# Classifying the Alpines:
# Developing a Methodology to Track Environmental Changes in the Alpines Utilizing Remote Sensing and Ecozone Vegetation Patterns

by

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To the special people in my life.

First to my parents, for always encouraging me to pursue my interests, passion, and freedom, even when they didn’t understand them. Mom, thank you for continuingly supporting me in finding my way and staying true to myself. Dad, thank you for believing in me and encouraging me to be a better person. Second to Michael who believes in my abilities to succeed even when I didn’t, who never tears me down even when things are difficult, and has been there with encouragement, compassion, and an open ear. Thank you for being that person to me.

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# List of Abbreviations

| | |
|---|---|
| DEM | Digital Elevation Model |
| DOI | United States Department of Interior |
| EMT+ | Enhanced Thematic Mapper Plus |
| ERTS | Earth Resources Technology Satellite |
| FGDB | File Geodatabase |
| GIS | Geographic Information System |
| GISci | Geographic information science |
| IRS | Indian Remote-Sensing Satellite |
| MSS | Multispectral Scanner System |
| NDVI | Normalized difference vegetation index |
| NIR | Near-infrared |
| NLCD | National Land Cover Data |
| QC | Quality Control |
| RBV | Return Beam Vidicon |
| SSI | Spatial Sciences Institute |
| USC | University of Southern California |
| USGS | United States Geological Survey |

# Abstract

Vegetation growth patterns are indicators of environmental change. However, sampling and recording landscape-scale studies over time are challenging using traditional methods. This study used remotely collected imagery of montane forests through alpine over thirty years, 1984 to 2018, to classify and examine changes in vegetation patterns. The imagery analysis methodology focused on the San Juan Mountains of Colorado. Imagery from Landsat satellites was utilized to derive normalized difference vegetation index (NDVI) values examining vegetation patterns throughout an elevation gradient. Elevations from 3000 meters above sea level to the peak of the tallest mountain in the study area (Uncompahgre Peak 4365 meters) then classified into the land cover types of the local ecozones. Ecozones examined were the nival and subnival of the alpine and the montane forest of the subalpine. The corresponding land cover types where soil and rock, shrubs and grass, and mixed forest, deciduous forest and coniferous forest respectfully as defined by the U.S. Geological Survey.

When sampling of changes focused on single peaks, a slight rise in altitude over time is observed (m= 0.1754). When sampling included more broad sampling throughout the study area, an even more minor negative trend resulted (m= -0.1369). The study discusses that the broad standard array sampling type was possibly skewed due to samples being taken from across long distances with little elevation change overall throughout. The discussion includes suggestions for further research.

# Chapter 1 Introduction

Environmental changes and their impacts are a topic of great discussion within the scientific community. The effects of these fluctuations are still being discovered by scientists from a wide variety of fields. Full comprehension of these changes lies well beyond any single scientific study, as each study observes one or more changes.

The artic has been a major focus of global climate change. The inherent aspects that comprise this biome are attractive to scientists for several reasons. Overall, the region has been minimally impacted by humans. Distinctive vegetation growth patterns can be observed, which are typically consistent with latitudes. Arctic tundras are considered a fragile ecosystem. A fragile ecosystem is when environmental conditions are easily impacted. In the event, conditions are impacted too significantly, flora and fauna can drastically change, not excluding extinctions. These factors all make this biome ideal for studying changes in landscape ecology. However, artic tundras are limited by global location: surrounding the northern pole, thus limiting researchers to a few applicable latitudes to represent worldwide changes. Similar environments do exist, yet, with more widespread distribution throughout latitudes. Notably, the montane alpine regions found in multiple mountain ranges worldwide. Some researchers have taken artic-based studies and applied them to the alpine areas where restrictions from latitude are interchanged with elevation.

This study examined whether there were changing vegetation growth patterns within alpines zones by developing a monitoring workflow through remote sensing and applying the workflow to an alpine area. The foundation is in the normalized difference vegetation index (NDVI) data from a mountain range that contain alpine and subalpine regions. These values reflect the location and density of healthy vegetation. “Alpine,” as defined here, is the area in a montane environment above treeline (Nagay 2009). The term “treeline” denotes the elevation where trees stop appearing along an elevation gradient. The elevation of treeline is approximately 12,000 ft. or 3657 m. in the San Juan Mountains of Colorado, where this study occurs. Treeline can vary by mountain range worldwide, though the alpines are consistent in vegetation patterns (Nagay 2009). Within the lower reaches of the alpine is the subnival, which is the area bordering treeline with vegetation consisting of forbes (flowering plants), shrubs, and grasses. Eventually, these give way to the higher part of the alpine that is generally non-vegetated. This area, with a land cover of predominantly bare rock or soil, is referred to as the nival zone in technical terms. In this study values of NDVI are used to determine the presence or absence and density of vegetation to identify the area of these biomes. By repeating this locational analysis through a period of thirty-five years, this study observes how vegetation growth patterns, and thus the location of these biomes, have changed through time.

The change that was expected was that subalpine vegetation and possibly even treeline, are occurring at increasingly higher elevations. This assumption is based on similar observations in other alpine areas, as well as the well-documented movement of shrubs to more northern latitudes in the arctic. Other studies have mentioned that these changes are occurring, and are related to the increase in global temperatures. This study focused on how much change has occurred that can be monitored via satellite. Of course, why this change has occurred, while important, lies outside the scope of this study. By identifying the location and area of the alpines utilizing NDVI values and satellite data, then the rates of change and potential impacts can be investigated.

## 1.1. Background

The biophysical world is constantly changing. These changes are reflected in ecosystems: desertification, global temperature, glacier lifecycles, and more. Some of these changes are happening quickly; others are decades in the making. To understand these changes, scientists employ multiple field-based methodologies. These include ice cores, water gauges, tree rings, population counts, and many studies monitoring of indicators through time. With an array of biological indicators and a continual development in technology, methodologies evolve to fill the gaps of knowledge inherent in the study of the world.

Sometimes that biological indicator can be large, and sometimes it's smaller than a cell. NDVI utilizes one such small indicator in the form of chlorophyll. This study strives to propose a methodology to use the available technology as it applies to this small yet powerful biological indicator. The way in which chlorophyll reflects light in the near-infrared spectrum is used as an indicator of plant health and location (Callenbach 2008). This reflectance is captured by an orbiting satellite that contains sensors to capture the near-infrared wavelengths (Bolstrad 2016). The brightness and the location of that light signature over a landscape can indicate vegetation health, type, and growth pattern (Campbell 2012).

The ecozones focused on within this study are the nival, subnival, and subalpine, which consequently lend themselves well to clear classification from NDVI values in several ways. The limitations of a satellite image's quality tend to be obstructions between the sensor and the object(s) it is trying to capture (Bolstrad 2016). For example, in many studies the forest canopy can obscure the focus of a study. In the subalpine, however, the vegetation density associated with a canopy becomes, in fact, a benefit to identifying the ecotone between alpine and subalpine areas. Then, by nature the canopy is absent when investigating the ecotone between the nival and subnival regions (Campbell 2009). The terrain surrounding the alpines is typically uninhabited, reducing the likelihood of buildings and other human-made structures interfering with the imagery. The ecosystem is also fragile, meaning it is are susceptible to changes in the environment. Thus changes are more clearly reflected, namely with respect to vegetation growth patterns (Negay 2009). Most importantly, however, these areas are found worldwide, since alpine vegetation patterns are restricted by elevation rather than latitude. The final criteria are pragmatic, namely time and cost.

Concerning time, there are two components. The first is that the data needed for this type of analysis and interpretation has been collected for nearly 50 years and is directly comparable back 35 years (Bolstrad 2016). The second is how often a single area is captured. With satellites such as the Landsat mission, this is the time the satellite revolves around the planet. Other satellites hang in orbit in a single location. Landsat captures imagery once every sixteen days. In the scale of many ecological changes, even seasonal, this temporal resolution is sufficient to observe the changing landscape.

Finally, there is the idea of cost. It could be argued that the cost of a satellite system is expensive. Especially since costs include designing and launching a satellite. Then, assuming everything works correctly, the cost of labor, hardware, and software that goes into any processing, storage, and publishing of resulting data. Perhaps these expenses should be considered when developing methodologies reliant on this program. However, a full capture of a cost-benefit analysis of imagery data is not the intention of this paper. For the end-user, however, it is generally accepted that the expense of downloading free public data, obtaining software licenses that are typically used for multiple projects, and several hours' computer labor of one person is greatly reduced in comparison to ground studies. Ground studies costs include hiring multiple people each year of study as well as equipping, transporting, accommodating, and sometimes training them. Remote sensing, when applicable, takes far less time, human resources, and funding than ground studies. (The Nature Conservancy and Environmental Systems Research Institute 1994).

### *1.1.1. Alpine Ecology*

Mountains are unique and complex ecosystems that are vital to a diverse set of organisms. The gradual to extreme changes in elevation create zones with specific microclimates that allow individual species to thrive in their particular niche (Negay 2009). Along these elevation gradients fluctuations in biotic and abiotic factors. These factors included variations in soil composition, soil microorganisms, slope aspects, annual precipitation, and duration of sunlight. Topography plays a major role in all of the listed factors.

The ecological phenomenon can be seen in vegetation that changes with elevation. In lower elevations trees compose forests; these montane forests are considered subalpine. The ecosystem consists of shrubs, grasses, and flowering plants, called the subnival ecozone, this is considered a part of the alpines. As environmental stress increases, tree growth is no longer sustained. The key conditions that are related to this occurrence are oxygen availability and temperature ranges, which are both directly impacted by altitude. As elevation increases, stress on vegetation also increases until the landscape is predominantly bare rock and soil, called the nival zone. The nival and subnival zones comprise the highest elevation levels within the alpine ecosystem and are found only on the summits of high altitude mountains. The elevations at which these ecozones occur differ by region. In southwest Colorado, where this study was focused, treeline is typically found between 11,000 and 12,000 ft. (3353-3658 meters). The elevation of subnival to nival is less well-defined and more varied (Nagy 2009). Each microbiome in these transition zones offer highly specialized niches that host vast amounts of biodiversity to occur throughout both flora and fauna (Walther 2005).

Ecozones are shifting upward along the elevation gradient (Jurasinski et al. 2007). In the arctic, vegetation is moving further north (Myers-Smith et al. 2015). Similarly, but less well documented, alpine vegetation is being pushed higher in altitude. While at first glance this may not seem alarming, much of the world's freshwater is housed in these biomes. Furthermore, they contain high levels of biodiversity (Nagy 2009). Jurasinski et al. (2007) observed that biodiversity is already decreasing in the Swiss Alps. Singh et al. (2011) found vegetation patterns moving higher in altitude in the Himalayas of India. How far up the mountain can these biomes be pushed before they disappear?

Climate change is disrupting plant abundance, growth patterns, and variation by altering the microclimates for which these plants are adapted. As temperatures rise worldwide, there is a growing concern about how sensitive alpine systems will be impacted (Jurasinski et al. 2007, Walther, 2005). Also, due to their topology, these areas are hard to monitor. Sending humans into these hazardous environments can be both risky and costly. The alpines, with their distinctive landcover per ecozone, offer the perfect opportunity for the study of changes through time (Buytaert 2010). One way to understand these peaks is through the sensor of a satellite.

### *1.1.2. Remote Sensing*

The first satellite that observed the Earth was a US satellite that flew over the Soviet Union from 1956 until it was shot down by the Soviet Union in 1960. Formal missions of satellites started in 1960 with the launch of the CORONA Program. The need for this project stemmed from a desire for intelligence gathering on the Soviet Union. Since then, satellites have been used to observe the patterns on Earth's surface, and remote sensing has grown exponentially. Since the CORONA Program, which continued until 1972, more civil applications emerged. In 1972, the Landsat Program- formerly called the Earth Resources Technology Satellite (ERTS) - launched with the mission to observe Earth's resources from space. Onboard the Landsat 1 (1972-1978) were two image sensor systems: the Return Beam Vidicon (RBV) and the Multispectral Scanner System (MSS).

The RBV only operated for a short time, and the MSS outperformed the RBV. The MSS recorded four spectral bands ranging from visible green to second near-infrared. Each band was recorded separately and was processed into a composite image. Landsat 2 (1975-1982) also recorded bands separately. It was not until Landsat 3 (1978-1983) that these bands were condensed during collection into a single broad spectral band. The resolution of images was 30 by 30 meters. Landsat 4 (1982-2001) and 5 (1984-2013) had the same sensors as Landsat 3. Landsat 6 (1993) failed to reach orbit. Landsat 7 (1999-2003) improved the sensors to the Enhanced Thematic Mapper Plus (EMT+). This sensor included a thermal IR channel of 60-meter resolution and a panchromatic band with a 15-meter spatial resolution. The Landsat program has since grown resulting in the launch of Landsat 8 in 2013. In addition to the previously mentioned spectral bands, two more bands are recorded. The first is a deep blue visible band focused on water resources. The second is a shortwave infrared sensor focusing on cirrus clouds. Figure 1 shows all the bands currently gathered by Landsat, though most have been collected by previous Landsat satellites as well (U.S. Department of the Interior and U.S. Geological Survey 2017.). Landsat 9 is planned to launch the end of 2020 (Irons et al. 2017). The new satellite will be a replica of Landsat 8, as it will collect data continuously.

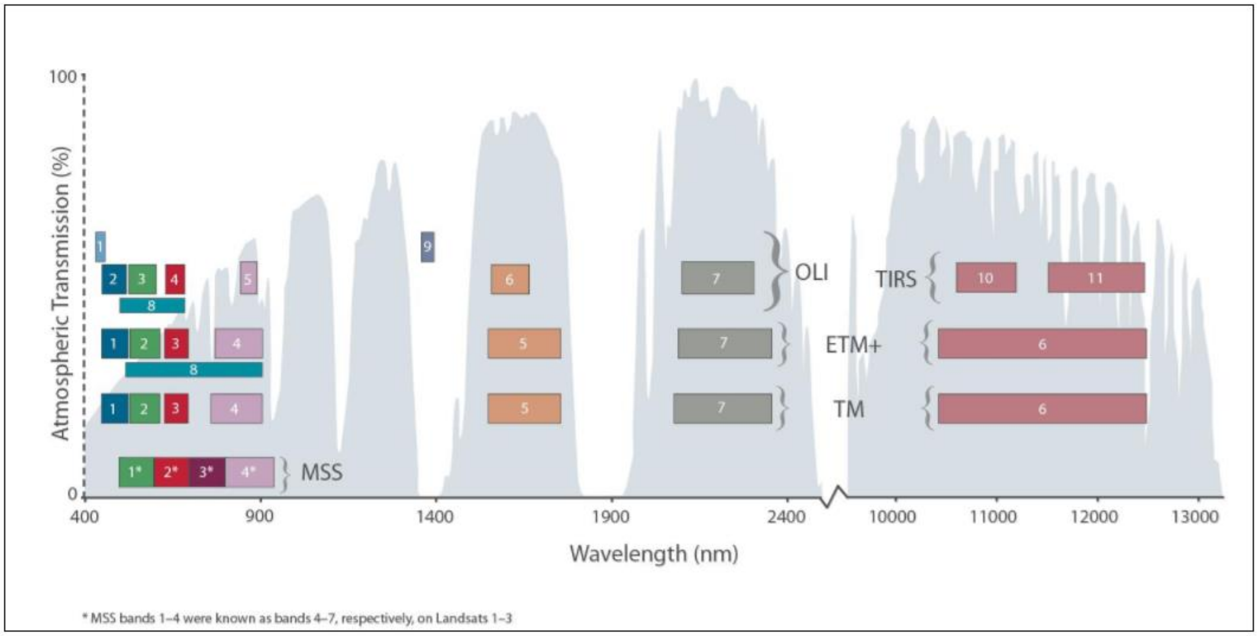



Figure 1. Spectral Bands collected via Landsat. Bands recorded by the Landsat satellite program are displayed in boxes. NDVI data utilize the bands appearing between 400 nm and 900 nm[1].

1.1.2.1. NDVI

The Landsat imagery can produce NDVI values, which can be indicative of vegetation location and density. To understand the NDVI, it is vital to comprehend how the properties of a plant lend themselves to measurement via remote sensing. The NDVI relies on chlorophyll that is contained in greenery. The chlorophyll pigment absorbs solar radiation in the blue and red visible spectrums, which is why most plants appear green. In the near-infrared (NIR) spectrum, green leaves reflect more strongly, generating positive NDVI values. Plants, when healthy, contain more chlorophyll than a stressed or dead plant. Thus a healthy plant will reflect the near-

1. U. S. Department of the Interior and U.S. Geological Survey. *The Multispectral Scanner System (MSS) aboard Landsats 1–5 had four bands*, 1365 by 651 pixels, https://landsat.gsfc.nasa.gov/wp-content/uploads/2016/10/all_Landsat_bands.png

infrared band more strongly than a dying plant. This is illustrated in Figure 2. Other surface types such as concrete, bare soil, snow, or clouds have almost no reflectance in this spectrum. Water also interferes with near-infrared rays, causing negative NDVI values (Pettorelli et al. 2011). Near-infrared light is not detected by the human eye but can be recorded through a camera lens, after which it is recolored in a false-color image for observation and analysis. Each pixel of the image uses the following equation:

$$\text{NIR} - \text{red}/\text{NIR} + \text{red}$$

Since the only bands used in this formula are near-infrared and red, any capture containing both can be computed into NDVI values. The remainder of the visible spectrum bands is useful for true-color imagery examples. Thus, as far back as Landsat 1, with the onboard MSS, data is reasonably available for input into an NDVI analysis.

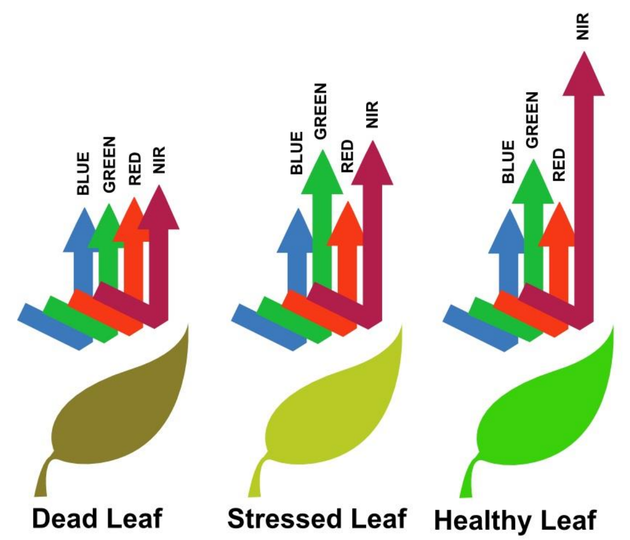



Figure 2. Near-infrared and visible light spectrum as reflected by plant matter in various stages of health. The illustration shows a basis for utilizing NDVI is a remote sensing technique to measure the health of plant life [2].

2. Physics Open Lab. *Leaf Health Reflectance,* 6 by 5 in., http://physicsopenlab.org/2017/01/30/ndvi-index/

# Chapter 2 Related Works

There are libraries of knowledge focused on climate change that are expanding every day, one study at a time. These studies are global in nature and have focused on many topics. One indisputable indicator of climate change are the impacts on ecosystems. Vegetation composition is a defining aspect of any ecosystem (Callenbach 2008), and thus growth patterns are one of the most common indicators for changes in landscapes (Liu et al. 2011, Zhang et al. 2015, Young et al. 2006). One validated difference that vegetation in the arctic is changing, where shrubbery is moving north (Myers-Smith 2015, Jia 2003). The use of satellite imagery, as well as NDVI values, to identify and track the location of vegetation has been applied in several studies both in the alpines and in other locations (Palchowdhuri 2018, Siahaya 2015).

## 2.1. Studies in Alpine Vegetation Changes

Researchers have studied the way alpine ecosystems are changing in different locations around the world. In Indonesia, Eastern Africa, and South America, changes observed in 2010 confirmed that the tropical alpines are shrinking in size and becoming more isolated (Buytaert 2010). The importance of alpines in freshwater systems were examined since these areas are the source of many of the world's freshwater lakes and rivers and the location of many seasonal or year-round glaciers (Buytaert 2010). Perhaps the most commonly recognized attribute of alpines is their biodiversity. Biodiversity arises from unique and stressful conditions that have encouraged the evolution of organisms both resistant to environmental factors, as well as survival strategies to fill limited niches within the habitat (Negay 2009, Buytaert 2010). Biodiversity in flora and fauna increases the ability of systems to adapt to change. Such uniqueness in overcoming environmental can offer possible solutions to problems being faced by other ecosystems. With the shrinking of these habitats comes the loss of this potential

(Callenbach 2017). This upward shift was also observed in the Swiss Alps, and biodiversity was also found to decrease over time (Jurasinski 2007). Treeline was also detected as shifting into higher elevations in the Austrian Central Alps from 1954 to 2006 (Wallentin 2008). Trends regarding the treeline in the Andes in South America show that forests have resilience towards environmental changes (Young 2006). In Tibet, an increase in grassland vegetation was found from 2000 to 2013 (Zhang 2015). An extensive geographical study was undertaken investigating forest and grassland land cover throughout a growing season in Northeastern Asia (Liu 2011). This survey linked climate impact on NDVI values. Overall, the studies agree that the alpines are reflecting on changing vegetation patterns. Several of these studies used Landsat data and NDVI values, typically as they relate to land cover.

## 2.2. Studies Utilizing Remote Sensing

The principle of using Landsat data and NDVI values has been established through numerous studies. Studies utilize remote sensing data from various satellite missions, including MODIS, SPOT, and LiDAR data. However, Landsat is a common choice for the long term, large scale studies (Liu 2011, Siahaya 2015, Xie 2008). A direct correlation between vegetation productivity and type to NDVI values has been observed (Pettorelli 2005, Pettorelli 2011). The phenology of some vegetation can be determined by NDVI values (Pettorelli 2011). Land cover studies utilizing NDVI values have been used to monitor change in many environments, especially within agriculture (Bhunia 2013, Liu 2011, Zhang 2015). In some cases, NDVI is the base for classification (Palchowdhuri 2018). This is where landcover is identified by NDVI values and a classification process based on the identified NDVI values can help identify landcover types. Using NDVI as it represents landcover and that landcover types can indicate ecozone locations is the base of this study.

# Chapter 3 Methods

This chapter outlines the methodology used in this study. The goal was to delineate the alpine and subalpine ecozones using land cover through the classification of NDVI values in order to examine if the elevations at which those zones occur have changed in the selected 35 years. The general workflow is shown in Figure 3 and is detailed throughout the methodology. In the image, general steps within the process are yellow blocks. These are grouped a purple outline that indicates the sub-section within the methods section of this paper where they are described in detail. Geographic area is discussed in two extents: study area and scene. Study site refers to a mountain range that contains the alpine region. A scene is the extent of Landsat data, either bands or composite of bands. When discussing raster data, the term “imagery” is inaccurate since analysis relies on wavelengths outside of the visual spectrum. Therefore, an image refers to a true color composite, which is included in Landsat data. The study area is an area within the scene that is montane, specifically over 3000 m elevation for Colorado. This elevation varies depending on location. The methodology is intended for use in multiple regions as described below, but the study area elevation is dependent on the region. The selection of the San Juan Mountains is further discussed in section 3.1.1.2. The removal of locations below the target elevation allows the noise of the desert area and other land types that are not the focus of this study but is within the downloaded scene to be removed (Figure 4).

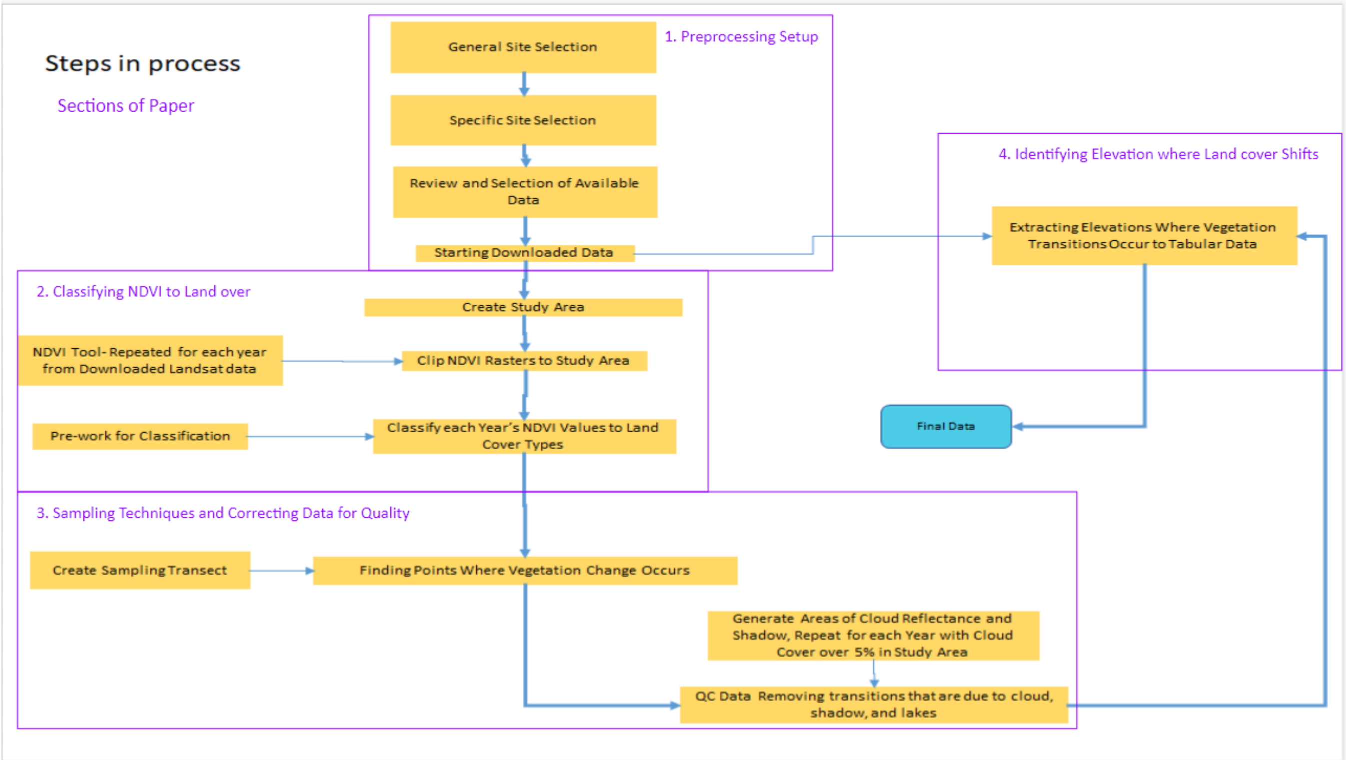



Figure 3. The general workflow of analysis and sections within the methods details are provided.

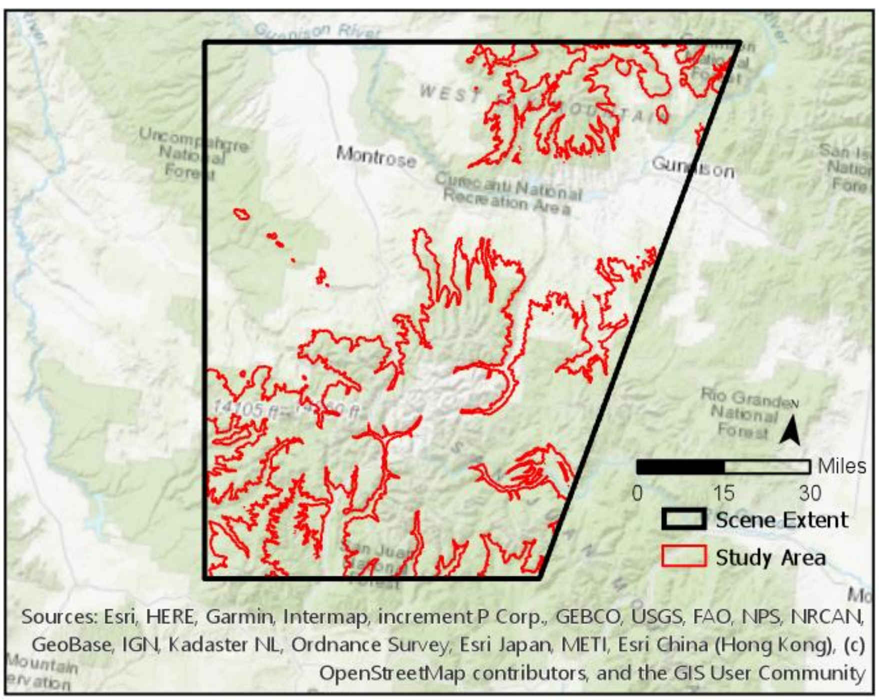



Figure 4. The scene extent and study area within the scene of downloaded data centered on the San Juan Mountains of Southwest Colorado.

## 3.1. Preprocessing Setup

Several steps are needed before downloading Landsat data before analysis can begin. First, a general area for investigation was chosen. Second data quality and coverage was carefully assessed to ensure accurate results. Finally, the study area was confirmed based on the available data and local region. Other needed data includes elevation, national land cover data (NLCD), and the location of water within the study area; these layers must be sourced and downloaded.

### *3.1.1. Study Site Selection*

There were two criteria for selecting a study area for this project. The first was a general selection, focused primarily on mountain ranges with alpine ecosystems that could be available for investigation. Ideally, the area will have a minimal human impact and small locations of development. Given that high altitudes occur typically in rough terrain, many ranges and sub-ranges around the world exhibit these characteristics. The second consideration before selecting a specific study area was the availability of satellite data. Data was selected that met a certain level of quality as well was consistent enough that almost every year in the temporal range of analysis could be represented. Once data was consolidated, then the study area was confirmed and drawn based on the lowest elevation to be analyzed.

#### *3.1.1.1. General Site Selection*

For a mountain range or sub-mountain range to be considered, several criteria were met. First, the field of view via satellite contained a full range of montane elevations and biomes. Since this analysis was based on vegetation density and location as an indicator of differing biomes, each biome is present. Alpine can occur at slightly different elevations based on region. Therefore, a specific elevation is not defined for general site selection but is in specific site selection. Second, minimal surface area is developed, since these areas interrupt the surrounding biome vegetation patterns. Finally, the selected mountain range contained multiple peaks that are capped by the alpine biome. These peaks provided focus points for sampling. Numerous focus points increase the sampling availability of where these vegetation transitions occur, limiting the impact of aspect and other conditions, such as rain shadow, on elevation averages.

#### 3.1.1.2. Specific Site Selection

Once an appropriate geographical area was identified, data availability and quality were assessed before final study location was chosen. The availability of public data further limits viable locations. The United States and most of North America has reliable and free public data. However, countries with differing information sharing policies and resources, may not have readily available data. For example, the alpine areas in New Zealand were considered for comparison use within this study, but Landsat data was not found. Not all mountain ranges have continual data available to the public, therefore only areas where data is available can be considered; this may not be immediately evident without a basic data search. A location could only be valid if data were available each year. The temporal scale used was 1983 to 2018 for a total of 35 years. This time scale allows data to be directly comparable between satellites and is a scale of time that is easily understood. Once data has been found for each year the quality of the data must meet basic standards. When choosing the study site, a general review of data was completed to ensure most years had clear views of the land within the proposed study area. More specific considerations were taken into account when the final scene was selected and is described below. During the basic review, an omission threshold of 5 years throughout the temporal scale was allowed. Meaning up to 5 years could be left out of analysis if quality data was not found. For this study, only one site was selected to work through the methodology.

Once both data quality and geographic characteristics were confirmed, the study was chosen, namely the San Juan Mountains of southwest Colorado. This site met the criteria outlined above, containing contains several peaks over 14,000 feet and showing ample areas of sub-alpine and alpine regions. Development in this area is limited to two high altitude locations, Silverton and Animas Forks, with minimal connecting roads throughout the region and little surface disturbance due to subsurface activities. Overall, developed areas comprised less than 5% of the study area. Sixty-five peaks located throughout the study area were used as focal points for analysis. Data was available for every year, though one year was omitted (2012) due to lack of quality in the scene. All selection criteria described were met by the San Juan Mountain region, and thus the final study area polygon was developed.

*3.1.1.3. Study Site Confirmation*

The final physical and temporal boundaries of the study site were adjusted to the area of the highest data quality. These adjustments were made after data was downloaded as described in the next section. Thirty-five scenes, one per year, were downloaded. Each scene had data for 7043 square miles. Of this area, 2746 square miles were above 3000 meters in elevation. This comprised the final study area (see Figure 3). All calculations were based from UTM NAD 83 Zone 13 projection. The extensive study area aims to lessen the impact of inherent error due to aspect, shadow, and environmental conditions on overall calculations.

*3.1.2. Review and Selection of Available Data*

The nature of capturing landscape ecology through satellite imagery is prone to atmospheric scrambling. Also, the steep slopes of mountains can shadow large areas. Mountains are known to be gathering points for clouds, which change reflectance values. The southwest in particular is the fire-prone landscape, where smoke plumes can travel for miles. Smoke also interferes with the values in the red and infrared bands.

Since atmospheric scattering is common, it was essential to establish the data quality of each scene to be used in the analysis. The goal was to select 35 images of the San Juan Mountains that met all the criteria listed in section 3.1.3 “Scene Data Quality.” The workflow was created to allow a threshold of 5 years to be omitted from the analysis if no scenes met qualifications. Also, a quality control process was established and is described in section 3.3.

Data selected consisted of one scene per year taken within a month of midsummer. Midsummer is defined as the astrological midsummer: the longest day of the year or the solstice (June 24 in Colorado). The meteorological (temperature) midsummer may have a more significant impact on vegetation growth, but the astronomical solstice is more specific to vast landscapes. These scenes comprised the base data used in the analysis.

*3.1.2.1. Scene Selection from Earth Explorer*

Earth Explorer was used to identify a single scene from each year to be further analyzed. All Landsat data was sourced from Earth Explorer, which is an archive of imagery data hosted by the USGS and has a 30-meter resolution (USGS). Though the products from several satellite missions are available through this portal, Landsat data is the most relevant to this study. Landsat has the most extended comparable set of images over time, thus applicable to the long-term observation of environmental patterns.

To access and download the data, several of Earth Explorer’s filters were used. The first was to establish location, which was achieved by zooming in to the area of interest. The site allows the user to search for data corresponding to a specific path and row location as defined by the orbit pattern of the satellite. The path and row option was rejected because it varies between satellites, leading to a lack of consistency over time. Instead, a polygon was drawn over the study site. The next step was to enter a date of collection. Since the area of interest was in the northern hemisphere and the astronomical midsummer is June 21, the search range spanned from May 1 to July 31. However, if results didn't return a quality image, dates were expanded to include the meteorological summer as far as Aug 31. The dates of the data captured within a year are plotted in Figure 5. Next, the data to be searched was selected from the larger dataset. Bands 1 thru 7 must be available and be consistent in their measurement of light waves to be directly comparable. The analysis-ready data in Earth Explorer allows for this to be pre-established. In the final filter labeled "Additional Criteria", two criteria were entered. Time collected was set to 'day,' and cloud percentage is set to '<50%'. Images with the highest quality were selected for further analysis and downloaded. A quality image is defined in the next section.

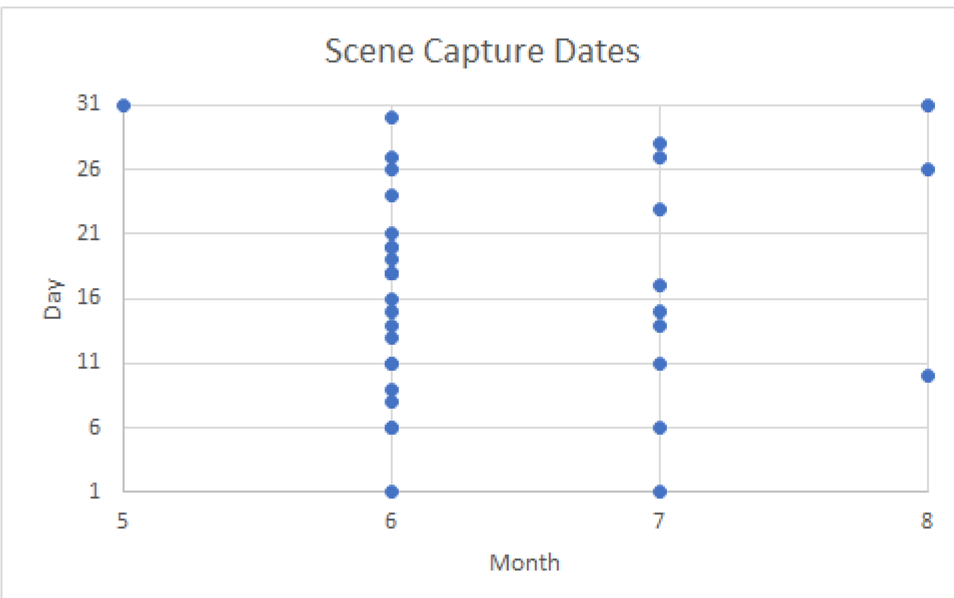



Figure 5. Dates of data collection. The time of year data was captured was mostly in June and July but some outliers in May and August were used when quality data was not available in June or July.

| Year | Date Collected | Landsat | Year | Date Collected | Landsat |
|---|---|---|---|---|---|
| **2018** | 6/18/2018 | 8 | **2000** | 5/31/2000 | 5 |
| **2017** | 6/15/2017 | 8 | **1999** | 6/30/1999 | 5 |
| **2016** | 7/14/2016 | 8 | **1998** | 6/27/1998 | 5 |
| **2015** | 6/26/2015 | 8 | **1997** | 6/24/1997 | 5 |
| **2014** | 8/10/2014 | 8 | **1996** | 7/23/1996 | 5 |
| **2013** | 6/20/2013 | 8 | **1995** | 6/19/1995 | 5 |
| **2012** | 6/9/2012 | 7 | **1994** | 6/16/1994 | 5 |
| **2011** | 7/1/2011 | 5 | **1993** | 6/13/1993 | 5 |
| **2010** | 8/31/2010 | 5 | **1992** | 6/18/1992 | 4 |
| **2009** | 7/27/2009 | 5 | **1991** | 6/8/1991 | 5 |
| **2008** | 6/6/2008 | 5 | **1990** | 6/21/1990 | 5 |
| **2007** | 6/20/2007 | 5 | **1989** | 6/18/1989 | 5 |
| **2006** | 6/1/2006 | 5 | **1988** | 7/17/1988 | 5 |
| **2005** | 6/14/2005 | 5 | **1987** | 7/15/1987 | 5 |
| **2004** | 6/11/2004 | 5 | **1986** | 7/28/1986 | 5 |
| **2003** | 7/11/2003 | 5 | **1985** | 8/26/1985 | 5 |
| **2002** | 6/6/2002 | 5 | **1984** | 7/6/1984 | 5 |
| **2001** | 6/11/2001 | 7 | | | |

Table 1. Data used. The date data was collected and the Landsat that collected the image.

*3.1.2.2. Scene Data Quality Criteria*

Data quality for this study of a Landsat scene hinges on factors that can skew light reflectance values, such as smoke, shadow, water, and cloud cover. The previous filter removed the most shadow by restricting the collection time of the scene daytime. A quality-control step was later implemented to guarantee final data quality in shadow, water, and minimal cloud cover. However, for sampling to be comprehensive, scenes with high cloud cover within the study area were rejected. With the use of Earth Explorer's filter, the scene could contain up to 50% cloud cover though ideally scenes containing less than 10% were selected. Cloud cover can occur within the scene but outside of the study area. To determine if a scene contained less than 20% cloud cover within the study area, a rapid visual assessment technique commonly used in vegetation plot analysis was used. In this approach, a perimeter is established, typically a meter squared. Then the data recorder compares the amount of vegetation in that parameter usually by breaking it into 1/4s and offering a percentage of plant matter vs. soil. This process was conducted with the study area as the perimeter. If two scenes were available for the same year, the one with the less cloud cover was chosen.

Similarly, other criteria were taken into account. Snow cover can hide the upper sub-alpine vegetation, as vegetation is often found under the snow. Therefore, scenes with less snow coverage were selected if more than one quality scene was available within a single year. However, scenes that contained snow cover were not immediately rejected to keep gaps between years reduced. Snow cover was expected to be classified as its own entity. In this case, to be considered a part of alpine, required a clear line of vegetation to rock shift occur below the snowline. However, once data was compiled, snow cover was only found within alpine and therefore not classified in this study area.

Data was available for each year except 2012, which had a line error from the satellite. Twelve years had between 5% and 20% cloud cover within the study area. Extra steps were taken to remove compromised samples from final data results; these steps are described in the following section 3.3.

*3.1.2.3. Other Data*

Several other data sets were used in this study. The first was a digital elevation model (DEM) that covers the entire scene. A DEM from the USGS with a 1-meter resolution was used to determine elevation. It was found that the overall difference in elevation values over 35 years was negligible when working with 30-meter resolution Landsat data. Therefore, only a single DEM of the study area was used. The elevation for the entire scene was needed, which was tiled into 4 DEMS. These were then mosaicked into a single DEM. This data was used to determine the study area polygon at 3000 meters. It was also later used to extract elevation values at the final points where vegetation transitions occurred.

The third data set utilized was the national land cover data (NLCD), produced by the USGS. This data is a raster layer that depicts the land cover types in the US. This layer was used to identify NDVI values that correlate with the six land cover types relevant in this study. In turn, they represent the vegetation composition of the three biomes: montane forest, subnival, and nival alpine. Training samples for classification of the NDVI layers were generated from this data.

A layer of the location of water was also downloaded. This data came from the State of Colorado. In this case, it was lakes, but note that if a coastal mountain range is used in a similar study, ocean would have to be included. The water layer is used in the QC step to remove data that may have been skewed by the presence of water.

Finally, Esri's World Topographic Map was used to identify peaks within the study area and create a point feature class for those locations. Transects were then run from these points to sample the place where the classified vegetation types changed. More details on all these steps are in the following sections.

A full workflow is shown in Figure 7, and it is broken down in Figures 8, 14, and 19. Once a scene had been validated as quality data and downloaded, it was loaded into ArcPro for analysis. This study utilizes Esri's ArcPro, though other GIS software may also be suitable for conducting similar analysis (i.e., ArcMap). Several tools were built using Model Builder in ArcPro and are denoted and later explained. An image of the full toolbox is shown in Figure 6. Numbers are placed in front of the title to keep order in which they were run clear. Most tools are iterators to process the data layers that represent each year.

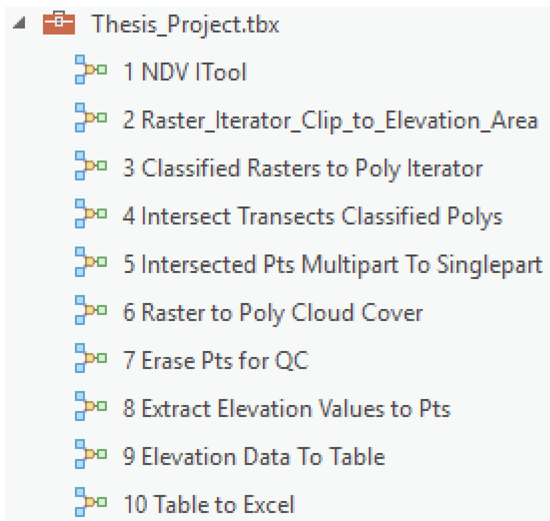



Figure 6. Toolbox of custom tools generated through ModelBuilder for this project.

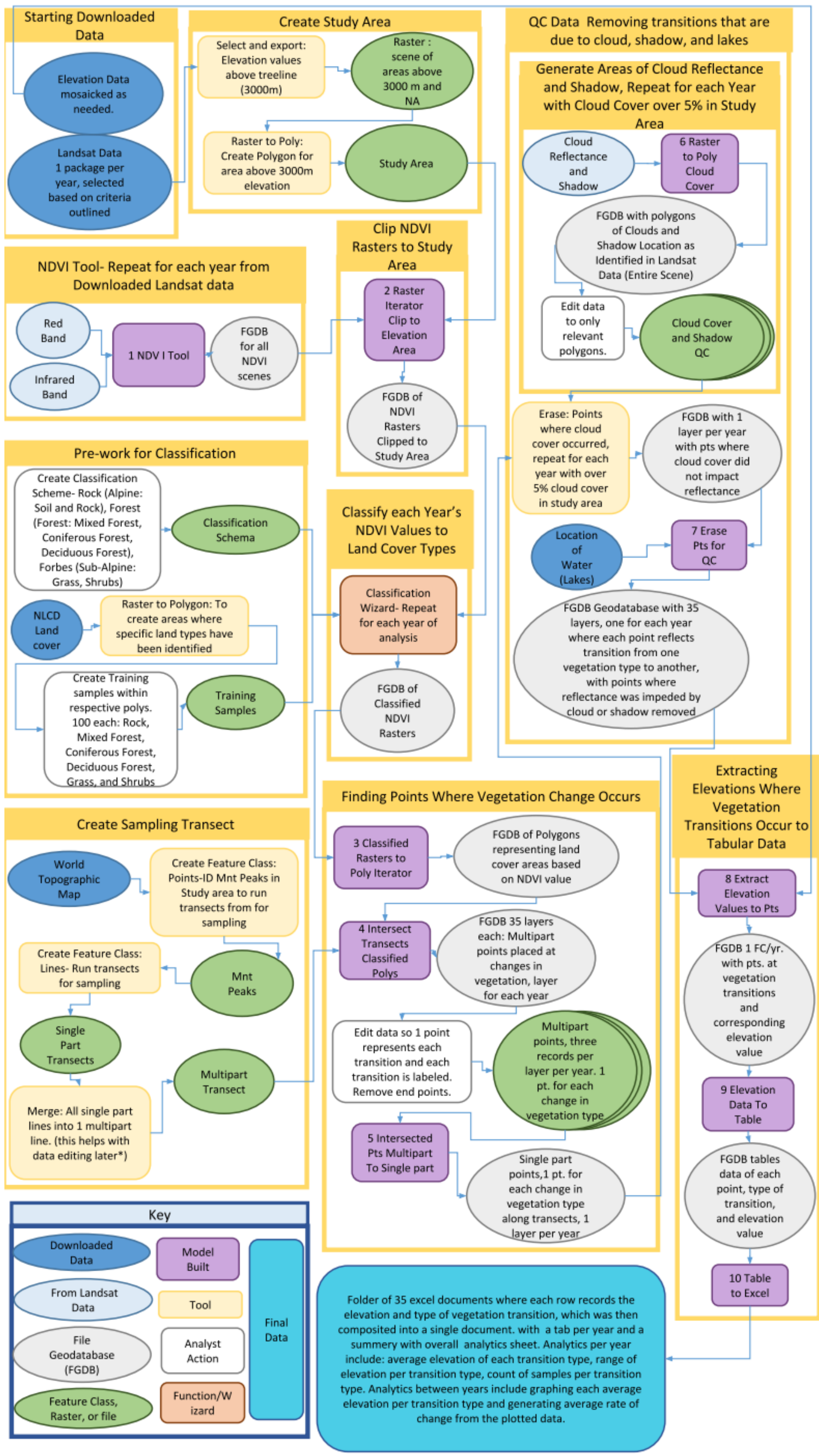



Figure 7. Full Workflow. Entire workflow of project

## 3.2. Classifying NDVI values to Land cover

This section describes the creation and supervised classification of NDVI scenes to land cover type using NLCD and Esri's Classification Wizard. Several intermediate steps are discussed, including a custom NDVI tool, the development of the study area polygon, creation of inputs needed for supervised classification, and the tailored tool to extract NDVI data from scene extent to study area. This section's methods are summarized in Figure 8.

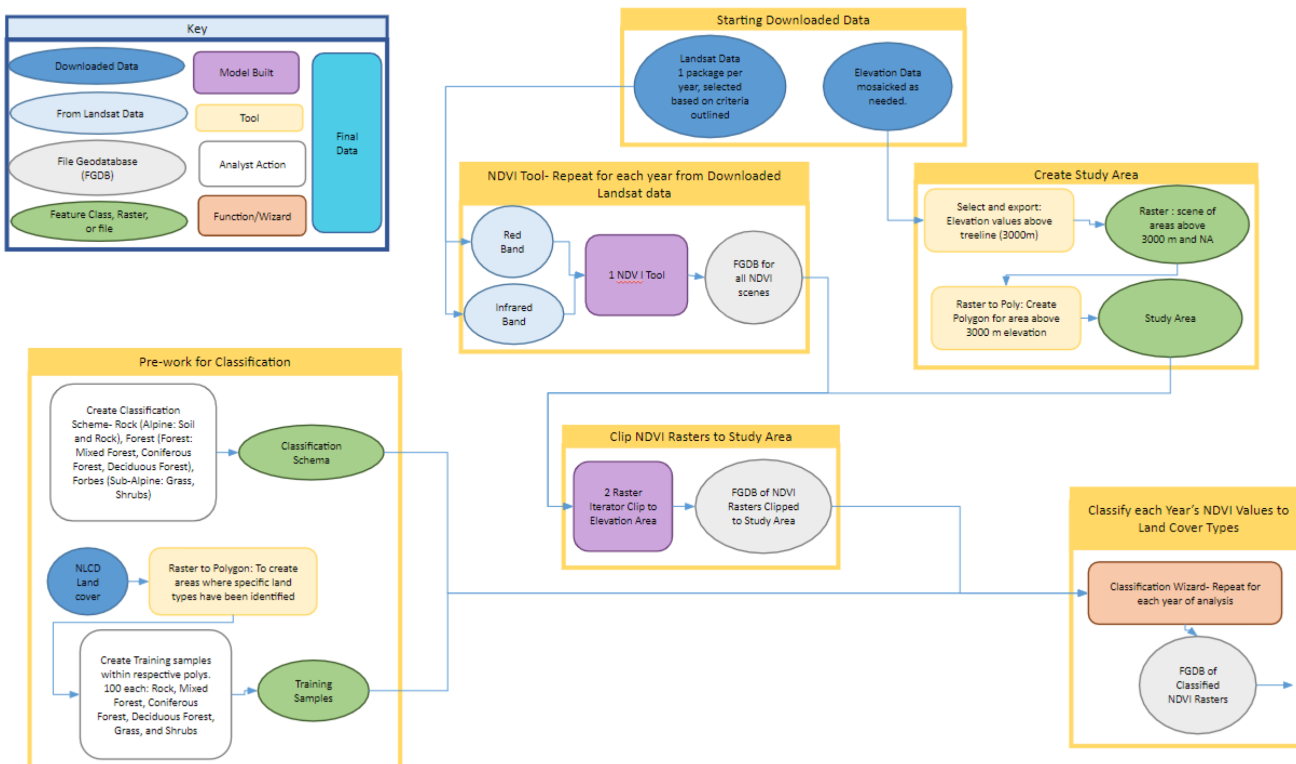



Figure 8. Workflow from downloading data to classified rasters

### *3.2.1. NDVI Tool*

The first step towards generating land cover types from NDVI values was to take the red and infrared bands of each package of Landsat data per year and create a scene of NDVI values by year. Esri's ArcPro has two main methods of doing this. Located in the Raster Function pane, are the NDVI and NDVI Colorized functions. These create temporary layers based off of an input raster that is a composite of the relevant bands. The NDVI function can be manipulated to give scientific outputs, but the NDVI Colorized function applies a color map. Once this color map is used, further classification is not possible, thus for this purpose it was rejected. The NDVI function can work but requires compositing the red and infrared bands into a saved raster, running the function, and then exporting the output to have a scene of NDVI values. The NDVI calculation is a simple function: NIR – red/NIR + red. The solution used in this study was to build a tool with the inputs being the red and NIR bands (as downloaded). The output is then a saved raster of NDVI values in a file geodatabase (FGDB). This tool was built using Raster Calculator (Figure 9).

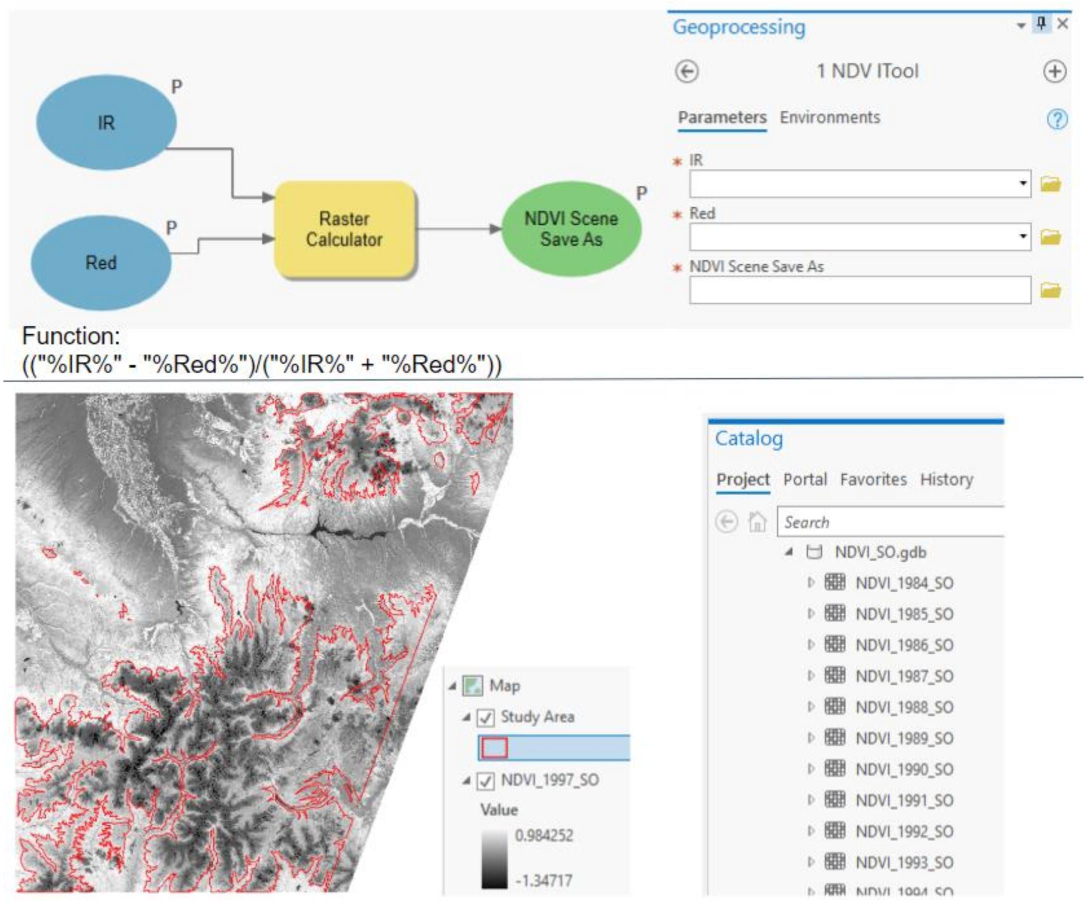



Figure 9. NDVI Tool Model Builder and output

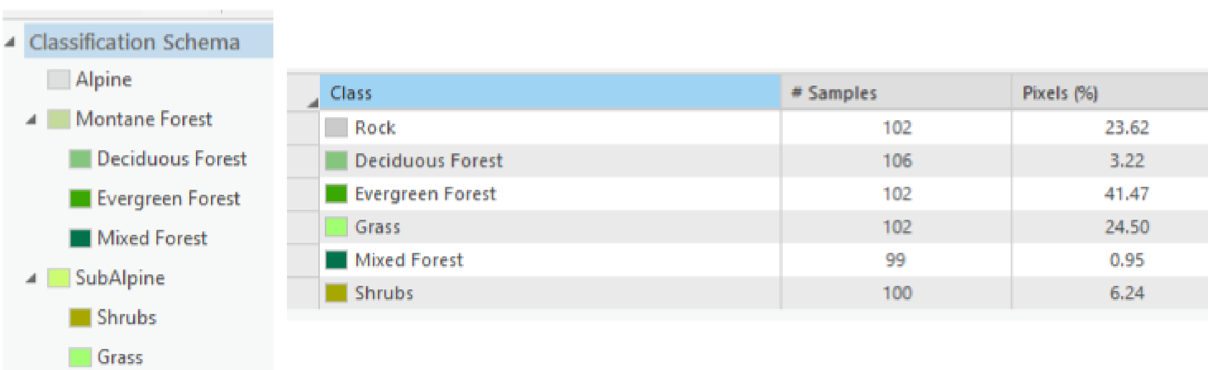
*3.2.2. Create Study Area and Clip NDVI Rasters to Study area*

The study area polygon (Figure 4) was created by utilizing the downloaded and mosaicked elevation data. All elevations above 3000 meters were Selected and Exported. The output was then converted to a polygon using Raster to Polygon. This process created the polygon titled Study Area. An iterator tool was then built called "2 Raster Iterator Clip to Elevation Area". The tool clipped all the NDVI value scenes to the Study Area and saved them to a new FGDB. The input to this tool was the FGDB created for the NDVI tool. The model with the output is shown in Figure 10.


Figure 10. Raster Iterator Clip to Elevation Area tool, model and output.

*3.2.3. Pre Work for Classification*

To use Esri's Classification Wizard in a supervised classification, two inputs are needed in addition to the raster to be classified that was generated in the previous step. Those two other inputs are a classification schema and training samples. The classification schema represents the output classes desired from classification. For this study, the three outputs desired are Montane Forest, Sub-alpine, and Alpine represented by the land cover types of rock/soil, deciduous forest, coniferous forest, mixed forest, shrubs and grass as defined by the NLCD. Classification schema and groupings are shown in Figure 11.




| Class | # Samples | Pixels (%) |
|---|---|---|
| Rock | 102 | 23.62 |
| Deciduous Forest | 106 | 3.22 |
| Evergreen Forest | 102 | 41.47 |
| Grass | 102 | 24.50 |
| Mixed Forest | 99 | 0.95 |
| Shrubs | 100 | 6.24 |

Figure 11. Classification Schema and Sample Training Samples

Training samples were then created from NLCD data. For this study, the raster to polygon tool was utilized to draw training samples within the defined land covered classes. The conversion of land cover to polygons was just a step to make drawing training samples easier; they could be drawn directly from raster data, as seen in Figure 12. Roughly a hundred training samples were drawn per class type, as seen in Figure 11.

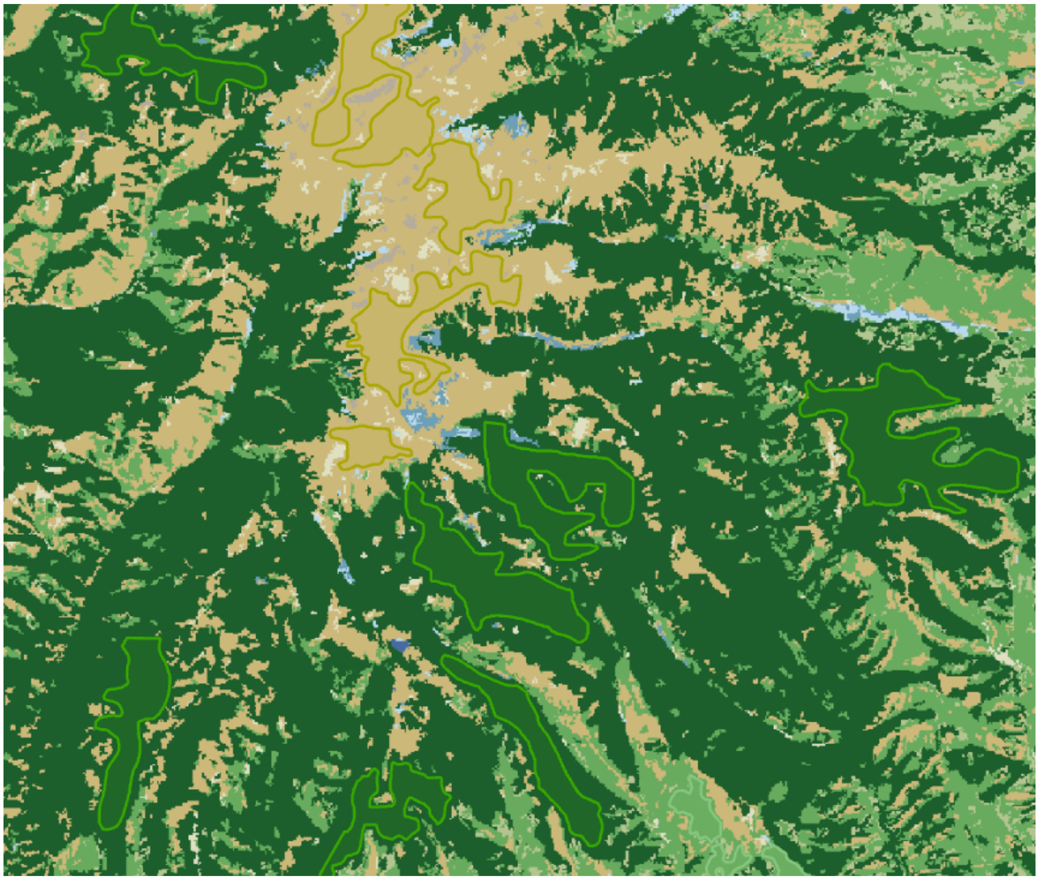


Figure 12 Training samples over NLCD layer.

*3.2.4. Supervised Classification - Classification Wizard*

Once the training samples, classification schema, and NDVI rasters were generated, they were all used to walk through Esri's Classification Wizard. This wizard was run for each year of analysis. The wizard starts with a configure pane. Here the classification method was set to supervised and classification type set to pixel-based. These parameters tell the tool to use the NDVI values of the pixels from the selected raster and classify them to the inputs. These inputs were the classification schema and training samples. The following pane allows for any editing of classification schema but since the one generated in the previous step was saved no changes were made here. The next window of the Classification Wizard is titled Train. Defaults of support vector machine for the classifier parameter and 500 for the maximum number of samples per class were selected. Once run a preview of classification is generated. In the Classify pane, the output was named to reflect the year of the NDVI data. The wizard then allows for a reclassification which is the final output. It was saved in a new FGDB titled Classified, and each layer was named 'Reclassified_%year%'. The '%' allows the computer to read the year from the input file and apply it to the new file's name. The result is classified data that is indicative of biozones based on the NDVI values of vegetation land cover types, as seen in Figure 13.

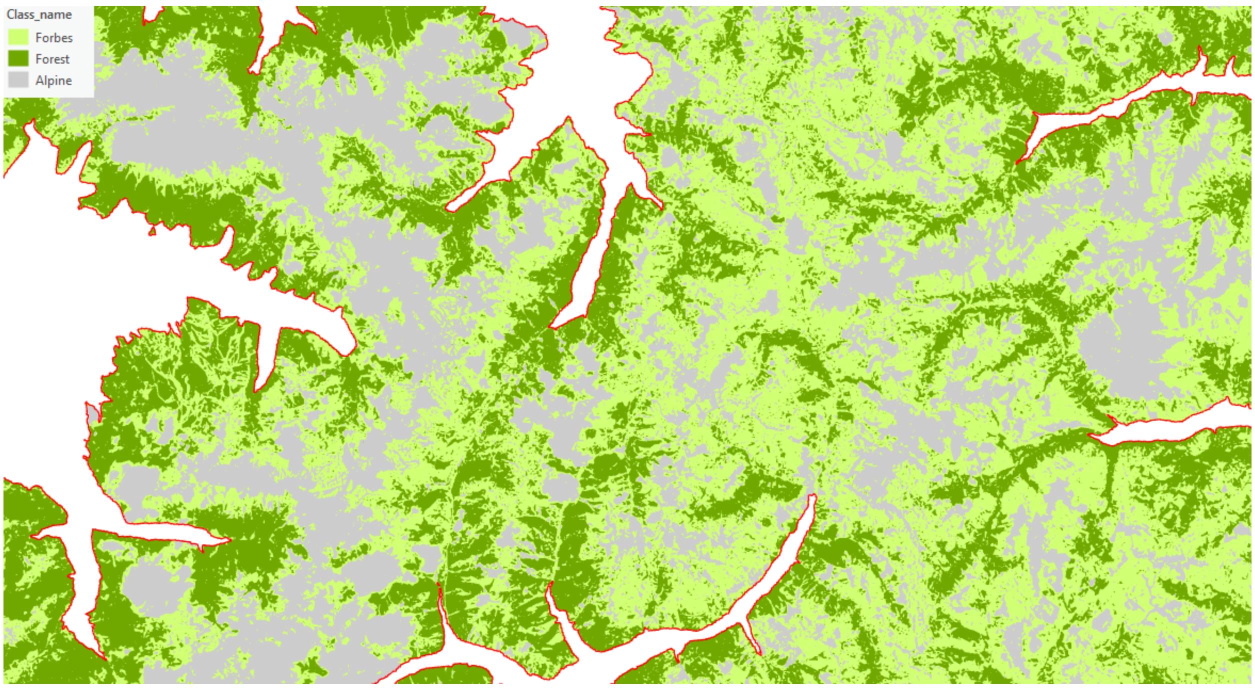



Figure 13. Classified data indicative of biozones based on the NDVI values of vegetation land cover types.

## 3.3. Sampling Techniques

Once an idea of where different biomes began across was established, the elevation as which those transitions occur was extracted. The following steps describe the sampling technique used to answer that question. Scenes with significant (higher than 5%) cloud cover were modified to ensure data quality. This process is described below. The procedures of this section are summarized in Figure 14.

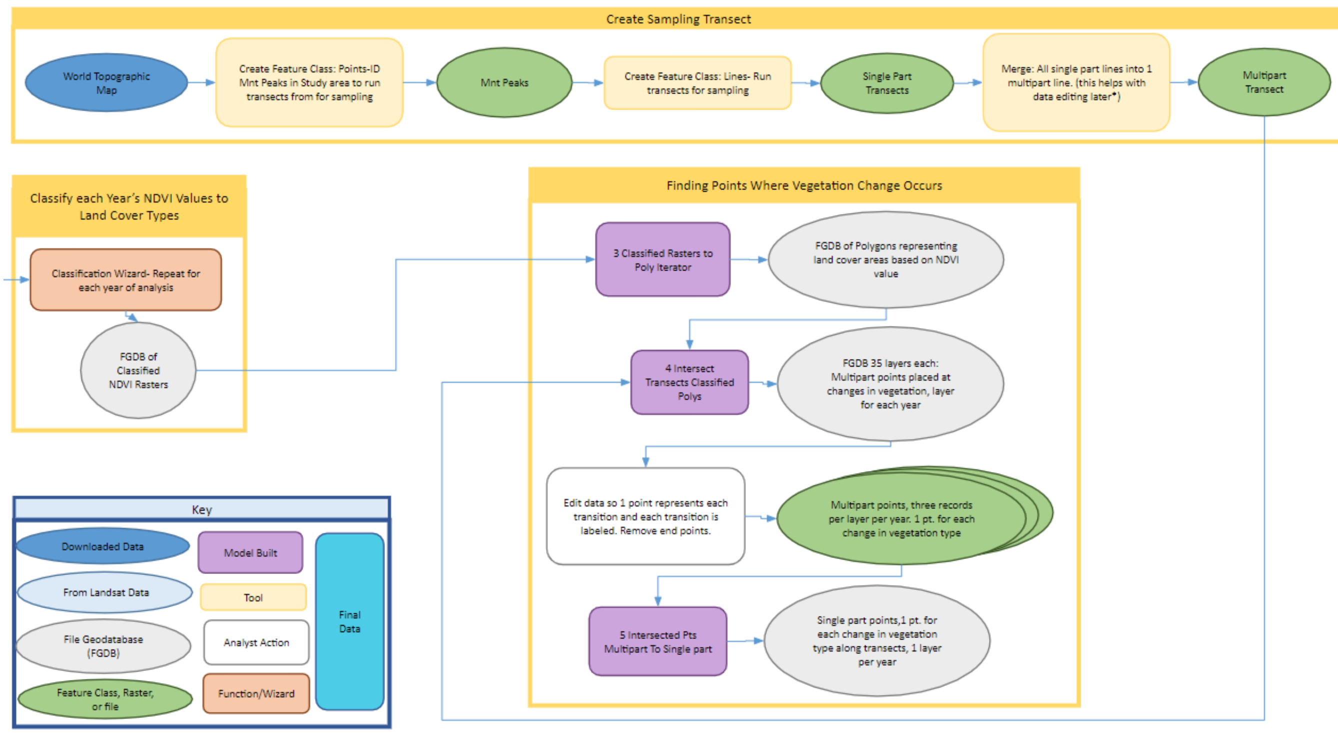



Figure 14. Workflow to generate points where vegetation transitions occur based on classified rasters.

### *3.3.1. Creating Sampling Transects*

Transects are conventional sampling methods when studying mountains and other ecosystems. Transecting is where lines are drawn, and sample points are taken along the lines. In this study, transects were drawn based on two methods: a geologically impacted method and a standard array method (Figure 15). Both ways originated from the 65 peaks located within the study area to ensure the full range of the elevation gradient was sampled. Using Esri's World Topographic Map and the create feature class (points) tool, these 65 peaks were located and labeled. From these peaks, lines were drawn using the create feature class (lines) tool.

Two types of lines were drawn. The geological transect method contained five lines per peak. These lines were drawn from the point of the summit to the lowest elevation areas directly near the mountain, with 3000 m being the preference insofar as it was the study area boundary. This method was similar to transects commonly drawn when ground-truthing methods are utilized. The standard array method was a compass-like star of eight lines radiating from the peak to the study area boundary (set at 3000 m). This method was tried to ensure the full range of elevation was considered. However, this is very much a remote method of sampling as terrain from peak to 3000 m can cover very long distances and have varied elevations in between (Figure 15). It is crucial, however, regardless of how transects are drawn that they are merged into a single multipart feature. A single part feature made data identification and editing later much smoother.

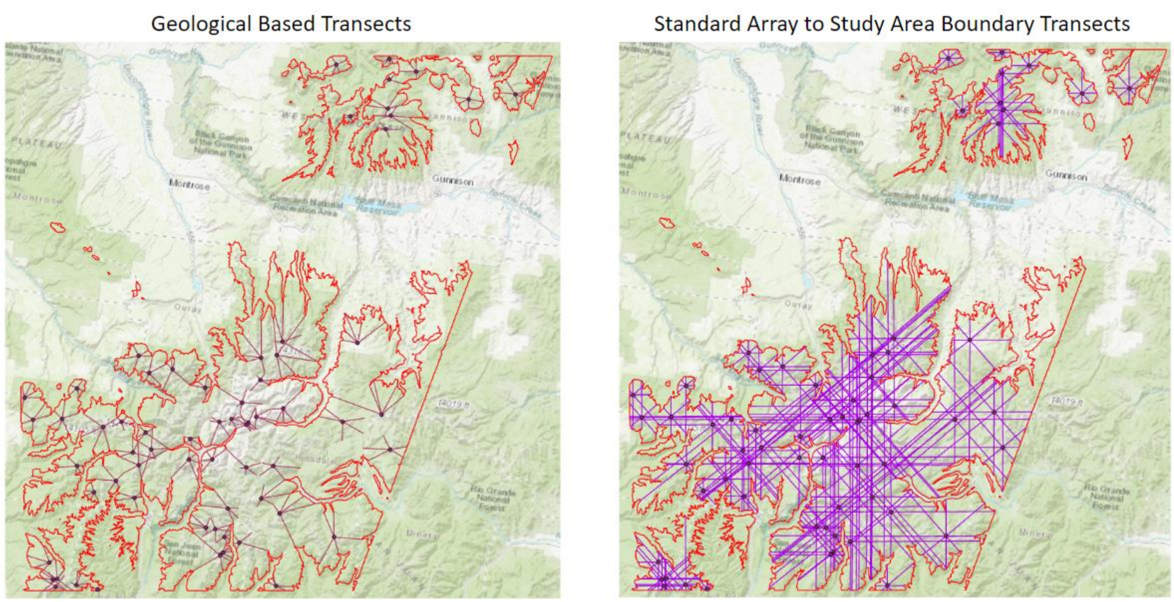



Figure 15. Two types of transects drawn for sampling elevation where vegetation changes occur.

*3.3.2. Finding Points Where Vegetation Change Occurs*

With the creation of classified rasters and transects to sample where vegetation occurs, the procedure can continue to plot the points where vegetation changes occur. The first process is a model that was built for this project titled “Classified Rasters to Poly Iterator”. Like the previous tool, this one is a raster iterator. However, instead following with a clip tool, it followed by a raster to polygon tool. This tool takes the classified rasters and converts them to polygons of land cover type. The input required is the FGDB containing the classified rasters. The output was saved to a new FGDB, here titled “Classified Polys.” This FGDB is then the one input for the next model as well as the transects created in the previous step. The 4th model consists of an iterate feature class and the intersect tool. The output type of the intersect tool was set to point. This step generates 35 point layers, each with nine records. Three records are the endpoints, these are not meaningful changes in vegetation and thus were removed from each layer. The remaining six records comprise 3 pairs of identical points, one labeled for each type of vegetation at the transition. Rename the class name to indicate the ecotone. In this study, R_t_T was used to represent Rock to Forest, later left out of the statistical analysis. Rock to Forest was the smallest grouping, non-existent for several layers, as can be seen in Figure 15. The next record was coded to R_t_G. These points represented a shift from the rock and soil of high alpine to the grasses and forbes of subnival. The final record was renamed to T_t_G. This vegetation transition is where the montane forest gives way to the sub-alpine. The letters stand for rock, trees, and grass for uniqueness and to reduce confusion of forbes to forest.

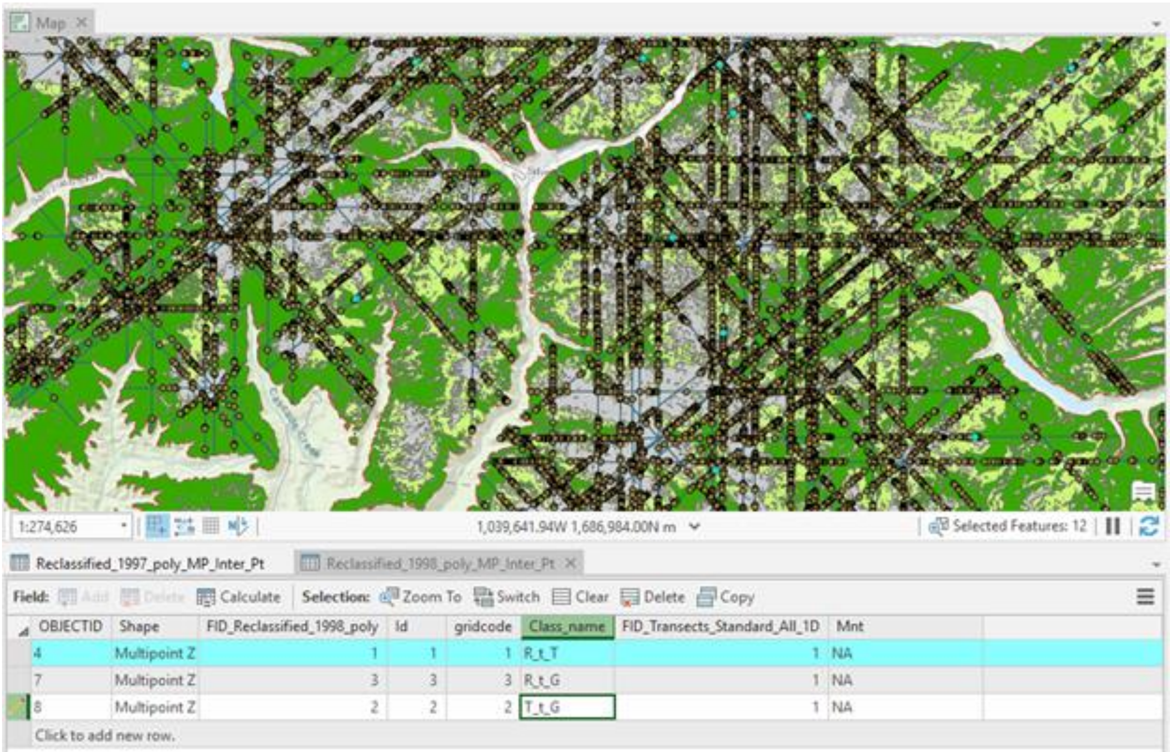



Figure 16. R_t_T, points where vegetation transitioned from rock and soil to forest. Note these are few and far between and not included in final statistics as discussed in section 3.4.

Figure 17. R_t_G, points where vegetation shifts from rock and soil, representing high alpine, to grasses and forbes, representing subnival.

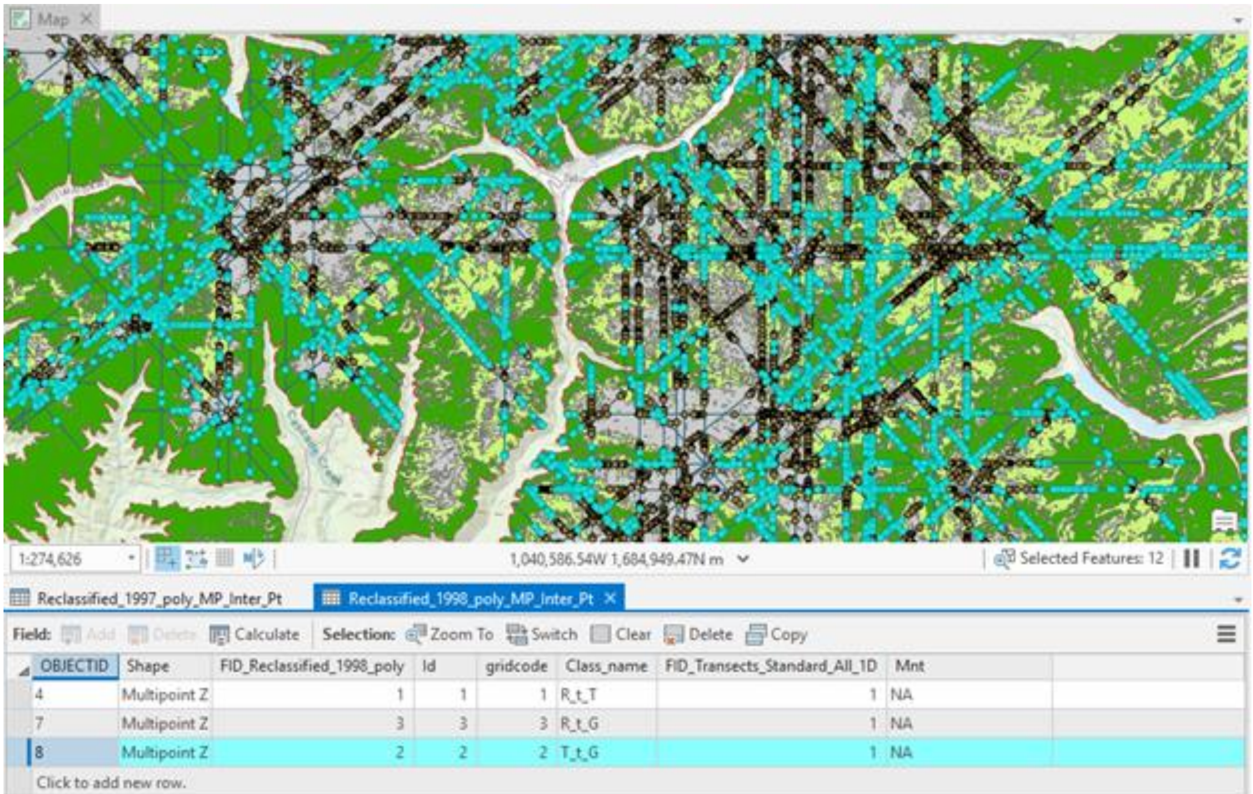



Figure 18. T_t_G, points where vegetation shifts from dense trees, representing montane forests, to grasses and forbes, representing subnival.

Once all layers were focused on relevant points, and those points were clearly labeled, the fifth model was used. The fifth model was a simple feature class iterator with the multipart to single part tool. 35 layers of single part points indicating the location of changes in vegetation were saved in a file geodatabase. For the standard array sampling, approximately 30,000 points were identified per year. Through the geological sampling technique, roughly 8,000 sampling points were generated.

## 3.4. Correcting Data for Quality

Points between classes were identified in the previous section. However, due to cloud cover in 12 of the years, some points were wrongly placed due to inaccuracy in land cover classification. Clouds, water, and shadow all were classified into alpine polygons. The points at these incorrect transitions were removed through the following QC steps. A summary of this and the final processing steps are seen in Figure 19.

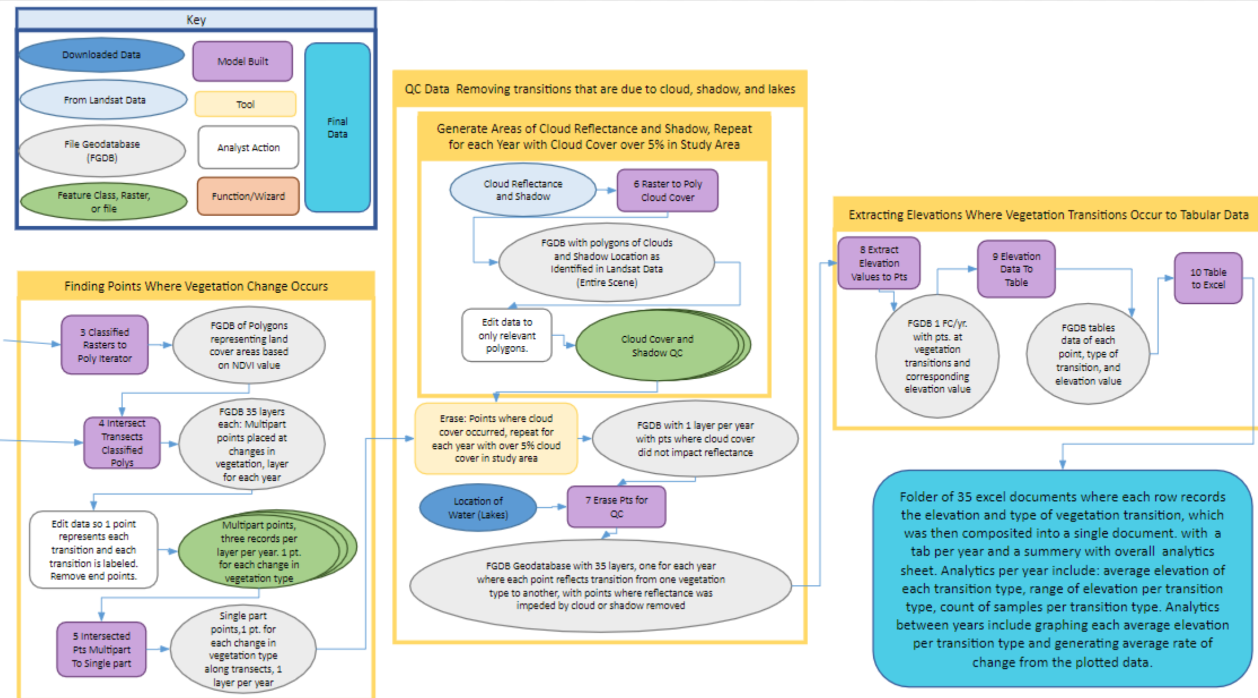



Figure 19. The final steps in the methodology used in this study.

### *3.4.1. Generate Areas of Cloud Cover*

For each year cloud cover was greater than 5% in the study area, an additional step was taken to remove the points that were skewed by the presence of clouds. To locate clouds, the layer representing atmospheric interference from the initial Landsat data download was used. These layers were copied into a FGDB. Then the FGDB was used as an input in the 6th model, a raster iterator with a raster to poly tool. This model created polygons of cloud locations. The resulting data reflected the entire scene. It was then edited to just the relevant polygons, as a general background polygon is included with the initial output. The result is a series of polygon layers locating clouds within the scene. Then for each respective year, the cloud cover polygon was used to erase points that intersected the polygons. This process removed anywhere from approximately 5,000 points (in the standard array sampling) to 10 (in the geological sampling) per year. Once this was done, these point layers replaced the original single part points in the FGDB.

### *3.4.2. QC Data*

The entire database then has a similar process enacted in the 7th model, where the location of water bodies were also erased from all layers. Note that the lakes within the study area are natural. All human-made lakes were lower in elevation; it was assumed that a single layer of lake data was adequate for the temporal scale in this study. This assumption may not be the case if this methodology is applied elsewhere. This process removed roughly 20 points per year — a sample of where the final locations of points are shown in Figure 20.

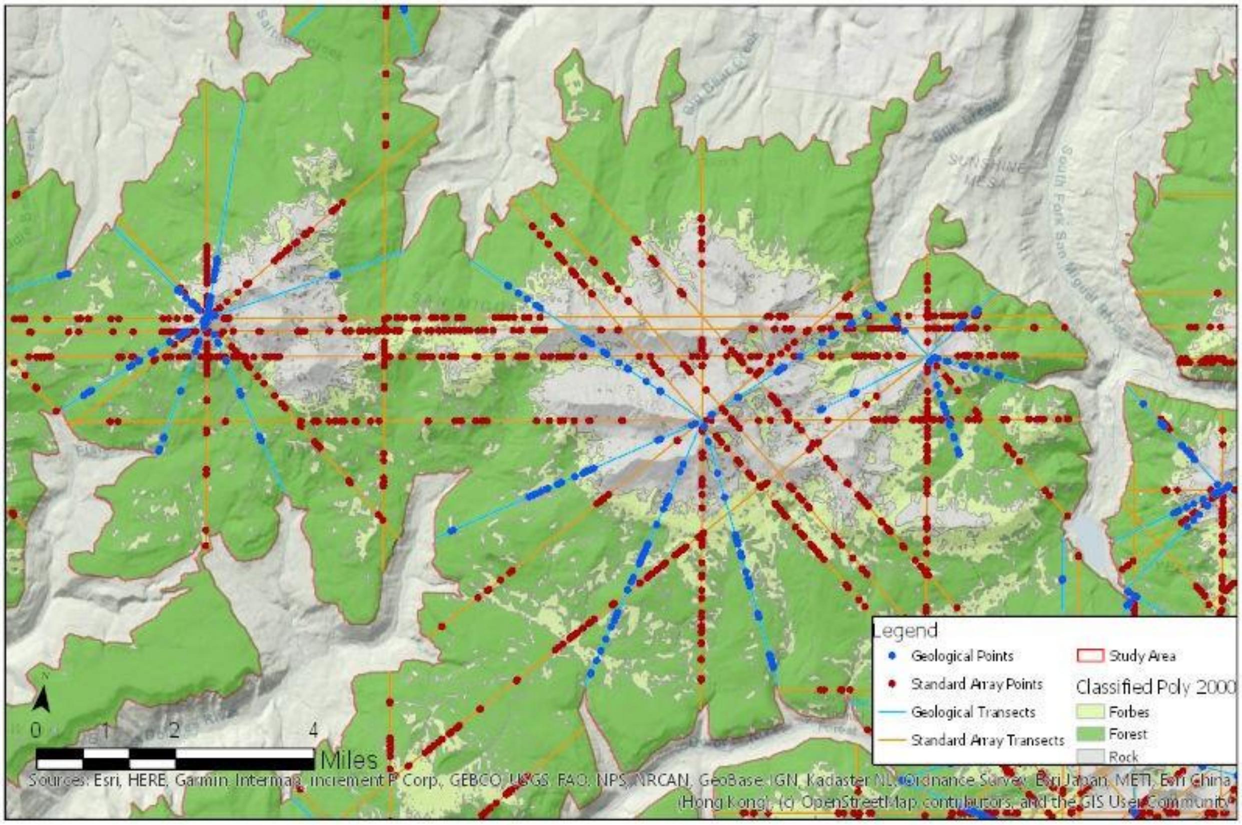



Figure 20. Detailed map of final sampling points as they relate to vegetation classification and elevation featuring both sampling techniques.

## 3.5. Identifying Elevation where Land Cover Shifts

Once the final points were confirmed, the next steps aimed to investigate the elevations at which the vegetation types shifted. This data was extracted through the points from the original elevation layer then exported to excel sheets to allow for final statistical analysis. Three models were built and later combined for a cleaner workflow (Figure 21).

### *3.5.1. Extracting Elevations to Tabular Data*

To gain table data that recorded the type of vegetation shift, as well as the elevation at which it occurs, a series of models were built and later worked into a single model. This model consisted of an iterate feature class to read each layer in the FGDB where final point data was saved. The first tool each layer underwent was an extract values to points. The values were from the original elevation data. This generates a point layer with vegetation shift and elevation values in the attribute table. This attribute table is then copied to just table data through the copy rows tool. Finally, an Excel spreadsheet was created per year with all the tabular data using the table to excel tool. The full process of this model is shown in Figure 21. For ease of calculations, these excel documents were then combined into a single document with a tab per sheet and a cover sheet to compare yearly data. All steps mentioned in this section were repeated for each sample type.

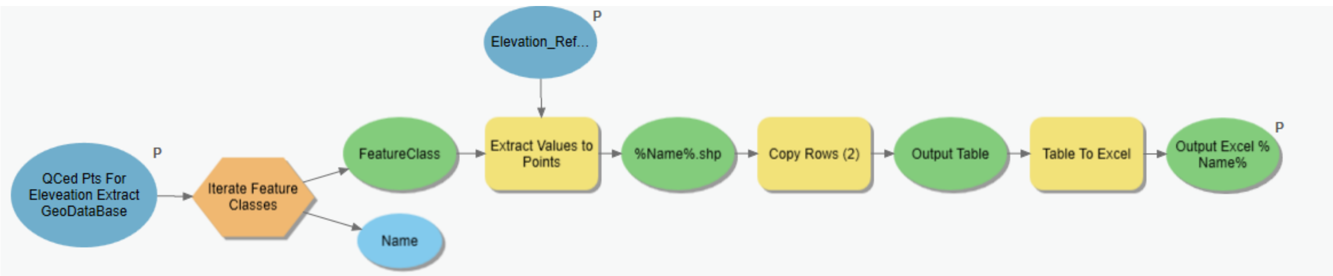



Figure 21. Extracting elevation values by identified points and exporting to Excel.

## Chapter 4 Results

This project was undertaken to investigate if the demonstrated methodology could discern a change in the elevation at which biomes occur. Two sampling techniques of classified data were used. The average elevation per vegetation transition was calculated for each year. The averages were then plotted, and a trend line was generated as seen in Figures 22, 23, 24, and 25. Through geological sampling, the transition between alpine and subalpine did show a positive trend (m= 0.18) with an average elevation overall of 3673 m and a range of 152 m. The transition between montane forests and subalpine showed a negative shift (m= -0.14) with an average overall of

3390 m and a range of 182 m. Through standard array sampling, the transition between alpine and subalpine showed a negative trend (m= -.23) with an average elevation of 3687 m and a range of 130 m. The transition between montane forests and subalpine showed a negative shift (m= -0.09) with an average overall of 3433 m and a range of 183 m. However, the r-squared values indicates these trends are inclonclusive in nature. The possible reasons for this result are expanded on in the disscussion.

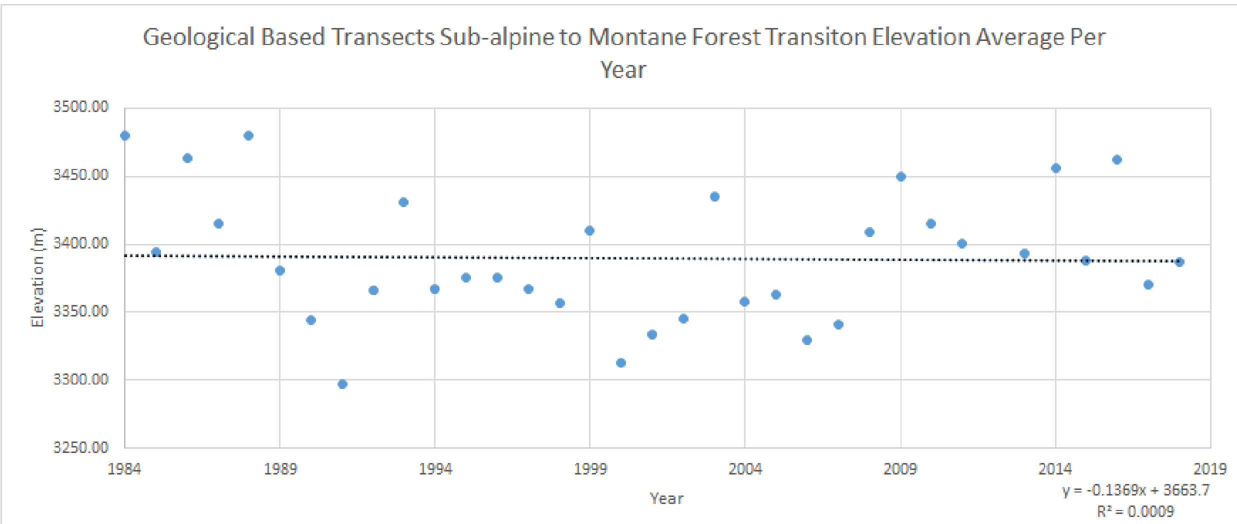



Figure 22. Geological transect results of alpine to subalpine transitions average elevations per year.

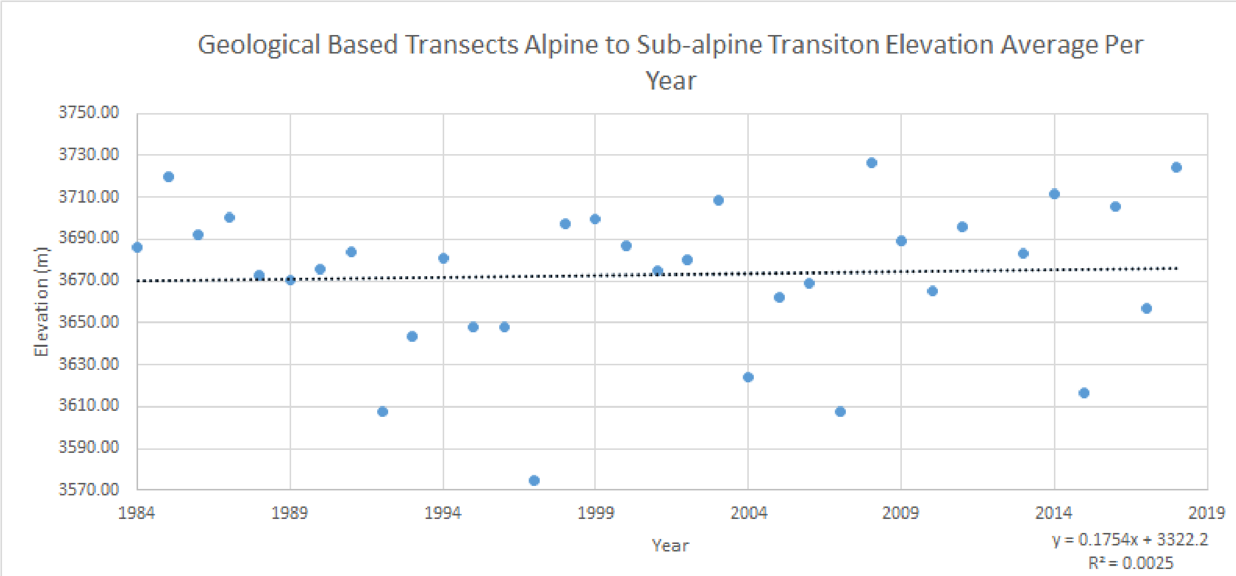



Figure 23. Geological transect results of subalpine to montane forest transitions average elevations per year.

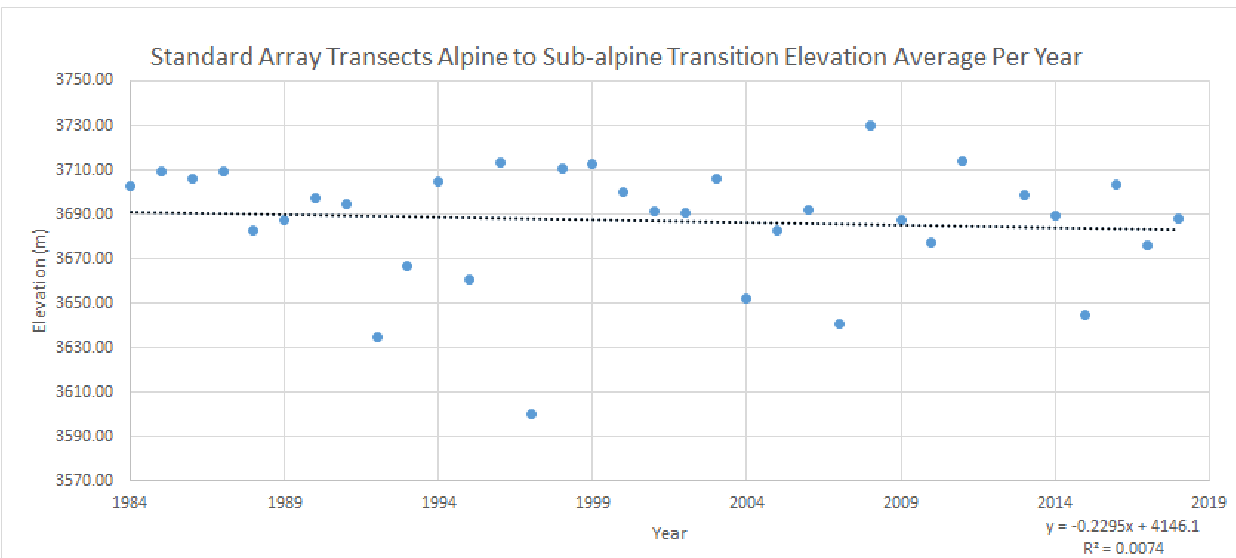



Figure 24. Standard array transect results of alpine to subalpine transitions average elevations per year.

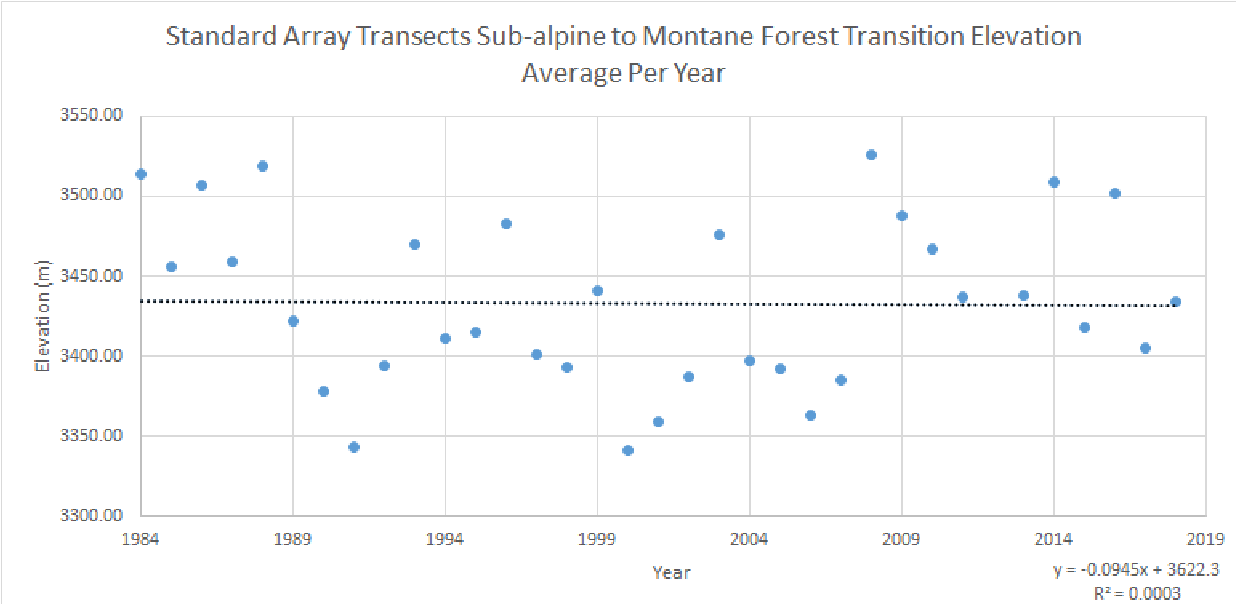



Figure 25. Standard array transect results of subalpine to montane forest transitions average elevations per year.

# Chapter 5 Discussion

There are several findings of this study that merit discussion, namely what the results seem to imply. Also, how and why different sampling techniques arrived at different conclusions is considered. This relationship between this study and related literature is also reviewed. Further research is discussed.

## 5.1. Result Implications

Overall the results don't suggest a significant trend in changes where the alpine ecozones occur. There were slight changes from the alpine to subalpine. However, it is indicated that this is not a reliable trend to fully support a claim. In the geologically based sampling type, this did indeed show grasses occurring at higher elevations in the later years of the study. This trend was expected. However, when sampling from 3000 meters and up to the peaks, the averages fell slightly. The likely reason for this result is the nature of sampling points spread across the landscape. Perhaps vegetation changes were not as focused on the edges of the biozones. Instead, they reflected the patchy quality between bare soil and grasses throughout high elevations. It is evident when examining the results of classification that, while imperfect, the ecozones are present. Perhaps a further refinement of polygons less than an established area (i.e., 1 km) could clean up points that are not impacted by elevation. It was interesting to note how rarely rock and soil transitioned directly to the forest. The rarity of this occurrence seems to indicate that the methods were successful in mapping where ecozones occur.

In both sampling techniques, there is very little change as to where treeline occurs. The lack of change at the scale of this study was expected, with the possibility of a shift as trees are longer lived than grasses, and the forest is more resistant to incremental changes. An investigation could look at the health, population, and size of trees along the border of treeline to determine if the edge is thriving and in a pre-establishing phase before new forest reaches into higher elevation. Such a study, however, would not be possible strictly through NDVI value classification but may be partially or fully possible through the use of LiDAR.

There are several other possible reasons for the inconclusiveness of the sampled data. It could be the change this study is aimed at is not as evident in the San Juan Mountains as the literature shows happening elsewhere. It could also be that the change in elevation at which ecozones occur may not be captured in 30 meter data within the time frame studied. Temporal scale may also not be ideally focused to capture any changes that are happening at this study site. Perhaps a longer study with the same resolution or a shorter study with a finer resolution would indicate clearer ecological results. These are questions of the ecological shift happening and to what extent as well as resources used in the methodology. The location of the ecozones was successful however.

## 5.2. Improving Upon Methods

Areas of the methodology that could be improved focus mostly on the scale, both temporal and geographic, resolution, and classification. In regards to scale, this could easily be adjusted to either smaller, single-peak focused sampling, similar to many ground-based studies. It would require, however, much higher resolution satellite data, which would limit the temporal scale. Or an even larger geographical scale may be appropriate when focused on different alpine areas, such as the Himalayas perhaps.

Like most studies that utilize satellite data, a call for higher resolution data will always refine findings. Higher resolution means more precise values and location of vegetation. In time this is likely to become possible; however, the temporal scale will always be limited by the availability of original high-resolution data. A comparison between this study and a high-resolution analysis may offer further insight into the precision and margin of error resulting here.

Finally, there is room to investigate a more refined classification. This study used a supervised classification method with a schema and classes based on identified land cover types that were related to reflect the ecosystems within they occur. An unsupervised classification could be as accurate and less time consuming since this study observed that the relevant vegetation types could be determined based on their NDVI values. While vegetated vs. non-vegetated is expected to be indicated in NDVI, it was not clear before the study if forest and subalpine vegetation could be distinguished. It was found that they could. The nature of a forest to have denser vegetation on a 2D plane that is captured by the satellite. The 2D plane concept is because the satellite is reading light reflectance. This light is being reflected off of plant matter.

As light hits grass, there is less than a meter of vegetation, making it likely some light will reflect from the surrounding soil. The forest contains a full canopy which intercepts light. The reflectance is captured from a 2D plane through the lens onboard the satellite. However, the error within classification could be more clearly understood through further study.

## 5.3. Comparing to Other Studies

In this study, the ecotones, the edges of the ecozones, had shifted slightly. Given the solid argument for an upward shift in ecotones from the literature, this minimal movement was unexpected. However, one sampling did show a small change, and the literature does imply this is the expected result. There was some discussion within the literature that mentions that the ecotone between forest and grassland less likely to show significant shifts (Young 2006). It was considered that the resilience of the vegetation within a forest would resist environmental changes. The observed minor changes to treeline in this study seem to confirm this assessment.

# Chapter 6 Conclusion

With the rising temperatures associated with global climate change, observing the changes to landscapes is vital in understanding the impacts of this change. The alpines offer a unique ecosystem that is found worldwide with distinct vegetation patterns through elevation gradients (Negay 2009). It has been observed that as temperatures rise, grasses are finding conditions at higher elevations conducive to growth where before conditions were too harsh (Jurasinski 2007). A method of utilizing remote sensing technology, classification of NDVI values into land cover classes, and transect sampling techniques was conducted in this study. It aimed to help provide a way to observe these changes through with readily available data throughout a region. It was found that classifying land cover from NDVI values was possible to locate the ecotones of the alpines from Landsat data (Pattorelli 2011). A positive trend was observed through localized transect method per peak. This trend shows that grasses were occurring at higher elevations in the later years of the study. There was a negative trend through a standard array sampling from peak to 3000-meter elevation, regardless of terrain throughout the transect. However in both cases the numbers didn't show it to be significant. The inconclusiveness of this study is attributed to scale of data, temporal scale and the possible lack of such extravagant change at the study area. The classification methodology for locating the ecozones of the alpines was successful however. In both cases, 65 peaks were used, and there was not a significant change in the elevation is which treeline occurred. In the event, an upward trend occurs, there are likely to be a loss of alpine area and the biodiversity associated with that habitat loss (Jurasinski 2007). These areas are imperative to the fauna and flora that live there as well as the role they play in water systems. Given the importance of these biomes, it is important to develop a way of tracking these changes. This study is a step in that direction. By classifying and thus remotely locating where these biomes occur the changes through time can be observed. As higher resolution data becomes more generally available the approach presented becomes more capable of showing significant as well as subtle shifts.

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