DEVELOPING REMOTE SENSING METHODS FOR BEDROCK MAPPING OF THE FRONT RANGE MOUNTAINS, COLORADO

by
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ABSTRACT

The Colorado Front Range Mountains have a history of significant debris flow hazards capable of causing losses to both property and life. The flash floods in Larimer, Boulder, and Jefferson Counties exhibited this when a storm event on September 9-13, 2013 triggered over 1,138 debris flows in the Colorado Front Range leading to eight fatalities and causing damage to buildings, highways, railroads, and infrastructure. Following this event, the U.S. Geological Survey (USGS) studied the debris flows that were triggered by the rainstorm with the intention of modeling debris flow susceptibility in this region.

The objective of this project is to assist in constraining the susceptibility modeling by creating and executing a methodology for using existing remote sensing technology to map bedrock outcrops. Calibrating against six smaller study areas that span different geologic formations and ecoregions of the Front Range Mountains, the goal was to produce a map of exposed bedrock outcrops over nine, 7 ½ minute quadrangles that encompass portions of the St. Vrain and Big Thompson watersheds. The benefit of using remote sensing is the ability to map the bedrock exposures in a time-efficient and cost-effective manner for a significantly sized area of interest.

The primary purpose of this thesis project is to: (1) develop a land cover classification methodology capable of discriminating bedrock and colluvium and (2) compare the classification accuracy of each individual remote sensing method to select the best land cover classification method. Through the use of imagery data sets from the multispectral Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS); the high resolution hyperspectral imagery from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor; and the Advanced Land Observing Satellite’s (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) sensor, four methods were employed to attempt mapping bedrock outcrops. These methods included unsupervised classification, supervised classification, supervised classification with iterative unsupervised classifications, and sequential land cover classification.

The sequential land cover classification method yielded the best overall results producing the highest sensitivity (user accuracy), precision (producer accuracy), and $F_1$ measure for the classification of Bedrock and Colluvium. The highest observed agreement (observed accuracy) an overall method was generated by the sequential classification scheme (77.72%). Considerable difference between the performance metric values for the bedrock and colluvium land cover classes versus all other land cover classes remains quite significant. Further research should be conducted to examine combining existing passive remote sensing methods with active remote sensing methods to map bedrock outcrops.
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For Kathryn, Henrik, & Alfred
CHAPTER 1
INTRODUCTION

The flash flood from storms during September 9-13, 2013 resulted in numerous debris flows in the Colorado Front Range (Coe et al., 2014). In the months that followed, the United States Geological Survey (USGS) studied the debris flows that were triggered by the rainstorm by identifying and mapping these hazards in the St. Vrain and Big Thompson watersheds.

The flooding and debris flows from the September 2013 rainfall event led to fatalities; damage to homes, buildings, roads, and infrastructure; and disruption to the local economy. A debris flow susceptibility map for the Colorado Front Range Mountains could provide an understanding of areas vulnerable to debris flows. An improved understanding of debris flow susceptibility could result in: improved county zoning; the identification of slope mitigation methods, potential slope stabilization methods, and on-going monitoring for potentially unstable slopes; disaster management and planning for emergency services; and development of early-warning systems for residents near potential debris flow areas.

One of the attempted products of the debris flow research conducted by the USGS was to develop a model for debris flow susceptibility for the region. The preliminary susceptibility map that was developed included areas of exposed bedrock in regions that were modeled to have high susceptibility. Since the exposed bedrock areas are not potential debris flow source areas, the regions of exposed bedrock included in the susceptibility map need to be accounted for to better constrain the debris flow hazard. The primary goal of this thesis project is to map exposed bedrock within nine, 7 ½ minute quadrangles in the St. Vrain and Big Thompson watersheds that experienced debris flows resulting from the September 2013 rainfall event.

1.1 Statement of Purpose

The primary purpose of this thesis project is to: (1) develop a land cover classification methodology capable of discriminating bedrock and colluvium and (2) compare the classification accuracy of each individual remote sensing method to select the best land cover classification method.

Given the size of the area of interest, it is not viable to field map exposed bedrock outcrops for the entire region. To accomplish mapping of the area of interest, remote-sensing methods were selected to identify bedrock outcrops. The benefit of using remote sensing is to map the bedrock exposures in a time-efficient and cost-effective manner for a significantly sized or inaccessible area.

Methods for mapping bedrock outcrops were carried out using imagery from the multispectral Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). These methods included:

- Unsupervised Classification
- Supervised Classification
- Supervised Classification with Iterative Unsupervised Classification
Higher spatial and spectral resolution, hyperspectral imagery from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor and the Advanced Land Observing Satellite's (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) sensor were also used to create an integrated methodology for land cover classification, i.e. sequential land cover classification.

1.2 Scope of Research

The scope of this project is to develop an integrated remote sensing approach to predict the location of bedrock outcrops in a nine-quadrangle area spanning Boulder County and Laramie County in the Front Range Mountains of Colorado. The primary deliverable for this research project is a land cover classification map capable of discriminating bedrock and colluvium for the nine-quadrangle area of interest. Both optical and radar remote sensing platforms were used and the methods employed range from single step procedures to those that integrate multiple methods to establish a land cover classification that can identify outcrops of bedrock and colluvium. The remote sensing methods were assessed by examining the classification accuracy and deriving a land cover classification map from the most accurate method.
CHAPTER 2
BACKGROUND

This chapter discusses background data that is pertinent to this study and consists of three main parts. This includes discussing the rainfall event that resulted in numerous debris flows; an examination of the area of interest and field study area with respect to geology, ecology, and hydrology; and a literature review of remote sensing approaches for land cover mapping that could be utilized to design a unique approach for mapping bedrock and colluvium.

2.1 September 2013 Rainfall Event

In September 2013, an unusual weather event in the Colorado Front Range resulted in record-breaking rainfall, flooding, and numerous debris flows. While large September rainfalls are rare along the Colorado Front Range, unique meteorological conditions resulted in a multi-day rainfall event. These conditions included a Southwest monsoon, a region of low pressure that captured the tropical air mass over the region, and weak southwesterly winds (Walsh, 2013). While the affected areas included large portions of Larimer, Boulder, and Jefferson Counties, Boulder, Colorado experienced heavy, record-breaking rainfall and flooding (Coe et al., 2014). The rainfall began on Monday, September 9th and continued to Friday, September 13th, 2013 with a record-breaking daily rainfall amount of 9.08 inches falling between 6 PM on Wednesday, September 11th and 6 PM on Thursday, September 12th (Brennan & Aguilar, 2013). The Boulder area, which typically receives 1.7 inches of rain during September (Walsh, 2013), received a record-breaking 17.59 inches of rain during September 2013 (NOAA).

On September 12th Boulder Creek crested at 7.78 feet, which was the highest water level recorded in the area since 1894 (Scott, 2013). While the flooding event was initially sensationalized as a 1,000-year flood event, in reality, the flood that occurred in Boulder in September 2013 had a much higher probability of occurring. Estimates following the flood by John Pitlick of the University of Colorado found the flood to be between a 25- and 50-year flood event (Walsh, 2013). The rainfall event on the other hand was significantly rarer than the flooding event. Russ Schumacher of Colorado State University concluded that the precipitation in Boulder County and surrounding Colorado counties qualified as a 1,000-year rainfall event (Scott, 2013).

Aside from the flooding, another major impact of the precipitation was the numerous debris flows that occurred. High rainfall totals throughout the St. Vrain watershed resulted in saturated ground conditions causing stream channels to build in volume and carry a heavy sediment load (Williams & Chronic, 2014). The September 2013 rainfall event caused at least 1,138 rainfall-triggered debris flows, that in combination with the flooding resulted in extensive damage to buildings, highways, and infrastructure (Coe et al., 2014). The flooding and debris flows resulted in eight deaths (three directly from debris flows), 125 destroyed homes, 3,773 damaged homes, and many major canyon roads being closed until the end of November 2013, resulting in disruption to transportation, local economies, and tourism (Coe et al., 2014).
2.2 Area of Interest

The project location is an area that encompasses nine, 7-½ minute quadrangles in Boulder County and Laramie County, Colorado (Figure 2.1). This area of interest was selected as it includes the St. Vrain Watershed and Big Thompson Watersheds that experienced the highest amounts of rainfall during the September 2013 rainfall event. The region is both geologically and ecologically diverse. Site geology varies from uplifted, steeply dipping sedimentary bedrock to metamorphosed, intrusive igneous bedrock that comprises the Front Range Mountains. Significant topographic relief from the east to west sides of the area of interest has provided a number of different ecoregions ranging from the high Alpine Zones along the Continental Divide to the Foothill Shrublands and Front Range Fans at the lower elevations.

Figure 2.1 Nine Quadrangle Area of Interest
2.3 Geology

The area of interest is geologically diverse containing igneous-intruded metamorphic bedrock, uplifted sedimentary bedrock, and Quaternary depositional and erosional features due to glaciation and stream flow (Figure 2.2).

The oldest rocks in the area of interest were formed approximately 1.7 billion years ago and are comprised of metasedimentary rock, amphibolite, various schists, and gneiss. Igneous rocks of similar age consist of tonalite, quartz diorite and hornblendite, gabbro and pyroxenite, Trondhjemite of Thompson Canyon, and the Boulder Creek Granodiorite (Colton, 1978; Gable, 1980; Braddock et al., 1988; Punongbayan et al., 1989; Gable & Madole, 1976). The schist and gneiss were likely composed of a combination of metamorphosed volcanic and sedimentary rocks that comprised an ancient island arc and were deposited prior to 1.7 billion years ago (Gable, 1980; Williams & Chronic, 2014). Younger Precambrian bedrock includes 1.4 billion year old coarse-grained pegmatites, mafic dikes, intrusion breccia, granite aplite, leucogranite, garnet-sillimanite granite, Gabbro of the Iron Dike, Granite of Hagues Peaks, and the Silver Plume Quartz Monzonite (Colton, 1978; Punongbayan et al., 1989; Braddock & Cole, 1990). The metamorphic Precambrian rocks were likely to have been laid down as sediments, on an ancient seafloor before being deeply buried resulting in metamorphism (Runnells, 1976). Granitic intrusions were formed when magma was injected into these metamorphic rocks during mountain building events. This includes the formation of the granite batholith of the 1.4 billion year old Berthoud Plutonic Suite (Williams & Chronic, 2014).

During the Paleozoic Era, starting about 600 million years ago, ocean waters deposited sands, and lime muds over the eroded surfaces of Precambrian rocks resulting in the formation of sandstone and limestones (Runnells, 1976). Beginning approximately 300 million years ago during the Pennsylvanian period, the Ancestral Rocky Mountains were uplifted and formed (Runnells, 1976). The uplifted Precambrian rock was then eroded forming the iron oxide stained, interstratified arkosic conglomerate and feldspathic sandstone of the Fountain Formation (Colton, 1978). A lowering of sea levels resulted in an arid, desert climate that produced vast sand dune deposits (Runnells, 1976). These well-sorted sands formed the quartzose sandstone of the Lyons Formation (Colton, 1978).

During the Mesozoic, the Boulder area saw the deposit of soft muds and silts along broad, flat floodplains. These silts and muds formed the main constituents of the Lykins Formation (Runnells, 1976). The Lykins Formation consists of multiple members containing shales, siltstones, and limestones (Colton, 1978). Floodplain geomorphology again existed in the Late Jurassic resulting in the deposition of the Morrison Formation which is comprised of marly shale, silty limestone, sandstone, and marlstone (Colton, 1978; Runnells, 1976). Approximately 135 million years ago at the beginning of the Cretaceous Period, the presence of the sea resulted in the deposit of the Dakota Group. During the remainder of the Cretaceous Period, the rise and fall of the sea level resulted in the deposition of several sedimentary units suggestive of sandy beach, shallow sea, deep sea, and coastal swamp depositional environments (Runnells, 1976). These include the Mowry Shale, Graneros Shale, Greenhorn Limestone, Carlile Shale,
Between 72 and 40 million years ago during the Cenozoic, the Laramide Orogeny or uplift of the present day Rocky Mountains occurred, during which the Fountain Formation and overlying sedimentary rocks were pushed and faulted upward along the eastern edge of the area of interest (Williams & Chronic, 2014). Intrusion of magma during this period resulted in the deposition of various minerals and metallic ores in fractures among the bedrock of the present day Front Range Mountains (Runnells, 1976). In the area of interest, this includes intrusions of sills and dikes of rhyodacite, basalt, and dacite during the Paleocene; quartz monzonite, quartz syenite, feldspar syenite, limburgite, biotitic hornblende latite, granodiorite and felsite during the Eocene; and andesite, granodiorite, monzonite, rhyolite, granite, quartz latite, and basalt during the Oligocene (Colton, 1978; Gable, 1980; Braddock et al., 1988; Braddock & Cole, 1990).

Erosion and transport of bedrock during the Quaternary resulted in the formation of numerous alluvial deposits. The presence of numerous glacial and interglacial periods during the Pleistocene shaped the valleys in the western edge of the area of interest by the Continental Divide. Floods of meltwater from the glaciers quickened the pace of erosion that formed the numerous Quaternary-aged deposits in the area of interest (Runnells, 1976).

### 2.4 Ecology

The diverse geology and significant topographic relief across the east-west of the area of interest has produced unique ecological conditions. Five distinct ecosystems (see Figure 2.3) can be defined based on the Environmental Protection Agency’s (EPA) Ecoregions of Colorado (Chapman, et al., 2016). These ecoregions were established based on the spatial composition of various phenomena including: geology, physiography, vegetation, climate, soils, land use, wildlife and hydrology (Omernik & Griffith, 2008). The different ecoregions in the area of interest were examined to ensure that land cover in each unique ecoregion was used as training samples for land cover classification and accuracy assessment.

#### 2.4.1 Front Range Fans

The Front Range Fans ecoregion is defined by streams that are typically cooler with numerous Front Range aquatic species. Given the proximity to the mountains, the soils tend to have more outwash gravels than in areas to the east. The ecoregion’s geomorphology is comprised of terraces, benches, and alluvial fans. Soils are formed from weathered parent rock that includes arkosic sedimentary rocks, gravelly alluvium, and red-bed shales and sandstones. Over time, land use has shifted from agricultural cropland and rangeland to more urban-use as a result of Front Range development and sprawl. As a consequence of this development there has been an increase in the number of gravel pits and anthropogenic lakes in this area (Omernik & Griffith, 2008).

#### 2.4.2 Foothill Shrublands

This ecoregion marks the transition from the drier, lower elevation Great Plains ecoregions to the higher elevation forests of the Colorado Front Range Mountains. In geomorphological terms, this semiarid...
Figure 2.2 Geology of area of interest with field study areas shown (base credits: Stoeser et al., 2005)
region is characterized by rolling to irregular hills, ridges, and foot-slopes. The Foothill Shrublands are typically located between elevations of 6,000 to 8,500 feet. Flora is primarily comprised of sagebrush and mountain mahogany shrubland, pinyon-juniper woodland, and scattered oak shrublands. Aside from shrubs, regions of blue grama, Junegrass, and western wheatgrass can be found. Land use is primarily agricultural in nature, ranging from livestock grazing to harvesting hay crops in areas that can be irrigated (Omernik & Griffith, 2008).

2.4.3 Crystalline Mid-Elevation Forests

Crystalline Mid-Elevation Forests are an ecoregion that is typically found between 7,000 and 9,000 feet on the eastern half of the Southern Rocky Mountain Range. Vegetation including aspen, ponderosa pine, Douglas-fir, lodgepole pine, and limber pine that are located above crystalline and metamorphic bedrock. Additionally, smaller vegetation including shrubs, grasses, and wildflowers can grow in some areas. The forests in this ecoregion are becoming extremely dense due to decades of anthropogenic control of wildfires. This ecoregion supports a variety of land uses including wildlife (bird and mammal) habitat, livestock grazing, logging, mining, recreation, and residential areas (Omernik & Griffith, 2008).

2.4.4 Crystalline Subalpine Forests

Above the Foothill Shrublands and Crystalline Mid-Elevation Forest the higher elevation Crystalline Subalpine Forests can be found. This ecoregion exists between 8,500 and 12,000 feet and are most extensive on the northern aspects of mountain slopes. The forest vegetation is dominated by Englemann spruce and subalpine fir with pockets of aspen and lodgepole pine. Meadow regions may exist between forested areas as well. Vegetation at this elevation has been impacted by blowdown, insect outbreaks, wildfires, avalanches, and mass movements. Soils consist of weathering byproducts from gneiss, schist, granite, and igneous intrusive rock. The presence of a nearly annual snowpack limits the land used of this area to wildlife habitat, logging, mining, and recreation (Omernik & Griffith, 2008).

2.4.5 Alpine Zone

In the area of interest, this ecoregion extends from the treeline at about 10,500 to 11,000 feet to the peaks of mountains. The area is characterized by alpine meadows and steep exposed rock. Due to the high elevations, annual precipitation varies between 35 inches to more than 70 inches and is therefore a major source of water for lower elevation, semi-arid to arid regions. Vegetation consists of low shrubs, cushion plants, wildflowers, and sedges in wet meadows. The transition between forests and alpine areas demarked by stunted and deformed Englemann spruce, subalpine fir, limber pine, and bristlecone pines. Given the inaccessibility of this ecoregion, land use is limited to wildlife habitat and recreation (Omernik & Griffith, 2008).

2.5 Watersheds

The area of interest contains two major watersheds (Figure 2.4). The southern two-thirds of the area contain the St. Vrain Watershed while the northern third of the area of interest contains the Big Thompson Watershed. Both of these watersheds are similar in that they have major precipitation source
Figure 2.3 Ecoregions in AOI based on EPA's *Ecoregions of Colorado* with field study areas shown.
Figure 2.4 Hydrology showing boundary between two major watersheds in area of interest
areas high in the mountains along the Continental Divide and transition down to more semi-arid, lower elevation regions containing vegetation ranging from grasslands and shrubs to ponderosa pine and Douglas-fir forest (Natural Resources Conservation Service, 2010).

For both watersheds, the temperatures can vary widely, with temperature increases and the difference between daily minimum and maximum temperatures increasing as one descends in elevation. The majority of precipitation falls in the mountain regions of the watersheds during the winter and spring months. Subsequent snow melt provides high flow to the St. Vrain and Big Thompson and their tributaries during the spring and summer months (Murphy, 2006). During these months, precipitation occurs as frontal storms (spring) or high intensity, convective thunderstorms (summer) (Natural Resources Conservation Service, 2010). Discharge will vary dependent on the depth of the snowpack and air temperature. Low flow conditions exist during the fall and winter months when runoff from precipitation and meltwater is low (Murphy, 2006).

The overall semi-arid climate of the region means that droughts can frequently impact these watersheds. Since 1900, five major droughts impacted these watersheds, including droughts in: 1) the 1910s, 2) the 1930s during the dust-bowl era, 3) the second worst drought in Colorado history during the mid-1950s, 4) the late 1970s, and 5) the drought beginning in 2002. The 2002 drought was the most severe drought in Colorado since 1723, though dendrochronology has revealed the many severe, multi-year droughts have occurred in the two watersheds prior to the 1700’s (Natural Resources Conservation Service, 2010).

2.6 Field Study Areas

Field areas were selected to provide a range of land cover classification from which training samples would be extracted. These field study areas were then used as: (1) training samples to develop remote sensing methods for classifying the overall area of interest and (2) areas to assess the classification accuracy of the predictive land cover classification methods. Areas were recommended by Rex Baum (USGS) and Jeff Coe (USGS) who provided a list of regions that contain representative bedrock exposures and that experienced debris flows as a result of the September 2013 rainfall event. Consequently, these field study areas spanned a variety of geologic, ecologic, and geographic settings, thereby establishing diversity in the land cover training sample data set.

Boundaries for the six field study areas were based on the location, size, and distribution of bedrock outcrops; the location of debris flows; and the overall accessibility of the site (Figure 2.5). Since all of these areas experienced debris flows as a result of the September 2013 rainfall event, the primary consideration in defining the field study area boundaries was site accessibility. Five of the six field study areas were accessible by publicly maintained trails. The sixth area was on private property but could be remotely viewed from along the side of publicly maintained roads surrounding the site. All six field study areas featured significant outcrops of bedrock that would be used as training samples.
2.6.1 **Blue Lake/Mitchell Lake**

This field study area is located 5.7 miles west of Ward, CO and contains outcrops of alpine bedrock interspersed among large areas of colluvium. The area is located within the Brainard Lake Recreation Area that is maintained by American Land & Leisure under a special use permit from the U.S. Forest service. Parking at the Mitchell Lake Trailhead allowed for access to the field study area via a network of trails.

Bedrock in the area consists of Laramide Intrusive Rocks (TKi), and Granitic Rocks of 1,400 MY (Yg). Ecologically, the Mitchell Lake study area is located in the Alpine Zone and Crystalline Subalpine Forest ecoregions (see Figure 2.3).

2.6.2 **Twin Sisters Peak**

The trailhead is located along CO-7, 7.1 miles south of Estes Park, CO adjacent to Lily Lake Visitor Center. This area experienced a significant debris flow that crosses the west end of the field study area and destroyed a portion of the trail. The peaks feature numerous bedrock outcrops surrounded by colluvium and densely forested slopes.

The bedrock is composed of Biotitic Gneiss, Schist Migmatite (Xb) and Granitic Rocks of 1,400 MY (Yg). The ecoregion is a combination of Crystalline Subalpine Forests and Crystalline Mid-Elevation Forests.

2.6.3 **North St. Vrain**

Parking for the trailhead is located 3.0 miles east of Allenspark, CO along Taylor Mountain Road. A U.S. Forest Service road allowed access to a couple of vantage points to view the south-facing slope of Deer Ridge where the field study area is located. The field study area features numerous outcrops of bedrock and debris flow scars.

Exposed bedrock consists of Granitic Rocks of 1,400 MY (Yg). The field study area is located within the Crystalline Mid-Elevation Forests.

2.6.4 **Porphyry Mountain**

This field study area is located immediately north of Jamestown, CO along James Canyon Drive. The field study area is located on private property but can be viewed from various public streets in Jamestown as well as from Boulder County Road 87J.

The field study area was impacted by Four-Mile Canyon Fire in 2010. Bedrock outcrops consist of igneous Laramide Intrusive Rocks (TKi). Ecologically, the field study area is located within the Crystalline Mid-Elevation Forests ecoregions.

2.6.5 **Hall Ranch Open Space**

The Hall Ranch Open Space Park is located 1.5 miles southwest of Lyons on CO-7. The network of maintained Open Space trails provides direct or indirect access to numerous outcrops within the field study area. A few debris flow scars are also visible within the boundary of the field study area.
Figure 2.5 Field study areas (hatched) within area of interest (red)
Hall Ranch contains numerous bedrock types including the Granitic Rocks of 1,400 MY, the Ingleside Formation, and the Fountain Formation. The field study area is located within the Foothill Shrublands ecoregion.

2.6.6 Mount Sanitas

Mount Sanitas is located within Boulder County Open Space that is situated on the west side of Boulder, CO along Sunshine Canyon Drive. The study area contains numerous trails that allow access to the valley bottom and various bedrock outcrops along the hogback.

Geologically, this study area contains numerous steeply dipping bedrock units including the Dakota, Morrison, and Sundance Formations (Klds), the Colorado Group (Kc) and the Lykins, Lyons, and Fountain Formations. The study area is located within the Foothill Shrublands and the Crystalline Mid-Elevation Forests ecoregions.

2.7 Past Research

In examining remote sensing methods to distinguish bedrock from colluvium, it is important to understand the engineering geological difference between bedrock and colluvium. Bedrock, for the purpose of this research, is considered to be an “aggregate of mineral particles connected by strong cohesive forces” that usually form a continuous system (Vallejo & Ferrer, 2011). Colluvium on the other hand is the product of in situ weathering of rocks that are then transported by gravity, freeze-thaw action, and by water. Colluvium can be considered potentially unstable as its “strength is low, especially in contact with the underlying rock, or when high pore pressures develop as a result of rain” (Vallejo & Ferrer, 2011).

Literature review of various journals has revealed that no direct optical or radar remote sensing method exist for the expressed purpose of differentiating bedrock from colluvium. While no direct method exists for this purpose, numerous methods do exist that could be adapted in a classification scheme to delineate zones of bedrock from colluvium:

**Composite Images**

Dehnavi et al. (2010) used Landsat ETM+ imagery to explore epithermal mineral deposits by detecting hydrothermal alteration zones in Iran. Zones of high, medium, and low degree hydrothermal alteration were identified using color composites of ETM+ bands RGB (7,5,1), RGB (7,4,1) and RGB (b1-b2, b4-b2, b5-b7). The color composite of bands 5, 3 and 1 produced the best combination of bands for identifying and discriminating areas of hydrothermally altered rock.

Lorenz (2004) used Landsat TM bands 7, 4, & 3 in the high arctic region of Northern Canada to differentiate between bedrock and soil. The RGB (7,4,3) band combination was also able to distinguish sedimentary and igneous units.

**Band Ratios**

Literature review has shown that band ratios have been used to produce index-derived images by dividing land cover into three components—impervious surface material, green vegetation, and exposed soil—to allow for the mapping of urban areas by selecting NDBI (Normalized Difference Build-up Index),
SAVI (Soil Adjusted Vegetation Index) and MNDWI (Modified Normalized Difference Built-up Index) (Xu, 2007). Xu (2007) showed that comparing this method to principle component analysis and maximum likelihood supervised classifications, a higher accuracy can be achieved with the combined NDBI, SAVI, and MNDWI methods.

Deng et al. (2015) developed the Ratio of Normalized Difference Soil Index (RNDSI) while creating an approach to enhance soil information in Landsat TM imagery. To accomplish this, Deng et al. randomly selected trainings samples in three major land cover types: soils, impervious surface areas, and vegetation. The resulting RNDSI was the ratio of the Normalized Difference Soil Index (NDSI) using Landsat TM bands 7 and 2 and the first component of a tasseled cap transformation.

Yue et al. (2013) used imagery from the multispectral ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) and hyperspectral Hyperion satellites to estimate karst rock desertification in a karstic ecosystem. To accomplish this, areas of photosynthetic vegetation were estimated using a Normalized Difference Vegetation Index Spectral Mixture Analysis (NDVI-SMA) model, while areas of visible bedrock were estimated using a Karst Rocky Desertification Synthesis Index (KRDSI) and Lignin Cellulose Absorption (LCA) index were used to estimate visible bedrock. The study concluded that hyperspectral imaging allowed for more accurate classification of rock and vegetation. Also improved accuracy was achieved by segmenting the imagery into relatively homogenous sections.

**Classification**

Southwork (1985) used a combination of Landsat Multispectral Scanner (MSS) imagery and laboratory tested spectra of field samples to differentiate lithologic units in bedrock and surficial deposits in Antarctica. Quaternary surficial deposits were difficult to discriminate from bedrock since the surficial deposits were derived from the same parent materials.

Rencz et al. (2000) also used land cover classification as a means of bedrock mapping in the Canadian Arctic. Using Landsat TM imagery and topographic data, statistical analysis of the individual variables at14 training sites with different bedrock types was used to highlight any potential differences between the bedrock classes. The highest classification accuracy was achieved when Landsat TM imagery was combined with topographic information.

Leverington and Moon (2012) compared Landsat TM and EO-1 Hyperion data to create remote sensing products capable of discriminating soil and bedrock. Their results revealed that the hyperspectral data set (EO-1 Hyperion) provided the best classification results when the imagery sets were compared to linearly unmixed ground-truth spectra. It was concluded that ground reflectance data gathered in the field was crucial in creating methods to discriminate geological land cover classes with Landsat TM data.

Landsat TM and SPOT panchromatic data were used by Mickus and Johnson (2001) to build a geological map of the Petrified Forest National Park. Using a maximum likelihood supervised classification approach, the method was able to discriminate between sedimentary and volcanic bedrock.
**Integrated Methods**

Crowley et al. (2003) used hyperspectral optical imagery to remotely evaluate altered rock masses that could become potential source areas for volcanic debris flows on Mount Shasta and the Shastina cones. Using NASA’s aircraft-based Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) and the satellite-based EO-1 Hyperion imaging spectrometer, Crowley et al. (2003) were able to identify areas of hydrothermally altered rocks. Field samples of altered rock were collected and the reflectance for each sample was measured using a visible to short-wave infrared (0.4 – 2.5 µm) laboratory spectrometer. Using the remote sensing imagery and digital elevation data sets to examine the mineralogy, spatial extent, and local slope conditions, researchers were able to identify potential volcanic debris flow source areas.

Inzana et al. (2003) combined Landsat TM and radar JERS-1 SAR (L-band) imagery in Madagascar to create a structural geology map. The first of three methods the authors used included the use of Landsat TM band ratios 5/7, 5/1, and the product of 5/4 and 3/4 to create a false color image. Band 5/7 was used to emphasize pelitic schist, band 5/1 highlighted mafic igneous rock, and the product of band ratios 5/4 and 3/4 was used to discriminate mafic from non-mafic rocks. This method has an accuracy of 89.3%. The second method replaced band 5/7 with the L-band radar imagery which had been useful in distinguishing granite, granodiorite, diorite, and serpentinite, but had a similar classification accuracy of 89.0%. The final method selected nine classes of cover and proceeded to perform a supervised classification of the 5/7, 5/1, product of 5/4 and 3/4 band ratios and the L-band radar imagery. This result provided the highest classification accuracy at 91.2%.

Boettinger et al, (2008) used the short-wave infrared (SWIR) bands of Landsat ETM+ imagery, to discriminate soils and parent materials. The research also found that multiple layers of band ratios, data layers, digital elevation models, and normalized difference ratios could be stacked to create a supervised and unsupervised classification of an area of interest.
CHAPTER 3
LAND COVER CLASSIFICATION METHODS

Approaches for developing land cover classification methods capable of discriminating bedrock and colluvium were devised by following a multistep procedure. The following sections will outline these steps in detail but broadly this included the acquisition of remote sensing data; preliminary site mapping and field verification; examining existing and developing new approaches for land cover classification; and devising a means of comparing the land cover classification accuracy for each method.

3.1 Remote Sensing & Image Preprocessing

To carry out the land cover classification and discriminate between bedrock and colluvium, both active and passive remote sensing methods were employed. This included the use of Landsat-8 OLI/TIRS, Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), and Phased Array type L-band Synthetic Aperture Radar (PALSAR).

3.1.1 Landsat-8 OLI/TIRS

The primary active sensor that was employed was Landsat-8, which was formerly known as the Landsat Data Continuity Mission, and is a collaboration between the U.S. Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA) (NASA, 2016). Launched on February 11, 2013, Landsat-8 carries a pair of sensors including the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) (U.S. Geological Survey, 2013). The OLI is a multispectral, along track scanner that collects data from the visible, near-infrared, and shortwave wavelengths (Table 3.1) (NASA, 2016). The TIRS was included on Landsat-8 to continue thermal imaging and support emerging scientific applications. Thermal imagery from Landsat-8 was not employed for this project due to the 100 m spatial resolution of the data being considered too coarse for bedrock outcrop mapping.

Landsat-8 scenes were found using the U.S. Geological Survey’s Global Visualization Viewer (glovis.usgs.gov), which is an online tool that allows for spatial and temporal searches for downloading imagery from a variety of sources. Given the relatively large 16-day temporal resolution of the Landsat-8 spacecraft, Landsat imagery for the area of interest was selected with an emphasis on finding data that met as many of the following criteria as possible:

- Snow-cover should be limited over the area of interest;
- Cloud-cover should be limited over the area of interest; and
- Imagery should be acquired from after the rain storm event, i.e. post-September 2013.

Consequently, given these criteria, the availability of imagery was significantly limited. The criteria for limited snow-cover was viewed as the most important since the western-edge of the area of interest extended to the Continental Divide where the elevation reaches to greater than 4,000 meters (~13,000 feet) and a great deal of bedrock outcrops and colluvium exist. These areas experience significant snow- and ice-cover during the majority of the year so selection of imagery was limited to
months when snow and ice would be limited at higher elevations or about from late-June into late-October.

Table 3.1 Landsat-8 OLI/TIRS band spatial resolution and spectral width (NASA, 2016)

<table>
<thead>
<tr>
<th>Landsat-7 ETM+ Bands (µm)</th>
<th>Landsat-8 OLI and TIRS Bands (µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30 m Coastal/Aerosol 0.435 - 0.451</td>
</tr>
<tr>
<td>Band 1 30 m Blue</td>
<td>30 m Blue 0.452 - 0.512 Band 2</td>
</tr>
<tr>
<td>Band 2 30 m Green</td>
<td>30 m Green 0.533 - 0.590 Band 3</td>
</tr>
<tr>
<td>Band 3 30 m Red</td>
<td>30 m Red 0.636 - 0.673 Band 4</td>
</tr>
<tr>
<td>Band 4 30 m NIR</td>
<td>30 m NIR 0.851 - 0.879 Band 5</td>
</tr>
<tr>
<td>Band 5 30 m SWIR-1</td>
<td>30 m SWIR-1 1.566 - 1.651 Band 6</td>
</tr>
<tr>
<td>Band 6 60 m TIR</td>
<td>100 m TIR-1 10.60 – 11.19 Band 10</td>
</tr>
<tr>
<td></td>
<td>100 m TIR-2 11.50 – 12.51 Band 11</td>
</tr>
<tr>
<td>Band 7 30 m SWIR-2</td>
<td>30 m SWIR-2 2.107 - 2.294 Band 7</td>
</tr>
<tr>
<td>Band 8 15 m Pan</td>
<td>15 m Pan 0.503 - 0.676 Band 8</td>
</tr>
<tr>
<td></td>
<td>30 m Cirrus 1.363 - 1.384 Band 9</td>
</tr>
</tbody>
</table>

Further confounding the acquisition of quality Landsat imagery was the fact that during the summer months there tended to be clouds covering the area of interest when the Landsat imagery was taken. This was due to the prevalence of afternoon rain and thunderstorms during the late-spring and early-summer in Colorado’s Front Range Mountains and the fact that the available Landsat imagery of this area is acquired once per month in the mid- to late-afternoon during the summer.

In accordance with these criteria, three Landsat image sets from September 2013 (post-rainfall), July 2014, and September 2014, were downloaded. The September 2014 Landsat image set fit the overall criteria the best with limited snow-cover and a small set of clouds in the south-west quadrant of the area of interest. Using the ArcGIS10.3 software suite, the cloud-covered regions were removed from the primary image set and replaced with imagery extracted from the September 2013 image set. The result of this image manipulation was a composite image of the 11 bands captured by Landsat-8.

3.1.2 Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)

To carry out the land cover classification and discriminate between bedrock and colluvium, a hyperspectral imaging source was also employed. The active sensor that was used was NASA’s aircraft-based Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) that carries a hyperspectral optical sensor that samples continuously through 224 bands of the visible, near-infrared, and short-wave infrared spectra (0.360 to 2.500 µm) (Jet Propulsion Laboratory, 2015). Data was acquired from the Jet Propulsion Laboratory (JPL) website and a series of nine scenes were downloaded. These AVIRIS scenes were acquired August 7, 2011. Although the imagery was captured prior to the September 2013
rainstorm event, the availability of hyperspectral imagery was limited and the aircraft-based AVIRIS sensor combined hyperspectral imaging with higher (10 m) spatial resolution that cannot be found on similar satellite-based sensor platforms.

Preprocessing involved using ENVI 4.7 software to allow for use in ArcMap 10.3. Preprocessing included converting the digital numbers (DN) for each image to at-satellite radiance values. With AVIRIS imagery, this was accomplished by dividing the DN for each band by a correction factor given in the GAIN file associated with each downloaded scene. Next, the various scenes were combined in ENVI using the mosaic function. This provided a pair of GeoTIFF images—one containing the original DN values and a second containing the at-sensor radiance values. These images had a spatial resolution of approximately 10 meters.

Using the training samples that were obtained during preliminary mapping and field checking of the study areas, a graph was created displaying the spectral radiance curve for each of the land cover types that would be included in the land cover classification. This was accomplished by using the Classification toolbar in ArcMap 10.3 and creating a signature file for each of the land cover classifications. For each land cover type, the signature file calculated the average spectral radiance that was observed in each of the 224 bands of the AVIRIS imagery.

3.1.3 Phased Array type L-band Synthetic Aperture Radar (PALSAR)

The active sensor used in this land cover classification was the Phased Array type L-band Synthetic Aperture Radar (PALSAR) carried on the Japanese Aerospace Exploration Agency’s Advanced Land Observing Satellite (ALOS). A single scene for the area of interest was acquired on July 29, 2010 at approximately 17:27 MST and downloaded using UNAVCO’s Seamless SAR Archive (SSARA). While a Post-September 2013 radar data set would ideally have been used, there was none available.

PALSAR imagery was preprocessed using the Alaska Satellite Facility’s (ASF) MapReady 3.2 software. The MapReady software allowed for simple, one-step preprocessing of the ALOS PALSAR Level 1 data to provide the amplitude file that would be used in land cover classification. The software was used to terrain correct the imagery by using Shuttle Radar Topography Mission 1 arc second (SRTM-1) digital elevation model (DEM), geocode the imagery to the WGS84 Zone 13N datum, and export the file as a GeoTIFF for use in ArcMap. The ALOS imagery that was used had HH and HV polarizations.

3.2 Preliminary Site Mapping

Following the selection of the six field study areas, preliminary mapping of land cover was completed in the office prior to field verification. Using imagery available from Google Earth, each field study area was examined looking at different spatial resolutions, alternative lines-of-sight, three-dimensional imagery, and historical imagery to assist in identifying land cover types that could appear ambiguous when examining a single, two-dimensional image. Google Earth provided a dynamic platform that integrated numerous data sources to allow for preliminary land cover classification.

Upon identification of a land cover type and its approximate spatial extent, Google Earth’s Create Polygon tool was used to classify the area as Bedrock, Colluvium, Developed, Forest, Grass/Small
Vegetation, or Water land cover types. Final polygons of each land cover type were exported and converted to a vector file in ArcMap 10.3 using the KML to Layer tool.

Additional land cover training samples were selected outside of the six field study areas. These were limited to the Developed, Grass/Small Vegetation, and Water land cover types (see Appendix A). These three land cover types were not common in the six field study areas but were required as training samples to accurately classify land cover in the overall area of interest.

3.3 Field Work

Upon completion of preliminary mapping of the field study areas, verification of the land cover classification was carried out in the field over a three week period.

Five of the six field study areas were accessible by publicly maintained roads and trails that allowed suitable access to the field areas. Only a single field study area was inaccessible and had to be remotely viewed from the roadways as the bulk of the field area was located on private property trespassing was prohibited.

The completed land cover maps for each field study area can be found in the appendices (Appendix B).

3.4 Land Cover Classification Approaches

To identify bedrock and colluvium in the area of interest, traditional land cover classification methods—the unsupervised and supervised classification methods—were carried out using the multispectral Landsat-8 OLI/TIRS dataset. In addition to this, the Landsat-8 data was analyzed with a classification method that combined supervised and unsupervised classification schemes. The fourth and final method combined optical and radar datasets to examine if improved land cover classification and discrimination could be achieved using the hyperspectral AVIRIS data set and the PALSAR instrument on the ALOS satellite platform. This final method is a multi-step procedure that integrates multiple optical classification schemes and radar amplitude to achieve a land cover classification that discriminates bedrock from colluvium.

3.4.1 Unsupervised Classification

Unsupervised classification is a GIS-based cluster analysis method where image pixels are grouped into similar types of land cover based on related digital numbers (DN values). To accomplish this, methods discussed in Keranen and Kolvoord (2014) were employed for analyzing and manipulating the Landsat-8 data.

Following the manipulation of the Landsat imagery into composite images, the Image Classification toolbar was activated in ArcMap. After selecting the Landsat-8 composite image as the input raster, Iso (Iterative Self Organizing) Cluster Unsupervised Classification was selected from the Classification drop-down menu and ran for 40 classes. This tool is a type of cluster analysis that "works by identifying clusters of pixels in the scene that have similar attributes" (Keranen & Kolvoord, 2014). The Iso Cluster Unsupervised Classification is an algorithm that employs "a modified iterative optimization clustering procedure, also known as the migrating means technique [that] separates all cells into the user-
specified number of distinct unimodal groups in the multidimensional space of the input bands” (Environmental Systems Research Institute, Inc., 2016). The algorithm is essentially an iterative process for calculating the minimum Euclidean distance for each candidate pixel such that they can be assigned to a cluster.

Following this, the 40 classes (clusters of similar pixels) in the resulting image were identified by comparing individual classes to the type of land cover visible in an aerial imagery base map. Once all 40 classes were examined they were reclassified into one of the following six classes: 1) Bedrock, 2) Colluvium, 3) Developed, 4) Forest, 5) Grass/Small Vegetation, and 6) Water using the Reclassify tool.

3.4.2 Supervised Classification

Supervised classification is an additional GIS-based method where image pixels are grouped into similar types of land cover based on the DN values of training samples for each land cover type. Using the training samples for land cover gathered at each field study area during preliminary site mapping and field mapping, single training sample polygons were created for each land cover type (see Appendix A and B). The resultant training samples were then used to group the remaining area of interest into groups of pixels that contained DN values similar to the training samples.

To accomplish this, the Image Classification toolbar was activated in ArcMap 10.3 and the Training Sample Manager was opened. The training sample polygons for each land cover type were then added. The actual training samples for use in the supervised classification were randomly selected from the training sample polygons. In ArcMap, 200 random points were selected in each training sample class (i.e. 200 points in the bedrock training sample, 200 points in the colluvium training sample, etc.). For each training sample class a buffer around the point was created such that approximately 50% of the training sample class area was used for the supervised classification. The remaining area was used for establishing classification accuracy of the supervised classification method. To calculate the radius of the buffer around each random point, the area of each training sample type was measured. Using 50% of this area, the area per point was then calculated. As a circular buffer was employed, the area per point was then used to calculate the radius of the buffer for each class.

The actual size of the training samples for the supervised classification was less than 50% of the field sites due to a number of factors: (1) overlap with the training sample boundaries, and (2) overlap with the buffer from adjacent random points that were within a distance equivalent to one diameter. The Dissolve and Intersect tools were used to combine the buffered 200 random points into a single shapefile and eliminate any regions that fell outside the field training sample areas. Figure 3.1 shows the single shapefile (purple) used for the supervised classification at Blue Lake/Mitchell Lake field study area. The remaining area (green) was used for performing an accuracy assessment such that actual and predicted land cover data sets could be compared.

Finally a signature file was created reflecting the unique DN values observed in the training samples for each land cover type.
To perform the supervised classification, the *Interactive Supervised Classification* tool was selected which created a supervised classification of the area of interest based on the signature file of the training samples.

### 3.4.3 Iterative Supervised/Unsupervised Classification

To improve the classification accuracy of the Landsat-8 imagery—specifically the detection, classification, and discrimination of *Bedrock* and *Colluvium* land cover types—a combined methodology was devised. Essentially, this method involved combining the previous two methods by performing a supervised classification of the area of interest followed by a series of unsupervised classifications for each of the resulting land cover types.

Using the results of the supervised classification of Landsat-8 imagery, areas classified as *Bedrock* were subject to an unsupervised classification similar to the method previously outlined. This secondary classification of *Bedrock* attempts to improve overall classification accuracy by providing multiple passes (visual inspection) of the Landsat-8 imagery. Areas of *Bedrock* identified in the supervised classification were then extracted from the Landsat-8 composite image. Subsequently, the *Iso Cluster Unsupervised Classification* was selected in ArcMap from the *Classification* drop-down menu and ran for 40 classes.
The unsupervised classification was carried out for Bedrock, Colluvium, Developed, Forest, Grass/Small Vegetation and Water land cover types. Following this first iteration of unsupervised classifications, a second round was carried out for all land cover types but was based on the land cover areas derived during the first unsupervised classification iteration.

3.4.4 Integrated Sequential Classification Approach

To classify the land cover, an integrated method of sequential classification was devised. That is, in previous attempts to classify Bedrock and Colluvium across the area of interest, using a single means of classification provided minimal differentiation between these two land cover types and significant overlap with other land cover types. Conversely, sequential classification involves the use of multiple classification methods that successively classify individual land cover types, thereby removing classified land cover from future consideration when additional classification methods are applied. By integrating multiple data sources and means of classification, higher quality and quantity results can be extracted (Natural Resources Canada, 2013).

For the sequential land cover classification using AVIRIS and ALOS imagery, eight land cover types were classified—namely Bedrock, Burn, Colluvium, Developed, Forest, Grass/Small Vegetation, Ice, and Water. The inclusion of Ice as a land cover type is due to the presence of visible snow and ice in the true-color AVIRIS images in the high altitude regions on the west end of the area of interest. The inclusion of Burn as a land cover type is due to the presence of a trio of forest fires that occurred in the area of interest prior to the AVIRIS imagery being acquired.

The following sections will outline the sequential classification method that was used. While the following sections do provide the specific equations necessary for carrying out this method, the specific selection criteria and rationale used to develop the final maps will be discussed in Chapter 4. The reader is cautioned that the sequential classification method involved extracting one or more land cover types before developing any subsequent method. The results from a singular step inevitably influenced the selection or creation of any subsequent steps for the sequential classification methodology.

3.4.4.1 Normalized Difference Vegetation Index

NDVI is the difference of the spectral radiation of vegetation in the red and near-infrared bands. This index is typically used to distinguish healthy green vegetation that has high reflectivity in the near-infrared band versus stressed, dry, or diseased vegetation that has low reflectivity in the near-infrared band. To calculate NDVI, the near-infrared (IR) and red (R) spectral bands are used:

\[
NDVI = \frac{(IR - R)}{(IR + R)}
\]

Where IR is the digital number (DN) value of a particular pixel in the infrared band and R is the DN of the same pixel in the red band. Areas where the resulting NDVI value is negative corresponds to areas with water while regions with a resulting NDVI value of 0.1 and below is generally attributed to areas of rock or bare soil (Keranen & Kolvoord, 2014).
For the AVIRIS image, NDVI was calculated using Band 55 (near-infrared, 0.865 – 0.875 µm) and Band 31 (visible red, 0.652 – 0.662 µm). In ArcMap, the following equation was used to calculate NDVI for the AVIRIS image:

\[
NDVI = \frac{\text{Band 51} - \text{Band 31}}{\text{Band 51} + \text{Band 31}} \times 100 + 100
\]

This equation manipulates the output values such that instead of varying between -1 and 1, the values fall between 0 and 200 to ease graphing. A histogram of the NDVI pixel values for each type of land cover in the training samples was produced to allow for the extraction of unique land cover types from the area of interest.

### 3.4.4.2 Normalized Difference Build-up Index

NDBI is a land cover classification method developed to monitor and detect land cover changes that occur in urban areas as a result of urban sprawl (Zha et al., 2003). This classification method was selected to remove built-up and urban areas from further consideration in subsequent classification schemes. The southeastern portion of the area of interest is dominated by Boulder, Colorado and previous classification methods had indicated that there was similarity in the spectral signatures of Developed, Bedrock and Colluvium land cover types.

NDBI was originally calculated using the Landsat Thematic Mapper (TM) bands 4 and 5 or the near infrared (NIR: 0.76-0.9μm) and shortwave infrared (SWIR: 1.5-1.75 μm) bands. The equation used to calculate NDBI is given as (Zha et al., 2003).

\[
NDBI = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}}
\]

For the AVIRIS sensor, the NIR band selected was band 54 (0.855-0.865 μm) and the SWIR band selected was band 138 (1.657-1.667 μm). In ArcMap, the following equation was used to calculate NDBI for the AVIRIS image:

\[
NDBI = \frac{\text{Band 138} - \text{Band 54}}{\text{Band 138} + \text{Band 54}} \times 100 + 100
\]

Again, the normalized difference equation was manipulated so that values ranged between 0 and 200 as opposed to -1 and 1. A histogram of the NDBI pixel values for each type of land cover in the training samples was produced such that unique land cover types could be extracted from the area of interest.

### 3.4.4.3 Normalized Difference of Near-Infrared Bands

The spectral signature curves for each land cover types (see Figure 3.2) suggest the potential of developing a ratio or formula for differentiating some of the land cover types. By examining AVIRIS bands where radiance values vary and where the radiance values are approximately equal, a normalized difference equation was developed to accentuate any differences between the land cover types.

Examining the spectral radiance curves for the land cover types indicated significant differences between the peaks of Grass, Developed, Colluvium, and Bedrock existed at Band 68 (NIR: 0.991-1.000 µm).
These curves then converged to similar values at Band 81 (NIR: 1.115-1.125 µm). A normalized difference equation was developed to highlight any difference in these land cover types:

\[ ND_{68,81} = \frac{(\text{Band 68} - \text{Band 81})}{(\text{Band 68} + \text{Band 81})} \times 100 \]

A histogram of the normalized difference of near-infrared band pixel values for each type of land cover in the training samples was produced to allow for the extraction of unique land cover types from the area of interest.

3.4.4.4 Normalized Burn Ratio

The process of sequential classification highlighted the potential need to account for areas that were impacted by forest fires. The 2003 Overland Fire, 2010 Four Mile Canyon Fire, and 2011 Maxwell Fire appear as largely unclassified areas. To account for these burn areas, indices that predict burn severity were employed. The normalized burn ratio (NBR) typically utilizes the near infrared (band 4) and shortwave infrared (band 7) wavelengths of Landsat imagery to measure burn severity (Soverel et al., 2010). NBR is calculated using the following equation for Landsat TM/ETM+:

\[ NBR = \frac{(\text{Band 4} - \text{Band 7})}{(\text{Band 4} + \text{Band 7})} \]

For AVIRIS imagery, this corresponds to band 51 (NIR: 0.826 – 0.836 µm) and band 196 (SWIR: 2.232 – 2.242 µm). To calculate NBR for AVIRIS imagery, the following equation was used:
\[ NBR = \frac{(\text{Band } 51 - \text{Band } 196)}{(\text{Band } 51 + \text{Band } 196)} \times 100 + 100 \]

A histogram of the NBR pixel values for each type of land cover in the training samples was produced to allow for the extraction of burn areas and any unique land cover types from the area of interest.

3.4.4.5 Normalized Difference of Short-Wave Infrared Bands

In the discrimination of Bedrock and Colluvium land cover types, it was assumed that Colluvium would have experienced more weathering than more competent outcrops of Bedrock. As the overarching goal of the project is to identify competent bedrock outcrops such that the model of debris flow susceptibility for this region can be better constrained, it was assumed that less competent bedrock, colluvium, talus, scree, soil, etc. would have higher clay content. Advanced Spaceborne Thermal Emission and Reflection (ASTER) imagery from the TERRA satellite platform had previously been used to identify regions with clay using band 5 (2.145 – 2.185 μm), band 6 (2.185 – 2.225 μm), and band 7 (2.235 – 2.285 μm) in the following equation (Bierwirth, 2002):

\[ \text{Clay}_{\text{ASTER}} = \frac{(\text{Band } 5 \times \text{Band } 7)}{(\text{Band } 6)^2} \]

With hyperspectral AVIRIS imagery, this corresponds to the shortwave infrared band 189 (2.142 – 2.152 μm), band 193 (2.182 – 2.192 μm), and band 203 (2.282 – 2.292 μm), respectively. Using AVIRIS imagery, higher clay content can be detected using the following equation:

\[ \text{Clay}_{\text{AVIRIS}} = \frac{(\text{Band } 189 \times \text{Band } 203)}{(\text{Band } 193)^2} \]

A histogram of the pixel values for each type of land cover in the training samples was produced to allow for the extraction of unique land cover types and potential discrimination of Bedrock and Colluvium within the area of interest.

3.4.4.6 Combined Normalized Difference Ratio

To further assess the area of interest for the presence of Bedrock and Colluvium, an additional ratio was considered. Based on preliminary results and visual inspection of the aforementioned NBR and Clay Ratio, a normalized difference calculation was carried out to accentuate any differences that may exist between the pixel values of Bedrock and Colluvium. This ratio was calculated using the following equation:

\[ ND_{\text{combined}} = \frac{(\text{NBR} - \text{Clay}_{\text{AVIRIS}})}{(\text{NBR} + \text{Clay}_{\text{AVIRIS}})} \]

A histogram of the combined normalized difference pixel values for each type of land cover in the training samples was produced to allow for the extraction of unique land cover types from the area of interest.

3.4.4.7 ALOS Amplitude

The use of amplitude data from L-band radar has the potential to provide some measurable difference between Bedrock and Colluvium. Essentially, it was hypothesized exposures of Colluvium
would have higher amplitude values compared to areas with Bedrock. This is largely due to the hypothesis that outcrops of Bedrock have lower surface roughness compared to outcrops of Colluvium. With an active source, surfaces with higher roughness would tend to get increased returns to the satellite sensor, thus recording higher amplitude.

To extract land cover classes from the amplitude image, histograms with HH and HV polarizations were produced showing the range of amplitude values for each land cover training sample site.

3.5 Classification Accuracy

To better assess validity of the various remote sensing methods, classification accuracy analyses were carried out for the unsupervised, supervised, iterative supervised/unsupervised, and integrated sequential classification approaches. To compare the different land cover classification methods, confusion matrices were produced for each method. Confusion matrices allow for the comparison of several metrics including precision (producer accuracy), sensitivity (user accuracy), omission error, commission error, $F_1$ measure, specificity, accuracy, observed accuracy, expected accuracy, and Cohen’s kappa statistic.

**Precision**, also known as the producer accuracy, is defined as the fraction of predicted positive classifications that are correctly identified as true positives (Powers, 2011). The equation for precision is given as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Where, $TP$ refers to true positives—that is, the correct classification of a land cover type—and $FP$ denotes false positives or when an area is incorrectly identified as belonging to a land particular land cover type. For example, if a verification point is classified as Bedrock and is actually Bedrock, then a true positive condition exists for that point. Alternatively, if another verification point is classified as Bedrock but is truly Colluvium then a false positive condition exists for that particular point. The producer accuracy describes the number of pixels that are correctly classified into a certain category as a percentage of the total number of the pixels that actually belong within that predicted category.

The omission error can also be calculated (Schuckman, Dutton, & O’Neil Dunne, 2015). The omission error is simply:

$$\text{Omission Error} = 1 - \text{Precision}$$

Omission error measures the number of the pixels that were incorrectly classified into a particular category relative to the total number of pixels that actually belong within that predicted category.

**Sensitivity** or the user accuracy is the proportion of true positive cases that area correctly predicted to be positive (Powers, 2011). Sensitivity is given as:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Where, $TP$ refers to true positives and $FN$ refers to false negatives. An example of a false negative condition in the land cover classification of Bedrock could be a verification point being classified
as Colluvium while the actual classification is Bedrock. Commission error is the error type associated with sensitivity.

Commission Error = 1 − Sensitivity

Commission error is calculated using the number of incorrectly classified pixels for a certain classifier as a percentage of the total number of pixels that belong within an actual category (Schuckman et al., 2015).

The $F_1$ measure is the weighted harmonic mean that examines the tradeoff that exists between precision and sensitivity (recall) (Manning et al., 2009). A balanced, equally weighted $F_1$ measure is given as:

$$F_1\text{ measure} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

While precision and sensitivity and the related omission and commission errors focus on the positive examples, neither precision or sensitivity is able to examine how well a classification scheme handles negative cases (Powers, 2011). Specificity or inverse recall is the fraction of true negative cases that were correctly predicted to be negative (Powers, 2011). Specificity is defined as:

$$\text{Specificity} = \frac{TN}{FP + TN}$$

Where $FP$ denotes false positives and $TN$ denotes true negatives. For example, true negative conditions for Bedrock include all verification points that are not true positives, false positives, or false negatives for Bedrock.

Accuracy is the proportion of the true positives and true negatives for an entire sample population. Accuracy is given as (Powers, 2011):

$$\text{Accuracy} = \frac{TP + TN}{N} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where $N$ refers to the sample population size. Accuracy can be calculated for each individual classifier; however the observed accuracy or observed agreement using in calculating the kappa statistic can be used to examine the accuracy of the overall classification method by comparing the observed accuracy to the expected accuracy.

Cohen’s kappa is indicative of the extent to which observational probability of agreement (observed accuracy) is in excess of the agreement hypothetically expected (expected accuracy) under baseline constraints (Landis & Koch, 1977). Essentially, the kappa statistic finds the difference between the amount of agreement that is actually present and the agreement that would be expected to be present by chance (Viera & Garrett, 2005).

Observed agreement or observed accuracy is the ratio of the sum of the true positives for each classifier divided by the total number of observations (Viera & Garrett, 2005). Observed agreement ($\pi_0$) is given as:

$$\pi_0 = \frac{TP_1 + TP_2 + \cdots + TP_i}{N}$$
Where $TP$ represent the true positives, $N$ defines the total number of observations, and $\{1, 2, ..., n\}$ is the range of different classifiers (i.e. $1$=Bedrock, $2$=Colluvium, ..., $7$=Water). Expected agreement is given as (Viera & Garrett, 2005):

$$\pi_e = \sum_{i=1}^{n} \left( \frac{\sum (row \ i)}{N} \right) \left( \frac{\sum (column \ i)}{N} \right)$$

The expected agreement ($\pi_e$) is as summation of the product of two ratios for each classifier—the sum of observations in row $i$ divided by total number of observations ($N$) and the sum of the predictions in column $i$ divided by the total number of observations ($N$).

The kappa statistic can then be derived using the previous two calculations and is given by:

$$\kappa = \frac{\pi_0 - \pi_e}{1 - \pi_e}$$

Landis and Koch (1977) suggest that the kappa statistic can be subdivided into ranges that “provide useful benchmarks” to reflect the strength of agreement—particularly when comparing the kappa statistic of various classification methods to each other (Table 3.2).

Table 3.2 Benchmarks for strength of agreement of Cohen's kappa statistic

<table>
<thead>
<tr>
<th>Kappa Statistic</th>
<th>Strength of Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;0.00</td>
<td>Poor</td>
</tr>
<tr>
<td>0.00-0.20</td>
<td>Slight</td>
</tr>
<tr>
<td>0.21-0.40</td>
<td>Fair</td>
</tr>
<tr>
<td>0.41-0.60</td>
<td>Moderate</td>
</tr>
<tr>
<td>0.61-0.80</td>
<td>Substantial</td>
</tr>
<tr>
<td>0.81-1.00</td>
<td>Almost Perfect</td>
</tr>
</tbody>
</table>

For the purpose of analyzing the classification accuracy of the different methods, it was ensured that: (1) all field study area shapefiles were converted to rasters, and (2) all rasters contained the same numerical value for each classification type (Table 3.3).

Table 3.3 Raster values for land cover classification type

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>Raster Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bedrock</td>
<td>1</td>
</tr>
<tr>
<td>Colluvium</td>
<td>2</td>
</tr>
<tr>
<td>Developed</td>
<td>3</td>
</tr>
<tr>
<td>Forest</td>
<td>4</td>
</tr>
<tr>
<td>Grass/Small Vegetation</td>
<td>5</td>
</tr>
<tr>
<td>Ice</td>
<td>6</td>
</tr>
<tr>
<td>Water</td>
<td>7</td>
</tr>
</tbody>
</table>

The following sections detail the methods used to produce the confusion matrices and related performance metrics for each land cover classification method.
3.5.1 **Unsupervised Classification**

For the unsupervised classification, 5000 random points were selected within the boundaries of the field study areas’ shapefiles. The random points were created using the `genrandompnts` command within the Geospatial Modelling Environment (GME) suite of tools. In ArcMap, the shapefile containing the random points or verification points was added to a raster of the field study areas. Using the `Extract Values to Points` tool, the value of the raster at each of the 5000 points was extracted and recorded in the attribute table. These values provide a record of the actual land cover classification that was observed during field mapping of these sites. Subsequent to this, the resulting final unsupervised classification map for the area of interest was added in ArcMap. Again, using the `Extract Values to Points` tool, the values of the unsupervised classification raster for each verification point was recorded in the shapefile’s attribute table. These values that were recorded reflected the predicted land cover classification at each of the 5000 verification points.

Analysis of the unsupervised classification data was carried out using Matlab R2015a. The `confusionmatStats.m` function available from MathWorks File Exchange was employed (MathWorks, 2016). This command required the input of a 5000 by 1 matrix of actual values and the 1 by 5000 matrix of predicted values. The output of the `confusionmatStats.m` function included a 6 by 6 confusion matrix, and 6 by 1 matrices of accuracy, precision, sensitivity, specificity, and F-score ($F_1$ measure).

An additional Matlab function, `kappa.m` was used to calculate Cohen’s kappa statistic, observed agreement, and random agreement (Mathworks, 2009).

3.5.2 **Supervised Classification**

The analysis of the supervised classification was carried out in a similar fashion to the unsupervised classification (see Section 3.5.1). However, the supervised classification used approximately 50% of the field study areas as training samples. To perform the classification analysis, a shapefile of the remaining field study area not used as training samples in the supervised classification was created (see Figure 3.1 as an example). Using the `genrandompnts` command within the Geospatial Modelling Environment (GME) suite of tools, a new set of 5000 random points was generated.

A similar procedure was then followed in extracting the actual and predicted land cover classification for each verification point. Analysis of the data was carried out in Matlab using the previously discussed `confusionmatStats.m` and `kappa.m` functions.

3.5.3 **Iterative Supervised/Unsupervised Classification**

Analysis of the first and second unsupervised classifications was carried out using the 5000 verification points generated for the supervised classification. A procedure similar to the one outlined previously was used to the extract and analyze the actual and predicted land cover classification.

3.5.4 **Integrated Sequential Classification Approach**

The sequential method of land cover classification employed a different area of interest from the previous methods. For this method the AVIRIS data set used limited coverage to the southern half of the nine quadrangle area of interest. Consequently, a different set of 5000 verification points had to be
generated for the field study areas that were within the boundaries of the AVIRIS data set. The new set of 5000 verification points was generated using the *genrandompnts* command within the Geospatial Modelling Environment (GME) suite of tools.

Again, a method similar to the one previously outlined was used to extract the actual and predicted land cover. Analysis was carried out in Matlab using the *confusionmatStats.m* and *kappa.m* functions to generate the confusion matrix and the various associated metrics.
CHAPTER 4
RESULTS

This chapter discusses the results for each of the land cover classification approaches covered in the previous chapter. This includes a land cover classification map and accuracy assessment for each method. For each method following the first, a comparative analysis of the results with previous results was conducted to assess which land cover classification approach performed best.

4.1 Unsupervised Classification

The first map was produced by performing an unsupervised classification of the Landsat-8 composite image for the entire area of interest. The original unsupervised classification was based on 40 classes that were reclassified into six classes: 1) Bedrock, 2) Colluvium, 3) Developed, 4) Forest, 5) Grass/Small Vegetation, and 6) Water.

The resulting map from the unsupervised classification of the Landsat-8 imagery (Figure 4.1) displays land cover classification for the area of interest. Upon cursory examination of the map (and having an understanding of the general land cover in the region) there are a number of interesting results. The majority of the Bedrock and Colluvium is found near the western edge of the area of interest in the alpine regions by the Continental Divide. The location of Grass/Small Vegetation is primarily located on the eastern edge of area of interest by the local margins of the Front Range Mountains. Additionally, Grass/Small Vegetation appear around the larger peaks in the west and are possibly indicative of the local tree-line. Forests (darks green) tend to dominate the majority of the area of interest.

Another interesting observation of the unsupervised classification is the location of Water. Of the original 40 clusters, two were used to define the reclassified Water class. The reclassified map accurately shows the location of various reservoirs, lakes, and tarns across the area of interest. However, there appear to be a number of additional regions that indicate bodies of water or high water content. These areas tended to be on north facing slopes or in high elevation regions. This could possibly suggest the presence of snow or ice in the higher elevation regions or damp regions in areas with predominantly northern-facing exposures.

The mapping of the bedrock and colluvium classes appeared to not accurately discriminate between the two class types. This was observed by examining the Bedrock and Colluvium classes in the reclassified map in ArcMap. The unsupervised classification of the Landsat-8 imagery seems to show that these two areas could be composed of either class—that is, there appear to be very poor discrimination between exposed Bedrock and Colluvium across the area of interest. It should also be noted that some of the Developed regions were mapped as Bedrock and Colluvium though this result was expected as it was assumed that the spectral signature of these three classes likely overlaps.

The results of the error analysis of 5000 verification points for the unsupervised classification reveal an observed agreement of 58.46% for the overall classification scheme with an expected agreement or random agreement of 17.64% (Table 4.1). This results in a Cohen’s kappa value of 0.4957
Figure 4.1 Landsat-8 Unsupervised Land Cover Classification Final Map
## Table 4.1 Confusion matrix for unsupervised classification of land cover

<table>
<thead>
<tr>
<th>Actual</th>
<th>(1) Bedrock</th>
<th>(2) Colluvium</th>
<th>(3) Developed</th>
<th>(4) Forest</th>
<th>(5) Grass</th>
<th>(7) Water</th>
<th>Truth Overall</th>
<th>User Accuracy (Sensitivity)</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Bedrock</td>
<td>216</td>
<td>81</td>
<td>12</td>
<td>21</td>
<td>101</td>
<td>5</td>
<td>436</td>
<td>49.54%</td>
<td>50.46%</td>
</tr>
<tr>
<td>(2) Colluvium</td>
<td>833</td>
<td>693</td>
<td>1</td>
<td>10</td>
<td>125</td>
<td>5</td>
<td>1667</td>
<td>41.57%</td>
<td>58.43%</td>
</tr>
<tr>
<td>(3) Developed</td>
<td>229</td>
<td>7</td>
<td>283</td>
<td>1</td>
<td>40</td>
<td>0</td>
<td>560</td>
<td>50.54%</td>
<td>49.46%</td>
</tr>
<tr>
<td>(4) Forest</td>
<td>112</td>
<td>59</td>
<td>79</td>
<td>1031</td>
<td>279</td>
<td>19</td>
<td>1579</td>
<td>65.29%</td>
<td>34.71%</td>
</tr>
<tr>
<td>(5) Grass</td>
<td>0</td>
<td>13</td>
<td>21</td>
<td>11</td>
<td>194</td>
<td>0</td>
<td>239</td>
<td>81.17%</td>
<td>18.83%</td>
</tr>
<tr>
<td>(7) Water</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>1</td>
<td>506</td>
<td>519</td>
<td>97.50%</td>
<td>2.50%</td>
</tr>
<tr>
<td>Classification</td>
<td>1399</td>
<td>853</td>
<td>396</td>
<td>1077</td>
<td>740</td>
<td>535</td>
<td>5000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>1399</td>
<td>853</td>
<td>396</td>
<td>1077</td>
<td>740</td>
<td>535</td>
<td>5000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Producer Accuracy (Precision)**
- (1) Bedrock: 15.44%
- (2) Colluvium: 81.24%
- (3) Developed: 71.46%
- (4) Forest: 95.73%
- (5) Grass: 26.22%
- (7) Water: 94.58%

**Omission Error**
- (1) Bedrock: 84.56%
- (2) Colluvium: 18.76%
- (3) Developed: 28.54%
- (4) Forest: 4.27%
- (5) Grass: 73.78%
- (7) Water: 5.42%

**Accuracy**
- (1) Bedrock: 71.94%
- (2) Colluvium: 77.32%
- (3) Developed: 92.20%
- (4) Forest: 88.12%
- (5) Grass: 88.18%
- (7) Water: 99.16%

**Kappa (κ)**
- 0.4957

**Specificity**
- (1) Bedrock: 74.08%
- (2) Colluvium: 95.20%
- (3) Developed: 97.45%
- (4) Forest: 98.66%
- (5) Grass: 88.53%
- (7) Water: 99.35%

**Obs. Agreement (π₀)**
- 0.5846

**F₁ measure**
- (1) Bedrock: 23.54%
- (2) Colluvium: 55.00%
- (3) Developed: 59.21%
- (4) Forest: 77.64%
- (5) Grass: 39.63%
- (7) Water: 96.02%

**Exp. Agreement (πₑ)**
- 0.1764
Classification of *Bedrock* indicates a sensitivity of 49.54%—that is, nearly half the verification points that were actually mapped as *Bedrock* were correctly identified as being *Bedrock*. The precision of the unsupervised classification for *Bedrock* was significantly lower at 15.44% meaning that relatively few of the areas predicted to be *Bedrock* were actually *Bedrock*. More false positives for *Bedrock* were identified in areas that were truly *Colluvium* and *Developed*. The specificity for the prediction of *Bedrock* is 74.08% indicating that approximately three-quarters of the negatives were correctly identified as such.

The classification of *Colluvium* yielded different results. While the sensitivity of the classification was lower, at 41.57% the precision of the classification was significantly higher, at 81.24%. This suggests that while a lower proportion of points that were field mapped as *Colluvium* were correctly predicted by the unsupervised classification to be *Colluvium*, the majority of points predicted to be *Colluvium* were correctly identified as *Colluvium*. A specificity of 95.20% suggests that majority of negatives were correctly identified as being negatives and there were relatively few false positives (4.80%) associated with *Colluvium*.

The best results for a single classifier in the unsupervised classification were for *Water* with a sensitivity and precision of 97.50% and 94.58% respectively. The specificity of the unsupervised classification for *Water* was 99.35% suggesting that there were few false positives within the field study areas. A cursory examination of the final unsupervised classification map suggest that significantly more false positives for *Water* actually exist as significant portions of forested, sloped areas are incorrectly identified as *Water*.

### 4.2 Supervised Classification

The final supervised classification map of the Landsat imagery (Figure 4.2) shows the resulting land cover classification for the overall nine quadrangle area of interest. Examination of the final map clearly shows that no areas of *Bedrock* were identified by the supervised classification scheme. This is due to the similarity between the reflectance values of *Bedrock* and *Colluvium* (see hypotheses testing in Appendix C) which causes the supervised classification algorithm in ArcMap to be unable to discriminate between these two classifiers. Additionally, a visual comparison of resulting final map for the unsupervised classification method and for the supervised classification method, indicate improved classification of *Forest* and *Water* as significantly fewer false positive classifications of *Water* exist.

Again, the general location of *Colluvium* is relegated to the western, higher altitude portions of the area of interest along the Continental Divide. Additional major areas of *Colluvium* were identified within the Fourmile Canyon and Overland burn perimeters. The locality of *Grass/Small Vegetation* is primarily along the eastern edge of area of interest along the local margins of the Front Range Mountains. Unlike the unsupervised classification map, *Grass/Small Vegetation* does not appear around the larger peaks in the west. *Forests* dominate the majority of the area of interest.

While a subjective analysis of the supervised classification map does provide some results of note, it is more prudent to carry out an objective examination of the results by scrutinizing the confusion matrix that was created to analyze error (Table 4.2).
Figure 4.2 Landsat-8 Supervised Land Cover Classification Final Map
Table 4.2 Confusion matrix for supervised classification of land cover

<table>
<thead>
<tr>
<th>Actual</th>
<th>(1) Bedrock</th>
<th>(2) Colluvium</th>
<th>(3) Developed</th>
<th>(4) Forest</th>
<th>(5) Grass</th>
<th>(7) Water</th>
<th>Truth Overall</th>
<th>User Accuracy (Sensitivity)</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Bedrock</td>
<td>0</td>
<td>334</td>
<td>27</td>
<td>137</td>
<td>17</td>
<td>0</td>
<td>515</td>
<td>0.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>(2) Colluvium</td>
<td>0</td>
<td>1527</td>
<td>21</td>
<td>62</td>
<td>3</td>
<td>3</td>
<td>1616</td>
<td>94.49%</td>
<td>5.51%</td>
</tr>
<tr>
<td>(3) Developed</td>
<td>0</td>
<td>11</td>
<td>562</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>579</td>
<td>97.06%</td>
<td>2.94%</td>
</tr>
<tr>
<td>(4) Forest</td>
<td>0</td>
<td>119</td>
<td>17</td>
<td>1292</td>
<td>57</td>
<td>1</td>
<td>1486</td>
<td>86.94%</td>
<td>13.06%</td>
</tr>
<tr>
<td>(5) Grass</td>
<td>0</td>
<td>9</td>
<td>1</td>
<td>12</td>
<td>253</td>
<td>0</td>
<td>275</td>
<td>92.00%</td>
<td>8.00%</td>
</tr>
<tr>
<td>(7) Water</td>
<td>0</td>
<td>5</td>
<td>7</td>
<td>8</td>
<td>0</td>
<td>509</td>
<td>529</td>
<td>96.22%</td>
<td>3.78%</td>
</tr>
<tr>
<td>Classification Overall</td>
<td>0</td>
<td>2005</td>
<td>635</td>
<td>1514</td>
<td>332</td>
<td>514</td>
<td>5000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Producer Accuracy (Precision)</th>
<th>Omission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>--</td>
<td>76.16%</td>
</tr>
</tbody>
</table>

- Accuracy: 89.70% 88.66% 98.20% 91.68% 97.98% 99.50%
- Specificity: 100.00% 85.87% 98.35% 93.68% 98.33% 99.89%
- F1 measure: 0.00% 84.34% 92.59% 86.13% 83.36% 97.60%

Kappa (κ): 0.7718
Obs. Agreement (π₀): 0.8286
Exp. Agreement (πₑ): 0.2488
As with the unsupervised classification, a random selection of 5000 points in the field study areas indicated an observed agreement of 82.86% with a random or expected agreement of 24.88%. This results in a Cohen’s kappa statistic of 0.7718. Statistically, these results for the supervised classification clearly show a marked improvement over the unsupervised classification with a significantly improved overall observed agreement and a kappa statistic that suggests a much more substantial agreement between observed and predicted data.

Clearly, the major drawback of the supervised classification is the inability for this methodology to discriminate Bedrock from Colluvium. Though this result is not surprising, it is disappointing as the overall land cover classification showed that the supervised method was capable of high sensitivity for all of the classifiers—that is, with the exception of Bedrock, all land cover classes had user accuracy greater than or equal to 86.94%. This means that the majority of points that were field mapped as a certain land cover type were correctly identified as the same land cover type using the supervised classification method.

While the classification of Bedrock essentially yielded no results, the classification Colluvium yielded a sensitivity of 94.49% meaning the vast majority of areas of Colluvium were correctly identified. This is a significant improvement over the 41.57% sensitivity observed in the unsupervised classification method. However, the higher sensitivity resulted in a tradeoff with the precision of the classification. While the unsupervised classification of the area of interest had a precision of 81.24%, the precision of the supervised classification was less at 76.16%. This suggests that with improved sensitivity—more actual areas of Colluvium being correctly identified—there is a decrease in precision—that is, more false positives of Colluvium. A specificity of 85.87% suggests that many of negatives were correctly identified as being negatives and that there is a small proportion of false positives (14.13%) associated with Colluvium.

The best results for a single classifier in the unsupervised classification were for Water with a sensitivity and precision of 96.22% and 99.03% respectively. The specificity of the supervised classification for Water was 99.89% suggesting that very few false positives exist within the field study areas. Developed areas also performed significantly well with a higher sensitivity (97.06%) but lower precision (88.50%) and specificity (98.35%) compared to Water.

### 4.3 Iterative Supervised/Unsupervised Classification

The results of the supervised classification provided much higher observed agreement than the unsupervised classification map. However, due to the similarities in DN values between the Bedrock and Colluvium land cover types, the supervised classification was unable to discriminate these two classes. Using the results of the supervised classification an unsupervised classification of each land cover type was performed to provide some discernment between Bedrock and Colluvium (1st Iteration). Using the results of the supervised classification and subsequent unsupervised classification, a second unsupervised classification (2nd Iteration) was carried out to improve results.
4.3.1 First Iteration Unsupervised Classification

The 1\textsuperscript{st} iteration unsupervised classification map of the Landsat-8 imagery (Figure 4.3) shows the resulting land cover classification after carrying out an unsupervised classification on all six land cover types. Unlike the final supervised classification, this first iteration has now provided some discrimination which shows outcrops of \textit{Bedrock} in regions that in the supervised classification were predominantly \textit{Colluvium}.

Previous subjective observations of the supervised classification map still apply to this map. However, a more objective examination of the results is warranted by examining the confusion matrix for the first iteration unsupervised classification to analyze error (Table 4.3).

Using the same set of 5000 randomly selected points used in the supervised classification accuracy assessment, the first iteration yielded an observed agreement of 69.04\% with an expected agreement of 20.31\%. Consequently, the kappa statistic decreased from the supervised classification to 0.6115 but still suggests that substantial agreement between actual and predicted datasets still exists.

Unlike the supervised classification methodology, the first iteration of unsupervised classification yielded discrimination between \textit{Bedrock} and \textit{Colluvium}.

The classification of \textit{Bedrock} found a much lower sensitivity or user accuracy than the original unsupervised classification—that is, down from 49.54\% to 21.75\%. This suggests that approximately only 1 in 5 of the verification points that were actually mapped as \textit{Bedrock} were being correctly identified as \textit{Bedrock}. The precision of the first iteration unsupervised classification improved on the original unsupervised classification of \textit{Bedrock} yielding a producer accuracy of 20.70\% versus 15.44\%. This suggests that more of the areas predicted to be \textit{Bedrock} by the first iteration classification were actually \textit{Bedrock}. The specificity for the prediction of \textit{Bedrock} was 90.43\% (up from 74.08\%) indicating that the majority of the negatives were correctly identified as such.

The classification of \textit{Colluvium} found a sensitivity of 64.91\% that indicates an improvement on the user accuracy observed in the unsupervised classification (41.57\%) and a decrease in the user accuracy observed in the supervised classification (94.49\%). The precision of classification of \textit{Colluvium} was 72.15\% which represented a decrease in producer accuracy observed in the first two classification methods. The specificity of the classification was 88.03\% suggesting that many of negatives were correctly identified as being negatives and that there is a small proportion of false positives (11.97\%) associated with \textit{Colluvium}.

While comparing the precision and sensitivity of results across different methodologies can become convoluted, the \textit{F}\textsubscript{1} measure can be used to examine the tradeoff that exists between precision and sensitivity. Ignoring the results for land cover classification found with the supervised classification methodology, the \textit{F}\textsubscript{1} measure can be used to assess the user and producer accuracy for \textit{Bedrock} and \textit{Colluvium} in the unsupervised classification. For unsupervised classification, the \textit{F}\textsubscript{1} measures are 23.54\% and 55.00\% for \textit{Bedrock} and \textit{Colluvium}, respectively. For the first iteration unsupervised classification, the \textit{F}\textsubscript{1} measures are 21.21\% and 68.34\% for \textit{Bedrock} and \textit{Colluvium}, respectively.
Figure 4.3 Landsat-8 Iterative Supervised/Unsupervised Land Cover Classification Iteration One Final Map
Table 4.3 Confusion matrix for first iteration unsupervised classification of land cover

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Truth Overall</th>
<th>User Accuracy (Sensitivity)</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Bedrock</td>
<td>112</td>
<td>515</td>
<td>21.75%</td>
</tr>
<tr>
<td>(2) Colluvium</td>
<td>409</td>
<td>1049</td>
<td>1616</td>
<td>64.91%</td>
</tr>
<tr>
<td>(3) Developed</td>
<td>6</td>
<td>5</td>
<td>580</td>
<td>97.07%</td>
</tr>
<tr>
<td>(4) Forest</td>
<td>10</td>
<td>147</td>
<td>1485</td>
<td>64.31%</td>
</tr>
<tr>
<td>(5) Grass</td>
<td>1</td>
<td>3</td>
<td>275</td>
<td>96.00%</td>
</tr>
<tr>
<td>(6) Water</td>
<td>3</td>
<td>1</td>
<td>529</td>
<td>96.22%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classification Overall</th>
<th>541</th>
<th>1454</th>
<th>727</th>
<th>1050</th>
<th>715</th>
<th>513</th>
<th>5000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer Accuracy (Precision)</td>
<td>20.70%</td>
<td>72.15%</td>
<td>77.44%</td>
<td>90.95%</td>
<td>36.92%</td>
<td>99.22%</td>
<td></td>
</tr>
<tr>
<td>Omission Error</td>
<td>79.30%</td>
<td>27.85%</td>
<td>22.56%</td>
<td>9.05%</td>
<td>63.08%</td>
<td>0.78%</td>
<td></td>
</tr>
</tbody>
</table>

Accuracy | 83.36% | 80.56% | 96.38% | 87.50% | 90.76% | 99.52% |
Specificity | 90.43% | 88.03% | 96.29% | 97.30% | 90.46% | 99.91% |
F₁ measure | 21.21% | 68.34% | 86.15% | 75.35% | 53.33% | 97.70% |

Kappa (κ) | 0.6115 |
Obs. Agreement (π₀) | 0.6904 |
Exp. Agreement (πₑ) | 0.2031 |
The best results for a single classifier in the first iteration unsupervised classification were for *Water* with a sensitivity and precision of 96.22% and 99.22%, respectively for a $F_1$ measure of 97.70%. The specificity of the supervised classification for *Water* was 99.91% suggesting that very few false positives exist within the field study areas.

### 4.3.2 Second Iteration Unsupervised Classification

The 2nd iteration unsupervised classification map of the Landsat-8 imagery (Figure 4.4) shows the resulting land cover classification after carrying out a second unsupervised classification on all six land cover types. Visually, there appear to be relatively few changes that can be discerned between the first iteration and the second iteration. Any changes in land cover classification can be better observed through analysis of the error in the resultant confusion matrix for the second iteration unsupervised classification (Table 4.4).

As with the first iteration, the same set of 5000 verification points in the fields study area were used to analyze the agreement between the actual and predicted datasets. The second iteration found an observed agreement of 67.02% with an expected agreement of 19.18%. This resulted in a Cohen’s kappa approximately 0.01 less than the first iteration at 0.6031 but still suggests a substantial agreement exists between the datasets.

The classification of *Bedrock* had an increased sensitivity of 32.23% when compared to the first iteration but was still significantly below the user accuracy of 49.54% found with the original unsupervised classification method. This user accuracy suggests that about 1 in 3 of the verification points that were field mapped as *Bedrock* were correctly identified. The precision of classification remained virtually the same at 20.47% or that about 1 in 5 of the verification points predicted to *Bedrock* were actually found within outcrops of *Bedrock*. The specificity for the prediction of *Bedrock* was 85.62% up from 74.08% for the unsupervised classification method and down from 90.43% from the first iteration but still indicating that the majority of the negatives were correctly identified as such.

The classification of *Colluvium* showed a sensitivity of 54.64% that indicates an improvement on the user accuracy observed in the unsupervised classification (41.57%) and a decrease in the user accuracy observed in the supervised classification (94.49%) and the first iteration unsupervised classification (64.91%). The precision of classification of *Colluvium* was 77.52% represents a decrease in producer accuracy observed in the first two classification methods but an increase compared to the first iteration unsupervised classification. The specificity of the classification was 92.43% up from 88.03% suggesting that smaller proportion of false positives (7.57%) are associated with *Colluvium* in the second iteration unsupervised classification.

Using the $F_1$ measure to compare *Bedrock* and *Colluvium* land cover classification across different methodologies, the second iteration unsupervised classification found a $F_1$ measure of 25.04% for *Bedrock* and 64.10% for *Colluvium*. For the classification of *Bedrock*, this represents the highest $F_1$ measure while for *Colluvium*, this represents a slight decrease from the first iteration unsupervised classification. For unsupervised classification, the $F_1$ measures are 23.54% and 55.00% for *Bedrock* and
Figure 4.4 Landsat-8 Iterative Supervised/Unsupervised Land Cover Classification Iteration Two Final Map
Table 4.4 Confusion matrix for second iteration unsupervised classification of land cover

<table>
<thead>
<tr>
<th>Actual</th>
<th>(1) Bedrock</th>
<th>(2) Colluvium</th>
<th>(3) Developed</th>
<th>(4) Forest</th>
<th>(5) Grass</th>
<th>(7) Water</th>
<th>Truth Overall</th>
<th>User Accuracy (Sensitivity)</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Bedrock</td>
<td>166</td>
<td>172</td>
<td>48</td>
<td>57</td>
<td>72</td>
<td>0</td>
<td>515</td>
<td>32.23%</td>
<td>67.77%</td>
</tr>
<tr>
<td>(2) Colluvium</td>
<td>575</td>
<td><strong>883</strong></td>
<td>80</td>
<td>25</td>
<td>50</td>
<td>3</td>
<td>1616</td>
<td>54.64%</td>
<td>45.36%</td>
</tr>
<tr>
<td>(3) Developed</td>
<td>6</td>
<td>5</td>
<td><strong>563</strong></td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>580</td>
<td>97.07%</td>
<td>2.93%</td>
</tr>
<tr>
<td>(4) Forest</td>
<td>59</td>
<td>76</td>
<td>28</td>
<td><strong>1012</strong></td>
<td>309</td>
<td>1</td>
<td>1485</td>
<td>68.15%</td>
<td>31.85%</td>
</tr>
<tr>
<td>(5) Grass</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>7</td>
<td><strong>263</strong></td>
<td>0</td>
<td>275</td>
<td>95.64%</td>
<td>4.36%</td>
</tr>
<tr>
<td>(7) Water</td>
<td>4</td>
<td>0</td>
<td>7</td>
<td>9</td>
<td>0</td>
<td><strong>509</strong></td>
<td>529</td>
<td>96.22%</td>
<td>3.78%</td>
</tr>
<tr>
<td>Classification Overall</td>
<td>811</td>
<td>1139</td>
<td>727</td>
<td>1113</td>
<td>697</td>
<td>513</td>
<td>5000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Producer Accuracy (Precision)**

- Bedrock: 20.47%
- Colluvium: 77.52%
- Developed: 77.44%
- Forest: 90.93%
- Grass: 37.73%
- Water: 99.22%

**Omission Error**

- Bedrock: 79.53%
- Colluvium: 22.48%
- Developed: 22.56%
- Forest: 9.07%
- Grass: 62.27%
- Water: 0.78%

**Accuracy**

- Bedrock: 80.12%
- Colluvium: 80.22%
- Developed: 96.38%
- Forest: 88.52%
- Grass: 91.08%
- Water: 99.52%

**Kappa (κ)**

- 0.6031

**Obs. Agreement (π₀)**

- 0.6792

**Exp. Agreement (πₑ)**

- 0.1918
Colluvium, respectively, while for the first iteration unsupervised classification, the $F_1$ measures are 21.21% for Bedrock and 68.34% for Colluvium.

As no areas classified as Water changed from the first to second iteration, Water remained the best single classifier of the six land cover types.

4.4 Integrated Sequential Classification Approach

The final methodology examined land cover classification using AVIRIS and PALSAR imagery for the southern half of the nine quadrangle area of interest (see Figure 4.5). The integrated sequential classification approach involved the use of multiple land cover classification methods that sequentially classified individual land cover types. Once a land cover type was classified, the area that was encompassed by classified land cover was removed from future consideration when additional classification methods were applied. It is critical to perform each individual land cover classification method in the correct sequential order to extract the different types of land cover (see Figure 4.6).

For this land cover classification, eight land cover types were classified—namely Bedrock, Burn, Colluvium, Developed, Forest, Grass/Small Vegetation, Ice, and Water. The following sections discuss the results for the different land cover classification methods, the type of land cover that was extracted, the selection criteria, and rationale. Figure 4.6 shows the flowchart of the integrated sequential classification approach displaying the correct sequence of individual land cover classification methods and the resulting land cover outputs. Deviation from the application of these methods with this approach will result in invalid land cover classification as early results are used to mask later results.

4.4.1 Normalized Difference Vegetation Index

Using the AVIRIS image, Normalized Difference Vegetation Index (NDVI) was calculated using Band 55 (near-infrared, 0.865 – 0.875 µm) and Band 31 (visible red, 0.652 – 0.662 µm). In ArcMap, the following equation was used to calculate NDVI for the AVIRIS image:

$$NDVI = \frac{(\text{Band 51} - \text{Band 31})}{(\text{Band 51} + \text{Band 31})} \times 100 + 100$$

The resulting histogram (Figure 4.7) indicates that two of the land cover types have unique NDVI pixel values that would allow for the discrimination—that is, the forest and water land cover types.

The Forest NDVI pixel values were approximately normally distributed. Assuming the distribution is normal, NDVI pixel values greater than the mean minus one standard deviation (i.e. $\bar{x} - s = 124$; $\bar{x}$ is the sample mean and $s$ is the sample standard deviation) were used thereby accounting for approximately 84.1% of pixels classified as forest in the training samples. These values were extracted using the following conditional statement in the raster calculator in ArcMap:

$$\text{Con}("\text{NDVI}_\text{raster}" > 124, 1, 0)$$

Using this conditional statement, an assessment of the error associated with this step can be calculated. Within the field study areas, there are 19,459 Forest pixels and 27,955 total pixels with an NDVI value greater than 124. Consequently this means 8,496 pixels or 30.39% of the pixels classified by the conditional statement were improperly classified. Given the NDVI histogram (Figure 4.7), Colluvium
Figure 4.5 Project Area of Interest in: (A) State of Colorado, (B) Colorado Front Range, (C) showing field study areas (six small black polygons), (D) showing area with available AVIRIS imagery.
Figure 4.6 Integrated sequential classification approach process flowchart

Final Map
Figure 4.7 Histogram of NDVI of land cover classes from field study areas
Figure 4.8 Sequential land cover classification with *Forest* classified using NDVI
Figure 4.9 Sequential land cover classification with Water classified using NDVI
and to a lesser extent Developed land cover classes would be responsible for the majority of the false positive classifications of Forest.

The output map (Figure 4.8) shows values that have similar NDVI pixel values to the Forest training samples that were previously collected. As part of the sequential classification method, the areas classified as Forest were removed from consideration with future classification methods.

The Water NDVI pixel values were also approximately normally distributed. However, as there was essentially no overlap between NDVI pixel values for Water and any of the other land cover types, this land cover type could be easily extracted. To select the NDVI pixel values that would correspond to Water, values less than or equal to 70 were used. These values were extracted using the following conditional statement in the raster calculator:

\( Con("NDVI\_raster" \leq 70, 1, 0) \)

The output map (Figure 4.9) now shows areas classified as Forest and Water. The remaining area was classified using subsequent methods to allow for discrimination of Bedrock and Colluvium.

### 4.4.2 Normalized Difference Build-up Index

For the AVIRIS sensor, the Normalized Difference Build-up Index (NDBI) was calculated using band 54 (0.855-0.865 µm) for the NIR band and band 138 (1.657-1.667 µm) for the SWIR band. In ArcMap, the following equation was used to calculate NDBI for the AVIRIS image:

\[
NDBI = \frac{(\text{Band 138} - \text{Band 54})}{(\text{Band 138} + \text{Band 54})} \times 100 + 100
\]

Again, the normalized difference equation was manipulated so that values ranged between 0 and 200 as opposed to -1 and 1. A histogram of the NDBI pixel values (Figure 4.10) for each of the land cover types was produced. This histogram showed that there was some discrimination between Developed and its surrounding land cover types. However, there was significant overlap between the Developed, Bedrock, and Colluvium land cover classes. Fortunately, the NDBI calculation did isolate the Ice land cover class.

While the NDBI did not provide the desired discrimination, the training samples of Ice showed very unique NDBI pixel values. The overlapping Colluvium and Ice peaks in the histogram likely indicate areas that were field mapped as colluvium during the Summer months but contained snow or ice coverage when the AVIRIS image was captured in the late Fall. To extract the Ice land cover class, values less than 5 were selected. These values were extracted using the following conditional statement in the raster calculator:

\( Con("NDBI\_raster" < 5, 1, 0) \)

The output map (Figure 4.11) shows the location of ice or snow coverage in the AVIRIS image. This is primarily limited to the higher altitude regions on the western portion of the map. While these areas are relatively insignificant in size, they could be related to either Colluvium or Bedrock and may need to be taken into consideration in future analysis.
Figure 4.10 Histogram of NDBI of land cover classes from field study areas
Figure 4.11 Sequential land cover classification with Ice classified using NDBI
4.4.3 Normalized Difference of Near-Infrared Bands

While the NDBI formula was unsuccessful in discriminating Bedrock from Colluvium, the spectral signature curves for each land cover types (see Figure 3.2) allowed for the development of a normalized difference equation to highlight any difference in these land cover types:

$$ND_{b68,81} = \frac{\text{Band 68} - \text{Band 81}}{\text{Band 68} + \text{Band 81}} \times 100 + 100$$

A histogram of the resulting pixel values for each training sample (Figure 4.12) was produced that discriminated between multiple classes.

The normalized difference equation between bands 68 and 81 provided discrimination of the Grass land cover type. Though Grass shares a local maximum with the Forest land cover class in the histogram, the sequential classification method already accounted for Forest and was no longer being considered in the classification. Additionally, the local maximum for Forest could suggest the presence of grass cover or small vegetation in the Forest training samples.

Though the distribution of the Grass land cover in the histogram is left skewed, the main portion of the distribution appears to be normal, so the values extracted for classification were between the mean and ±1 standard deviation or between pixel values of 152 and 158. Under the assumed ideal normal distribution this would account for approximately 68.2% of pixels classified as Grass in the training samples. Visual inspection of the left-skewed distribution for Grass would suggest that this value is significantly higher.

These values were extracted using the following conditional statement in the raster calculator:

$$\text{Con} (\text{ND6881_raster} < 152, 0, \text{Con} (\text{ND6881_raster} > 158, 0, 1)$$

The output map (Figure 4.13) shows values that have similar pixel values to the Grass training samples. As part of the sequential classification method, the areas classified as Grass were removed from consideration with future classification methods.

Additionally, the normalized difference equation using bands 68 and 81 provided significant discrimination between the Developed class and all other land cover types. The Developed class shows some overlap with the Water land cover type, however Water was previously accounted for and extracted using the NDVI calculation.

As the mean and mode of the histogram of pixel values for the Developed class were similar, a normal distribution was assumed. Also, the distribution of pixels related to the Developed class does not significantly overlap with any other unclassified land cover types. Therefore, to extract developed pixels for classification values between the mean and ±2 standard deviations or pixel values between 158 and 164 were used. Under the assumed ideal normal distribution this would account for approximately 95.4% of the pixels classified as Developed in the training samples.

These values were extracted using the following conditional statement in the raster calculator:

$$\text{Con} (\text{ND6881_raster} < 158, 0, \text{Con} (\text{ND6881_raster} > 164, 0, 1)$$

The output map (Figure 4.14) shows values that have similar pixel values to the Developed training samples.
Figure 4.12 Histogram of normalized difference of AVIRIS Bands 68 and 81 of land cover classes from field study areas
Figure 4.13 Sequential land cover classification with *Small Grass Vegetation* classified using normalized difference of near-infrared bands ($\text{ND}_{668,661}$)
Figure 4.14 Sequential land cover classification with *Developed* classified using normalized difference of near-infrared bands (ND$_{b68,b61}$).
4.4.4 Normalized Burn Ratio

The process of sequential classification highlighted the potential need to account for areas that were impacted by forest fires. The 2003 Overland Fire, 2010 Four Mile Canyon Fire, and 2011 Maxwell Fire appeared as largely unclassified areas. To account for these burn areas, the normalized burn ratio that predicts burn severity was employed. For AVIRIS imagery, this ratio corresponds to band 51 (NIR: 0.826 – 0.836 µm) and band 196 (SWIR: 2.232 – 2.242 µm). To calculate NBR for AVIRIS imagery, the following equation was used:

\[
NBR = \frac{(\text{Band 51} - \text{Band 196})}{(\text{Band 51} + \text{Band 196})} \times 100 + 100
\]

The resulting raster (Figure 4.15) indicated areas that had experienced forest fires with the darkest areas being indicative of fires. However, the NBR pixel values for these \textit{Burn} areas do correspond with the pixel values from unmapped areas of \textit{Bedrock} and \textit{Colluvium} in unburned areas. Additional dark regions could be indicative of barren areas containing \textit{Bedrock} and \textit{Colluvium} (higher elevations) or dry, stressed vegetation (lower elevations).

To remove some of the \textit{Burn} area, a histogram was produced (Figure 4.16) showing the NBR pixel values for each of the training samples. Given the histogram, \textit{Burn} areas would be extracted by selecting NBR pixel values less than 130 as these values corresponded with very few of the land cover classes from the field study areas. While this selection criterion would not classify all \textit{Burn} areas, it would prevent areas of \textit{Bedrock} and \textit{Colluvium} outside of the forest fire perimeters from being misclassified as \textit{Burn} areas.

\textit{Burn} areas were extracted using the following conditional statement in the raster calculator in ArcMap:

\[
\text{Con(}"\text{NBR}_\text{raster}" < 130, 1, 0)\]

The output map (Figure 4.17) only shows portions of the \textit{Burn} area but prevented misclassification of the areas of \textit{Bedrock} and \textit{Colluvium}.

4.4.5 Ratio of Short-Wave Infrared Bands

As only \textit{Bedrock} and \textit{Colluvium} land cover types remain in the sequential classification methodology it was assumed that \textit{Colluvium} would have experienced more weathering than more competent outcrops of bedrock. With hyperspectral AVIRIS imagery, clays can be identified using shortwave infrared band 189 (2.142 – 2.152 µm), band 193 (2.182 – 2.192 µm), and band 203 (2.282 – 2.292 µm). Using AVIRIS imagery, higher clay content can be detected using the following equation:

\[
\text{Clay}_{\text{AVIRIS}} = \frac{(\text{Band 189} \times \text{Band 203})}{(\text{Band 193})^2}
\]

The resulting histogram (Figure 4.19) did not provide any distinguishable discrimination between \textit{Bedrock} and \textit{Colluvium}.

However, visual inspection of the Continental Divide along the western portion of the area of interest indicated that this ratio was providing some discrimination between \textit{Bedrock} and \textit{Colluvium}. In Figure 4.18, the raster displaying the output of the clay ratio clearly shows linear structures terminating
Figure 4.15 Normalized Burn Ratio (NBR) showing the perimeters of recent wildfires (red outline) in the area of interest.
Figure 4.16 Histogram of NBR of land cover classes from field study areas

AVIRIS Band 51 & Band 196
Figure 4.17 Sequential land cover classification with *Burn* classified using NBR
Figure 4.18 R_{b189,b193,b203} Raster image of Mount Audubon (on left) and true color satellite imagery of same area (on right)
Figure 4.19 Histogram of ratio of AVIRIS bands 189, 193, & 203 of land cover classes from field study areas
Figure 4.20 Sequential land cover classification with Colluvium classified using ratio of short-wave infrared bands ($R_{b189,b193,b203}$)
Figure 4.21 Histogram of combined normalized difference of land cover classes from field study areas

AVIRIS Band 51, Band 189, Band 193, Band 196, & Band 203
Figure 4.22 Sequential land cover classification with Colluvium classified using combined normalized difference of NBR and $R_{b189,b193,b203}$
in the valley bottom at lobate features. Comparison of the same area shows that these correspond with talus slopes descending from the north facing side of Mount Audubon. Given the shape of these features and their propensity to have certain clay ratio values, some regions of Colluvium could be extracted.

To extract these areas of colluvium, values greater than or equal to 95 were selected to correspond to more weathered areas—that is areas with higher clay. To extract these values the following statement was used:

\[
\text{Con}("\text{Clay\_raster}\geq 95, 1, 0)
\]

While this conditional statement was not assumed to have classified all of the colluvium in the area of interest (Figure 4.20), as part of the sequential classification method, it did remove some areas from consideration in future classification attempts.

### 4.4.6 Combined Normalized Difference

To further assess the area of interest for the presence of Bedrock and Colluvium, an additional ratio was considered. Based on visual inspection of the aforementioned NBR and Clay Ratio, a normalized difference calculation was carried out to accentuate any differences that may exist between the pixel values of Bedrock and Colluvium. This ratio was calculated using the following equation:

\[
ND_{\text{combined}} = \frac{(NBR - \text{Clay}_{\text{AVIRIS}})}{(NBR + \text{Clay}_{\text{AVIRIS}})}
\]

The resulting histograms of pixel values for each of the land cover training sample sites (Figure 4.21) provided a pair of local maximums for Colluvium’s distribution. The mode of the Bedrock distribution was approximately centered under the large local maximum of the Colluvium distribution. Consequently, values surrounding the minor local maximum of Colluvium were used to extract a second area of Colluvium from the area of interest (Figure 4.22). To extract these values, the following conditional statement was used:

\[
\text{Con}("\text{Combined\_raster}\geq 131, 1, 0)
\]

### 4.4.7 ALOS Amplitude

While previous attempts to classify Bedrock using optical methods had not yielded any tangible results, the use of amplitude from L-band radar could provide some measurable difference between Bedrock and Colluvium. Essentially, it was hypothesized that exposures of Colluvium would have higher amplitude values compared to areas with Bedrock. This is largely due to the idea that outcrops of Bedrock have lower surface roughness compared to outcrops of Colluvium. With an active source, surfaces with higher roughness would tend to get increased returns to the satellite sensor, thus recording higher amplitude. While both HH and HV polarizations were considered, the HH polarization results did not provide any means for discriminating areas of Bedrock from areas of Colluvium.

To extract land cover classes from the HV polarization amplitude image, a histogram was produced showing the range of amplitude values for each land cover training sample site (Figure 4.23).

In the histogram, it was observed that both Bedrock and Colluvium classes were normally distributed, however their modes were offset. To conservatively apply where Bedrock is in the area of interest, everything less than the mean value for Bedrock was selected, thereby classifying approximately
50% of the pixels identified as Bedrock in the training samples as Bedrock and the remaining 50% as Colluvium. These values were extracted using the following conditional statement in the raster calculator:

\[ \text{Con("Amplitude_HV_raster" > 1700, 1, 0)} \]

The output map (Figure 4.24) now shows a conservative estimate of where Bedrock outcrops are located.

Finally the remaining area was classified as Colluvium. Assuming the distribution is normal, amplitude pixel values greater the mean less half a standard deviation where used thereby accounting for approximately 69.1% of pixels classified as colluvium in the training samples.

4.4.8 Final Map & Confusion Matrix

The final map for the sequential classification shows the land cover classification of seven land cover types in regions where the AVIRIS imagery was available for the area of interest (Figure 4.25). Visual inspection of the final map shows that this portion of the overall area of interest is dominated by Forest land cover. The eastern portion of the area of interest shows large areas of Developed and Grass/Small Vegetation land cover that aligns with the location of Boulder, Colorado and the Front Range Fans and Foothill Shrublands ecoregions. Bedrock is primarily located in the western portion of the area of interest along the Continental Divide and in areas where vegetation was destroyed by wildfires. To better quantify the results of the final map, a confusion matrix was created to analyze the agreement between the actual and predicted datasets (Table 4.5).

Given the new area of interest, a new set of 5000 random points from the field study areas within the southern portion of the area of interest were selected. Using these 5000 verification points it was calculated that the actual and predicted datasets had an observed agreement of 77.72% with an expected or random agreement of 23.90%. This produced a Cohen’s kappa statistic of 0.7072 which, ignoring the kappa statistic for the supervised classification that was unable to differentiate Bedrock from Colluvium, represented the most substantial agreement between the actual and predicted datasets.

Classification of Bedrock had an improved sensitivity of 34.60% that represented an increase over the user accuracy observed in iterative unsupervised classifications but was still less that the sensitivity of 49.54% found during the original unsupervised classification methodology. This user accuracy suggests that the integration of methods is finding that 1 in 3 of the verification points that were field mapped as being Bedrock are being correctly identified as Bedrock. The sequential classification method found that producer accuracy for the classification of Bedrock was highest when compared to any other methods. The precision of Bedrock classification was 35.08% meaning that approximately one-third of verification points predicted to be Bedrock were actually field mapped as Bedrock outcrops. The specificity for the prediction of Bedrock was 94.93% meaning that a smaller proportion of false positives (5.07%) are associated with Bedrock in the integrated methodology.

The classification of Colluvium yielded a sensitivity of 73.55% that is significantly higher than the sensitivity observed for all other methods that were able to discriminate Bedrock and Colluvium. Approximately three-quarters of the verification points that were field mapped as Colluvium were
Figure 4.23 Histogram of PALSAR amplitude of land cover classes from field study areas
Figure 4.24 Sequential land cover classification with *Bedrock* classified using PALSAR amplitude.
Table 4.5 Confusion matrix for sequential classification of land cover

<table>
<thead>
<tr>
<th></th>
<th>(1) Bedrock</th>
<th>(2) Colluvium</th>
<th>(3) Developed</th>
<th>(4) Forest</th>
<th>(5) Grass</th>
<th>(6) Ice</th>
<th>(7) Water</th>
<th>Truth Overall</th>
<th>User Accuracy (Sensitivity)</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Bedrock</td>
<td>127</td>
<td>180</td>
<td>2</td>
<td>24</td>
<td>32</td>
<td>1</td>
<td>1</td>
<td>367</td>
<td>34.60%</td>
<td>65.40%</td>
</tr>
<tr>
<td>(2) Colluvium</td>
<td>232</td>
<td>1521</td>
<td>0</td>
<td>257</td>
<td>9</td>
<td>49</td>
<td>0</td>
<td>2068</td>
<td>73.55%</td>
<td>26.45%</td>
</tr>
<tr>
<td>(3) Developed</td>
<td>0</td>
<td>5</td>
<td>693</td>
<td>85</td>
<td>34</td>
<td>0</td>
<td>3</td>
<td>820</td>
<td>84.51%</td>
<td>15.49%</td>
</tr>
<tr>
<td>(4) Forest</td>
<td>2</td>
<td>63</td>
<td>2</td>
<td>869</td>
<td>70</td>
<td>0</td>
<td>1</td>
<td>1007</td>
<td>86.30%</td>
<td>13.70%</td>
</tr>
<tr>
<td>(5) Grass</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>14</td>
<td>79</td>
<td>0</td>
<td>0</td>
<td>94</td>
<td>84.04%</td>
<td>15.96%</td>
</tr>
<tr>
<td>(6) Ice</td>
<td>0</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>105</td>
<td>0</td>
<td>114</td>
<td>92.11%</td>
<td>7.89%</td>
</tr>
<tr>
<td>(7) Water</td>
<td>0</td>
<td>5</td>
<td>24</td>
<td>4</td>
<td>5</td>
<td>0</td>
<td>492</td>
<td>530</td>
<td>92.83%</td>
<td>7.17%</td>
</tr>
<tr>
<td>Classification Overall</td>
<td>362</td>
<td>1783</td>
<td>721</td>
<td>1253</td>
<td>229</td>
<td>155</td>
<td>497</td>
<td>5000</td>
<td>90.50%</td>
<td>94.93%</td>
</tr>
<tr>
<td>Producer Accuracy (Precision)</td>
<td>35.08%</td>
<td>85.31%</td>
<td>96.12%</td>
<td>69.35%</td>
<td>34.50%</td>
<td>67.74%</td>
<td>98.99%</td>
<td>90.50%</td>
<td>94.93%</td>
<td>64.92%</td>
</tr>
<tr>
<td>Omission Error</td>
<td>64.92%</td>
<td>14.69%</td>
<td>3.88%</td>
<td>30.65%</td>
<td>65.50%</td>
<td>32.26%</td>
<td>1.01%</td>
<td>90.50%</td>
<td>94.93%</td>
<td>64.92%</td>
</tr>
</tbody>
</table>

- **Accuracy**: 90.50% 83.82% 96.90% 89.56% 98.70% 98.82% 99.14%
- **Specificity**: 94.93% 91.06% 99.33% 90.38% 96.94% 98.98% 99.89%
- **F₁ measure**: 34.84% 78.99% 89.94% 76.90% 48.92% 78.07% 95.81%
- **Kappa (κ)**: 0.7072
- **Obs. Agreement (π₀)**: 0.7772
- **Exp. Agreement (πₑ)**: 0.2390
Figure 4.25 AVIRIS and PALSAR Sequential Land Cover Classification Final Map
predicted to be Colluvium. The precision of classification of Colluvium was highest for all methods, at 85.31% meaning that the majority of points predicted to be Colluvium were actually Colluvium.

Using the $F_1$ measure to compare Bedrock and Colluvium land cover classification across different methodologies, the integration of methods found a $F_1$ measure of 34.84% for Bedrock and 78.99% for Colluvium. For Bedrock classification, this represents the highest $F_1$ measure observed for all methods. For Colluvium, the $F_1$ measure is higher than any of the other methods that were able to discriminate Bedrock from Colluvium.

For the integrated approach, the best results for a single classifier were for Water with a sensitivity and precision of 92.83% and 98.99% respectively. The specificity of the supervised classification for Water was 99.89% meaning that very few false positives exist within the field study areas.
CHAPTER 5
DISCUSSION & CONCLUSIONS

5.1 Discussion

The four remote sensing methods for classifying land cover each produced unique results but the best results were found using the integrated sequential classification approach (see Table 5.1).

The unsupervised classification method produced some of the least reliable results. A disparity exists between the sensitivity and precision scores for all land cover types, except Water. That is, a tradeoff appears to exist between sensitivity and precision—that is, higher user accuracy results in a significantly lower producer accuracy or vice versa. Consequently, the unsupervised classification method resulted in the highest observed sensitivity across all methods for Bedrock (49.54%) but had the lowest observed precision (15.44%). For the classification of Bedrock with the unsupervised classification method, this suggests that approximately half of the verification points that were actually mapped as Bedrock were correctly predicted to be Bedrock while only a few areas predicted to be Bedrock were actually Bedrock. This notion is more clearly reflected in the $F_1$ measure, which is the weighted harmonic mean that examines the tradeoff that exists between precision and sensitivity. The $F_1$ measure for each land cover is either lowest or second lowest across all methods. While the unsupervised classification is one of the least time intensive methods, an examination of the performance metrics and the resulting land cover classification map indicate that it clearly produced some of the most questionable results.

The results of the supervised classification indicated that the spectral signatures of the Bedrock and Colluvium land cover types were too similar to discriminate. While this is unfortunate, the supervised classification method produced high sensitivity for all land cover types (except Bedrock) and significantly high precision values. This result is reflected in the high $F_1$ measures that were calculated for all land cover types. This means that with the supervised classification method, the majority of points that were field mapped as a certain land cover type were correctly identified as the same land cover type (high sensitivity). Also the majority of points that were predicted to be a particular land cover type were actually that same land cover type (high precision). However, this method was unable to discriminate between Bedrock and Colluvium thereby making it a completely ineffective method for mapping Bedrock outcrops.

In another attempt to develop a method that can provide some discrimination between Bedrock and Colluvium, the results of the supervised classification were used to perform two unsupervised classifications on each land cover type. This iterative method attempted to combine the high sensitivity and precision results observed in the supervised classification with the ability to distinguish Bedrock and Colluvium as observed in the unsupervised classification.

The results of this iterative method of land cover classification produced the best results for any method that employed the Landsat-8 data set. Higher combinations of sensitivity and precision were observed for each land cover type that resulted in improved $F_1$ measures when compared to the unsupervised classification (see Table 5.1). While there was a decrease in observed agreement and most
Table 5.1 Comparison of performance metrics of each classification method for every land cover class
(Unsupervised = A, Supervised = B, First Iteration Unsupervised = C₁, Second Iteration Unsupervised =
C₂, Sequential Classification = D), Bold values represent the highest achieved value for each metric
within each land cover type.

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>Sensitivity</th>
<th>Precision</th>
<th>Specificity</th>
<th>F₁ measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Bedrock</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>49.54%</td>
<td>15.44%</td>
<td>74.08%</td>
<td>23.54%</td>
</tr>
<tr>
<td>B</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>C₁</td>
<td>21.75%</td>
<td>20.70%</td>
<td>90.43%</td>
<td>21.21%</td>
</tr>
<tr>
<td>C₂</td>
<td>32.23%</td>
<td>20.47%</td>
<td>85.62%</td>
<td>25.04%</td>
</tr>
<tr>
<td>D</td>
<td>34.60%</td>
<td>35.08%</td>
<td>94.93%</td>
<td>34.84%</td>
</tr>
<tr>
<td>(2) Colluvium</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>41.57%</td>
<td>81.24%</td>
<td>95.20%</td>
<td>55.00%</td>
</tr>
<tr>
<td>B</td>
<td>94.49%</td>
<td>76.16%</td>
<td>85.87%</td>
<td>84.34%</td>
</tr>
<tr>
<td>C₁</td>
<td>64.91%</td>
<td>72.15%</td>
<td>88.03%</td>
<td>68.34%</td>
</tr>
<tr>
<td>C₂</td>
<td>54.64%</td>
<td>77.52%</td>
<td>92.43%</td>
<td>64.10%</td>
</tr>
<tr>
<td>D</td>
<td>73.55%</td>
<td>85.31%</td>
<td>91.06%</td>
<td>78.99%</td>
</tr>
<tr>
<td>(3) Developed</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>50.54%</td>
<td>71.46%</td>
<td>97.45%</td>
<td>59.21%</td>
</tr>
<tr>
<td>B</td>
<td>97.06%</td>
<td>88.50%</td>
<td>97.45%</td>
<td>92.59%</td>
</tr>
<tr>
<td>C₁</td>
<td>97.07%</td>
<td>77.44%</td>
<td>96.29%</td>
<td>86.15%</td>
</tr>
<tr>
<td>C₂</td>
<td>97.07%</td>
<td>77.44%</td>
<td>97.13%</td>
<td>86.15%</td>
</tr>
<tr>
<td>D</td>
<td>84.51%</td>
<td>96.12%</td>
<td>99.33%</td>
<td>89.94%</td>
</tr>
<tr>
<td>(4) Forest</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>65.29%</td>
<td>95.73%</td>
<td>98.66%</td>
<td>77.64%</td>
</tr>
<tr>
<td>B</td>
<td>86.94%</td>
<td>85.34%</td>
<td>93.68%</td>
<td>86.13%</td>
</tr>
<tr>
<td>C₁</td>
<td>64.31%</td>
<td>90.95%</td>
<td>97.30%</td>
<td>75.35%</td>
</tr>
<tr>
<td>C₂</td>
<td>68.15%</td>
<td>90.93%</td>
<td>97.13%</td>
<td>77.91%</td>
</tr>
<tr>
<td>D</td>
<td>86.30%</td>
<td>69.35%</td>
<td>96.94%</td>
<td>76.90%</td>
</tr>
<tr>
<td>(5) Grass</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>81.17%</td>
<td>26.22%</td>
<td>88.53%</td>
<td>39.63%</td>
</tr>
<tr>
<td>B</td>
<td>92.00%</td>
<td>76.20%</td>
<td>98.33%</td>
<td>83.36%</td>
</tr>
<tr>
<td>C₁</td>
<td>96.00%</td>
<td>36.92%</td>
<td>96.46%</td>
<td>53.33%</td>
</tr>
<tr>
<td>C₂</td>
<td>95.64%</td>
<td>37.73%</td>
<td>90.81%</td>
<td>54.12%</td>
</tr>
<tr>
<td>D</td>
<td>84.04%</td>
<td>34.50%</td>
<td>96.94%</td>
<td>48.92%</td>
</tr>
<tr>
<td>(6) Ice</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>B</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>C₁</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>C₂</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>D</td>
<td>92.11%</td>
<td>67.74%</td>
<td>98.98%</td>
<td>78.07%</td>
</tr>
<tr>
<td>(7) Water</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>97.50%</td>
<td>94.58%</td>
<td>99.35%</td>
<td>96.02%</td>
</tr>
<tr>
<td>B</td>
<td>96.22%</td>
<td>99.03%</td>
<td>99.89%</td>
<td>97.60%</td>
</tr>
<tr>
<td>C₁</td>
<td>96.22%</td>
<td>99.22%</td>
<td>99.91%</td>
<td>97.70%</td>
</tr>
<tr>
<td>C₂</td>
<td>96.22%</td>
<td>99.22%</td>
<td>99.91%</td>
<td>97.70%</td>
</tr>
<tr>
<td>D</td>
<td>92.11%</td>
<td>98.99%</td>
<td>99.89%</td>
<td>95.43%</td>
</tr>
</tbody>
</table>
other performance metrics when compared to the supervised classification, the iterative method was able to produce some discrimination between Bedrock and Colluvium. Examining the results of the individual iterations indicates that a tradeoff exists between the performance metrics for Bedrock and Colluvium. Improved $F_1$ measure for Bedrock from the first to second iteration was combined with a decrease in $F_1$ measure for Colluvium. This was largely reflected in the sensitivity which had an approximate 10% improvement for Bedrock and an associated 10% decrease for Colluvium from the first to second iteration.

Finally, the integrated sequential classification approach produced the best results when observing the performance metrics—especially those for Bedrock and Colluvium. The use of multiple sub-classification methods and two different data sets in the sequential classification yield the best combinations of the sensitivity and precision observed for Bedrock and Colluvium. This included the $F_1$ measures that were highest for Bedrock, Colluvium, and Developed and very close to the highest values for the remaining the land cover types.

The initial step of the integrated sequential classification method that classified areas of Forest showed that the conditional statement used resulted in a false positive identification rate of 30.39%. This result is observed in the confusion matrix (Table 4.5) which found that the classification of Forest yielded an omission error of 30.65% with the majority of false positives being classified as Colluvium and to a lesser extent Developed and Bedrock.

Examining the overall performance metrics for each land cover classification method showed that the highest observed agreement and highest kappa statistic were produced by the integrated sequential classification approach (Table 5.2). While higher observed agreement and kappa statistics were found with the supervised classification method, no discrimination between Bedrock and Colluvium could be discerned.

Table 5.2 Comparison of overall performance metrics of each classification (Unsupervised = A, Supervised = B, First Iteration Unsupervised = C₁, Second Iteration Unsupervised = C₂, Sequential Classification = D)

<table>
<thead>
<tr>
<th></th>
<th>Observed Agreement ($\pi_0$)</th>
<th>Expected Agreement ($\pi_e$)</th>
<th>Kappa Statistic ($\kappa$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>58.46%</td>
<td>17.64%</td>
<td>0.4957</td>
</tr>
<tr>
<td>A</td>
<td>82.86%</td>
<td>24.88%</td>
<td>0.7718</td>
</tr>
<tr>
<td>B</td>
<td>69.04%</td>
<td>20.31%</td>
<td>0.6115</td>
</tr>
<tr>
<td>C₁</td>
<td>67.92%</td>
<td>19.18%</td>
<td>0.6031</td>
</tr>
<tr>
<td>C₂</td>
<td>77.72%</td>
<td>23.90%</td>
<td>0.7072</td>
</tr>
</tbody>
</table>

A final interesting result (Table 5.3) shows the location of debris scarps in relation to the predicted land cover class for each respective land cover classification method. This suggests that for many of the methods, the vast majority of debris flow scarps are located in Colluvium, Forest, or Grass land cover types. Very few debris flow scarps were located in areas predicted to be Bedrock. While this does not
prove the accuracy of the land cover prediction methods, it is a result that suggests that if the Bedrock land cover class were used in future debris flow modeling, a significant portion of relatively competent material could be removed, thus constraining any debris flow susceptibility model.

While the results for the integrated sequential land cover classification approach are significant, the sensitivity and precision for Bedrock and to some extent, Colluvium is still low. This result could be an artifact of the conservative selection of Bedrock when examining the ALOS amplitude data. Better discrimination between these land cover types will be likely in the future as passive and active remote sensing technology improves. Improved discrimination between Bedrock and Colluvium could be possible as the spatial resolution and spectral width of long-wave thermal infrared bands becomes finer. While improved land cover classification was achieved with the integrated sequential classification approach that employed the hyperspectral and higher spatial resolution data set, the significant limit of hyperspectral, high resolution datasets could provide a barrier to employing this integrated sequential land cover classification approach in additional areas of interest. While future remote sensing methods will likely employ higher spatial and temporal hyperspectral data and could warrant the use of the integrated sequential approach for land cover classification, further research should employ combining readily available passive remote sensing methods (Landsat) with active radar methods to discern Bedrock from Colluvium.

Table 5.3 Observed debris flow scarps location and predicted land cover class for each respective land cover classification method

<table>
<thead>
<tr>
<th>Methods</th>
<th>Unsupervised</th>
<th>Supervised</th>
<th>Iteration 1</th>
<th>Iteration 2</th>
<th>Sequential</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Bedrock</td>
<td>18 2.1%</td>
<td>0 0.0%</td>
<td>64 7.4%</td>
<td>132 15.3%</td>
<td>24 4.8%</td>
</tr>
<tr>
<td>(2) Colluvium</td>
<td>38 4.4%</td>
<td>291 33.7%</td>
<td>246 28.5%</td>
<td>141 16.3%</td>
<td>75 15.0%</td>
</tr>
<tr>
<td>(3) Developed</td>
<td>131 15.2%</td>
<td>26 3.0%</td>
<td>91 10.5%</td>
<td>91 10.5%</td>
<td>1 0.2%</td>
</tr>
<tr>
<td>(4) Forest</td>
<td>374 43.3%</td>
<td>401 46.5%</td>
<td>160 18.5%</td>
<td>166 19.2%</td>
<td>167 33.5%</td>
</tr>
<tr>
<td>(5) Grass</td>
<td>51 5.9%</td>
<td>144 16.7%</td>
<td>301 34.9%</td>
<td>332 38.5%</td>
<td>232 46.5%</td>
</tr>
<tr>
<td>(6) Ice</td>
<td>251 29.1%</td>
<td>1 0.1%</td>
<td>1 0.1%</td>
<td>1 0.1%</td>
<td>0 0.0%</td>
</tr>
<tr>
<td>(7) Water</td>
<td>1 0.2%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burn</td>
<td>2 0.4%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.2 Conclusions

The integrated sequential land cover classification approach yielded the best overall results in terms of sensitivity, precision, and $F_1$ measure for Bedrock and Colluvium, and the same method produced the highest observed agreement (observed accuracy) for a method that was able to discriminate Bedrock and Colluvium. To optimize the performance metrics for land cover classification that discriminates Bedrock and Colluvium, a combination of the supervised classification and sequential classification methods could be employed. Optimally, this could require using the AVIRIS dataset to carry out the supervised classification approach to identify Developed, Forest, Grass, Ice, and Water with high confidence. Then using the AVIRIS and PALSAR data sets, the methods outlined in the integrated sequential classification approach would be used to identify Bedrock and Colluvium. This method would
require the creation of a Barren land cover class for the supervised classification that would subsequently be used to identify Bedrock and Colluvium with the sequential land cover classification method.

Given the current limited spatial coverage of AVIRIS data, an additional approach could be used which combines the Landsat-8 and PALSAR data sets. Again, this method would employ the use of the supervised classification approach to identify Barren, Developed, Forest, Grass, Ice, and Water with high confidence. As Landsat-8 is a multispectral scanner, the methods outlined for the hyperspectral AVIRIS sensor in the integrated sequential classification approach would no longer be applicable. However, the PALSAR dataset could be used to perform the final step of the integrated sequential classification approach which discriminates Bedrock and Colluvium.

Considerable difference between the performance metric values for Bedrock and Colluvium and all other land cover types remain quite significant. Improved sensitivity and precision will be possible as active and passive remote sensing technology improves.

The integrated sequential land cover classification approach is currently limited in its application to other areas of interest due to the unavailability of high spatial resolution, hyper spectral data. Further research should be conducted to examine combining existing passive remote sensing methods with active remote sensing methods.
REFERENCES CITED


http://www.mathworks.com/matlabcentral/fileexchange/46035-confusionmatstats-group-grouphat-


NASA. (2016, March 3). *Landsat 8 Overview*. Retrieved from Landsat Science:
http://landsat.gsfc.nasa.gov/?page_id=7195


APPENDIX A
LOCATION OF FIELD TRAINING SAMPLES

The following map shows the general location of all sites across the area of interest that were used as training samples for classification and accuracy assessment. For further detail regarding the type of land cover in each field study area, see Appendix B.

![Field Training Samples Map]

Figure A.1 Location of training samples within area of interest
APPENDIX B

FINAL LAND COVER MAPS FOR FIELD STUDY AREAS

Figure B.1 Blue Lake/Mitchell Lake Field Study Area
Figure B.2 Twin Sisters Field Study Area
Figure B.3 North St. Vrain Field Study Area
Figure B.4 Porphyry Mountain Field Study Area
Figure B.5 Hall Ranch Field Study Area
Figure B.6 Mount Sanitas Field Study Area
APPENDIX C
HYPOTHESIS TESTING OF BEDROCK & COLLUVIUM REFLECTANCE DATA

Table C.1 F-test and t-test results for **Bedrock** and **Colluvium** reflectance data showing that they are from the same population.

<table>
<thead>
<tr>
<th>Landsat-8 Band 1 Coastal/Aerosol 0.435-0.451μm</th>
<th>F-Test Two-Sample for Variances</th>
<th>t-Test: Two-Sample Assuming Equal Variances</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Variable 1</strong></td>
<td><strong>Variable 2</strong></td>
</tr>
<tr>
<td>Mean</td>
<td>0.125274</td>
<td>0.124916</td>
</tr>
<tr>
<td>Variance</td>
<td>0.000709</td>
<td>0.000678</td>
</tr>
<tr>
<td>Observations</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>df</td>
<td>499</td>
<td>499</td>
</tr>
<tr>
<td><strong>F</strong></td>
<td>1.0451</td>
<td></td>
</tr>
<tr>
<td><strong>P(F&lt;=f) one-tail</strong></td>
<td>0.311206</td>
<td></td>
</tr>
<tr>
<td><strong>F Critical one-tail</strong></td>
<td>1.158827</td>
<td></td>
</tr>
</tbody>
</table>

F < F Critical one-tail, therefore fail to reject the null hypothesis \( H_0: \sigma_1^2 = \sigma_2^2 \)

<table>
<thead>
<tr>
<th>Landsat-8 Band 2 Blue 0.452-0.512μm</th>
<th>F-Test Two-Sample for Variances</th>
<th>t-Test: Two-Sample Assuming Equal Variances</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Variable 1</strong></td>
<td><strong>Variable 2</strong></td>
</tr>
<tr>
<td>Mean</td>
<td>0.121097</td>
<td>0.120434</td>
</tr>
<tr>
<td>Variance</td>
<td>0.001213</td>
<td>0.001152</td>
</tr>
<tr>
<td>Observations</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>df</td>
<td>499</td>
<td>499</td>
</tr>
<tr>
<td><strong>F</strong></td>
<td>1.053516</td>
<td></td>
</tr>
<tr>
<td><strong>P(F&lt;=f) one-tail</strong></td>
<td>0.280299</td>
<td></td>
</tr>
<tr>
<td><strong>F Critical one-tail</strong></td>
<td>1.158827</td>
<td></td>
</tr>
</tbody>
</table>

F < F Critical one-tail, therefore fail to reject the null hypothesis \( H_0: \sigma_1^2 = \sigma_2^2 \)

P-value > 0.05, therefore cannot reject the null hypothesis \( H_0: \mu_1 = \mu_2 \)
### Landsat-8 Band 3 Green 0.533-0.590μm

**F-Test Two-Sample for Variances**

<table>
<thead>
<tr>
<th></th>
<th>Variable 1</th>
<th>Variable 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.123099</td>
<td>0.122633</td>
</tr>
<tr>
<td>Variance</td>
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<tr>
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<td>500</td>
<td>500</td>
</tr>
<tr>
<td>df</td>
<td>499</td>
<td>499</td>
</tr>
</tbody>
</table>

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>1.041137</td>
<td></td>
</tr>
<tr>
<td>P(F&lt;=f) one-tail</td>
<td>0.326345</td>
<td></td>
</tr>
<tr>
<td>F Critical one-tail</td>
<td>1.158827</td>
<td></td>
</tr>
</tbody>
</table>

F < F Critical one-tail, therefore fail to reject the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$

### Landsat-8 Band 4 Red 0.636-0.673μm

**F-Test Two-Sample for Variances**

<table>
<thead>
<tr>
<th></th>
<th>Variable 1</th>
<th>Variable 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.134801</td>
<td>0.13428</td>
</tr>
<tr>
<td>Variance</td>
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<td>500</td>
</tr>
<tr>
<td>df</td>
<td>499</td>
<td>499</td>
</tr>
</tbody>
</table>

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>1.029504</td>
<td></td>
</tr>
<tr>
<td>P(F&lt;=f) one-tail</td>
<td>0.372744</td>
<td></td>
</tr>
<tr>
<td>F Critical one-tail</td>
<td>1.158827</td>
<td></td>
</tr>
</tbody>
</table>

F < F Critical one-tail, therefore fail to reject the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$
### Landsat-8 Band 5 NIR 0.851-0.879μm

F-Test Two-Sample for Variances

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Variance</th>
<th>Observations</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable 1</td>
<td>0.213257</td>
<td>0.005408</td>
<td>500</td>
<td>499</td>
</tr>
<tr>
<td>Variable 2</td>
<td>0.212924</td>
<td>0.00535</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

F: 1.010807

P(F<=f) one-tail: 0.452241

F Critical one-tail: 1.158827

F < F Critical one-tail, therefore fail to reject the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$

### Landsat-8 Band 6 SWIR-1 1.566-1.651μm

F-Test Two-Sample for Variances

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Variance</th>
<th>Observations</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable 1</td>
<td>0.244346</td>
<td>0.007071</td>
<td>500</td>
<td>499</td>
</tr>
<tr>
<td>Variable 2</td>
<td>0.243619</td>
<td>0.006935</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

F: 1.01965

P(F<=f) one-tail: 0.414014

F Critical one-tail: 1.158827

F < F Critical one-tail, therefore fail to reject the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$

---

### Landsat-8 Band 5 NIR 0.851-0.879μm

t-Test: Two-Sample Assuming Equal Variances

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Variance</th>
<th>Observations</th>
<th>df</th>
</tr>
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<tbody>
<tr>
<td>Variable 1</td>
<td>0.213257</td>
<td>0.005408</td>
<td>500</td>
<td>499</td>
</tr>
<tr>
<td>Variable 2</td>
<td>0.212924</td>
<td>0.00535</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Hypothesized Mean Difference: 0

P(T<=t) one-tail: 0.471383

t Critical one-tail: 1.646382

P(T<=t) two-tail: 0.942767

t Critical two-tail: 1.962344

P-value > 0.05, therefore cannot reject the null hypothesis $H_0: \mu_1 = \mu_2$

---

### Landsat-8 Band 6 SWIR-1 1.566-1.651μm

t-Test: Two-Sample Assuming Equal Variances

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Variance</th>
<th>Observations</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable 1</td>
<td>0.244346</td>
<td>0.007071</td>
<td>500</td>
<td>499</td>
</tr>
<tr>
<td>Variable 2</td>
<td>0.243619</td>
<td>0.006935</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Hypothesized Mean Difference: 0

P(T<=t) one-tail: 0.445406

t Critical one-tail: 1.646382

P(T<=t) two-tail: 0.890812

t Critical two-tail: 1.962344

P-value > 0.05, therefore cannot reject the null hypothesis $H_0: \mu_1 = \mu_2$
Table C.4 Continued

Landsat-8 Band 7 SWIR-2 2.107-2.294μm
F-Test Two-Sample for Variances

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable 1</th>
<th>Variable 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.187198</td>
<td>0.187312</td>
</tr>
<tr>
<td>Variance</td>
<td>0.004825</td>
<td>0.004764</td>
</tr>
<tr>
<td>Observations</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>df</td>
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</tr>
</tbody>
</table>

F 1.012815

P(F<=f) one-tail 0.44348

F Critical one-tail 1.158827

F < F Critical one-tail, therefore fail to reject the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$

---

t-Test: Two-Sample Assuming Equal Variances

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable 1</th>
<th>Variable 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.187198</td>
<td>0.187312</td>
</tr>
<tr>
<td>Variance</td>
<td>0.004825</td>
<td>0.004764</td>
</tr>
<tr>
<td>Observations</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>df</td>
<td>998</td>
<td>-0.02611</td>
</tr>
</tbody>
</table>
| Hypothesized Mean Difference | 0
| df       | 998        |
| t Stat   | 1.646382   |
| P(T<=t) one-tail | 0.489587
| P(T<=t) two-tail | 0.979174
| t Critical one-tail | 1.962344

P-value > 0.05, therefore cannot reject the null hypothesis $H_0: \mu_1 = \mu_2$
APPENDIX D
SUPPLEMENTAL ELECTRONIC FILES

The supplemental electronic files listed below are comprised of data for use in a geographical information system (GIS) such as ArcGIS. The provided data includes preprocessed remote sensing imagery and intermediate results for the methods outlined in this document. Data is arranged in alphabetical order by file name. Files with a single letter prefix refer to the method for which the data file is relevant (Unsupervised = A, Supervised = B, Iterative Supervised/Unsupervised = C, Integrated Sequential Classification = D). Data descriptions provide further detail.

<table>
<thead>
<tr>
<th>GIS Data Files</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>quads24k_a_co.gdb</td>
<td>This File Geodatabase Feature Dataset contains the Feature class named QD24K_9quads which outlines the 9 quadrangle area of interest.</td>
</tr>
<tr>
<td>9_quad_SRTM1_DEM.grd</td>
<td>Digital Elevation Model for the 9 quadrangle area of interest.</td>
</tr>
<tr>
<td>A_Unsupervised_Classification.tif</td>
<td>Raster dataset reclassified into six different types of land cover for the Unsupervised Classification approach.</td>
</tr>
<tr>
<td>B_Supervised_Classification.tif</td>
<td>Raster dataset reclassified into six different types of land cover for the Supervised Classification approach.</td>
</tr>
<tr>
<td>C_iteration1.tif</td>
<td>Raster dataset reclassified into six different types of land cover for the first iteration of the Iterative Supervised/Unsupervised Classification approach.</td>
</tr>
<tr>
<td>C_iteration2.tif</td>
<td>Raster dataset reclassified into six different types of land cover for the second iteration of the Iterative Supervised/Unsupervised Classification approach.</td>
</tr>
<tr>
<td>D1_NDVI.tif</td>
<td>Raster dataset of the Normalized Difference Vegetation Index (NDVI) for the AVIRIS dataset. Used in the first step of the Integrated Sequential Land Cover Classification approach to extract areas of Forest and Water.</td>
</tr>
<tr>
<td>D2_NDBI.tif</td>
<td>Raster dataset of the Normalized Difference Build-up Index (NDBI) for the AVIRIS dataset. Used in the second step of the Integrated Sequential Land Cover Classification approach to extract Ice.</td>
</tr>
<tr>
<td>D3_ND_b68_b81.tif</td>
<td>Raster dataset of the normalized difference between AVIRIS bands 68 and 81. Used in the third step of the Integrated Sequential Land Cover Classification approach to extract Grass and Developed land cover types.</td>
</tr>
<tr>
<td>D4_NBR.tif</td>
<td>Raster dataset of the Normalized Burn Ratio (NBR) for the AVIRIS dataset. Used in the fourth step of the Integrated Sequential Land Cover Classification approach to extract areas of Burn.</td>
</tr>
<tr>
<td>File Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td>D5_clay_ratio.tif</td>
<td>Raster dataset of the clay ratio for the AVIRIS dataset. Used in the fifth step of the Integrated Sequential Land Cover Classification approach to extract areas of <strong>Colluvium</strong>.</td>
</tr>
<tr>
<td>D6_combined_ND_NBR_clay.tif</td>
<td>Raster dataset of the combined normalized difference between the NBR and clay ratio for the AVIRIS dataset. Used in the sixth step of the Integrated Sequential Land Cover Classification approach to extract areas of <strong>Colluvium</strong>.</td>
</tr>
<tr>
<td>D7_PALSAR_amplitude_HV.tif</td>
<td>Raster of the amplitude of the Phased Array type L-band Synthetic Aperture Radar (PALSAR) dataset. Used in the seventh step of the Integrated Sequential Land Cover Classification approach to extract areas of <strong>Bedrock</strong> and <strong>Colluvium</strong>.</td>
</tr>
<tr>
<td>fieldstudyareas_training_samples.shp</td>
<td>Shapefile containing the actual land cover classification obtained from the six field study areas and supplemental areas across the area of interest.</td>
</tr>
</tbody>
</table>