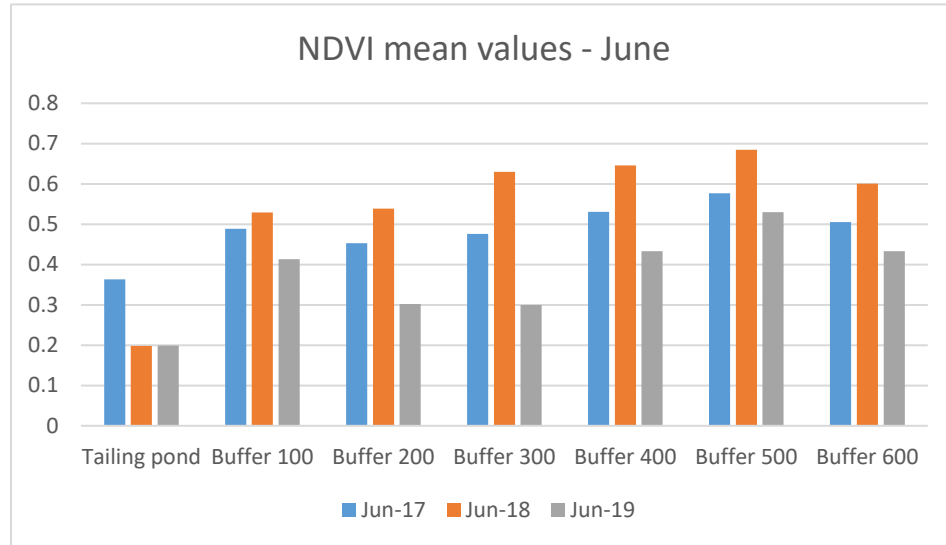


Figure 26: NDVI mean values for each buffer zone in the last three years for the month of June.

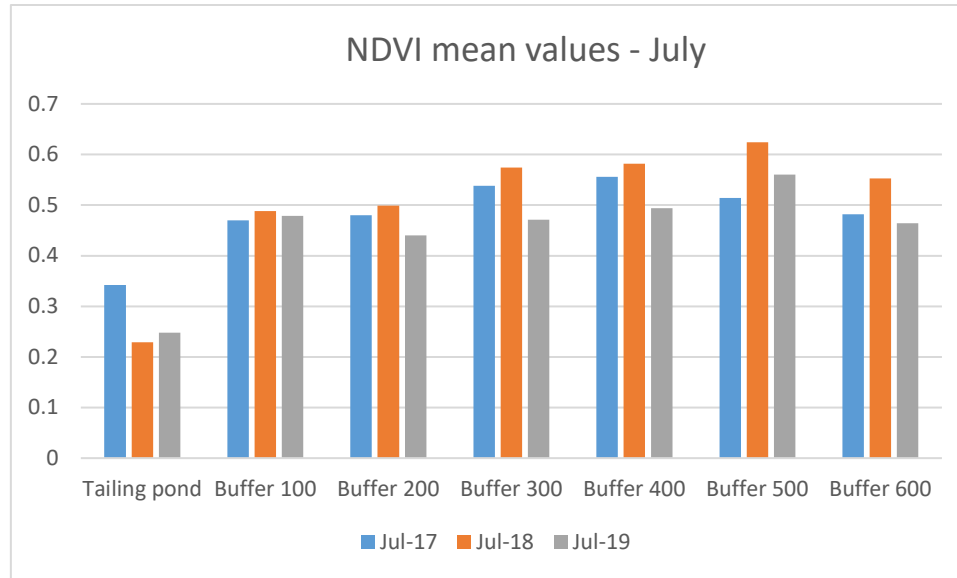


Figure 27: NDVI mean values for each buffer zone in the last three years for the month of July.

Table 16: Post-hoc analysis Tukey's Honestly test for different years (months of June and July) in different radial buffer distances (*Significant differences, $p < 0.05$).

Zone / Distance (m) radial buffer comparison	Month	Years		p value
Tailing pond	June	2017	2018	0.00*
		2017	2019	0.00*
		2018	2019	0.995
	July	2017	2018	0.00*
		2017	2019	0.00*
		2018	2019	0.457
Buffer 100	June	2017	2018	0.339
		2017	2019	0.022*
		2018	2019	0.00*
	July	2017	2018	0.730
		2017	2019	0.927
		2018	2019	0.923
Buffer 200	June	2017	2018	0.00*
		2017	2019	0.00*
		2018	2019	0.00*
	July	2017	2018	0.737
		2017	2019	0.389
		2018	2019	0.111

Buffer 300	June	2017	2018	0.00*
		2017	2019	0.00*
		2018	2019	0.00*
	July	2017	2018	0.008*
		2017	2019	0.00*
		2018	2019	0.00*
Buffer 400	June	2017	2018	0.00*
		2017	2019	0.00*
		2018	2019	0.00*
	July	2017	2018	0.241
		2017	2019	0.00*
		2018	2019	0.00*
Buffer 500	June	2017	2018	0.00*
		2017	2019	0.00*
		2018	2019	0.00*
	July	2017	2018	0.00*
		2017	2019	0.00*
		2018	2019	0.00*
Buffer 600	June	2017	2018	0.00*
		2017	2019	0.00*
		2018	2019	0.00*
	July	2017	2018	0.00*
		2017	2019	0.511
		2018	2019	0.00*

Figure 28 shows the difference in NDVI mean values in the tailing pond and the different radial buffer distances. The pattern is similar for every buffer radial distance, NDVI mean values rise in June 2018 and start decreasing until the lowest value in June 2019. In order to analyze these results, it was necessary to know what has happened in the AOI in the last three years. In Section 6.2.1 the actions in the AOI are explained and detailed.

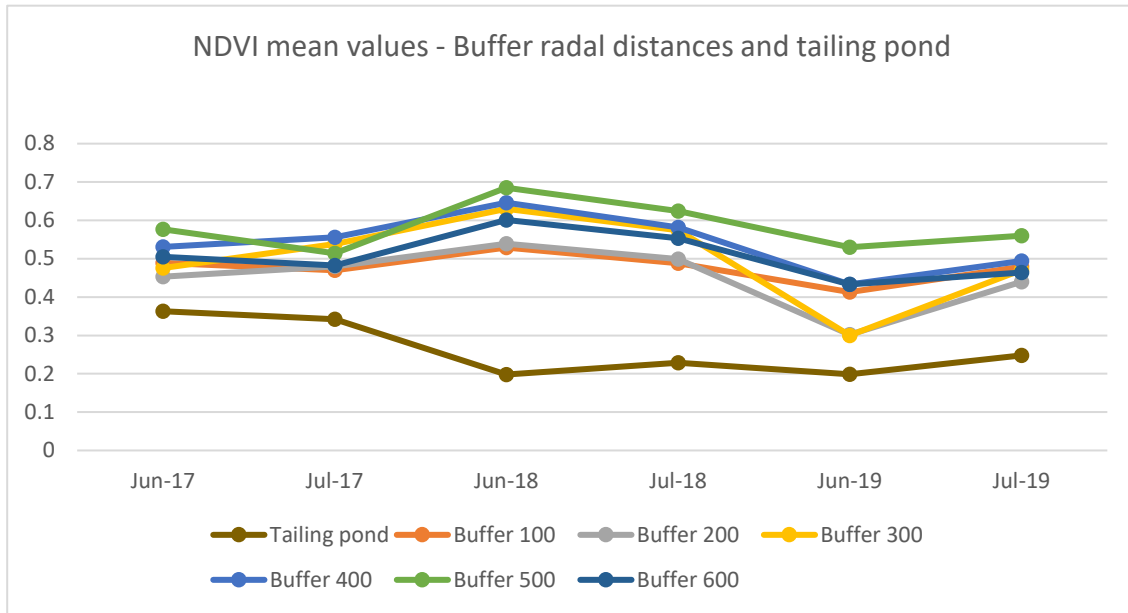


Figure 28: NDVI mean values changes for each buffer zone in the last three years.

5.2.2. Comparison between satellite image NDVI and UAS-based NDVI products

One of the objectives of this study was to compare the similarities between data taken from satellite images and data taken from a multispectral camera mounted on a UAS. The CubeSat image used for this comparison was the one taken on July 7th, 2019 and the UAS images were the NDVI maps derived from reflectance imagery taken at 120 meters above ground and 66 meters above ground. Moreover, a comparison between UAS multispectral imagery taken at different altitudes was developed. As mentioned in Section 4.1.1, the images are properly co-aligned. The three images cover the same area and the comparison was made for all the images, which means that all land cover types were taken into account. Once the comparisons were made, Table 17, Table 18, and Table 19 show the results of the comparison of the statistics of each UAS-based NDVI map with the PlanetScope image.

Table 17: Statistical comparison matrix between UAS-based NDVI map – GSD of 11.4 cm/pixel before resampling and Satellite Image NDVI map – GSD of 3 meters.

STATISTICS OF INDIVIDUAL LAYERS				
Layer	MIN	MAX	MEAN	STD
Satellite imagery (GSD = 3 meters)	-0.0251	0.6952	0.4595	0.1527
UAS imagery (Original GSD = 11.4 cm/pixel)	-0.4903	0.8996	0.4960	0.2194
CORRELATION MATRIX				
Layer	Satellite imagery	UAS imagery		
Satellite imagery (GSD = 3 meters)	1.00000	0.88343		
UAS imagery (Original GSD = 11.4 cm/pixel)	0.88343	1.00000		

Table 18: Statistical comparison matrix between UAS-based NDVI map – GSD of 6 cm/pixel before resampling and Satellite Image NDVI map – GSD of 3 meters.

STATISTICS OF INDIVIDUAL LAYERS				
Layer	MIN	MAX	MEAN	STD
Satellite imagery (GSD = 3 meters)	-0.0251	0.6952	0.4594\5	0.1527
UAS imagery (Original GSD = 6 cm/pixel)	-0.3987	0.7754	0.4952	0.2072

CORRELATION MATRIX				
Layer	1	2		
Satellite imagery (GSD = 3 meters)	1.00000	0.89991		
UAS imagery (Original GSD = 6 cm/pixel)	0.89991	1.00000		

Table 19: Statistical comparison matrix between UAS-based NDVI map – GSD of 6 cm/pixel before resampling and UAS-based NDVI map – GSD of 11.4 cm/pixel before resampling.

STATISTICS OF INDIVIDUAL LAYERS				
Layer	MIN	MAX	MEAN	STD
UAS imagery (GSD = 11.4 cm/pixel)	-0.4903	0.8996	0.4960	0.2194
UAS imagery (GSD = 6 cm/pixel)	-0.3987	0.7754	0.4952	0.2072
CORRELATION MATRIX				
Layer	1	2		
UAS imagery (GSD = 11.4 cm/pixel)	1.00000	0.95225		
UAS imagery (GSD = 6 cm/pixel)	0.95225	1.00000		

The correlation matrix for satellite image against UAS-based imagery GSD = 11.4 cm/pixel and GSD = 6 cm/pixel show a correlation coefficient of $R = 0.88$ and $R = 0.9$

respectively. On the other hand, the correlation coefficient between the UAS-based products is $R = 0.95$. Since both UAS rasters were resampled, the comparison was made with equal spatial resolution; however, the original rasters had a different GSD. The correlation coefficient depicts the relationship between the cell value from one raster and the cell value from a second raster (Snedecor & Cochran, 1968). In this case, all comparisons show positive and high correlation.

Regarding the similarities between satellite imagery NDVI raster, and UAS-based NDVI rasters, as mentioned previously, a strong relationship was found between the two different sources. For this study, Figure 29, Figure 30, and Figure 31 show a strong coefficient of determination between UAS-based original high-resolution raster (6 cm/pixel) and satellite image-based raster, between UAS-based original medium-resolution (11.4 cm/pixel) raster and satellite image-based raster, and between UAS-based original medium-resolution and high-resolution raster.

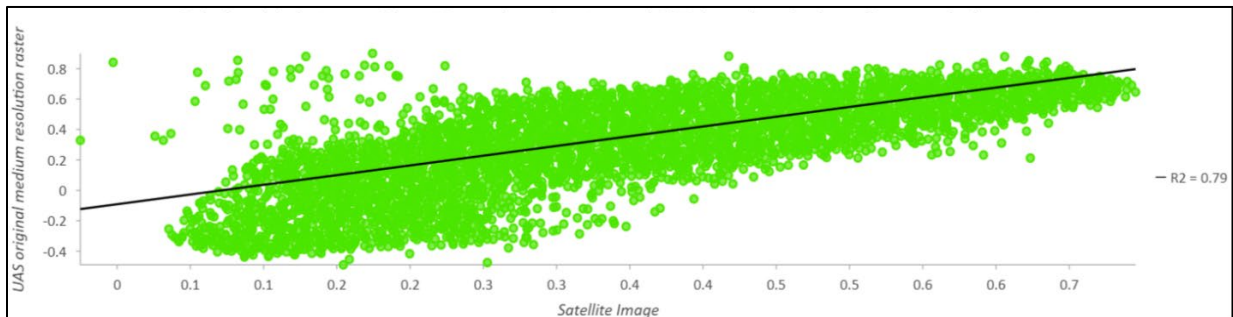


Figure 29: Relationship between UAS-based raster (original GSD = 11.4cm/pixel) NDVI values and Satellite Image NDVI values.

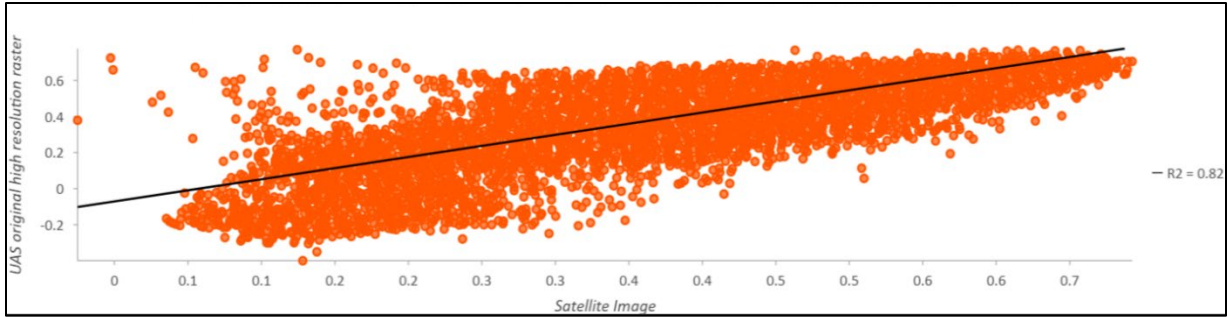


Figure 30: Relationship between UAS-based raster (original GSD = 6 cm/pixel) NDVI values and Satellite Image NDVI values.

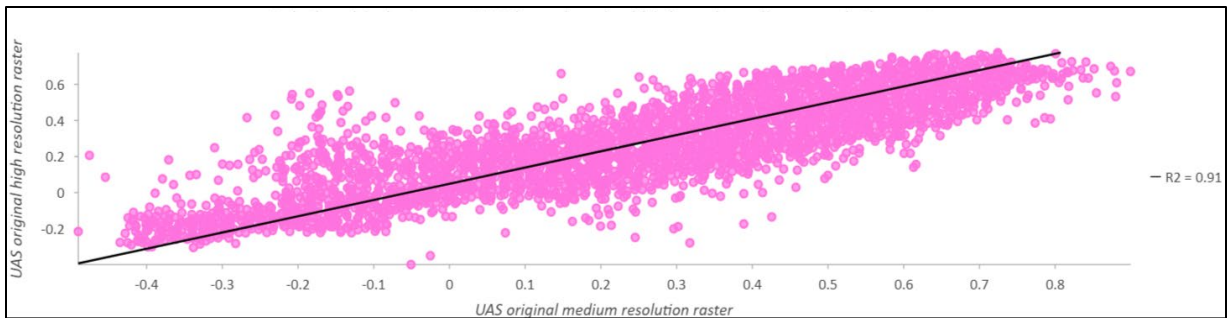


Figure 31: Relationship between UAS-based rasters (original GSD = 6 cm/pixel and GSD = 11.4 cm/pixel).

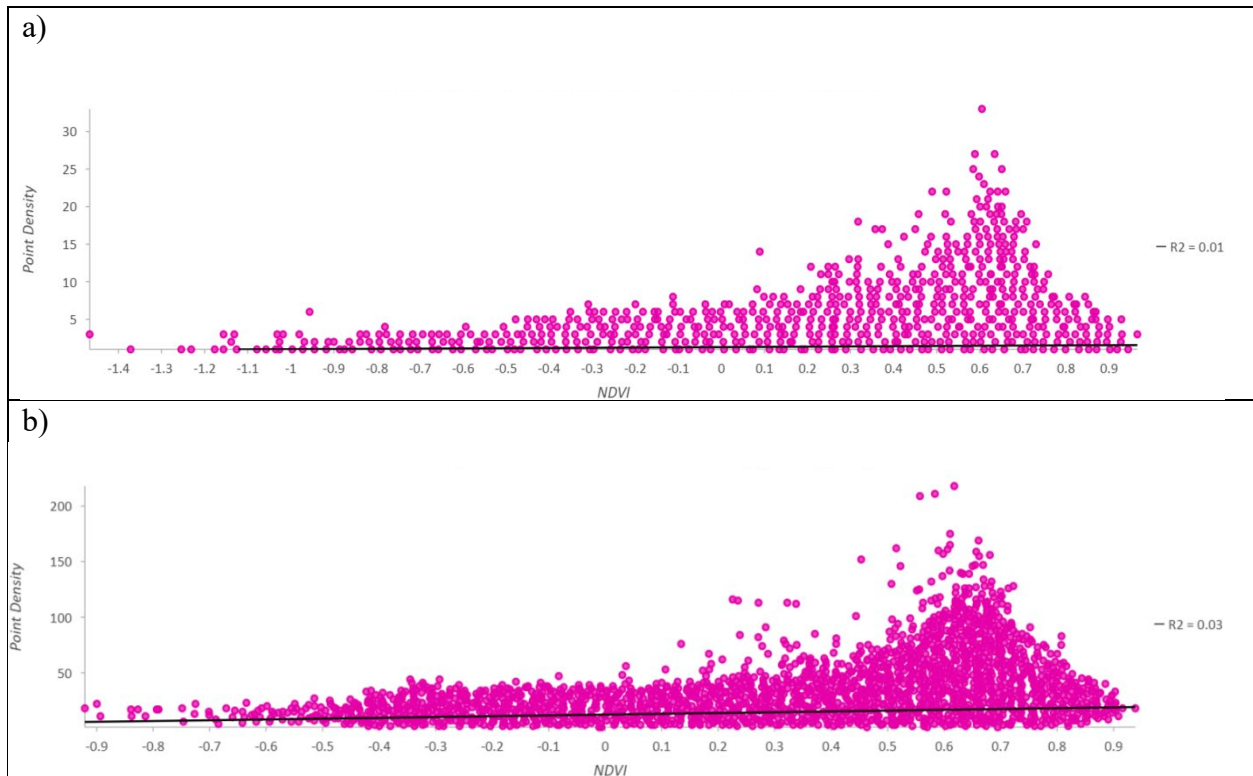
Figures 29 and 30 display a coefficient of determination of $R^2 = 0.79$ (medium resolution original raster vs satellite image) and $R^2 = 0.82$ (high resolution original raster vs satellite image) demonstrating similar values to the ones obtained by Dash et al. (2018). On the other hand, the coefficient of determination for UAS-based high and medium resolution NDVI maps is 0.91.

5.3. Correlation between point cloud metrics and NDVI (Objective 3 of the study)

Different point cloud metrics were obtained from the point clouds derived after SfM photogrammetry. The principal assumption was that some of these metrics may serve as proxy for NDVI values in the AOI enabling an additional method to monitor vegetation health.

5.3.1. Point cloud density

Point cloud density and NDVI relationship was compared for medium and high resolution flights. With the objective of eliminating the possible effects of ground sample distance, the point cloud density of each flight (i.e. Flight 1 and Flight 3) was rasterized at three different spatial resolutions. In order to determine a correlation between these two parameters, 6 different scatterplots are presented. Three for medium resolution taken at 120 meters AGL (i.e. 11 cm/pixel, 50 cm/pixel, and 1 m/pixel (Figure 32) and 3 for high resolution taken at 66 meters AGL (i.e. 6 cm/pixel, 50 cm/pixel, and 1 m/pixel) (Figure 33) where point cloud density and NDVI are the analyzed variables, taking into account that the two rasters for each scatter plot count with the same spatial resolution.



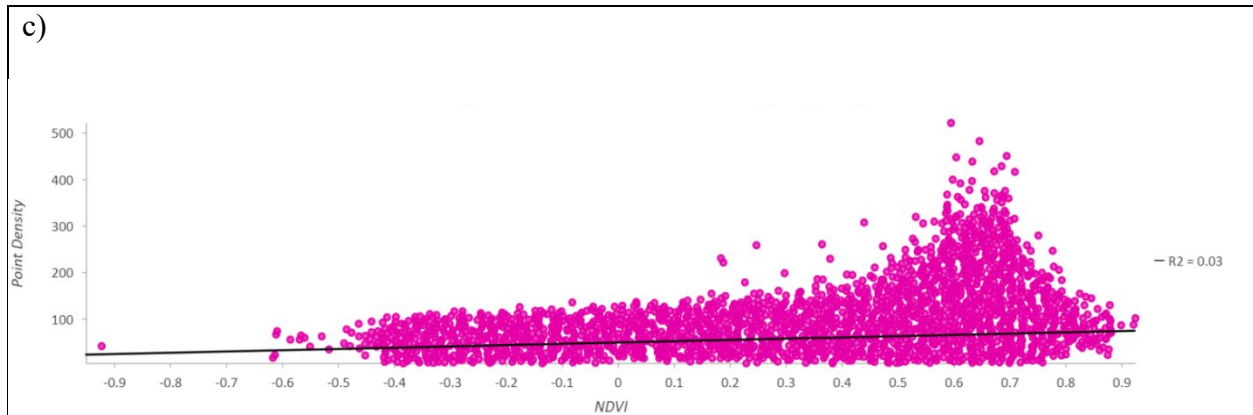
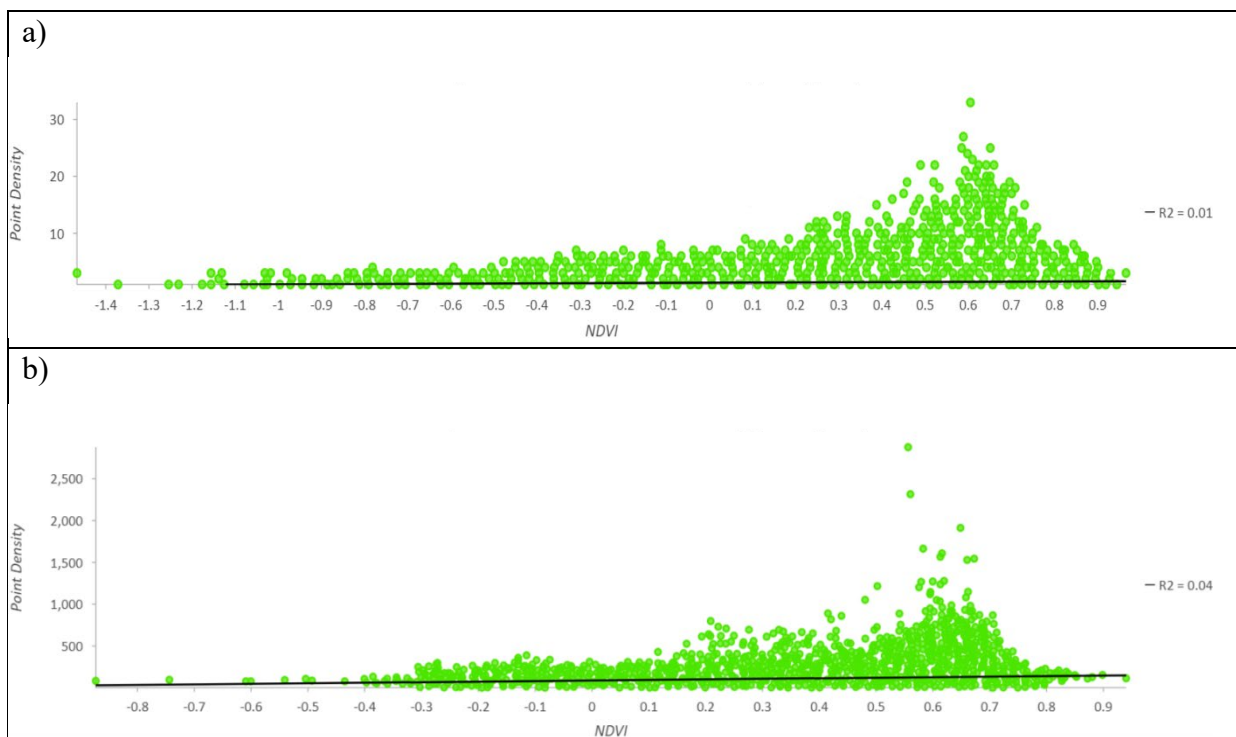


Figure 32: Point cloud density vs. NDVI in medium resolution flights. a) Relationship between Point cloud density and NDVI at a spatial resolution of 11.4 cm/pixel. b) Relationship between Point cloud density and NDVI at a spatial resolution of 50 cm/pixel. c) Relationship between Point cloud density and NDVI at a spatial resolution of 1 m/pixel.



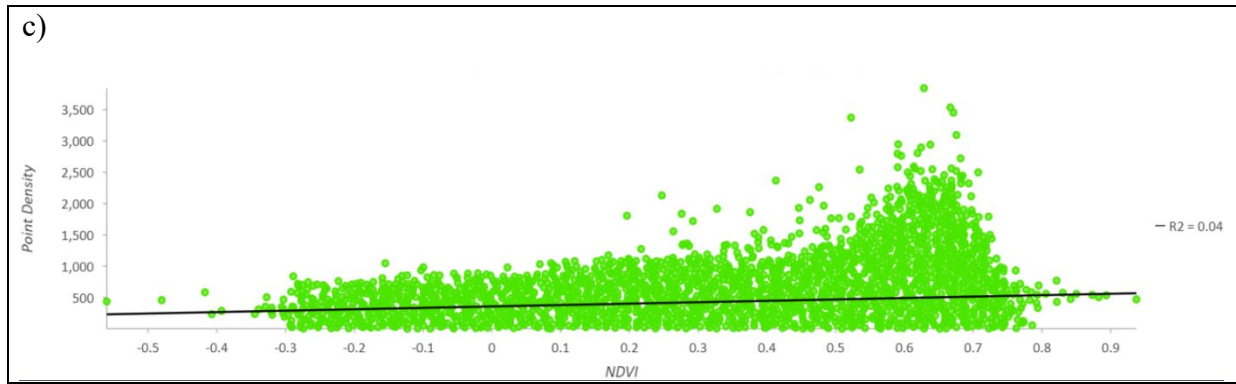
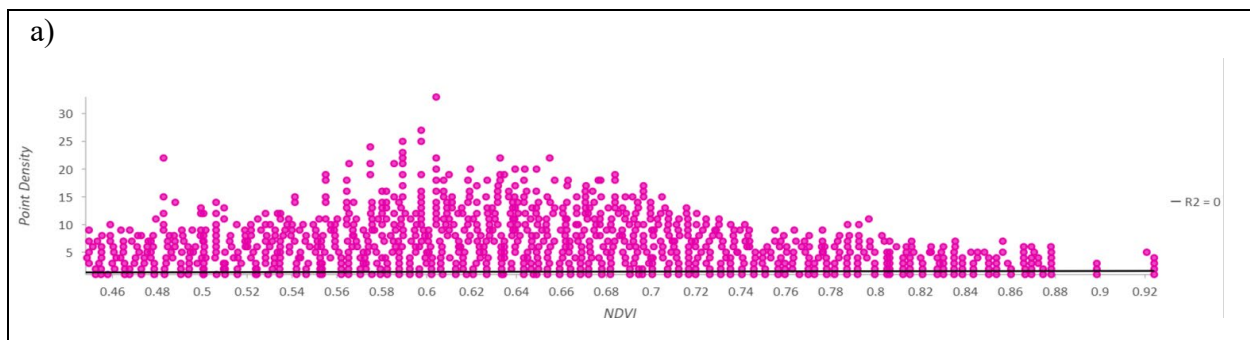


Figure 33: Point cloud density vs. NDVI in high resolution flights. a) Relationship between Point cloud density and NDVI at a spatial resolution of 6 cm/pixel. b) Relationship between Point cloud density and NDVI at a spatial resolution of 50 cm/pixel. c) Relationship between Point cloud density and NDVI at a spatial resolution of 1 m/pixel.

Figures 32 and 33 shows that point density values are dispersed across the whole NDVI range, marking a weak relationship between these two variables. The amount of variability in point density that is explained by NDVI for the six comparisons is low (Rahetlah et al., 2013). Section 6.3.1 analyzes the possible reasons for these results.

The same process was repeated taking into account only vegetation landcover. Figure 34 shows the relationship for medium resolution rasters, with three different GSD: 11.4 cm/pixel, 50 cm/pixel, and 1 m/pixel. Figure 35 shows the relationship for high resolution rasters, with three different GSD: 6 cm/pixel, 50 cm/pixel, and 1 m/pixel.



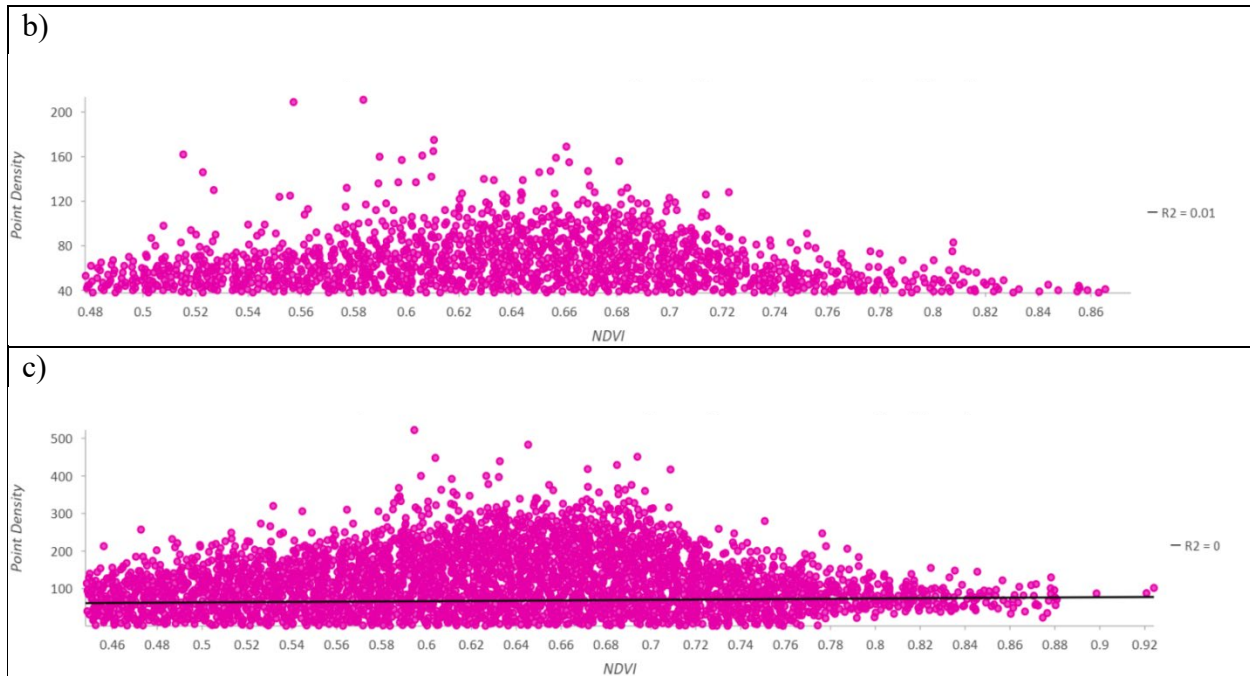
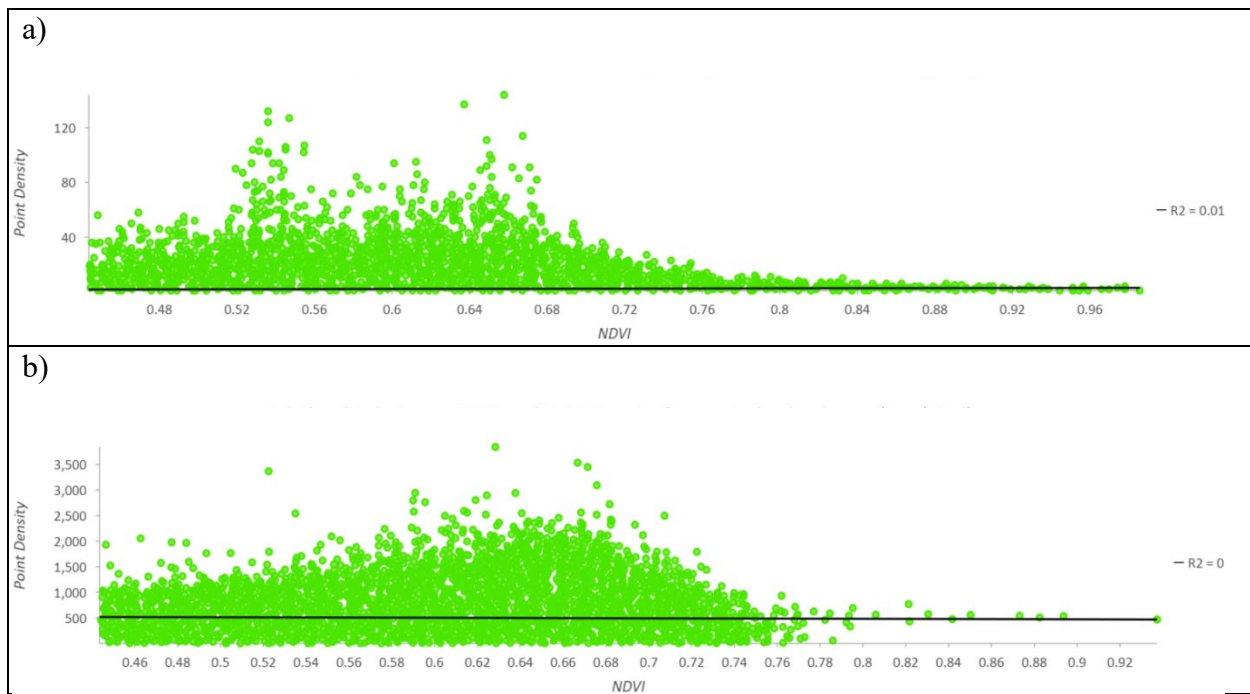


Figure 34: Point cloud density vs. NDVI in medium resolution flights for vegetation landcover. a) Relationship between Point cloud density and NDVI at a spatial resolution of 11.4 cm/pixel in vegetation landcover. b) Relationship between Point cloud density and NDVI at a spatial resolution of 50 cm/pixel in vegetation landcover. c) Relationship between Point cloud density and NDVI at a spatial resolution of 1 m/pixel in vegetation landcover.



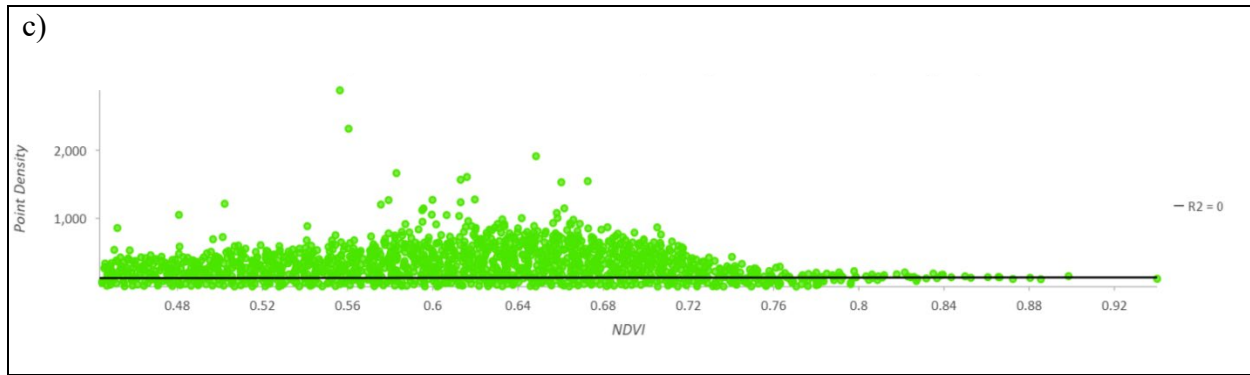


Figure 35: Point cloud density vs. NDVI in medium resolution flights for vegetation landcover. a) Relationship between Point cloud density and NDVI at a spatial resolution of 11.4 cm/pixel in vegetation landcover. b) Relationship between Point cloud density and NDVI at a spatial resolution of 50 cm/pixel in vegetation landcover. c) Relationship between Point cloud density and NDVI at a spatial resolution of 1 m/pixel in vegetation landcover.

Again, the relationship between the two variables is low or almost nil. This indicates that there are pixels with a high NDVI but with a low point density and vice versa. Even though point density values are dispersed across the whole NDVI range, it is notable that some areas count with a higher point density range.

5.3.2. Heights of trees

Height of vegetation and NDVI relationship was compared for medium and high resolution flights in three different spatial resolutions for each one. Through the utilization of scatterplots, a linear relationship was found. Figure 36 shows the relationship in medium resolution flights between NDVI and vegetation height, each pair of rasters was analyzed at the same spatial resolution. With the objective of analyzing the possible effects of GSD, high resolution flight products were analyzed as well. Figure 37 shows the relationship between vegetation height and NDVI in high resolution flights.

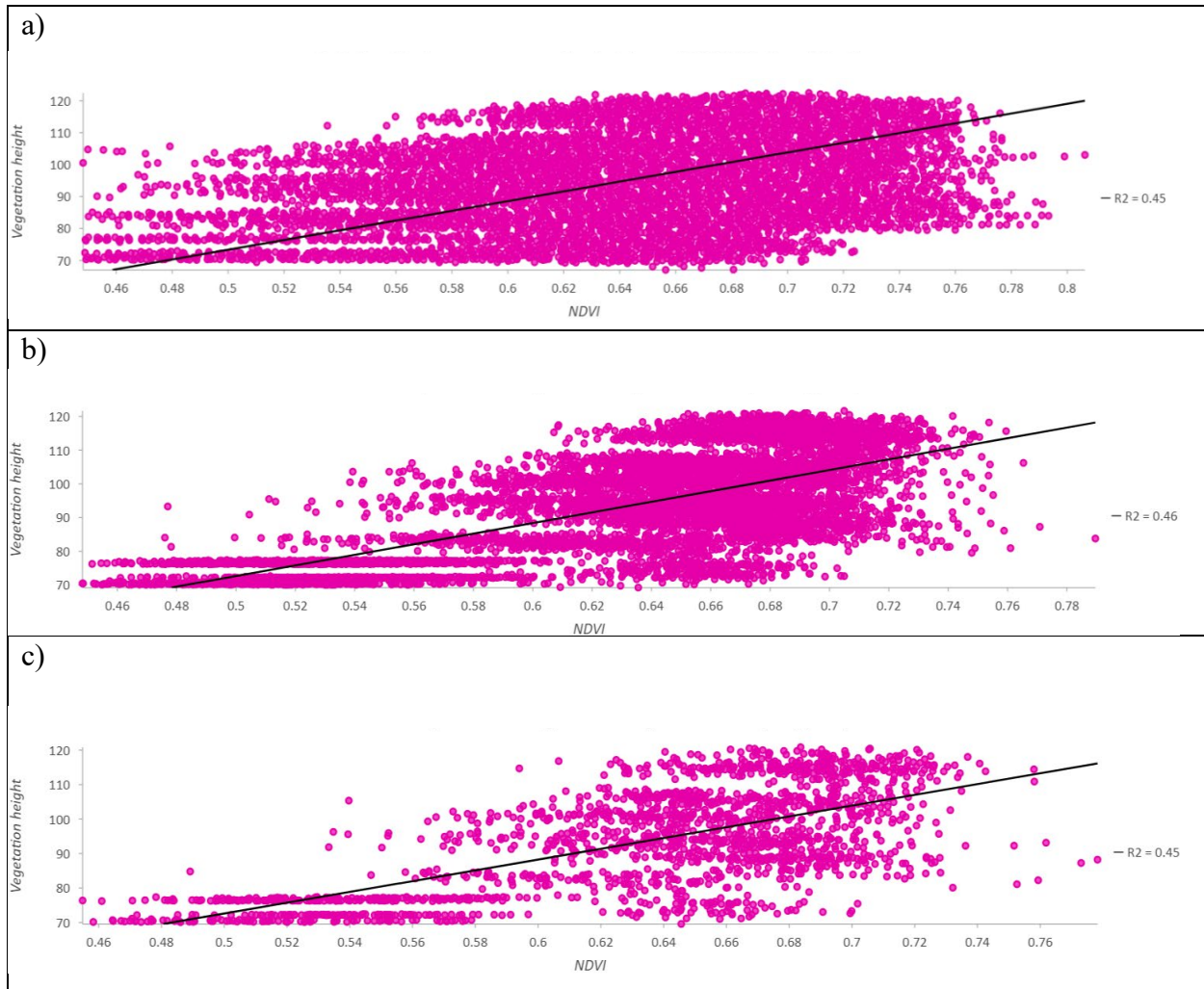
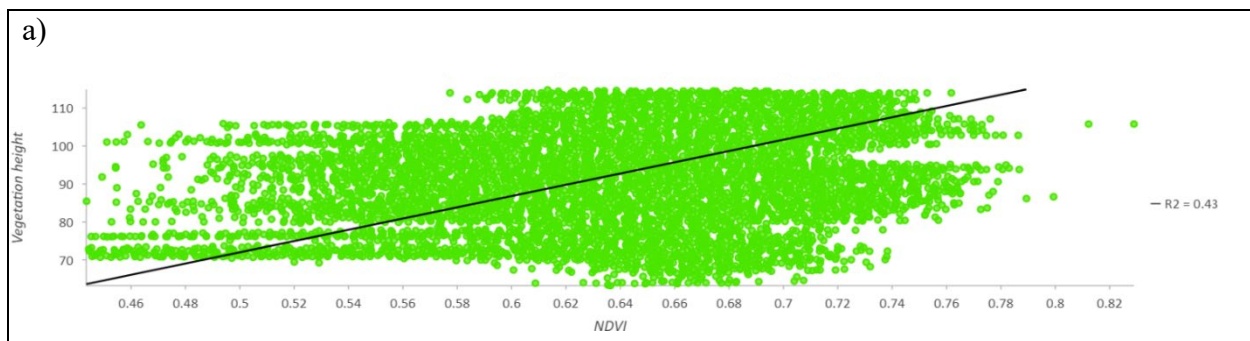


Figure 36: Vegetation height vs. NDVI in medium resolution flights for vegetation landcover. a) Relationship between vegetation height and NDVI at a spatial resolution of 11.4 cm/pixel in vegetation landcover. b) Relationship between vegetation height and NDVI at a spatial resolution of 50 cm/pixel in vegetation landcover. c) Relationship between vegetation height and NDVI at a spatial resolution of 1 m/pixel in vegetation landcover.



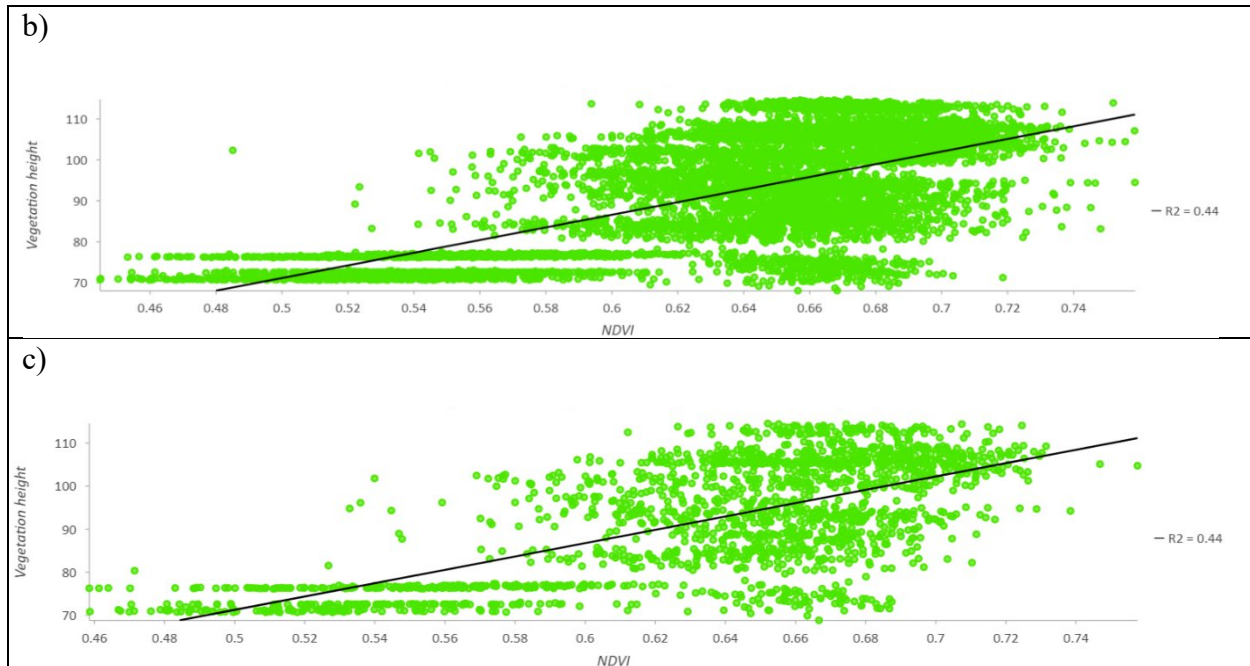


Figure 37: Vegetation height vs. NDVI in high resolution flights for vegetation landcover. a) Relationship between vegetation height and NDVI at a spatial resolution of 6 cm/pixel in vegetation landcover. b) Relationship between vegetation height and NDVI at a spatial resolution of 50 cm/pixel in vegetation landcover. c) Relationship between vegetation height and NDVI at a spatial resolution of 1 m/pixel in vegetation landcover.

As can be seen in Figure 36 and Figure 37, there is a positive relationship between vegetation height and NDVI when medium and high resolution flights are analyzed, with an R^2 from 0.43 to 0.46. The correlation coefficient varies from 0.66 to 0.69 indicating a direct relationship between vegetation heights and NDVI. A correlation between 0.5 to 0.9 denotes a strong association between variables (Rahetlah et al., 2013).

CHAPTER VI: DISCUSSION AND LIMITATIONS

6.1. NDVI – UAS Analysis (Objective 1 of the study)

6.1.1. NDVI comparisons based on different landcover categories

After the supervised landcover classification process was performed in medium and high-resolution multispectral imagery, 4 types of landcover were obtained. The AOI has a total area of 59.65 hectares. Table 8 results show small differences in the area of each category between medium and high resolution dataset. According to the classification results, 4.9% of the area is classified differently when taking account the medium and high-resolution multispectral imagery. The classification accuracy results show a small discrepancy between the two different resolutions, this might impact the classification results. This difference may be caused by the differences in the GSD, for instance, Tian et al. (2017) demonstrated that spatial resolution has a more dominant influence than other factors when landcover classification is developed. The authors suggest that this type of inaccuracy can be solved if spatial resolution is improved. However, Yu et al. (2014) made an area-estimation analysis for different land cover types at different resolutions, finding that at different resolutions, the results contain at least 5% error in area estimation for most land cover types. In this study, it has been shown that Sentra High Precision Single Sensor can give similar results in supervised classification for multispectral imagery taken at 120 meters AGL and for multispectral imagery taken at 66 meters AGL with a GSD of 11.4 cm/pixel and 6 cm/pixel respectively.

Regarding statistical comparisons between multispectral imagery taken at two different altitudes (GSD of 11.4 cm/pixel and 6 cm/pixel) based on landcover categories, we found a high correlation between categories. The statistical indicators in Table 10 are similar between categories. Thus, we conclude that there is not much difference in statistical indicators such as

the minimum value, maximum value, mean value, median value, range value, and standard deviation value, between imagery taken at 120 meters AGL and imagery taken at 66 meters AGL.

As indicated earlier, CV is a measure of relative variability between samples with different means. Tian et al. (2017) also analyzed the CV between the NDVI values for different sensors over various landcover categories and found that mean values vary greatly between sensors. In contrast, the results of this study show that CV did not change significantly within landcover categories for images at different resolutions (11.4 cm/pixel and 6 cm/pixel) examined with the Sentra sensor. It is necessary to mention that the examined resolutions are very similar, and it is very likely that if the same statistical analysis were done between low resolution and high resolution imagery, the results would be different.

A correlation analysis between images taken at different resolutions (11 cm/pixel and 6 cm/pixel) across various landcover categories was made, and a high correlation coefficient, $R = 0.974$ was obtained (see Figure 25), indicating that the coefficients of variations of different land cover categories are strongly related between different resolutions imagery. Tian et al. (2017) stated that the differences in the CV depend on the details that the multispectral imagery can obtain from an image with higher spatial resolution, as the amount of information provided is more abundant.

Finally, in order to determine if there are significant differences between multispectral UAS-based imagery at a spatial resolution of 11.4 cm/pixel against 6 cm/pixel (see Table 12) within each landcover category, a separate Student's t-test was run for each landcover category with an alpha level of 5%. Differences are not significant for forest, grass, and bare soil landcover categories; however, water category shows significant differences between the two

different resolution imagery. This may be produced by the different components of water, especially in the tailing pond. Some chemicals may not be recognized by the medium resolution multispectral imagery. Jiang et al., (2005) analyzed the impact of spatial resolution in NDVI in different landcover categories, finding that a large difference in NDVI values can be found in water. In this study, the biggest differences in NDVI values for landcover categories in medium and high resolution imagery can be found in water category. For instance, mean values for forest in medium and high resolution imagery are 0.66 and 0.65 respectively, while for water is -0.22 and -0.13 respectively; even though, the difference is not big it is important to take into account in future work.

6.1.2. Vegetation NDVI differences based on contamination source

In order to determine if the tailing pond is affecting NDVI values of closer vegetation more than in distant vegetation, a one way ANOVA between vegetation in six radial buffers of 100 meters of difference was performed. Forest and grass categories inside each buffer distance were analyzed. The results show that there is a significant difference among the six radial buffers zones for the forest category. While for grass category, there is not a significant difference. These results are the same for imagery taken at 120 meters AGL and 66 meters AGL (11.4 cm/pixel and 6 cm/pixel respectively). One conclusion that ANOVA test indicates is that for grass category it can be assumed that the groups differentiated by distance are not statistically different from each other. For forest category, a Tukey's post-hoc test was performed. 13 out of 15 buffer distances combinations do not show significant differences. The comparisons between

radial buffer 200 and 600, and radial buffer 300 and 600 show significant differences. Figure 38 displays the locations of the 200, 300, and 600 radial buffers.

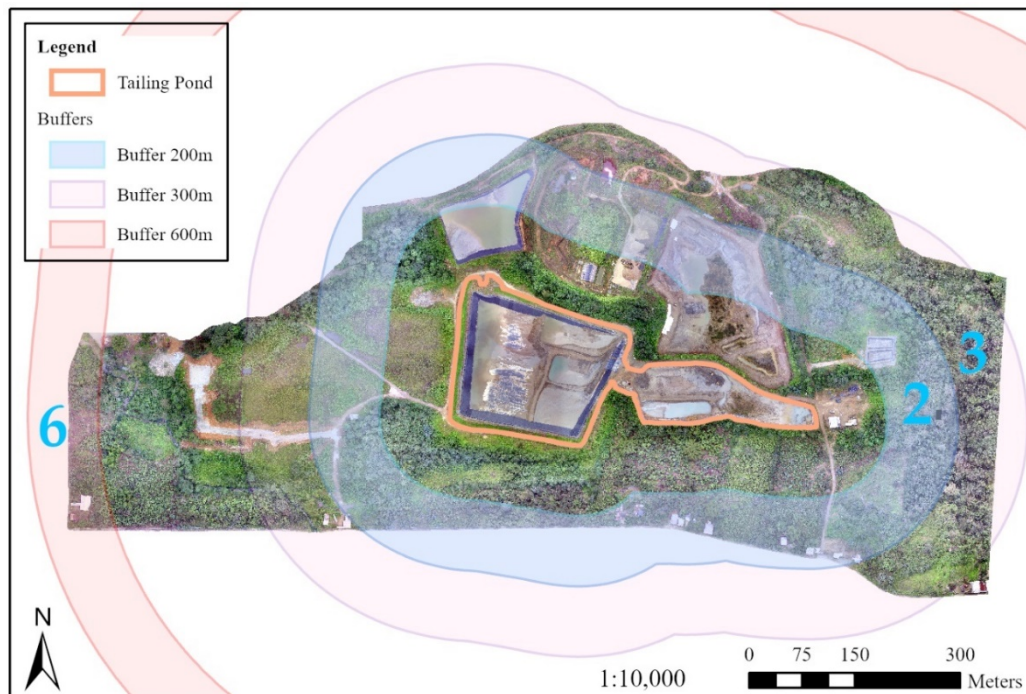


Figure 38: Location of buffer radial distances that show significant differences between each other for forest category. As a base, RGB orthomosaic from Flight 3 taken at 66 meters AGL.

Buffer 300 (see Figure 38) contains some untouched forest. Some of the untouched forest is located in buffer 200 as well (see Figure 38). It is important to note that buffer 600 represents a small portion of the AOI where forest has been highly manipulated; moreover, this area limits with one external road. Consequently, it can be stated that the significant differences among the forest radial buffer zones located at different distances from the tailing pond are present between untouched and manipulated forest areas. Even though, buffer 300 and 200 have been referred to as untouched forest, it is important to mention that this forest was not compared with control site in protected or undeveloped areas. The forest in this study has a certain grade of intervention, there are roads very close to the forest. As stated previously, there are no statistical differences

for the grass vegetation among radial buffer zones. Further 13 of 15 comparisons of combinations of forest radial buffer zones do not show a significant difference. However, as it is shown in Figure 39, the NDVI map shows differences within the forest category. These differences may be associated with forest or tree health; however, an alternative explanation is that they are associated with different species of trees located within the forest category. This led us to conclude that the tailing pond is not the principal cause for the observed differences, but the condition of the forest, that can be manipulated, may be the reason for NDVI having different statistical values.



Figure 39: RGB orthomosaic from flight taken at 120 meters AGL, landcover classification derived from flight taken at 120 meters AGL, and NDVI map from multispectral imagery taken at 120 meters AGL (11.4 cm/pixel).

One possibility the forest and grasslands growing in zones near the tailing pond are not different from forests and grasslands in zones that are located more distant may be that the

chemicals, such as cyanide and mercury, are not filtering into the ground so the growth and health of vegetation is not being affected by these chemicals (Hidayati et al., 2009). The tailing ponds are lined with a geomembrane as shown in Figure 40. This may explain the statistical similarity between grassland and forest growing in radial buffer zones located near the tailing pond and more distant radial buffer zones. Additionally, it may be stated that the forest close to the tailing pond has not been removed or manipulated to the same degree as forest coverage of radial buffer 600. However, more analysis of the status of the forest is needed in order to determine the level of alteration of each part of the forest within the AOI.

The heavy metals such as the mercury and some mining waste such as cyanide are likely retained by the geomembrane. Rowe et al., (2003) found that a similar geomembrane stopped being effective as a contaminant barrier after the fourth year of installation. The geomembrane in the tailing ponds was installed in the year 2017, so based on the results we can conclude that geomembrane is still effectively retaining contaminants that might affect forest and trees health.



Figure 40: Geomembrane in the tailing pond.

6.2. NDVI from Satellite Imagery (Objective 2 of the study)

6.2.1. PlanetScope imagery – Changes in NDVI values in the AOI

After the mean values of each buffer radial distance in different years were obtained, the significant differences in each buffer radial distance for different years was calculated. Firstly, it can be noticed that mean values in each year are different for each buffer radial distance. In order to determine if there are significant differences among years, a one way ANOVA and a post-hoc analysis Tukey's Honestly Significant Difference were applied. As was expected in the tailing pond, values from the year 2017 are different from values in 2018 and 2019. In year 2018 the tailing pond started to be used as a mining waste deposit, this may be the reason why 2017 values in NDVI shows significant differences with values from the other two years. Between 2018 and 2019 there is no significant difference (see Figure 41). Figure 41(a) shows that the tailing pond was being used. In 2018, the tailing pond started to function as a deposit of mining waste, and in the year 2019, the function was the same (Figure 41 b and c). Regarding the buffer radial distances, almost all show significant differences. Buffer 100 between the years 2017 and 2018 does not show significant differences; however, a significant difference is found between 2018 and 2019. This may be produced because mining activities around the tailing pond and the constructions of more internal roads were intensified in 2019.

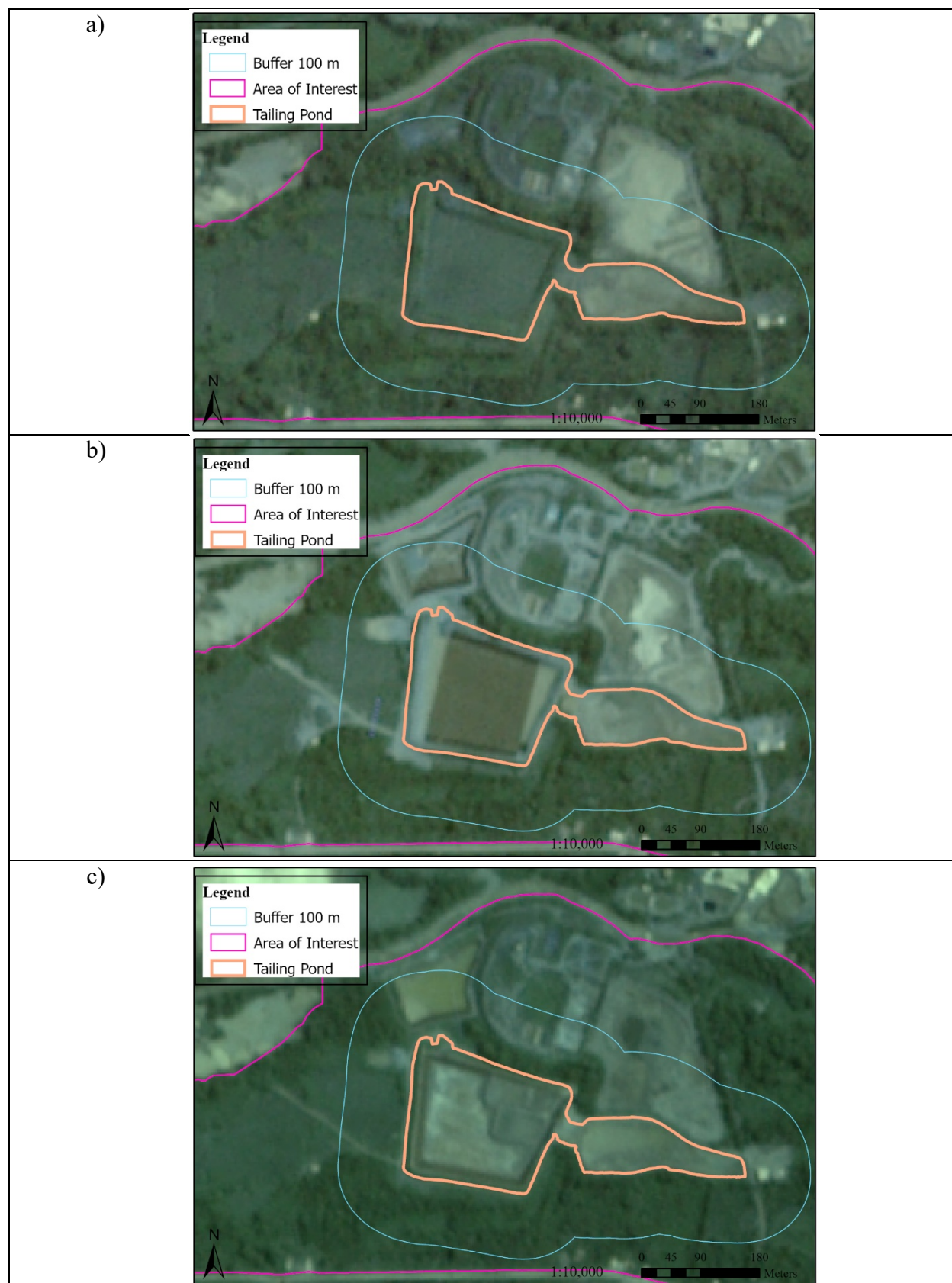


Figure 41: Tailing pond and Buffer 100 from PlanetScope imagery. a) Image taken in June 2017 b) Image taken in June 2018 c) Image taken in June 2019.

As Buffer 100, Buffer 400 shows significant differences due to the same reasons. In 2019, internal roads and platforms were built in this area, which is why between the years 2017 and 2018 no significant differences were observed. Until 2018 vegetation of Buffer 400 was untouched, so it can be seen how mining activities alter NDVI values.

It was necessary to analyze what has happened in the AOI in the last three years. Figure 28 shows that the NDVI mean values of each buffer radial zone change according to the activities that were developed in each sector. Generally, NDVI curves reached their lowest values in the months where human activities were being developed. The highest NDVI values were reached in months where human activities have stopped. In 2017 all mining waste was being deposited in the tailing pond. As mentioned before, at the beginning of 2018, the activities in many areas of the AOI stopped. That is the reason why the highest values in each buffer radial zone are found in the year 2018. After the AOI was not used in many zones in 2018, a deforestation process started in the first's months of the year 2019. Moreover, that year, they started constructing internal roads and warehouses, so it can be seen that the NDVI started increasing in 2018; however, in 2019 it goes down again.

It is interesting to notice in Figure 28 that NDVI mean values increase in the buffer zones as they move away from the tailing pond. Regardless of the tailing pond, the lowest mean value is in Buffer 100, while the highest value is in Buffer 500. Buffer 500 zone is the less intervened zone and shows the lowest levels of fragmentation and human constructions. Also, it shows a high, dense, and contiguous vegetation patch. Buffer 600 presents a lower mean NDVI value;

this may be caused because this small area is close to a fragmentation element, which is an external road.

6.2.2. Comparison between Satellite Image NDVI and UAS-based NDVI products

Even though the UAS-based NDVI maps had different original GSD, the correlation coefficient with the PlanetScope NDVI map obtained from CubeSat satellites was similar. For the purpose of this study, we assumed that the original GSD of UAS-based data did not affect the results of the correlation between UAS NDVI maps and the satellite image NDVI map, at least for these two different resolutions (i.e. 11.4 cm/pixel and 6 cm/pixel). Dash et al. (2018) compared UAS imagery with satellite imagery and showed that the general trends in indices such as NDVI, Green Normalized Difference Vegetation Index (GNDVI), and Red Edge Normalized Difference Vegetation Index (RENDVI) were very similar between the original UAS imagery and the resampled imagery. The authors resampled the original UAS imagery from a GSD of 6 cm/pixel to a GSD of 5 m, which is the spatial resolution for RapidEye data. In this study, the procedure was very similar, and the results showed a similar trend as well.

Regarding the similarity between CubeSat satellite imagery products and UAS-based products, in this study a strong relationship was found between these two different sources products. Other researches have shown similar results where UAS-derived NDVI was strongly related to satellite image derived indices. For instance, Schut et al. (2018) demonstrated a strong relationship ($R^2 = 0.8$) between these two different types of data in heterogeneous fields. In other research, Dash et al. (2018) obtained a relationship of $R^2 = 0.82$ for NDVI collected from UAS and satellite imagery in mature *Pinus Radiata* plantation in Kinleith Forest in New Zealand's Central North Island.

The relationship between rasters shows a high level of similarity. These results could suggest that Sentera Single Sensor mounted on a low-cost platform can reach similar results to satellite imagery from PlanetScope regarding NDVI values. It can be useful for small farmers and local producers that want to increase their level of productivity through new technologies that in previous years have been expensive and even unattainable in developing countries such as Ecuador. Even though this study did not assess the absolute accuracy of satellite multispectral imagery and UAS multispectral rasters since these assessments were based on relative comparisons, other studies have suggested that satellite images may be more useful and even more accurate in obtaining multispectral data than UAS-based images (Khaliq et al., 2019). It is important to mention that even though UAS-based imagery is limited to local scales, the level of detail that can be obtained from this source is very high; high resolution of NDVI maps can reach a plant level detail. On the other hand, satellite imagery such as CubeSat imagery can provide regional scales but a lower spatial resolution. The resolution plays an important role, having similar results using different spatial resolution could mean that a bigger area can be covered in less time, and the results will be reliable. Satellite imagery can provide multispectral information over vast areas, while coverage for small UAS is limited to local scales at the present time. Covering large areas with UAS can be limited due to a nation's airspace regulations and can result in high relative cost and more difficult levels of operation. This study demonstrated that for CubeSat imagery and Sentera multispectral camera, a high correlation was found, which could mean a valid alternative for the detection of plant health in forests and heterogeneous plantations.

6.3. Correlation between point cloud metrics and NDVI

Different point cloud metrics were obtained from the point clouds derived after processing the UAS imagery with SfM photogrammetry. The principal assumption was that some of these metrics may be related to NDVI values in the AOI and therefore serve as an additional proxy or metric to monitor mining impacts on surrounding vegetation with UAS.

6.3.1. Point cloud density

The results of the analysis of the relationship between point cloud density and NDVI show a weak relationship with an R^2 not higher for 0.04 in any case. When taking into account all landcover categories, there was a low relationship between these two variables based on the methods employed here. It is important to note that point density was computed for each analyzed spatial resolution (i.e. 11.4 cm/pixel, 50 cm/pixel, and 1 m/pixel for flight taken at 120 meters AGL and 6 cm/pixel, 50 cm/pixel, and 1 m/pixel for flight taken at 66 meters AGL). There is a somewhat tighter relationship when comparisons are made at the lowest GSD (1 m/pixel). This could be an indicator of the impact of spatial resolution; however, the comparison still shows a weak relationship between NDVI and point cloud density.

Even though there was a low relationship between these two variables, across all landcover categories, point density values did start increasing rapidly in NDVI values of 0.6 to 0.75, which is land mostly occupied by forestry or agroforestry (Rizvi, et al., 2009). Analyses indicated that the highest values of point density are in areas where untouched forest predominates (see Figure 42). Although statistically, a correlation between NDVI and point cloud density is not clear, it is important to emphasize how the point density varies in a forest type of vegetation. When taking into account all landcover categories, point density will vary since point cloud density depends on many factors such as elements structures, and textures

among others. Consequently, elements such building roofs, houses, or other human constructions elements will have a high point density values; however, NDVI values in these areas will be low. This will clearly affect the relationship between point cloud density and NDVI. Dandois and Ellis (2013) analyzed SfM point cloud density over different landcover categories. The authors found that point cloud density varied significantly depending on landcover category, generally, reaching the highest values in forested areas. The latter study mentioned that highest point cloud density values were found in areas with great structural and textural complexity such as forest and rocks, in contrast, the lowest values were found in structurally simple areas. Interestingly, the study showed that building roof tops presented similar point density to forested areas.

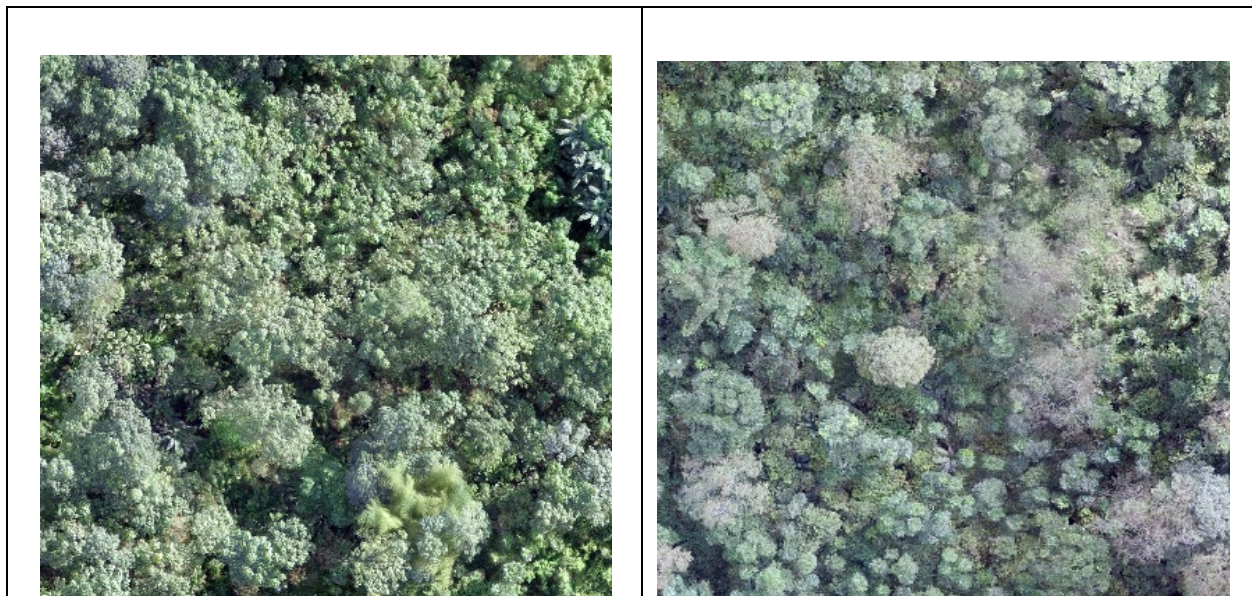




Figure 42: Areas where the highest levels of Point Density were found.

After these results were found, the same process was applied to just the vegetation landcover. The results of these comparisons using these types of sensors suggest that in the AOI there is a weak relationship between NDVI and point density, even when just vegetation landcover is analyzed. However, in this case, we again found that point density values started to increase rapidly at NDVI values of 0.6 to 0.75. These results may suggest that photogrammetry point cloud density increases according to the type of vegetation. Kodors and Illmars (2016) mentioned that a high density of points is not always an indicator of high quality, but it can represent a forest that typically is characterized by a high density of points. Structurally complex surfaces such as the forest canopy generally present higher point density and it is the result of high textural variation in image intensity and the height complexity of forested areas (Dandois & Ellis, 2013).

It should be noted that point cloud density can vary according to certain parameters sent during SfM photogrammetry and this allows the user to determine how many points are required for a certain process. However, point density cannot be higher than UAS imagery GSD. In SfM

photogrammetry, the number of points that are generated depends on many factors such as the image content, the image size, and the processing options entered by the user (Pix4D Support, (n.d.)).

6.3.2. Vegetation height

When NDVI in vegetation areas and vegetation height are compared, the results show a high relationship between these two variables in imagery taken at 120 meters AGL and 66 meters AGL (11.4 cm/pixel and 6 cm/pixel respectively). The correlation coefficient between these two variables goes from 0.66 to 0.69 demonstrating a strong association (Rahetlah et al., 2013).

NDVI is directly associated with vegetation health; phenotypic data of many species has been evaluated and studied through the usage of different techniques such as UAS that can give a high accuracy while assessing vegetation heights (Ampatzidis et al., 2019). Ampatzidis et al. (2019) found that NDVI has a strong association with tree height with a correlation coefficient of $r = 0.65$. Ampatzidis et al. (2019) mentioned that many studies that analyze phenotyping systems in agriculture and forestry utilize high-cost technologies such as LiDAR, hyperspectral cameras, and ultrasonic sensors; however, an alternative is this relative low-cost technology that can reconstruct 3D scenes.

The latter statement aligns with what was demonstrated by Cao et al. (2010) where a correlation comparison between LiDAR point cloud and Digital Aerial Photogrammetry (DAP) point cloud was developed; the study demonstrates that DAP point cloud was useful and presents the similar results than LiDAR in forest inventory. Forest structural attributes estimations are similar between these two types of technology. For instance, when comparing height metrics in dawn redwood and poplar trees, a high correlation coefficient was found ($R = 0.96$, $R = 0.95$

respectively) (Cao et al., 2010). Ampatzidis et al. (2019) found a strong and significant relationship ($R = 0.84$) between manually and UAS measured tree canopy area for rootstock cultivars as well.

Even though current technology provides a wide variety of possibilities to obtain geospatial information, this study intended to show that low-cost geospatial techniques can provide accurate information to analyze these data and making decisions based on the results obtained for assessing impacts to surrounding forests from mining. To the best of this researcher's knowledge, this study is the first to use a low-cost and rapid UAS-based technique to evaluate impacts of mining activities within in heterogeneous forests in Ecuador.

6.4. Limitations of the study

Even though the present study uses a range of geospatial and reflectance data sets acquired using UAS-SfM photogrammetry, UAS multispectral remote sensing, and CubeSat satellite imagery; it is necessary to recognize the limitations of the study and analysis methods conducted. One limitation of this study is the lack of ground truthing verification, especially in two aspects: the accuracy of UAS-based NDVI values and forest conditions. Regarding the accuracy of UAS-based NDVI values, the study did not count with ground truth verification or camera calibration. Some studies mention the direct relationship between NDVI and vegetation health; however, in order to compare the results of this study with information from other sources, values from a calibrated camera is needed. NDVI values derived from different sensors cannot be compared in a fully meaningful way unless both sources give vegetation indices from calibrated sensors (Holman et al., 2019).

The lack of ground truthing to determine forest conditions is another limitation of this study. The forest that was analyzed cannot be considered as a completely untouched forest. The forest is disturbed to a certain degree, for example, there are roads constructed close to some forest fragments; however, it is not possible to determine the degree of degradation of the forest. Comparing forest zones with a control site of protected or undeveloped areas would be helpful for this study. More analysis of the status of the forest is needed in order to determine the level of alteration of each part of the forest within the AOI.

Differences in the distances of radial buffers may have affected the results. If smaller radial zones were used, then it is possible that bigger differences could have been found between these zones. More analysis considering different distances of radial buffer zones is needed in order to enhance the results of this study. Moreover, considering different spatial resolutions may

have affected the results as well; smaller GSD of NDVI maps may produce more homogeneous areas, greatly affecting the results.

Another limitation of the study was the generation of a DTM. Even though the results for the comparison between vegetation height and NDVI values would not change significantly, the generation of a DTM could give more accurate results and a broader analysis capability. For instance, getting an accurate UAS-based DTM would be helpful in order to obtain a CHM giving the possibility of analyzing vegetation characteristics in the entire AOI. As mentioned in Section 4.4.2, LiDAR data have many advantages in the generation of DTMs compared to UAS-SfM photogrammetry, consequently, this study suggests the combination of multispectral UAS imagery with LiDAR data for analyzing the effects of mining in vegetation growth and health in activities such as mining.

CHAPTER VII: CONCLUSIONS AND FUTURE WORK

7.1. Conclusions

This study used photogrammetry and remote sensing techniques to gather multispectral and RGB imagery with a relatively low-cost platform. UAS-based RGB and multispectral imagery, and satellite imagery from CubeSat imaging array operating by PlanetScope were processed and used to assess environmental impacts on the vegetation surrounding a gold mine. These two types of sources were chosen due to their differences in spatial resolution (under 11 cm/pixel vs. 3 meters/pixel) and the capability to provide imagery from recent and past years. The gold mine is located in the province of El Oro southwest of Ecuador in South America. Some chemicals such as mercury and cyanide are used in the process of gold extraction.

Regarding UAS-based imagery, multispectral and RGB imagery were processed using SfM image processing to obtain point clouds, orthomosaics, and reflectance maps that were used to create NDVI maps in the AOI. By using GIS, NDVI values were extracted from satellite imagery of different months of the last three years. NDVI was used to determine the impact that mining and human activities have had on the AOI.

Since one of the objectives of the study was to analyze the impacts of mining on vegetation areas, an image classification was performed by following a supervised classification using ML algorithms. The place where all mining waste is deposited is called a tailing pond. These areas were drawn in the orthomosaics assuming that the tailing pond could be leaking and thus causing contamination in the AOI. Each land cover category was analyzed, and it was found that the highest CV for NDVI values between categories was for water and bare soil. Outputs from imagery taken at 120 meters AGL and 66 meters AGL produced highly similar results.

To find NDVI differences based on the distance of vegetation to the tailing pond, six radial buffers were constructed. Vegetation NDVI values were analyzed and a one way ANOVA test was performed between radial distances. Forest category shows significant differences between radial distances, while grass category does not show a significant difference. The differences are found between areas where untouched forest and manipulated forest are found. Because the fact that some areas close to the tailing pond do not show significant differences with areas far from the tailing pond, it can be assumed that the manipulation of the forest can be the reason for NDVI's different statistical values instead of the direct influence of the tailing pond. Secondary information affirms that a geomembrane, similar to the one that is used in this mine, prevents the infiltration of contaminants up to four years, leading us to conclude that the heavy chemicals may not be interfering with NDVI values.

Regarding CubeSat (PlanetScope) satellite imagery, the radial distances used in previous steps were used. NDVI mean values of each buffer radial distance were calculated and a one way ANOVA was performed to find significant differences between buffer radial distances based on different years. Almost all radial distances show a significant difference between the last three years; many activities have been developed in the AOI. NDVI maps showed that images from June and July of the last three years present similar patterns where the highest NDVI values are reached when human activities stop. The pattern also shows that NDVI mean values increase in the buffer zones as they move away from the tailing pond. It can be concluded that NDVI changes in each sector according to the mining and human activities that are being developed and the level of fragmentation and intervention in vegetation patches.

A comparison between CubeSat imagery NDVI and UAS-based products, and between UAS-based products with a different spatial resolution was made. In order to reach the same

GSD, UAS-based NDVI maps were resampled to match PlanetScope satellite imagery spatial resolution. The comparison between rasters shows a high similarity between NDVI maps derived from UAS multispectral camera and NDVI maps derived from PlanetScope satellite imagery. The coefficient of determination values suggests a high similarity between these two sources, implying that Sentera Single Sensor mounted on a UAS can give similar outputs than PlanetScope satellite imagery regarding NDVI values in this AOI. Moreover, the two GSDs stemming from the two different flight altitudes showed very high correlation in NDVI maps, suggesting that for Sentera Single Sensor, and flights altitudes analyzed in this study, bigger areas with a lower spatial resolution could be covered expecting similar results than high resolution products.

Finally, the point cloud derived from the UAS-SfM photogrammetry survey was analyzed through point cloud metrics. Point cloud density was the first analyzed metric; products from flights taken at 120 meters AGL and 66 meters AGL were rasterized to different spatial resolutions (i.e. original GSD, 50 cm/pixel, and 1 m/pixel for each one) to be compared with NDVI maps with equal spatial resolutions. The process was made for all the AOI, and also made specifically for vegetated areas. The correlation coefficient for all landcover categories and for the vegetation category shows a low degree of relationship between point cloud density and NDVI values in all comparisons and for all resolutions; however, point cloud density shows a rapid increase in NDVI values where forest type vegetation predominates. Other studies have proved that forest is characterized by a high density of SfM points, in this study, the areas with the highest point density values were visually analyzed, and it was found that these areas are located in zones of untouched and dense forest.

The second analyzed point cloud metric was vegetation height. The high and low altitude point cloud was rasterized at three different spatial resolutions (11 cm/pixel, 50 cm/pixel, and 1 m/pixel for high altitude flight and 6 cm/pixel, 50 cm/pixel, and 1 m/pixel for low altitude flight). These rasters were compared with reflectance maps of equal GSD only in flat areas, taking as a base an official Ecuadorian DTM. The results show a high correlation coefficient between vegetation height and NDVI values for both resolutions. Many studies have found that NDVI is strongly related to vegetation heights leading us to suggest that UAS-based point cloud can be utilized to determine phenotypic aspects of vegetation such as height.

In conclusion, it can be determined that the construction of the tailing pond could be causing an alteration of NDVI values on surrounding and most distant vegetation; however, there are other elements such as fragmentation and other human activities that may be altering NDVI values. According to PlanetScope CubeSat satellite imagery analysis, it can be stated that changes through the years are related to human activities and that the tailing pond has caused high changes in NDVI values. Point cloud metric results indicate that some phenotyping characteristics that can be obtained from the UAS-SfM photogrammetric process can be useful to assess vegetation characteristics. Furthermore, low cost UAS-derived multispectral imaging proved useful for determining NDVI at high resolution and assessing the possible elements that could alter these values. This study shows that low-cost geospatial techniques, such as the utilization of UAS, can provide similar information comparing with PlanetScope CubeSat satellite imagery; many environmental and planning decisions can be based on the results obtained from the fusion of these two remote sensing platforms.

Finally, as previously mentioned, to the best of this researcher's knowledge, this study is the first to use a low-cost and rapid UAS-based technique to evaluate impacts of mining

activities within heterogeneous forests in Ecuador. Results from this study do suggest that this activity has altered NDVI values, and in return vegetation growth, in the AOI. Due to regulations and environmental obligations in Ecuador, it is necessary to develop and monitor reforestation and vegetation restoration after mining processes were developed. This study strongly suggests low-cost UAS equipped with consumer-grade digital cameras and miniaturized multispectral sensors are an effective tool to monitor these activities.

7.2. Future Work

Multispectral imagery was used to determine if mining activities alter NDVI values in the AOI. Moreover, results suggest that PlanetScope satellite imagery and UAS-based reflectance maps present a strong degree of similarity. Finally, it was shown that some point cloud metrics can be used to determine vegetation characteristics. As mentioned in Section 6.4, one downfall of this research was the lack of ground truthing verification. Even though relative comparisons can lead us to make some important and useful conclusions, having field metrics would help us to better assess healthy vegetation and compare to UAS-derived NDVI or other measures. Moreover, it would be interesting to assess NDVI changes over a longer period of time; examining satellite imagery from more years or decades could help to assess and identify changes in landcover and vegetation index. CubeSat satellite imagery has a great capability of monitoring the earth at a high temporal repeatability, it would be interesting to apply this characteristic for assessing NDVI and other monitoring vegetation indices in a shorter timeframe in order to determine impacts of mining and other activities.

The Margarita river passes the north end of the AOI. Mining activities have been rejected by many environmental caring groups that state that mining alters chemical water composition. Some remote sensing techniques can detect contamination in water. Heavy metals can be identified through the usage of hyperspectral satellite images. It would be necessary to assess this water composition and test the relationship between water composition and satellite imagery heavy metals identification.

Ecuador is a country that is well-known for its mineral wealth. Different types of mining are developed in the region. A future goal for this study is using the techniques developed here to analyze the characteristics of other mines where different chemicals and processes are used.

Moreover, it would be interesting to analyze the effects of mining in other ecosystems with different types of vegetation structures. For instance, highlands are one of the most threatened ecosystems in Ecuador, and there many types of mines operating in these areas that could be analyzed.

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