University of Redlands

Identifying Oak Tree Mortality Using Image Analysis

A Major Individual Project submitted in partial satisfaction of the requirements
for the degree of Master of Science in Geographic Information Systems

by

Zemenu Teshome Ambelu

Douglas Flewelling, Ph.D., Committee Chair

Mark Kumler, Ph.D.

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Zemenu Teshome Ambelu

The report of Zemenu Teshome Ambelu is approved.

Mark Kumler, Ph.D.

Douglas Flewelling, Ph.D., Committee Chair

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Abstract

Mapping Oak Tree Mortality Using Image Analysis

by

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Oak trees cover more than 8 million hectares of land in California. They have a significant role in providing an anchor for many wildlife habitats, settling soil for a watershed, and preserving the beauty of nature and the environment. Drought stress, wildfires, sudden outbreak of native pest occurrence, and improper interaction with humans, threaten California oaks. The Wildlands Conservancy's Wind Wolves Preserve has a great concern for oak tree mortality. But has had difficulty finding and mapping oak tree health. To assess and monitor oaks field data collection has been expensive and time-consuming, and field data collection may not be accessible to field survey. Using satellite imagery, aerial photography and drone imagery, areas of stressed and dead trees were identified. Python geoprocessing tools were developed that automate calculation of NDVI, identification of tree-clusters, and calculation of tree-cluster difference from season to season or year to year. Satellite imagery showed clusters of trees but were unable to identify oaks specifically due to resolution limitations. Spatial resolution was a very determinant factor in assessment of oak tree health. Thus, Sentinel-2 at 10m resolution was better at finding tree-clusters than Landsat-8 at 30m resolution.

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List of Acronyms and Definitions

CDF	California Department of Forestry and Fire Protection
CO ₂	Carbon dioxide
DBH	Diameter at breast height
ESA	European Space Agency
Esri	Environmental Systems Research Institute
FIA	U.S. Forest Service Forest Inventory Analysis
GIS	Geographic information science
IDE	Integrated Development Environment
LCMMP	Land Cover Mapping and Monitoring Program.
NAIP	National Agriculture Imagery Program
NDVI	Normalized difference vegetation index
NIR	Near-infrared
QC	Quality check
RGB	red, green and blue
SOD	Sudden Oak Death
TWC	The Wildlands Conservancy
U.S. FS ADS	United States Forest Service Aerial Detection Surveys
UAV	Unmanned aerial vehicles
USFS	US Forest Service
USGS	United States Geological Survey
VI	Vegetation indices
WGS	World Geodetic System

Chapter 1 – Introduction

In California, oak trees cover no less than 20 million acres (8 million ha) of land. From this composition, more than 9 million acres (3.6 million ha) of land cover open forest mixed with other evergreen broadleaf and coniferous trees. Even though oak trees have less an incentive for timber, they have a huge potential as a source of biomass for energy creation. They also play a more remarkable role in settling soil for a watershed, providing an anchor for many wildlife habitats, and preserving the beauty of nature and the environment (Plumb and Gomez, 1983).

The Wildlands Conservancy (TWC) is committed to protecting the excellence and biodiversity of the earth. TWC is working with numerous species of plants for the matter of treatment, monitoring, and management. Observing a change in place, before and after treatment is an incredible concern. The client is also in high demand to monitor the health of plants and their mortality with locations and seasonal variables. Plant species like oak tree are in an endangered situation which needs care and attention to preserve. They have been applying different methods to treat and restore the environment at different time and place in a haphazard manner as indicated by the customer. The present biological system is exceedingly convoluted and fluctuated which requires close checking to measure change and react successfully and proficiently with different procedures to deal with the abatement in plant biodiversity.

Oaks are dying due to different factors. An oak tree disease named Sudden Oak Death (SOD), caused by an invasive living pathogen, *Phytophthora ramorum*, is the greatest known killer of oaks. *Phytophthora* root rot fungus (*Phytophthora cinnamomi*) and oak root fungus (*Armillaria mellea*) are also common killers of oaks. These diseases and others will be aggravated in different places and ecological conditions mostly by drought. Figure 1.1 illustrates healthy and dying oak trees.

Image: <https://cdn.hswstatic.com/gif/diseased-or-dead-tree-1.jpg>

Figure 1-1: healthy oak tree (left) and dying oak tree (right)

An inappropriate human intervention like root pruning, soil compaction, excessive-watering and toxicant use may contribute to oak tree mortality. Going the closest separation from the oak's trunk to California bay foliage builds SOD incidence, seriousness, and death rate (Swiecki & Bernhardt, 2013).

SOD incidence is greater in coastal areas than in southern California because of temperature and humidity limitations. However, *Camellias* have been found infected by *Phytophthora ramorum* at some places in Southern California (County of Los Angeles, 2010).

1.1 Client

The client for this project was the Wildlands Conservancy (TWC). The point of contact at TWC was Elizabeth Perez. She is a ranger and member of Wind Wolves management team which is a department in TWC. The client's main responsibilities for this project included providing domain knowledge, such as what important prioritization criteria should be considered, providing the relevant resources, and deciding data acquisition time and collecting data accordingly.

1.2 Problem Statement

Oak trees are native in TWC's Wind Wolves Preserve. Oak tree mortality caused by drought stress has been broadly reported in California. Extreme wildland fires threaten California which is also induced by drought. Improper interactions between humans and oak trees is also a cause for the involvement of pathogens or living pests. Furthermore, in a smooth and calm natural environment, sudden outbreaks of native pest occurrence are also a problem for California oaks. TWC has difficulty finding and mapping oak tree mortality. To trace and map this problem in time and place, field data collection has been cumbersome, expensive and time-consuming, and oak tree locations may not be accessible to field survey.

1.3 Proposed Solution

There was a high demand to address oak tree mortality trends in Central California with remote sensing and GIS tools such that preservationists, botanists, scientists and decision-makers could quickly take necessary mitigation measures in preservation. This project proposed to fulfill this need by creating a geodatabase, creating a customized GIS tool, and mapping oak tree mortality locations within the target area. Using the normalized difference vegetation index (NDVI) parameter with simplified analysis, preservationists can easily locate oak tree mortality and could compare mortality trends with time and place. This could enable them to take the necessary measures to preserve trees.

1.3.1 Goals and Objectives

The goal of this project was to apply remote sensing technologies and GIS tools to protect and preserve oak tree habitats for human use. Protecting oak trees has been essential for preserving ecosystem functionality. It is likewise vital for individuals,

particularly for youngsters to figure out how the earth they live in acts and how everything in nature is connected.

To achieve these goals the project completed a series of more specific objectives. The first objective of the project was to deliver a customized GIS tool that could identify oak tree mortality for TWC. In order to achieve this objective, this project used satellite imagery, drone imagery, Esri image service, and supporting information like base maps. The second objective was the development of a file geodatabase which organized and stored all the data so that the client could easily plan, monitor, manipulate, and manage their preserves. The final deliverable was the analysis result and a map of identified stressed or dead tree areas.

1.3.2 Scope

The scope of the project was limited to focusing on oak tree mortality to determine mortality locations and trends. The project study area included four areas in central California named Mid Slope, Los Osos Wetland, Echo Canyon and Tecuya. The scope of the project included three deliverables.

The first deliverable was a customized GIS tool and its Python script that could enable the client (or other stakeholders) to repeat identification of tree mortality, as well as to update the analysis with a new and current input data. The second deliverable was a file geodatabase which stored and organized all data and information. The third deliverable was a map showing tree mortality trends in the targeted areas.

The project used satellite imagery, drone imagery, Esri image services and other GIS data layers like base maps. ArcGIS Pro and Python programming language were applicable for the project. The client was responsible for providing the necessary software, hardware, and other information. The developer was not responsible to give support and database maintenance after delivery of the product. The developer was responsible for gathering and documenting background information about the project's topic, creating the tool's methodology, and developing the tool.

Figure 1-2: Project Study Area

1.3.3 Methods

The custom ArcGIS toolbox created as part of this project was created using a Python script and integrated in ArcGIS Pro. The project used the arcpy module to create a customized ArcGIS tool. The project also used Wing IDE 101 6.0 to write the Python scripts that were applicable in the Python geoprocessing tools. Satellite imagery analysis results and polygons of the study area were organized in a geodatabase. After oak tree mortality areas were identified by the customized ArcGIS toolbox, the mapping was done using ArcGIS Pro.

1.4 Audience

The audience being addressed by this project are mainly preservationists, biologists, scientists, botanists, and decision-makers who will have little or limited knowledge of GIS to those with extensive knowledge. Thus, the results of this project are written in an easy and justifiable approach even by non-GIS persons.

1.5 Overview of the Rest of this Report

In the following six chapters, a detailed method of mapping oak tree mortality methods and technologies, and information products produced by this project are briefly illustrated. Chapter 2 details the literature review of this project and reviewed works that were conducted by others. Chapter 3 describes the systems analysis and design. Chapter 4 illustrates the conceptual and logical data model (database design of the project), and data sources for the project. Chapter 5 clarifies how the project was implemented and Chapter 6 illustrates the results and detail analysis of those results. Chapter 7 covers summary from this project and recommendations for future work. Finally, there are the reference section and appendix providing Python script to achieve the project goals.

Chapter 2 – Background and Literature Review

The chapter begins with a literature review that was conducted on previous efforts in identifying oak tree mortality trends. Different methodologies and technologies in mapping oak tree health and mortality are then assessed and reviewed. A brief literature review is then given on the trend of tree mortality and its causes, spatial based management, and treatment methodologies. Lastly, a brief discussion on the Normalized Difference Vegetation Index (NDVI) parameter and its importance for identifying healthy trees were illustrated. These were key concepts for how the client of this project expected to use the final products.

2.1 Factors Affecting Tree Health

The healthy growth of trees can be negatively influenced by human and environmental factors, which can be indicated by various sorts of harm that reduce the energy and yield of a tree (Boa, 2003). Boa (2003) argued that tree health can be identified by watching its reaction to various climate conditions, and an unhealthy tree has a more negative response to climatic conditions than a healthy tree. Climate conditions also influence the presence of primary and secondary pests such as insects. These pests normally influence trees effectively debilitated by numerous causes, like weather conditions. Waterlogging or absence of nutrient usually aggravate insect pests by a weakening of the tree's photosynthetic energy and a reducing of its natural resistance to harsh conditions.

The well-being of a tree can be also affected by human practices. One such practice is insufficient nursery management, one of the greatest liabilities in tree health which negatively affects their root growth during plantation (Boa, 2003).

2.2 Tree Death and its Consequences in California

In California, long periods of dry season and a bark beetle epidemic have caused one of the biggest tree deaths in the state history. Between 2010 and end of 2015, 40 million trees died in California according to U.S. Forest Service Aerial Detection Surveys (USFS ADS) report in 2018 (California Tree Mortality Task Force, 2018). From this report, drought and insects from September 2014 to October 2015 alone caused 75 percent of tree mortality. Nearly 62 million more dead trees were also surveyed in 2016 flight time. There was better rainfall during the 2016-2017 water season, as a result a low mortality rate with 27 million dead trees were recorded in observation of 2017 flight period. Mortality of trees were not only limited to less precipitation or drought-related insect activity. Most researchers believed that drought and related insect activities were the only reason for tree mortality. However, there are a variety of agents that caused tree mortality before the start of the drought in California (California Tree Mortality Task Force, 2018).

Byer and Jin (2017) also argued that continuous drought has killed more than 135 million trees in California since the summer of 2016. Byer and Jin thought that an increase in tree mortality had many negative consequences such as risk to public safety, a potential source of fuel for big and extreme wildfires in the short term, and changes in

water balance and quality, habitat loss, and atmospheric and climatic changes by releasing more carbon to the atmosphere over the long term.

Generally, tree death and its regional patterns incited by drought has a consequence of human, ecological, hydrological and environmental damages (Byer & Jin, 2017).

2.3 Live Trees in California Forest Land

California backwoods face several dangers. The most known danger is not loss of woods because of harvesting and the absence of consequent regrowth yet change to non-backwoods from genuine disastrous occasions, for example, huge out of control fires and land use transformation to horticultural and private land uses. The standing timberland volume keeps on expanding on both private and open woods lands. Nonetheless, there are a critical increment in the event of huge rapidly spreading fires which have been decreasing live trees (California Tree Mortality Task Force, 2018).

The U.S. Forest Service Forest Inventory Analysis (FIA) has been doing a tree survey every 10 years since 1930. By centralizing annual plot data surveyed over a 10-year time (2007-2016), U.S. Forest Service FIA estimated 4.1 billion live trees in California. The estimated number of live trees were for the whole California districts, with a canopy diameter at breast height (DBH) greater than 5-inches. This was the most recent pattern conditions for which tree information was accessible (California Tree Mortality Task Force, 2018).

2.4 Oak Trees in California

Oak trees cover around 8 million hectares of land in California. However, the entire population of oak trees are subject to partial or total destruction by wildfires. Oaks are found mixed with other evergreen trees and shrubs which are easily susceptible to fire. Examining and understanding tree's reaction to fire is important to limit the danger of fire and for proficient and powerful administration. As different oak tree species have different responses to fire, effectively recognizing species will permit quick administration as needs be. However, some oak tree species are hard to identify when the trees are densely spaced (Plumb and Gomez, 1983).

2.5 The Application of Remote Sensing in Monitoring Oak Death

Oak tree death has been examined by several different agencies in California. The California Department of Forestry and Fire Protection (CDF), US Forest Service (FS), and California Oak Monitoring Task Force performed a monitoring project for Sudden Oak Death (SOD). The point of this monitoring project was to evaluate the potential of remotely sensed images in identification of oak tree death. The result was validated by airborne imagery, aerial survey, and field observation. Using multi-resolution remote sensing data with a combination of aerial observation and ground check points, assessments of problematic areas negatively affected by SOD were done. The study found that remote sensing images had a substantial role in assessment and identification of SOD, but they alone were not enough to identify SOD. Identification nn

demands additional supportive information such as vegetation phenology data, land use information, timberland asset photography, fire history record, and timber reap records. Furthermore, previous infected areas of SOD were essential to correlate with the current data and yield better result (California Department of Forestry and Fire Protection, 2000).

Satellite images have a capability to distinguish regions containing dead trees, yet there was an issue of an excess mixing of spectral signatures with other land cover types. Vegetation indices alone were insufficient to distinguish dead trees and scrub due to spectral signature overlap. To correctly identify dead trees using satellite imagery, the supportive landcover datasets that recognize non-vegetated regions and the zones with a known reason for death were necessary (Gillis, 2014).

For the quicker reaction of forest disease aggravations and danger of further dead trees, preservationists, environmentalists, land administrators, and state and federal government agencies should continuously observe change in time and location, and the amount of tree death in a different location. This would bolster diagnosing tree wellbeing relationship with forest pattern, condition, and climate at an expansive scene level (Byer and Jin, 2017)

Satellite remote sensing techniques can provide a large area coverage and wide electromagnetic range, essentially visible and infrared, which have potential to detect vegetation wellbeing and mortality with the support of field survey and other land use information (Byer and Jin, 2017). Byer and Jin likewise contended that the impact of drought on vegetation health in California have been poorly assessed by satellite images without the support of other supportive data.

Tree disease hazard models and affected trees in a moderately reduced zone can be better distinguished by aerial imagery. It is true that pixel spectral signature overlap diminishes with high-resolution imagery; specialists smoothed the yields to minimize noise. However, unable to fly the inaccessible region, the expense and small area coverage upset specialists who are keen on examining tree sickness in a wide region with restricted spending plan and assets (Gillis, 2014).

These days unmanned aerial vehicles (UAVs) are used in many applications as a remote sensing innovation. The UAV innovation is developing and most normally utilized in precision agriculture, they have been likewise changing different biological, natural and protection applications. Since UAVs fly at a low altitude, they can give centimeter spatial resolution and precision which can give an opportunity of distinguishing individual tree species (Baena, Moat, Whaley and Boyd, 2017).

Plants reaction to electromagnetic radiation is exceptionally subject to the amount chlorophyll and nitrogen content. Remote sensing technologies can evaluate the substance of chlorophyll and nitrogen using different vegetation indices (VIs). By joining near infrared band, which reflect more chlorophyll, and red band which is absorbed by most chlorophyll vegetations, analysts can investigate the health of plants (Clevers and Gitelson, 2013).

2.6 Vegetation Indices (VI)

Around 70 percent of the world's land surface is covered by vegetation. The climatic, ecologic, geologic, and topographic attributes of a zone is exceedingly impacted by plant

species, society settlement design, and phenology of vegetation and plant morphology (Jensen, 2009). Jensen argued that there are different technologies used to study vegetations which are comprehensive in nature and used to study an assortment of vegetated scenes, for example, farming, woodlands, rangeland, and wetland.

2.6.1 Factors Controlling Leaf Reflectance

The reflectance and transmittance properties of leaves are influenced by leaf colors, internal structure, and leaf water content. *Photosynthesis* is an energy storage procedure that happens in leaves and other green pieces of plants within the sight of light where plants can store and transform their energy eventually producing their own food from carbon dioxide and water (Jensen, 2009).

The photosynthetic process is:

Sunlight is the only source of energy necessary for *photosynthesis* to happen. Energy storage in plants forms a sugar molecule ($\text{C}_6\text{H}_{12}\text{O}_6$) yielded from the mixture of carbon dioxide (CO_2) and water (H_2O). This chemical reaction of (CO_2) and water (H_2O) also gives us the air we breathe, as “oxygen gas (O_2) which is released as a by-product”, and the oxygen spread out into the surrounding air (Jensen, 2009 P. 316).

Plants have *chlorophyll*, which is a green substance covered by *chloroplasts* that capture the energy from sunlight, convert it, and store it in the energy-storage molecules. When sunlight hits *chlorophyll* a photosynthetic chemical reaction procedure begins. This is the process of how plants make their food and determine each plant’s appearance in a remotely sensed image. The type of plant species and the prevailing environment affects the leaves’ cell structure and consequently influences their interaction with sunlight energy (Jensen, 2009).

For *photosynthesis* to happen plants adjust their internal and external leaf structure according to the prevailing environment. The upper layer of a leaf structure has a surface which reflects very little energy but diffuses more light. However, the energy reaction of plants varies based on the prevailing environment and type of plant species. In areas having too much sunlight the plant leaves cover themselves with a thick waxy layer that can protect them from unnecessary water loss. In contrast, plants like ferns and some shrubs have a thin waxy layer, and they shade themselves to collect dim sunlight and use it for *photosynthesis* (Jensen, 2009).

The concern of numerous remote sensing kinds of research is investigating the collaboration of photosynthetically active radiation with individual plant leaves. To accurately gauge the absorption and reflectance attributes of the photosynthetically dynamic radiation, high spectral resolution imaging advancements are helpful (Jensen, 2009).

2.6.2 Near-Infrared Energy Interaction with Plant Cells

With direct daylight, the near-infrared portion of the electromagnetic spectrum has very strong energy. Plants never utilize this strong near-infrared energy; it is possible that they reflect or transmit the energy to the ground. If plants absorb this strong near-infrared energy like that of the visible portion they could lose their normal protein on account of being excessively warm. As a result, a healthy green leaves near-infrared reflectance increases in a range from 700-1200 nm. In contrast, healthy green leaves absorb the visible part of the range where incoming light is essential for *photosynthesis* (Jensen, 2009).

2.6.3 Normalization Difference Vegetation Index (NDVI)

Vegetation might be unhealthy because of nutrient and water inadequacy, plant disease, or by various biotic or abiotic factors. We can recognize stress on vegetation by breaking down near infrared reflectance (almost 750 nm) and red absorption through normalization difference vegetation index (NDVI) parameter. NDVI parameter is the most generally used parameter in a fundamental rule that plants with more chlorophyll reflect the near-infrared range. At the point when the vegetation is stressed, its reaction to near-infrared energy diminishes and vegetation reflects the redder electromagnetic range (Mahajan & Bundel, 2016). As can be seen from Figure 2-1, the healthy tree reflects more near-infrared electromagnetic spectrum than an unhealthy tree. In contrast, the unhealthy tree reflects more visible light than a healthy tree. Figure 2-1 illustrates NDVI in healthy and unhealthy trees.

Image: <https://eos.com/ndvi/>

Figure 2-1: illustration of NDVI

By using the numerical formula of near-infrared and red band, we can distinguish plant from non-plant and a green plant from a dying one (Mahajan & Bundel, 2016).

$$NDVI = \frac{NIR-Red}{NIR+Red} \quad (2.2)$$

NDVI is straightforward and efficient, and the most widely used vegetation index used to measure green vegetation. The scope of NDVI ranges from negative one to positive one. Negative estimations of NDVI values drawing nearer to negative one related to water. Most ordinarily, exposed land, urban zones, and ice gems have an estimation of - 0.1 to 0.1. Bushes and prairies have low positive values from about 0.2 to 0.4. The most elevated estimation of NDVI (almost 0.5 to 1) goes to calm and tropical rainforests (GIS Geography, 2018).

In the meantime, NDVI value depends on the absorbed and reflected photosynthetically dynamic radiation in near-infrared and red bands, and there are such many elements that influence the NDVI estimation of the object to be watched. Those conditions incorporate image resolution, barometrical conditions, soil and vegetation moisture, kind of soil, and the board practices, and so on (Rouse, Haas, Schell & Deering, 1974).

Distinctive stakeholders such as environmentalists, preservationists, scientists, and managers ought to consider factors that impact NDVI result as indicated by their business reason before interpreting the outcome (Rouse *et al.*, 1974).

Temporal resolution also impacts NDVI values. The amount of reflected and absorbed electromagnetic energy by particles shifts in time, and vegetations have an alternate measure of chlorophyll in various seasons. In this manner, the use of NDVI is appropriate to assess regular variety of vegetation development in various years over long periods of time (Rouse *et al.*, 1974).

Atmospheric particles disperse electromagnetic energy toward all path. The red portion of electromagnetic energy has more dissipated by environmental particles than near-infrared energy. This has an impact of diminishing NDVI values (Rouse *et al.*, 1974).

Soil type especially soil moisture, have a significant effect on NDVI values, a probability of up to 20 percent change in NDVI result. Soil with greater radiance reflected have lower NDVI values even in similar vegetative conditions (Qi, Chehbouni Huete, Kerr, & Sorooshian, 1994).

In the low-resolution satellite images, a solitary pixel may cover diverse land uses like streets, structures, exposed land, water bodies, regular vegetation, and horticulture land. Along these lines, the NDVI value recorded with various items with a solitary pixel is a mixed and may not be the best indicator (Rouse *et al.*, 1974).

2.7 Summary

Living and nonliving variables are disturbing the sound development of a tree. Oak trees which are native to California have been stressed, and their mortality incited by the dry spell is expanding. Expanding the information of oak tree mortality utilizing remote sensing innovation would support preservationists, researchers, naturalists, and

supervisors to avert further mortality and take important treatment measures. Satellite and more recently drone imageries are the most basic wellspring of information to delineate tree mortality. It is conceivable to evaluate the stressed trees by scientifically consolidating the absorbed and reflected electromagnetic radiation using NDVI parameter. Chapter 3 will briefly illustrate the system analysis and design of this project.

Chapter 3 – Systems Analysis and Design

This chapter identifies the system design requirements to map oak tree mortality and solutions that led to reaching the project's objectives as the client demanded. The problem statement of the project is restated in section 3.1. The project's requirements are included in section 3.2. In section 3.3, the system design of the project and how it met the requirements is briefly explained. Section 3.4 illustrates the project plan and what changes (deviations or modifications) were made due to different project challenges. Finally, a summary of this chapter is provided.

3.1 Problem Statement

Oak trees are common in The Wildlands Conservancy's (TWC) Wind Wolves Preserve. An increase in oak tree mortality caused by drought has occurred in California, and the drought has brought an extreme danger of wildland fires to the state. The interaction between humans and oak trees is also an additional reason for the involvement of pathogens or living pests. Furthermore, occasional episodes of local pests occurring in an undisturbed regular environment is likewise an issue for trees. TWC had difficulty finding and mapping oak tree mortality. To trace and map this issue in time and location, field data collection has been lumbering, costly and tedious. Notwithstanding, those oak tree areas also may not be accessible to field survey.

3.2 Requirements Analysis

Without understanding and analyzing the requirements of the project, achieving the project's goals and objectives would be difficult. This project included functional and non-functional requirements.

The deliverables that the client of the project anticipates from the final product were incorporated under functional requirements. The functional requirements of this project are better explained in relation to the main deliverables of the final product. The first deliverable was a customized ArcGIS toolbox with script tools that enables the client to calculate the Normalized Difference Vegetation Index (NDVI), identify healthy tree clusters using the NDVI values as input, and calculate the difference in NDVI values, and tree-cluster from season to season. The second deliverable was a file geodatabase that organizes data inputs and analysis results properly. The third deliverable was a map of the analysis result. Table 1 summarizes the functional requirements of each of the deliverables.

Table 1. Summary of Project Functional Requirements

Functional Requirement	Description
Calculate NDVI	The customized ArcGIS tool should take infrared and red bands as input to give NDVI layer as output. The customized ArcGIS tool should able to support different NDVI layers from different data collection platforms like satellite imagery, aerial photography and drone imagery
Identify healthy tree-cluster areas	The customized ArcGIS tool should take NDVI value as an input to filter healthy tree clusters. The customized ArcGIS tool should allow the user to enter NDVI threshold which will identify vegetation and non-vegetation areas usually between NDVI value of -1 up to 1
Calculate raster difference	The customized ArcGIS tool should calculate difference in NDVI and tree-cluster from season to season
Store raster and vector GIS data layers	The geodatabase should allow storing input raster data and analysis results
Map/reports of the analysis result	There should be a map/report showing results and findings

The non-functional requirements included the technical and operational aspects of the system produced by this project. It was compulsory that all hardware, software, and data in the framework were fit with the customer's product for progressively powerful execution and productivity. For this matter, the system needed to run on ArcGIS for Desktop, use computers with a Windows operating system, and required all data and information be in Esri's ArcGIS data formats. ArcGIS Pro supported the technical requirements for compiling data and for the developed tools, maps, and reports. Table 2 summarizes the non-functional requirement of the project

Table 2. Summary of Project Non-functional Requirements

Non- functional Requirement	Description
Esri ArcGIS Pro 2.3	Contains the geodatabase file, creates and edits the data, contains toolbox of customized tool
Operating System	Windows 7,8,10, 64-bit operating system, 8 GB RAM, core i7, and minimum of 2.20 GHz processor speed
Data format	All processed data and final information products configured for ArcGIS
Coordinate system	Projected coordinates system, WGS84 Zone 11

3.3 System Design

To address the client’s requirements, the system design included five major components. The “Multispectral image” component served as the source of multispectral data, contains near-infrared and red bands and was used as a base for all other parts of the project. The second component, the “Custom ArcGIS Pro Toolbox,” was designed around the input multispectral image and contains Python script tools. This custom toolbox then processed the input data to create the “NDVI Output”. Then, the custom toolbox component also processes the NDVI output to classify tree-clusters and non-tree areas, and it can also calculate difference in NDVI and tree-clusters from season to season. In the last component, the final processed information was analyzed considering different factors using ArcGIS Pro.

Figure 3-1: System design

3.4 Project Plan

To fulfill the client's major requirements and expectations, the project designed a plan that could be implemented within a given time. The plan was divided into five phases, including requirement gathering and analysis, data collection and clean up, Geoprocessing Tool Development, organizing data in a geodatabase, and presenting analysis results. These phases are shown in Figure 3-2 below.

Figure 3-2: Project Plan

The project requirement gathering, and analysis phase was started in November 2018. The objective was to clearly understand the client's goal to be achieved. This process involved email, WebEx meetings, and phone discussions with the client, TWC and the point of contact (Ms. Elizabeth Perez) to determine what functionality the system would need to achieve the desired goals.

At the beginning, the project was planned to use multispectral drone imagery to achieve the project goal. However, the client was not able to provide the required multispectral drone imagery due to technical difficulty. So, the project was done with multispectral satellite imagery, visible band drone image (only one study area) and processed imagery from National Agriculture Imagery Program (NAIP) compromising the quality and scope of the project. Although drone data collection was planned from the fall 2018 to the winter 2019 seasons for all of study area polygons, only one study area (Los Osos) was collected at the beginning of March and first week of May 2019. Thus, drone data collection time plan did not go according to the plan.

After the required data was collected, data preparation was done. All data were downloaded and collected in a Projected Coordinate System, WGS 84 Zone 11. Data preparation was conducted, and the data were loaded into an ArcGIS environment.

After data was downloaded and ready for processing, a geoprocessing tool was created that could identify the condition of the trees and classify tree and non-tree objects in the study area. Then, input data and processed output were organized in a geodatabase to better manage it. The geodatabase contained processed satellite images, visible band drone images, processed NAIP images, and polygons of the study area.

The final phase was presenting the analysis results; the analysis results of the NDVI in different seasons and potential tree mortality, or unhealthy tree areas, were mapped. All analysis results were displayed as layers in ArcGIS Pro. The project also

provided detailed reports and a poster of the results to illustrate the project procedures and describe the analysis results. The overall procedure of the project methodologies and analysis were documented to make sure that the development process could be replicated by anyone, and to provide complete and detailed information about the metadata during the project. This documentation would allow the client or anyone, to re-do and perform updates when needed. Likewise, the documentation additionally guarantees that all information was utilized properly and that all constraints were recorded. Table 3 illustrates the project time schedule.

Table 3. Project Time Schedule

		Years									
		2018		2019							
		Months*		Months*							
Phases	Tasks	11	12	1	2	3	4	5	6	7	
Requirement gathering and analysis	Gather Requirements										
	Analyze requirements										
Data model design, and data collection	Identify industry data models										
	Create a logical data model										
	Map source to a logical model										
	Design QC methodology										
	Collect data										
	Design customized ArcGIS toolbox										
Geoprocessing tool development	Develop customized ArcGIS toolbox										
	Develop QC methodology										
	Perform QC										
	Build physical data model										
Organizing data in ArcGIS Geodatabase	Organize and store input data										
	Organize and output data										
	Store analysis results										
	Pilot implementation										
Analysis and presentation	Present analysis result										
	Final implementation										
	Reports, Review, rework										

3.5 Summary

In conclusion, to help TWC in monitoring and managing oak trees, the project developed a geoprocessing tool integrated in ArcGIS Pro which could identify tree clusters and non-tree objects from imagery. An ArcGIS Geodatabase was also built to store and organize raw images and analysis results in a more productive way. The project data plan did change as the project progressed, thus the project compromise quality and scope. Chapter 4 describes the database design and data used in the project.

Chapter 4 – Database Design

This chapter portrays the database design and implementation concepts including the data gathering techniques required to accomplish the project. The client did not demand a complicated database, so the database configuration depicted here was made to fit only the requirements of the project. All things considered; the customer could utilize it as a base for further improvement in other comparative activities. Section 4.1 clarifies the conceptual database design for the project's attribute and spatial data while Section 4.2 explains the implementation of the design with a logical data model. Section 4.3 illustrates the data sources for the project, and Section 4.4 describes the strategies that were employed to prepare the data.

4.1 Conceptual Data Model

All inputs and outputs of the project were raster images; thus, the project did not demand a very complicated database design. The conceptual model describes the main problem of the project. The project's conceptual model entities included oak tree-clusters, drought, fire, water, and fungus. Drought decreases the water content of oak trees and it aggravates fire. Water nourishes oaks to produce their own food, however, water also activates fungus that attacks oaks. Nevertheless, the project had such a complicated and interrelated conceptual model, entities of interest integrated for analysis were only oak tree stress and mortality trends. Figure 4 illustrates the conceptual data model and the relationship between entities.

Figure 4-1: Conceptual Data Model

4.2 Logical Data Model

The project information was broken down into input and output entities which were project area images and analyses outputs. As the project was based on satellite imagery downloaded from the United States Geological Survey (USGS) website, the row/column that contains images of the study area were stored as raster files. However, the analyses were done only in the study area polygons. Not all the entities described in the conceptual data model were maintained in the geodatabase in order to keep the scope of the project more specific. The logical model of the project's database included "multispectral satellite image", "NDVI output", "Tree-Cluster output" and "High resolution drone image" and "NAIP imagery". All the analyses output information was stored as raster datasets in a geodatabase and the input satellite raster datasets which were simply stored as a raster file. This model can be seen in Figure 4-2.

Figure 4-2: Logical database schema

The project used Landsat-8 and Sentinel-2 imagery. Even though the project used the infrared and red bands for the purpose of analysis, the ArcGIS geodatabase stored eight bands of Landsat imagery and thirteen bands of Sentinel-2 imagery, and it could be used as a starting template for future development. The ArcGIS Geodatabase also contained the project area's four polygons.

4.3 Data Sources

The main source of the data was downloaded from the USGS website. As the purpose of the project was observing a change of oak tree mortality in time, Landsat-8 data were downloaded every year at leaf-on time in July starting from 2015 up to 2018. The resolution of Landsat-8 used for analysis was 30 meters and its revisit time was once every 16 days. Sentinel-2 data was collected by the European Space Agency (ESA) and downloaded from the USGS website for both years of 2017 and 2018. The Sentinel-2 images used for this analysis were composed of thirteen bands which had variable resolution of 10 meters, 20 meters, and 60 meters, with a revisit time of every five days. In the case of Sentinel-2, for the purpose of observing the change in seasons, data were downloaded in May, July, and October or November (based on cloud absence). The

project used red and infrared bands which had better resolution of 10 meters. All the data were downloaded in a projected coordinate system of WGS 1984 UTM Zone 11N. Drone data were also provided by the client. Although the project had four study area polygons, drone data were provided only for one polygon (Los Osos), and it was restricted to three visible bands (red, green & blue). Table 4 illustrates data source of the project.

Table 4. Data Source for the Project

Data type(name)	Used Bands	Band number	Data format	Resolution	Image download size	Source	Revisit time
Sentinel-2	Infrared and Red	Band 8b Band 4	.jpg	10m	801MB	ESA	5 days
Landsat-8	Infrared and Red	Band 5 Band 4	.tif	30m	1.74GB	USGS	16 days
Drone image	RGB	N/A	.tif	3.6cm	747MB	TWC	1month
NAIP imagery	IRRGB	NA	.tif	1m	1.7MB	Esri image services	4 year

4.4 Data Collection Methods

The project's satellite data used for analysis was downloaded from the USGS website. The project also used drone imagery provided by the client. The client used a Phantom 4 Pro+ V2.0 drone equipped with a FC6310_8.8_4864x3648 camera to collect the imagery. The camera was designed to collect four bands including infrared which would be able to calculate NDVI, but due to technical problems, only RGB bands were collected. Thus, the client's drone images were not complete to perform NDVI analysis since there were only RGB bands. The project also used National Agricultural Imagery Program services (NAIP) from Esri to check the accuracy of the satellite imagery and to know when the trees were stressed or had died by comparing NAIP NDVI and drone orthomosaic image.

4.5 Data Scrubbing and Loading

The client provided the study area polygons in the projected coordinate system of NAD 1983 State Plane California FIPS 4100 Feet. Since all the satellite data were downloaded in the projected coordinate system of WGS 1984 UTM Zone 11N, the study area polygons were re-projected to WGS 1984 UTM Zone 11N and migrated to ArcGIS Geodatabase. The data downloaded from USGS was in row/column format and contained areas beyond the area scope of the project. Before migrating NDVI analyses results and tree cluster outputs to the ArcGIS Geodatabase, the project areas of interest were masked based on study area shapefiles.

4.6 Summary

The conceptual design created in the project planning was implemented to a logical design. Not all entities in the conceptual design model were implemented to a logical design to be more specific. Even though having a geodatabase was not the requirement of the project, a geodatabase was built which was editable and ready for future use. All the project's satellite data used for analysis were downloaded from the USGS website. After NDVI calculation and identification of tree clusters, the areas of interest for the project were masked based on study area polygons.

Chapter 5 – Implementation

This project created geoprocessing tools utilizing Python scripts which were integrated into ArcGIS Pro. The scripts automate quantification of normalized difference vegetation index (NDVI), filter tree-clusters, and calculate differences in NDVI and tree-clusters in different seasons. Thus, The Wildlands Conservancy (TWC) could re-do the analysis for different areas and data types. These geoprocessing tools could be used to automate and compare change in different seasons at constant NDVI value, permitting the client to take necessary measures to preserve oaks. This chapter begins by giving a brief discussion of the development and use of a Python geoprocessing toolbox. It also gives a general overview of multispectral satellite and drone image preparation necessary in analysis of different factors related to vegetation health.

5.1 The Wildlands Conservancy NDVI and Tree-Cluster Python Tool

A Python geoprocessing tool was developed to achieve the client's objective that was monitoring and assessing oak tree health. The purpose of this geoprocessing tool was to simplify tasks and maximize efficiency through doing NDVI calculation and classify the output into tree and non-tree area so that TWC can easily integrate the tool into their workflow. NDVI calculations use the red and near-infrared band images as input. The results are used as input in tree-cluster calculations. The tool can calculate NDVI layers from optical sensor data such as satellite image, aerial photography and drone image. The tool is fast when the input data is a low-resolution image. Landsat-2 imagery at resolution of 30m that covered an area of 4000 square km were processed within six seconds. The same area of Sentinel-2 imagery at 10m resolution were processed within 60 seconds. Thus, as resolution of input raster image increases, the system demands more disk space and it has slower processing speed. The tool was integrated in ArcGIS Pro version 2.3. Figure 5-1 illustrates the user interface of the tool.

Figure 5-1: TWC NDVI and Tree-Cluster Python Tool User Interface

As shown in figure 5-1, the tool has data input buttons “Near-infrared” and “Red”. Here, the user should give near-infrared and red band raster datasets respectively. The mathematical combination of these two bands provides NDVI as output. On the “NDVI” button the user should specify a destination folder and data format like “.tiff” to save the NDVI output. The user should also specify “Tree-cluster Threshold” which is usually the NDVI value for the target tree-cluster and should be a “float” data format number, which ranges from -1 to 1. The threshold value will vary according to the area and the purpose of the project. The basic idea behind the “Threshold” is to quantify change in seasons using a consistent NDVI value. Then using a consistent number, the system gives output tree-cluster and non-tree areas. This output would compare this year to last year and give an input for decision makers to consider necessary measures.

5.2 Implementation of TWC NDVI and Tree-Cluster Python Tool

The geoprocessing tool created for the purpose of achieving this project was implemented using Landsat-8 and Sentinel-2 images. The sentinel-2 data were downloaded from the USGS website in May, July, and November or October (based on cloud cover) for the years 2017 and 2018 for the matter of observing change in different seasons. The data were downloaded in the project coordinate system of WGS 84 Zone 11 and it was in .jpg format. Although Sentinel-2 data has 13 bands, the project used only infrared and red bands in calculation of the NDVI. Initially the project was planned to consider all seasons of the year. However, the winter season was excluded from consideration due to cloud cover of satellite images. The tool was used in calculating NDVI and filtering tree-cluster locations within the study area polygons.

5.2.1 Implementation of TWC NDVI and Tree-Cluster Python Tool Using Sentinel-2 Data

To filter tree-clusters from NDVI value, the project considered phenology information of oak trees. Oaks have no leaves in the winter season, and grasslands and shrubs are green in May due to better moisture from the winter season. At the middle of summer season in July, grasslands and shrubs are dry due to absence of moisture, and this season is leaf-on time for oaks and oaks are green. Considering this approach, the project used data collected in July to identify healthy cluster of trees.

The project applied the tool in all the study area polygons named Los Osos, Midslope, Tecuya and Eco Canyon. The NDVI values were normalized from 0.0 to 0.8 for comparison. Although all the study areas were included in the built geodatabase, Figure 5-2 shows the NDVI calculation for only one of the study areas, Los Osos. Figure 5-2 represents NDVI calculation results from 2017.

Figure 5-2: NDVI Value of the Los Osos study area in 2017

As shown in Figure 5-2(a), the 2017 NDVI value of May was greener than July and October. The reason was in the study area, the winter season was the wettest season, which made grasslands and shrubs remain green until the summer season. In the summer season, as shown in Figure 5-2(b), July had less NDVI than October since grasslands and shrubs were dry and only trees were green. The monthly trend was the same in 2018 with slight differences in NDVI values. As illustrated in Figure 5-3, the 2018 NDVI of May was uniformly distributed and showed more greenness than others. In all seasons, the left corner of the Los Osos study area was green as shown in both Figure 5-2 and Figure 5-3. According to the visual check of drone imagery, the left corner of the study area was covered with all-weather dense shrubs. The negative value shown in the bottom of Figure 5-3(c) was in November. According to the visual check of the satellite images before NDVI calculation, the area which is indicated in light blue color in the bottom of Figure 5-3(c) was covered by cloud. Hence, the presence of cloud on satellite imagery highly affects NDVI analysis and the quality of the image should be checked before calculating NDVI and interpreting the results. Figure 5-3 illustrates NDVI of the Los Osos study area in 2018.

Figure 5-3: NDVI Value of the Los Osos study area in 2018

The NDVI value ranges from - 1 to 1. Water bodies reported a negative value of roughly - 1 as the project was realized using satellite images. Although the negative values varied based on the content of water, scientific NDVI values of water bodies are negative irrespective of sensor type. In contrast, studies showed that thick temperate and tropical rainforests have high NDVI values around 1. Bushes and fields likewise have low positive values (GIS Geography, 2018).

The project used an NDVI value of greater than 0.25 to filter tree clusters shown in Figure 5-4. Different numbers below and above 0.25 were also tested to identify healthy tree-clusters. When the project used tree-cluster threshold greater than 0.2 as indicated in Figure 5-4(a), the tool considers most of the area as healthy tree-cluster including the stressed trees. In contrast, when project used tree-cluster threshold greater than 0.3 as indicated in Figure 5-4(b), the tool missed health tree-clusters and considers as non-tree object. Consequently, the project suggested that NDVI values greater than 0.25 shown in Figure 5-4(c) better for extracting healthy trees-clusters. After calculation of NDVI, the project overlaid the results of NDVI with National Agriculture Imagery Program (NAIP) imagery. The project observed those NDVI values over 0.25 had a tree under the overlay.

Figure 5-4: Tree-cluster of the Los Osos study in July 2017 using different tree-cluster thresholds

The project assumed NDVI values less or equal to 0.25 as either non-tree objects or unhealthy trees. Based on this logic, the project used this number to extract clusters of trees both in July 2017 and July 2018. Comparison of tree-clusters in July 2017 and July 2018 using consistent NDVI threshold of 0.25 showed slight differences and will be described in detail in chapter 6. Figure 5-5 shows tree-clusters in July 2017 and July 2018.

(a)

(b)

Figure 5-5: The Los Osos study area July 2017(a) and 2018(b) tree-clusters

5.2.2 Implementation of TWC NDVI and Tree-Cluster Python Tool Using Landsat-8 Data

The project used Landsat-8, 30-meter resolution data, collected in July from 2015 to 2018. The month of July was chosen since July is leaf-on time for oaks and oaks are green in the study area, and bushes and grasslands are less green. The NDVI values were normalized from 0.0 to 0.5 for comparison. There was no significant difference of NDVI values distribution in all the years. Thus, as resolution decreased the effect of spectral mixing minimized the capacity of differentiating tiny changes in tree health. Hence, doing NDVI analysis was impossible since the results were more generalized. The greener area shown in the left corner of each year in Figure 5-6 was dense shrubs. Figure 5-6 shows the NDVI results of the Los Osos study area using Landsat-8 data.

Figure 5-6: NDVI Result of the Los Osos study area in Landsat-8 image from July 2015-2018

Using the TWC NDVI geoprocessing tool, tree-clusters were extracted from the years 2015 to 2018. Since tree-clusters were extracted from NDVI values, there was also no significant differences in tree-clusters between July 2015 and July 2018. Images shown as tree-clusters in the left corner of Figure 5-6 were dense shrubs according to the visual check by drone imagery. So, assessing and monitoring tree health change by NDVI analysis demanded better resolution imagery. A detailed description of tree-clusters in the Los Osos study area will be in chapter 6. Figure 5-7 illustrates tree-cluster locations in the Los Osos study area.

Figure 5-7: Tree-Cluster of the Los Osos study area in Landsat-8 image from 2015-2018

For the purpose of comparison and determine the appropriate threshold value for this project, the project also did tree-cluster extraction using tree cluster threshold of 0.2 and 0.3, and there was better tree-cluster in densely located trees at 0.2 threshold value compared to tree-cluster threshold of 0.25. Although there was better tree-cluster in dense shrubs and densely located trees at the tree-cluster threshold of 0.2 as shown in Figure 5.8(a), it missed green trees located sparsely in the study area. There was no tree-cluster at threshold value of 0.3 as shown in Figure 5.8(b) except an area of dense shrubs. This showed how spectral mixing affects NDVI value and consequently identification of tree-cluster in low resolution satellite images. Figure 5-8 illustrates tree-cluster in different threshold.

Figure 5-8: Landsat-8 tree-cluster at 0.2(a), 0.3(b) and 0.25(c) thresholds

5.3 TWC Raster Difference Calculator Python Tool

A raster difference calculator geoprocessing tool was developed using Python programming language and easily integrated with ArcGIS Pro. The tool takes pixel values from two seasons and gives the difference as output. This tool created a more streamlined environment to observe tree health change in different seasons within a year or change from year to year. After calculation of the difference in trees between seasons or years, the tool provides changes like loss, no change, and gain based on the spectral signature values of objects. For instance, if there is tree-cluster of July 2017 and July 2018, it is possible to calculate the difference to observe tree health loss, no change and gain as shown in Figure 5-10. Figure 5-8 illustrates the user interface of TWC raster difference calculator tool.

Figure 5-9: TWC Raster Difference Calculator geoprocessing tool User Interface

As shown in Figure 5-9 the geoprocessing tool has data input buttons ‘Season1’, which is the first input, and “Season2”, which is the second data input. Finally, the user should specify a destination folder of the output information which is “Difference”. The difference is the result of NDVI or tree-cluster differences between season1 and season 2. The tool was implemented using Sentinel-2 data for all study area polygons, and the tree-cluster differences between July 2017 and 2018 were calculated, and the results will be described in chapter 6. Figure 5-10 shows tree-cluster difference in study area polygons.

Figure 5-10: Tree-Cluster Difference Tecuya(a), Eco Canyon(b), Los Osos(c) and Midslope(d) between July 2017 and 2018

5.4 Oak Tree Mortality Identification Using Drone Image

The project also used drone images to identify stressed and dead oak trees. To identify oaks during leaf-off time and leaf-on time, drone data was collected on leaf-off time on March 10, 2019 and leaf on time in May 8, 2019. Drone data was collected using a

Phantom 4 Pro+ V2.0 drone equipped with a FC6310_8.8_4864x3648 camera with focal length of 8.6 mm. Table 5 characterizes the drone and its data.

Table 5. Characters of Drone and its Imagery

Item properties	Drone	
Drone type	Phantom 4 Pro+ V2.0	
Camera type	FC6310_8.8_4864x3648	
Resolution	3.6 cm	
Flight altitude	338 feet	
Covered area	23 hectares	
Overlap	Forward	Side lap
	75%	65%
Positional accuracy	Horizontal	Vertical
	14cm	27cm

The images were processed by Pix4D Cloud software, the reason being that it accomplished top quality results and it has more robust photogrammetry capabilities. In addition, Pix4D allows projects to be handled utilizing default formats for client accommodation. Pix4D allows editing point clouds and cleanup unwanted features or extents, and it is the least demanding approach to share a task online with only a link. If including control points and manual tie points, altering the densified point cloud and changing a lot more settings which can improve the final outcomes were necessary, Pix4D desktop application would be more convenient. Nevertheless, the project did not demand ground control points. The client has Pix4D software. However, for the purpose of this project, Drone2Map would be also applicable. From the drone images, Orthomosaic, digital sample surface model (DSM), 3D Mesh, and point cloud data were produced. Although the project had four study area polygons, drone images were collected only in one of study area, Los Osos. Figure 5.11 shows the workflow of Pix4D.

Source: <https://www.google.com/search?q=pix4d+workflow&source>

Figure 5-11: General workflow of Pix4D

However, the project didn't use any ground control points and check points, the positional accuracy of drone data was 14 cm horizontally and 27 cm vertically which was enough for the intended purpose. Figure 5-12 illustrates image center and overlap.

Figure 5-12: Image centers (left) and overlap (right) of drone imagery

As shown in Figure 5-12, the drone image had six flight lines and 92 images. Images with no overlap had gaps on the boarder and they had fewer tie points to make bundle adjustment. Figure 5-13 shows drone images collected in different time.

Figure 5-13: Drone orthomosaic collected on March 10, 2019 (left) and on May 08, 2019 (right)

Oak trees had no leaves in March, and they had leaves starting from the end of April. This was very essential to differentiate oak trees from other tree species. However, according to visual observation of drone imagery, some of the shrubs within the study area were green even in March.

5.5 Summary

Customized tools integrated into ArcGIS Pro and developed to monitor and assess oak tree health were tested. The tools were implemented through Sentinel-2 and Landsat-8

satellite imagery. ArcGIS Pro was utilized to make and oversee GIS information, and to make the final mapping and information products. Pix4D Professional software performed drone image processing, and the processing results were visualized by ArcGIS Pro. The procedure for utilizing these technologies was explored in this section, and the outcomes and investigation of that procedure are examined in Chapter 6.

Chapter 6 – Results and Analysis

This chapter illustrates the results found from the implementation of the developed ArcGIS toolbox. The potential of Landsat-8, Sentinel-2, and drone images in identification of stressed and dead oak trees will be examined. Section 6.1 clarifies the potential of Sentinel-2 and Landsat-8 imagery in identifying tree-clusters by utilizing normalized difference vegetation index (NDVI). Section 6.2 describes seasonal variation of tree-clusters, and Section 6.3 illustrates the locational variation of tree-clusters. In section 6.4 the efficiency of drone image in observing stress and dead trees will be examined, and the drone images' appropriate ground sample distance (GSD) for the intended purpose will be examined. Finally, section 6.5 summarizes the chapter's main contexts.

6.1 The Wildlands Conservancy NDVI and Tree-Cluster Python Tool Performance on Sentinel-2 Data and Landsat-8

The performance of the TWC NDVI geoprocessing Python tool was evaluated using Sentinel-2 and Landsat-8 data. It is generally known that data size affects the processing speed, and high-resolution images have more data size than low resolution images for the same area coverage. So, resolution and the processing speed of the developed tool were inversely proportional. As illustrated in chapter five, the tool can process NDVI and tree-clusters of 4,000 square km area at resolution of 30m within six seconds. The same area with resolution of 10m took 60 seconds to process (10 times slower). Thus, the tool performs processing faster in Landsat-8 data, which was 30m resolution, than Sentinel-2 with 10m. But when comparing the performance of sensors in locating tree-clusters, Sentinel -2 had better capability of locating tree-clusters than Landsat-8. The same study area had significantly different results. This was tested using the same NDVI value of 0.25 and can be seen later in Figure 6-3.

As shown in Figure 6-1, greener NDVI distribution was seen in Sentinel-2 images of the Los Osos study area than in Landsat-8 images. The NDVI values were normalized from 0.0 to 0.8 for comparison. The study assessed the NDVI values of both sensors in different seasons, namely in May, July, and October or November. The study found this logic to observe change of different objects or species of trees in the study area. The study found that almost all the study areas were greener in May due to better moisture after the winter season. More NDVI values were recorded in May since shrubs and grasslands were green and reflected more near-infrared energy than red. At the middle of the summer season in July, grasslands were dry, and oaks and some other trees were green and reflected near-infrared energy.

Figure 6-1: NDVI of the Los Osos in July 2017 using Sentinel-2(left) and Landsat-8(right)

In addition to spatial distribution of NDVI values as shown in Figure 6-1, the histogram also briefly showed the difference of NDVI results in different resolutions. The histogram of both images was positively skewed. The Sentinel-2 images had high value of frequencies up to 330, and the maximum frequencies of Landsat-8 were around 75 as shown in Figure 6-2. Furthermore, the histogram of Sentinel-2 images showed more frequency in the NDVI value from 0.18 to 0.28, and the Landsat-8 imagery showed the highest frequency from 0.16 to 0.22 as shown in Figure 6-2(b). Figure 6-2 illustrates the histogram distribution of NDVI values.

(a)

(b)

Figure 6-2: Histogram distribution of NDVI Values in July 2017 using Sentinel-2 and Landsat-8

The project used an NDVI value of 0.25 to extract tree-clusters from both images, and the results varied significantly. This methodology tested for July 2017 and July 2018 images for both sensors and significance differences which can be seen in Figure 6-3.

As illustrated in figure 6-3, Sentinel-2 data had more tree-cluster than Landsat-8 even though both used the same consistent NDVI value which was 0.25. The Landsat-8 data, shown as tree-cluster, was dense shrubs, and the analysis failed to extract tree-clusters based on this logic. This implied that NDVI is significantly influenced by resolution and consequently limits our ability to assess and monitor tree health. This is because when resolution is low, a single pixel may cover different objects like wet soil, bare land, dry grasslands and so on. Thus, even if there were green trees within a single pixel, the near-infrared reflectance would be influenced by other objects and results in a lower NDVI value. This happened and was tested in the Los Osos study area where trees were healthy in Sentinel-2 observation and they were unhealthy in Landsat-8 observation. As illustrated in Figure 6-3(b), Landsat observation showed most of the area as non-tree objects. However, according to visual observation of drone imagery collected in this study area there were healthy trees that can be seen later in Figure 6-8. Figure 6-3 illustrates tree-cluster difference of Sentinel-2 and Landsat-8.

Figure 6-3: The Los Osos study area tree-cluster on July 2018

6.2 Seasonal Variation of Tree Clusters

The project assessed the seasonal variation of trees clusters from year to year with the assumption of an NDVI value greater than 0.25 as a tree cluster. To observe change from year to year NDVI was first calculated. Then, to extract healthy trees NDVI value greater than 0.25 were used. For this matter, the Landsat-8 data from July 2015 to 2018, on a yearly base were analyzed. As resolution was a very determinant factor and low-resolution leads to spectral mixing, no significant difference was observed from year to year as illustrated in Figure 6-4. Since trees were found sparsely in the study area, Landsat-8 analysis failed to extract tree clusters based on NDVI value. It only showed dense shrubs within polygon and the effect of spectral mixture was significantly noticed here. Figure 6-4 illustrates Los Osos study area tree-clusters using Landsat-8 imagery.

Figure 6-4: The Los Osos study area tree-clusters by Landsat-8 imagery from July 2015-July 2018

In the case of Sentinel-2, a difference was observed between the data processed on July 2017 and July 2018. There was better observation of tree-clusters in July 2017 than July 2018 due to better precipitation in the 2017 water year. According to “Water balance app” made by Esri, the precipitation and soil moisture in 2017 in the month of January was 143mm and 403mm respectively (Esri, 2019). In 2018, the same month was 18mm precipitation and 286 mm soil moisture. Studies also argued that soil moisture influences NDVI value at least by 20 percent (Huete and Jackson, 1994). Even in the month of July, both years had no precipitation and they had different soil moisture. Figure 6-5 illustrates tree-cluster differences between July 2017 and 2018 in Sentinel-2 imagery.

Figure 6-5: Tree-cluster of Los Osos Study area in Sentinel-2 data in July 2017 and July 2018

Although better tree-cluster were observed in July 2017, there were places which lost greenness in 2017 and became greener in 2018. The project also calculated the tree-cluster difference between 2017 and 2018 which is illustrated by Figure 6-6. The data were able to show some of the trees that were green in 2017 and lose their greenness in 2018. From this, the project suggested that drought might be the main reason for the observed change. Figure 6-6 shows the tree-cluster difference between July 2017 and July 2018 in Sentinel-2 imagery.

Figure 6-6: The Los Osos study area tree-cluster difference between July 2017 and 2018

6.3 Locational Variation of Tree-clusters

The project observed locational variations of tree-clusters in four study area polygons named Los Osos, Tecuya, Midslope, and Eco Canyon. Compared to others, Los Osos and Eco Canyon showed more loss of greenness of trees in 2018, and the loss and gain distribution was random in the Los Osos. Tecuya and Eco Canyon had more clustered pattern tree loss and gain; it showed a gain in some places and a loss in others. Finally, the project concluded that even the study area polygons were located within 15 miles distance, tree stress and mortality varied from place to place even in the same weather conditions as it can be seen in Figure 6-7. The project realized that the overall patterns and causes of tree stress were too complicated, and studies argued that drought and related insect activities have a significant contribution to tree stress in California (Boa, 2003). Tree-cluster variations of the study area polygons can be seen in Figure 6-7.

Figure 6-7: Tree-Cluster Difference Tecuya(a), Eco Canyon(b), Los Osos(c) and Midslope(d) between July 2017 and 2018

6.4 Oak Tree Stress and Mortality Identification Using Drone Image

The project was able to identify stressed and dead trees from drone imagery collected in one of the study area polygons, LosOsos. Observation of those stressed and dead trees back ten years were also performed using National Agricultural Imagery Program (NAIP) imagery. The project found that most stressed and dead trees in the study area were healthy before 2009. NAIP imagery NDVI with one-meter resolution, collected in 2009

was used to observe the historical tree health. As shown in Figure 6-8, the extracted stressed and dead trees were represented by black polygons. Using drone orthomosaic image, 69 stressed and dead trees were manually identified from 23 hectare of land in the Los Osos study area. Those black polygons were overlayed to NAIP Imagery NDVI in 2009. The NAIP imagery was collected during leaf-on time for oaks and enabled the project to observe individual trees. Figure 6-8 illustrates stressed and dead trees in drone image collected in May 8, 2019.

Figure 6-8: Stressed and dead tree polygons in drone image collected May 8, 2019

From the 69 stressed and dead trees in Los Osos study area, 20 (29 percent) were dead in the 2009 NAIP imagery. Figure 6-9 illustrates NAIP Imagery NDVI in 2009 and stressed and dead tree polygons.

Figure 6-9: NAIP Imagery NDVI in 2009 and stressed and dead tree polygons

The project also used NAIP imagery NDVI collected in 2016, and the stressed and dead trees extracted from drone imagery collected on May 2019 were overlaid on it.

In the time between 2009 and 2016, 42 oaks (61%) have died. Only 7 trees (10%) have died after 2016. From this, the project observed the most oak mortality in the study area coincided with drought period in California (2010-2016). Figure 6-10 illustrates 2016 NAIP Imagery NDVI and stressed and dead tree polygons.

Figure 6-10: 2016 NAIP Imagery NDVI and stressed and dead tree polygons

Most trees in the study area stressed after 2009 following the continuous drought in California. NAIP imagery collected in 2009 and 2016 played a great role in observe timing of tree stress and death. Generally, the project realized that oak tree mortality was not one-time event. For a tree to die it might take years, with a combination of various reasons. As shown in Figure 6-11 trees which were alive in 2009 were dead in 2016, and trees which were alive in 2016 were dead in in 2019. Figure 6-11 shows comparison of true color NAIP imagery and drone imagery in the years of 2009, 2016 and 2019.

Figure 6-11: Comparison of NAIP True Color Imagery 2009 and 2016, and Drone Imagery 2019

6.4.1 Appropriate Drone Image Resolution for Oak Tree Mortality Identification

The project realized that spatial resolution of image is a very determinate factor in assessment and monitoring of tree health. The drone data collected for the purpose of identifying stressed and dead trees had an average resolution of 3.6cm or 1.5 inches. This was too much detail and more time was needed for data collection and processing, and more storage space was also needed. Since the current drone technology is based on battery power, such high-resolution images consume time for image acquisition and consequently increases cost. For the purpose of deciding appropriate resolution for future monitoring and assessment of oak trees, the project resampled average resolution of 3.6 cm to 10, 20, and 30 cm. Based on the result found, a 10cm was the most convenient resolution which would save money and time for the client. Thus, the client can fly high altitudes following the rules of Federal Aviation Authority (FAA) and decrease the number of flight lines, and consequently save flight time and data storage costs. As it can be seen from Figure 6-12, 10 cm resolution was visible and better fit for future data

collection. The imagery became blurry at 20 and 30cm resolution and can be seen in Figure 6-13 and Figure 6-14. Figure 6-12 to Figure 6-14 show the original and resampled images.

Figure 6-12: Original drone image resolution 3.6cm (top) and resampled 10cm (bottom)

Figure 6-13: Original drone image resolution 3.6cm (top) and resampled image 20cm (bottom)

Figure 6-14: Original drone image 3.6cm (top) and resampled image 30cm (bottom)

6.5 Summary

The TWC NDVI and Tree-cluster geoprocessing toolbox performs fast in low resolution images and was faster in Landsat-8 than Sentinel-2. Sentinel-2 was better in identifying tree-clusters than Landsat-8 in which NDVI analyses failed to extract trees clusters due to spectral signature mixture. Resolution significantly affects NDVI values and consequently influences tree health analysis based NDVI, and high-resolution images had higher performance to identify tree and non-tree objects. Los Osos and Eco Canyon study areas showed more tree stress than Tecuya and Midslope study areas. Thus, trees stress and mortality varied in place and time. Drone images have a great potential to identify stressed and dead oak trees. The most trees in the Los Osos study area have died between 2009 and 2016 coinciding with drought in California. Drone imagery with resolution of 10cm would be better for oak tree assessment and monitoring purpose. Chapter 7 will illustrate the conclusion and recommendations for future work.

Chapter 7 – Conclusions and Future Work

This chapter gives a concise review of what this project achieved and ends with recommendations for future work.

7.1 Project Summary

Oak trees cover no less than 20 million acres of land in California. They play a significant role in stabilizing soil for a watershed, preserving the environment, and providing an anchor for many wildlife habitats. However, oak trees are dying due to drought stress and related insect activities. Drought also brings uncontrolled wildfires which threaten California oaks. The Wildlands Conservancy (TWC) is a non-profit organization that works on protecting the excellence and biodiversity of the earth. In TWC's Wind Wolves Preserve, oak tree habitats cover a significant portion of the total preserve area. TWC had difficulty mapping oak tree health for purpose of monitoring and treatment.

To solve the problem the project developed Python geoprocessing tools that enabled TWC to calculate NDVI, identify tree-clusters and non-tree zones, and calculate differences or changes of tree health from season to season, or year to year. Sentinel-2 satellite images were able to identify areas of tree-clusters and non-tree areas but failed to extract individual oaks due to resolution limitations. Thus, resolution is a very determinant factor to identifying tree health using NDVI as parameter. The National Agriculture Imagery Program (NAIP) images from Esri images services were helpful to observe the time of tree death comparing to the current drone imagery. Furthermore, the project also identified stressed and dead oaks using high resolution drone images, provided by TWC. Most oak tree mortality had been observed after 2009, coinciding with the recent California drought. Although the project had four study areas, drone data were provided for only Los Osos. Thus, the project compromised scope. In addition, a geodatabase was developed which included raw data and analysis results, and TWC could use it as a base for future development. Although the project compromised scope of the study area, the client was satisfied on the final delivery of the project and its functional and non-functional requirements were fulfilled.

7.2 Future Work

The project has at least three possible extension projects. The first possible extension will be collecting four bands drone imagery including near-infrared band in every season in the study area. Then, there is a possibility of observing change in every season by utilizing NDVI with high resolution drone images. This observation would enable the client to observe tiny changes in the health of oaks. These images will also be used as a record to compare the present condition with the future.

The second possible extension will be geotagging the current healthy oaks in the study area using high resolution drone imagery. This would help the preservers to follow up, even at the individual tree level. This also help botanists, environmentalists, biologists, and other scientists to study oak tree habitat in well managed and accurate

way. For those who are interested in studying the age of oaks, it will be beneficial if all individual oaks would have locational information.

The third possible extension will be an analysis of why oaks are dying. By including different scenarios like weather condition, insect activities, human activities, fire hazard, drought and others, the project could be extended broadly.

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Appendix A. Pix4D Quality Report

Quality Report

Generated with Pix4Denterprise version 4.4.9
Preview

- Important:** Click on the different icons for:
- Help to analyze the results in the Quality Report
 - Additional information about the sections

Click [here](#) for additional tips to analyze the Quality Report

Summary

Project	TWC Drone Project
Processed	2019-05-06 18:05:53
Camera Model Name(s)	FC6310_8.8_4864x3648 (RGB)
Average Ground Sampling Distance (GSD)	3.63 cm / 1.43 in
Area Covered	0.237 km ² / 23.6720 ha / 0.09 sq. mi. / 58.5251 acres
Time for Initial Processing (without report)	04m:41s

Quality Check

Images	median of 63522 keypoints per image	✓
Dataset	89 out of 91 images calibrated (97%), all images enabled	✓
Camera Optimization	2% relative difference between initial and optimized internal camera parameters	✓
Matching	median of 7122.85 matches per calibrated image	✓
Georeferencing	yes, no 3D GCP	⚠

Preview

Figure 1: Orthomosaic and the corresponding sparse Digital Surface Model (DSM) before densification.

Bundle Block Adjustment Details

Number of 2D Keypoint Observations for Bundle Block Adjustment	674042
Number of 3D Points for Bundle Block Adjustment	308836
Mean Reprojection Error [pixels]	0.130

Internal Camera Parameters

FC6310_8.8_4864x3648 (RGB). Sensor Dimensions: 11.407 [mm] x 8.556 [mm]

EXIF ID: FC63105_8.8_4864x3648

	Focal Length	Principal Point x	Principal Point y	R1	R2	R3	T1	T2
Initial Values	3666.955 [pixel] 8.600 [mm]	2432.001 [pixel] 5.704 [mm]	1823.999 [pixel] 4.278 [mm]	0.004	-0.017	0.019	-0.000	0.000
Optimized Values	3593.535 [pixel] 8.428 [mm]	2424.502 [pixel] 5.686 [mm]	1834.842 [pixel] 4.303 [mm]	0.004	-0.018	0.018	0.000	-0.001
Uncertainties (Sigma)	5.741 [pixel] 0.013 [mm]	0.140 [pixel] 0.000 [mm]	0.128 [pixel] 0.000 [mm]	0.000	0.000	0.000	0.000	0.000

Appendix B. TWC Python tool scripts

```
#Import all necessary modules
import os
import arcpy
from arcpy.sa import *
from arcpy import env
arcpy.env.overwriteOutput = True
env.scratchWorkspace = env.scratchFolder
env.workspace = env.scratchWorkspace
# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")
# Local variables:
Infrared = arcpy.GetParameterAsText(0)
Infrared02 = Raster(Infrared) #change data to raster
Red = arcpy.GetParameterAsText(1)
Red02 = Raster(Red) #change data to raster
NDVI = arcpy.GetParameterAsText(2)
Threshold = arcpy.GetParameterAsText(3)
Threshold2 = float(Threshold) #change to float
Vegetation = arcpy.GetParameterAsText(4)
#NDVI formula
ndvi3 = (Infrared02-Red02)/(Red02 + Infrared02)
veg = ndvi3 > Threshold2
#save NDVI and vegetation output which I got help from Ersi staff Liz Graham.
ndvi3.save(NDVI)
veg.save(Vegetation)
```

TWC Raster Difference calculator

```
#Import all necessary modules
import os
import arcpy
from arcpy.sa import *
from arcpy import env
arcpy.env.overwriteOutput = True
env.scratchWorkspace = env.scratchFolder
env.workspace = env.scratchWorkspace
# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")
# Local variables:
Season1 = arcpy.GetParameterAsText(0)#fisrt input data
Season01 = Raster(Season1) #change data to raster format
Season2 = arcpy.GetParameterAsText(1)#second input data
Season02 = Raster(Season2) #change data to raster format
Difference = arcpy.GetParameterAsText(2)#output data
#change data to raster format
Diff = Season01-Season02 #Difference formula
```

```
Diff.save(Difference)# save data to your disk
```