THE APPLICATION OF 

HYPERSPECTRAL IMAGING FOR SURFACE ALTERATION 

MAPPING: A CASE STUDY OF PINNACLE RIDGE, 

MT RUAPHEHU, NEW ZEALAND. 

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Abstract

Diagnostic absorption features in hyperspectral data can directly correlate to a specific mineral, or mineral assemblage. However, it is unknown how accurate hyperspectral mapping can be for identifying alteration mineral compositions at the resolution required to describe structures such as fossil intrusive systems, or whether it can accurately quantify the alteration present. This study explores the application of shortwave infrared (SWIR) hyperspectral remote sensing at a laboratory (cm-scale) and aerial (m-scale) scale, to characterise the abundance and map the spatial distribution of surface hydrothermal alteration on Pinnacle Ridge, Mt. Ruapehu, New Zealand.

Point count analysis quantified a range of alteration between 7.6 – 85.2% from thin sections of samples collected on the ridge, which are consistent with published x-ray diffraction data from the area. This facilitated the categorisation of the samples into six alteration groups, which was used to generate a geological map of the alteration distribution across the ridge. Laboratory hyperspectral data of the samples were manually compared to the USGS spectral library which identified alteration minerals of montmorillonite, ± kaolinite, ± goethite, ± jarosite.

Phyllosilicate minerals at less than 10 wt% still produced a relatively strong absorption feature in both the lab and aerial hyperspectral data between 2201 – 2215 nm. The data shows a strong correlation of the alteration percent from thin section point count and lab-based spectral data at 2207 nm wavelength. The aerial data does not have the same correlation with the alteration percent. This implies that the instrument signal to noise ratio and the spectral sampling intervals for the laboratory data might play a big role in this strong correlation.

A combination of a Principal Component Analysis (PCA) and Spectral Angle Mapper (SAM) classification was used to create an alteration map from the aerial hyperspectral data. Compared to the geologically derived alteration map, the image classification is a better representation of the heterogeneity of alteration at m-scale. It identified zones of alteration surrounding the larger intrusions which suggests the fluid migration from the intrusions was controlled by microfracture density and connectivity of the surrounding units. Alteration was also abundant in and surrounding a fault through the middle of Pinnacle Ridge which indicates that the alteration was also controlled by regional faulting. There were some inconsistencies between the two alteration maps which is either a result of a scaling issue or sample bias.

The alteration minerals identified in the laboratory hyperspectral data suggests argillic to intermediate argillic alteration assemblages implying lower temperature, and near neutral alteration compared to previous studies. Three hypotheses are proposed to explain this: 1) advanced argillic alteration was produced in the system but has been overprinted with supergene alteration at the surface; 2) the shallow system did not sustain degassing or high temperature fluids for sufficient timescales to
achieve advanced argillic alteration; or 3) the samples collected from the ridge thus far, do not encompass the full range of alteration. This study supports the utility of hyperspectral mapping in volcanic environments as it has provided a new perspective on the alteration history of Pinnacle Ridge, Ruapehu. It has also provided evidence that the use of hyperspectral imaging for alteration necessitates examination of multiple scales to make robust conclusions.
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Chapter 1: Introduction

1.1 Project background

Hydrothermal alteration in volcanic environments can record the eruptive and post-emplacement history of volcanic deposits. Hydrothermal alteration describes the process by which water, heated and ionized by plutonism or volcanic activity, circulates the surrounding rocks (Inoue, 1995; Galán & Ferrell, 2013). This process leads to material degradation as the warm to hot, ion-rich fluids dissolve the original minerals and structures in the rock, and deposit mineral assemblages in equilibrium with the new temperature and pressure conditions (Inoue, 1995; Mordensky et al., 2018a). Alteration can both weaken volcanic material via dissolution, resulting in rock fall or flank collapse events (Reid et al., 2010), or locally strengthen volcanic material via deposition, resulting in blocked degassing pathways that can drive explosive events (Heap et al., 2019). Remote monitoring and mapping of alteration is often required for remote, inaccessible, or hazardous environments.

Hyperspectral remote sensing (also referred to as imaging spectroscopy) is the measure of reflected, absorbed, and emitted radiation of objects, acquired in many narrow contiguous bands from the visible and near-infrared (350 – 1000 nm) to the shortwave infrared (1000 – 2500 nm) regions of the electromagnetic spectrum (Vane et al., 1993; Clark, 1999; Plaza et al., 2009). This data provides the opportunity to analyse the environment at the surface remotely (Goetz et al., 1985), and is particularly useful for measuring hydrothermal alteration due to altered indicator minerals with characteristic absorption features (Gersman et al., 2008; Kereszturi et al., 2018). With the vast improvements in bandwidth and spectral contiguity between multispectral and hyperspectral data, identification and geological mapping of hydrothermal mineral assemblages in volcanic environments is possible through remote sensing applications (Ramakrishnan & Bharti, 2015).

Identification and quantification of alteration becomes important two-fold: (1) to monitor ongoing changes in the volcano and ensure the safety of the population and infrastructure; and (2) to map pre-historic eruptive events and intrusions to better understand the effects of hydrothermal systems on the volcano. This study focuses on identifying the alteration on Pinnacle Ridge, on the north-western flank of Mt Ruapehu (Figure 1.2), using petrographic techniques complemented with hyperspectral lab measurements and aerial imagery. Pinnacle Ridge is an old (<205 ± 27 ka; Conway et al., 2015), eroded eruption centre of Mt Ruapehu with magma intrusions and associated hydrothermal alteration that varies throughout the outcrop (Hackett, 1985; Mordensky et al., 2018a and b). The erosion of the old Ruapehu cone from glaciation and sector collapse exposed the shallow intrusive system (Hackett, 1985). The internal plumbing system of young volcanoes are typically not exposed; therefore, Pinnacle Ridge is a unique opportunity to investigate volcanic process internal to the volcano.
The five main objectives of this study are: (1) to identify and map the pervasiveness of alteration using petrographic and spectroscopic methods; (2) explore what resolution is required to verify mineral signatures in remotely sensed data by comparing laboratory to aerial hyperspectral data; (3) to deconvolute aerial hyperspectral data to spatially map the abundance of alteration through image classification techniques; (4) to better understand how hyperspectral data can be used to inform the alteration history on Pinnacle Ridge, to determine if the alteration is a factor of intrusion or fracture density; and (5) to discuss the implications of hyperspectral imaging for alteration mapping in volcanic environments. With the comparison of multiple hyperspectral scales (laboratory and aerial) with laboratory petrography, this study will help highlight applications and address the limitations of aerial surveys for volcano alteration mapping.

1.2 Project objectives

1.2.1 Alteration mineral identification and quantification
How do we target specific minerals to quantify their abundance, i.e. clay minerals? To achieve this objective, methods such as thin section analysis, x-ray diffraction (XRD), and laboratory hyperspectral analysis are used to identify alteration mineral phases in selected samples and to describe the temperature ranges of the alteration zones. This data outlines important secondary mineral phases to target and map using the airborne data in Objective 1.2.3. XRD and point counting analysis are used to classify the abundance of alteration in the samples, which are used to create a ground-truthed geological map of the spatial distribution of the alteration mineral phases.

1.2.2 Spatial scales
What resolution is required to verify mineral signatures? This objective is to look at how the change in scale between the microscope (micron to mm scale), laboratory (cm-scale), and aerial data (m-scale) affects the mineral signatures. Since these datasets have different spatial resolutions, the microscope and laboratory data are more accurate in identifying the signatures of individual alteration minerals. Therefore, the alteration abundance identified in Objective 1.2.1 needs to be correlated with the laboratory hyperspectral data and lower spatial resolution aerial data, to determine whether aerial data can be used to accurately identify mineral associations in volcanic environments.

1.2.3 Image analysis
Hyperspectral data is often complex, multi-dimensional and highly co-linear (Ghamisi et al., 2017). How can aerial hyperspectral data be deconvolved to map strategic mineral signatures? Once the aerial data is correlated to the alteration abundance, supervised image classification will be used to map the spatial intensity of the alteration zones on Pinnacle Ridge.
1.2.4 Alteration history
How do secondary mineral compositions relate or inform the history of Pinnacle Ridge? This objective is to investigate the spatial distribution of the alteration on Pinnacle Ridge to determine if the alteration is a factor of the intrusion or the regional faulting, i.e. weathering vs hydrothermal alteration. Additionally, is there any overprinting on the ridge from more than one alteration type. This information will help inform the history of Pinnacle Ridge, post-emplacement.

1.2.5 Implications
This objective will look at the implications of utilising laboratory and aerial hyperspectral spectroscopy to map alteration assemblages in volcanic environments. Some questions that may be answered include: (1) how will the application of remote sensing techniques benefit volcanic research and in particular, alteration mapping? And (2) are there any challenges in using hyperspectral imaging for volcanology research?

1.3 Thesis structure
Chapter 1 will explore the geological setting of Pinnacle Ridge, Mt. Ruapehu, and the wider Taupo Volcanic Zone (TVZ) in which its located, before detailing the hyperspectral processes that will be used in this thesis and past studies. Chapter 2 will detail the methods of data collection, processing, and analysis that has been used in this thesis. Chapter 3 will present the results of the analyses, separated into geological and hyperspectral outcomes. Chapter 4 will discuss the results and explore the limitations of the datasets and processes used in this thesis, how the geological and hyperspectral mapping outputs compare, and future work that is needed. Chapter 5 will summarise the main outcomes of this thesis.

1.4 Geological setting
Mt. Ruapehu is an active andesitic-dacitic composite volcano, located in the southern tip of the Taupo Volcanic Zone (TVZ) and active Taupo Rift in central North Island, New Zealand. It is also the southernmost expression of the Tonga-Kermadec arc-trench system (Figure 1.1a; Hackett, 1985; Houghton et al., 1987; Hackett & Houghton, 1989; Pardo et al., 2012; Mordensky et al., 2018a, 2018b). The TVZ is an active continental volcanic arc and back-arc basin produced by the oblique subduction of the Pacific plate beneath the Australian plate (Figure 1.1a; Cole, 1990; Wright, 1992; Conway et al., 2015; Wilson & Rowland, 2016). It is commonly split into three main sections; the northern and southern TVZ hosts andesitic composite cones with limited geothermal systems, whereas the central TVZ is dominated by rhyolitic caldera systems and extensive hydrothermal activity (Figure 1.1b; Wilson & Rowland, 2016). The volcanism in the TVZ overlie Eocene – Miocene sedimentary rocks, which cover the basement Mesozoic greywacke of the Waipapa and Kaweka terranes (Tost et al., 2016; Conway et al., 2016; Townsend et al., 2017). The dominant tectonism in the TVZ is laterally discontinuous, NNESSW trending normal faults which propagate the length of onshore TVZ (Figure 1.1b; Wright, 1992; Townsend et al., 2017).
Ruapehu has produced varied eruptive styles over the last 250 kyr, including Subplinian, Strombolian, phreatomagmatic, and Vulcanian (Houghton et al., 1987; Hackett & Houghton, 1989). Therefore, the cone is dominated by interlayered lavas and autobreccias, and proximal pyroclastic deposits with a surrounding ring plain of reworked laharic, pyroclastic, and epiclastic deposits (Hackett & Houghton, 1989; Cronin & Neall, 1997; Donoghue & Neall, 2001; Conway et al., 2015). There are at least four major cone building episodes which have involved a combination of summit, flank, and satellite vents (Figure 1.2; Hackett, 1985; Hackett & Houghton, 1989). These vents follow a north-easterly alignment which has been influenced by the NNE-trending normal faults of the wider TVZ (Figure 1.1; Hackett, 1985). The four formations are the Te Herenga Formation (200 – 150 ka), the Wahianoa Formation (166 – 80 ka), the Mangawhero Formation (50 – 15 ka), and the Whakapapa Formation (<15 ka;
Hackett & Houghton, 1989; Conway et al., 2016; Townsend et al., 2017). The Te Herenga Formation is exposed on the northern and north-western flank of Ruapehu and represents the oldest exposed volcanic products on the volcano (Townsend et al., 2017). The Wahianoa Formation covers a wide spatial distribution which formed a now eroded large edifice. It is thought that this formation unconformably overlays the Te Herenga Formation (Hackett, 1985), however, no contact has been found (Townsend et al., 2017). The Mangawhero Formation includes lava flows erupted from two vents at the summit of Ruapehu, which were active over the same period (Townsend et al., 2017). This formation is extensively exposed over Ruapehu with flows extending towards the outer ring plain (10 – 12 km), but predominantly covers the summit and south-western flank (Figure 1.2; Hackett, 1985). Large flank glaciers that existed on Ruapehu between ~51-41 to ~27-15 ka contributed to the variable thickness of the lava flows in this formation (1 – 100 m; Conway et al., 2015; Townsend et al., 2017). The Whakapapa Formation has been erupted from four flank and two summit vents during the post-glacial period. The retreat of the glaciers gave these lava flows access to the valley floors, which produced long run-out flows (Townsend et al., 2017). Welded pyroclastic successions and vertical dikes from this formation appears along Pinnacle Ridge (Hackett, 1985).

Figure 1.2: Location of Pinnacle Ridge on Ruapehu, with the four formations: Whakapapa, Mangawhero, Wahianoa, and Te Herenga (Data source: GNS Science, 2017). Inactive and active vent locations inferred from Mordensky et al. (2018a).
Pinnacle Ridge is located on the northern to north-western flank of Ruapehu, neighbouring the Whakapapa Ski Field to the east. The ridge is largely composed of the Te Herenga Formation which includes altered and unaltered andesitic lava flows, welded pyroclastic deposits, vent breccias, and intrusions (Figure 1.2; Hackett, 1985; Hackett & Houghton, 1989; Smith et al., 1999; Mordensky et al., 2018b). The vent location for the Te Herenga Formation is inferred to be located near the summit of Pinnacle Ridge (Townsend et al., 2017), which agrees with the general slope of the lava flows away from this topographic high (Mordensky et al., 2018a). Post-emplacement erosion due to glacial activity and flank instabilities exposed the internal structure of the shallow intrusive system beneath the complex (Hackett, 1985). The ridge has been subjected to several dike and stocky finely crystalline diorite intrusions, which hydrothermally altered the volcanic host rock (Hackett & Houghton, 1989; Townsend et al., 2017). A 400 – 500 m wide alteration zone in the Te Herenga lavas and breccias surrounds the largest intrusion (~130 m wide; Mordensky et al., 2018a), and there are several smaller intrusions that penetrate the lava deposits in and out of the alteration halo. The intrusions are inferred to be of similar origin and age to the Te Herenga lavas due to chemical similarities (Hackett & Houghton, 1989; Mordensky et al., 2018b). However, cross-cutting relationships within the alteration zone suggests two generations of intrusions, with the older intrusions displaying a greater level of alteration (Mordensky et al., 2018a). The dikes represent the younger generation of intrusions and their chemical similarity to the Te Herenga lavas suggests the dikes were feeders for the upper sequence of lava flows (Hackett, 1985). The continuation of glaciation during the deposition of the Wahianoa and Mangawhero Formations resulted in deposition of the Whakapapa lava flows adjacent to Pinnacle Ridge (Hackett, 1985). A combination of intrusive events and glacial erosion has produced various jointing orientations in the lava, breccia, and intrusions on Pinnacle Ridge (Mordensky et al., 2018b), and is thought to be the mechanism that caused the initiation of the sector collapse 9500 years ago, that created the bulk of the Murimotu Formation (Palmer & Neall, 1989).

Since the geologic mapping efforts in Hackett and Houghton’s research during the 1980’s, only two studies have examined the Te Herenga Formation, including an analysis of tephra deposits on Pinnacle Ridge by Smith et al. (1999), and a PhD thesis on the mechanical properties of the Te Herenga Formation (Mordensky et al. 2018a, 2018b; Mordensky, 2019). The latter was aimed at understanding how intrusions change the physical and mechanical properties of volcanic host rock, to provide insight into the effects of shallow intrusion emplacement in a volcanic environment. To achieve this, Mordensky focussed on the intact rock physical and mechanical properties (e.g. porosity, strength) and rock mass characteristics (e.g. discontinuity spacing, orientation) in the altered host rock that encompassed the larger intrusion on Pinnacle Ridge, using field and laboratory measurements. Using physical and geomechanical properties and the abundance of alteration in the units, Mordensky split Pinnacle Ridge into seven geotechnical units, as follows (Figure 1.3):

Unaltered dense coherent lava (UDCL) is interlayered with UBLM and forms 1 – 3m high cliffs outside the alteration surrounding the largest intrusion. It contains pyroxene glomerocrysts with a groundmass of plagioclase, glass, and pyroxene, therefore, it is predominantly porphyritic.
Altered dense coherent lava (ADCL) is interlayered with ABLM and occurs within the altered zone that surrounds the largest intrusion. The alteration is composed of smectite and kaolinite clays which is interpreted to be advanced argillic alteration. This alteration occurs only along discontinuity boundaries as it is not pervasive, i.e. primary textures and mineralogy are observed in thin sections. ADCL shares similarities to UDCL in phenocryst size, distribution and frequency, however, ADCL has a higher frequency of microfractures in both the phenocrysts and groundmass.

Unaltered brecciated lava margin (UBLM) forms outside the alteration zone as low angled 1-3m high slopes, with a similar mineralogy to UDCL. The unit appears brecciated at outcrop scale and is interlayered with UBLM. The clasts are sub-angular to angular and the unit is matrix supported.

Altered brecciated lava margin (ABLM) forms red/orange units with predominant kaolinite and smectite alteration and are interlayered with ADCL. This unit is also matrix supported; however, it has a lower porosity to UBLM as smectite appears to fill pore space. Alteration is also found in crystals, clast groundmass, fractures, and the matrix. Sporadic unaltered crystals appear to have similar compositions to UDCL, ADCL, and UBLM.

Unaltered intrusions (UI) appear as both dikes and stocky intrusions and form protruding topographic features. Dikes appear throughout the ridge irrespective of the alteration zone, whereas stocky intrusions only appear inside the altered zone. Alteration is only found at the edge of the largest unaltered intrusion, as smectite clay. Sub-vertical fractures appear in the stocky intrusions and columnar joints are evident in the dikes. This unit retains primary textures and mineralogy of clinopyroxene, plagioclase, and opaques. The groundmass and phenocryst compositions are similar to UDCL, except the groundmass crystals are coarser (>10 µm). There are microfractures in the phenocrysts that do not link together or run through the groundmass.

Altered intrusions (AI) are only found within the alteration zone, predominantly close to UI, and do not have obvious cooling joints. They do have the same primary minerals and textures, except with alteration of kaolinite and smectite (montmorillonite) that is preferential to clinopyroxenes and microfractures. AI has interconnecting microfractures that run through the groundmass and are wider than the microfractures in UI.

Hydrothermal veining (HV) is not extensive along Pinnacle Ridge, with most veining only found immediately adjacent to the intrusions. The veins are typically hosted in ADCL and ABLM within the alteration zone. The majority of the veins are inaccessible except for the largest vein which is 1m thick and runs parallel to the ridge for ~50 m. The vein consists of albite grains in a matrix of predominantly aphanitic kaolinite (>90%) with minor smectite clay.
There are two primary types of alteration that can occur in a volcanic environment: supergene and hypogene. Supergene alteration describes weathering processes at the surface while hypogene alteration forms from hydrothermal solutions at depth.

1.5 Weathering alteration

Weathering occurs at or near the Earth’s surface by chemical, physical, and biological processes that differ from the conditions under which the rocks were formed (Montgomery et al., 2000). This causes the rock to disintegrate and form recrystallisation of secondary minerals that are more stable under the new conditions. The rate and type of alteration will depend on several factors, such as composition of the rock and fluid, grain size, texture, joints, fractures, and exposure time. Volcanic glass weathers to clay minerals like kaolinites and smectites (Bishop et al., 1998). Kaolin group minerals also form from feldspar minerals, whereas smectites typically form from feldspars and pyroxenes minerals (Haldar & Tišlar, 2014). Subaerial weathering of Fe-silicate minerals like olivine, and pyroxene, or sulphide minerals like pyrite can oxidise to produce secondary iron oxide minerals such as goethite and hematite (Montgomery et al., 2000).
1.5.2 Hydrothermal alteration

Hydrothermal alteration is the interaction of fluid with rock that changes the primary mineralogy, texture, and chemistry of the surrounding volcanic units (Hedenquist & Henley, 1985; Sillitoe, 1989; Hedenquist et al., 1993; Hedenquist & Lowenstern, 1994; Gifkins et al., 2005; van der Meer et al., 2014). Alteration forms when high temperature and low pH fluid is forced through the surrounding rock by convection processes (Figure 1.4). As this fluid cools, secondary minerals form unique alteration zones within the magmatic system. These zones can be classified as: propylitic (Prop), outer propylitic (also called transitional, Trans), argilllic (Arg), potassic (K), phyllic (Phy), and advanced argilllic (AA) (Figure 1.5; Corbett & Leach, 1998; Stimac et al., 2015). Potassic (K), phyllic (PHY), and advanced argilllic (AA) alteration zones relate directly to the magmatic fluid convection surrounding the volcano conduit and associated intrusions. Propylitic (Prop), transition (Trans), and argilllic (Arg) alteration zones are primarily formed by heated meteoric waters in the upper layers of the cover rock (Figure 1.5).

![Figure 1.4: Conceptual model of fluid circulation in an andesitic stratovolcano hydrothermal system. Cool, dense meteoric fluid descends through faults and/or fractures (1) and interacts with a magma intrusion/chamber to create hot magmatic fluid at depth (2). This magmatic fluid then rises through faults/fractures (3) due to heat causing the water to become more buoyant. If the water cannot penetrate the overlying rock layers (4), it will flow outward and start to cool again (5). Groundwater near the surface can enter the hydrothermal system (6). Model has been adapted from Stimac et al. (2015).](image)

Of the many factors effecting the minerology of hydrothermal alteration zones, temperature and pH are the most influential (Corbett & Leach, 1998). The pH of the given hydrothermal system is directly related to the elemental concentration of the volcanic gas, while the temperature relates directly to the hydro-magmatic system (Corbett & Leach, 1998). A summary of the stability ranges of pH and
temperature for common hydrothermal minerals can be found in Figure 1.6. Thus, the temperature and pH levels of a hydrothermal deposit can be devised, based on the alteration minerals present. For example, an assemblage of kaolinite and smectite minerals would infer an argillic alteration zone, indicating it would have formed from relatively low temperature (<250°C) and near neutral to moderately acidic (pH 4-6) fluid near the surface of the volcano.

![Figure 1.5: Conceptual model of a typical arc volcanic-intrusive system and the main alteration zones and isotherms. Propylitic (Prop), transition (Trans), and argillic (Arg) alteration are controlled by long term circulation of heated meteoric waters in the overlying cover rocks. Potassic (K), phyllic (Phy), and advanced argillic (AA) alteration are more directly related to the volcano conduit system with the associate flux of magmatic volatiles and circulation of magmatic-hydrothermal fluids controlling mineralisation. Model sourced from Stimac et al. (2015).](image)
Figure 1.6: Diagram of the stability ranges of common hydrothermal minerals, pH and temperature controls, and the alteration assemblage zones these minerals form in, identified in Figure 1.5 (adapted from Corbett & Leach, 1998). Fluid element concentrations/rations and pressures (such as gas, hydrostatic and lithostatic pressure), are constant in this
1.6 Hyperspectral sensing and imaging

Over the last 30 years, the rapid advancement of spectroscopic techniques (hyperspectral imaging) has enabled remote identification of mineralogy for geological surface mapping (Goetz, 2009; Simpson & Rae, 2018), as well as man-made materials, vegetation, water, snow, and ice (Kruse, 2012). Electromagnetic radiation can interact with matter through reflection, absorption, and transmission. Spectroscopy measures either reflected or emitted radiation of an object (van der Meer, 2018; Kereszturi et al., 2018). The wavelength at which these photons are reflected can be distinctive of the surface material’s composition and texture/roughness. Hyperspectral data can be acquired at a range of scales, through passive sensors. Passive sensors record the reflected or emitted light of an object from a naturally occurring light source (i.e. the sun), unlike active sensors which have their own source of light (Haldar, 2012). Some of the main passive sensors utilised in the literature are: laboratory and hand-held field sensors e.g. Beckman Spectrophotometer UV 5270 (Felzer et al., 1994), Analytical Spectral Devices field spectrometers (ASD; Chabrillat et al., 2002; Lau et al., 2003; Fox et al., 2018; Kereszturi et al., 2018; Garcia-Rivas et al., 2018; Xu et al., 2019), and Portable Infrared Mineral Analyser (PIMA; Lau et al., 2003); airborne sensors e.g. HyMap (Cocks et al., 1998; Bedini et al., 2009), Airborne Visible/Infrared Imaging Spectrometer (AVIRIS; Kruse et al., 1993a; Crowley & Zimbelman, 1997; Chabrillat et al., 2002; Crowley et al., 2003; Guinness et al., 2007; Spinetti et al., 2008; Kruse, 2012; Swayze et al., 2014), Airborne Imaging Spectrometer (AIS; Vane et al., 1984), and AisaFENIX sensor (Kereszturi et al., 2018; Pullanagari et al., 2016); and satellite sensors e.g. Hyperion on the New Millennium Earth Observing (EO)-1 (Crowley et al., 2003; Magendran & Sanjeevi, 2014; Raj et al., 2015; Tayebi & Tangestani, 2015) and the Environmental Mapping and Analysis Program (EnMAP) which is a satellite with a hyperspectral Imager to be launched in the upcoming years (HIS; Mücke et al., 2019).

The data is acquired over hundreds of narrow, contiguous bands measured in wavelengths, which covers the visible/near-infrared (VNIR; 350-1000 nm) and shortwave infrared (SWIR; 1000-2500 nm) regions of the electromagnetic spectrum (Goetz et al., 1985; Kereszturi et al., 2018). Spectroscopy is not limited to VNIR and SWIR domains as there are also midwave (3000 – 5000 nm) and longwave (8000 – 12000 nm) infrared spectrometers (Thompson & Salisbury, 1993; and their references within). The data is initially measured in irradiance, which is then converted to either radiance or reflectance during image processing (Shell, 2004). This means a specific radiance or reflectance spectrum can be derived for each pixel in the resulting imagery, based on the surface materials (Figure 1.7; Goetz, 2009).

The issue of spatial scaling in remote sensing has been a prevalent subject since the development of Earth observation satellites (van der Meer, 2018). The progress of portable reflectance spectrometers in the last 20 years allows for spectroscopic data to be gathered at thin-section, hand-sample, or drill core scales (e.g. Simpson & Rae, 2018; Kruse et al., 2012). Spectrometry does not have spatial resolution, but Instantaneous Field of View (IFOV), which is the area where the reflectance is measured (Mac Arthur et al., 2012). This area is smaller (on the scale of cm) than hyperspectral data acquired by sensors in aircrafts or satellites, which allows for data to be gathered at an outcrop scale.
(1.5 – 30 m; Kruse et al., 1993a; Kruse, 2012; Swayze et al., 2014; Kereszturi et al., 2018). The data gathered allows for an estimation of bulk mineralogy of rock samples at these different scales. Therefore, a scale issue arises when hand-held spectroscopic data is compared to lower spatial resolution data, as the aircraft/satellite data will have mixed spectral data (one pixel composed of multiple minerals) but the hand held data could be composed of only one or two minerals (Swayze et al., 2014; van der Meer, 2018). However, it is possible to separate the mineral mixtures if the components have unique spectral features (Goetz et al., 1985).

![Diagram](image)

*Figure 1.7: An example of the reflectance spectrum derived from a pixel of a hyperspectral image (adapted from Ghamisi et al., 2017).*

1.6.1 Why hyperspectral data for mineral identification?

The advancement of multispectral sensors, such as Landsat and ASTER, enabled the start of lithological and mineral mapping through band ratio techniques, decorrelation stretching, and feature extraction methods (van der Meer et al., 2012; Ramakrishnan & Bharti, 2015). However, hyperspectral data enabled the development of detailed understandings of mineral compositions and their relative abundances at the surface (Ramakrishnan & Bharti, 2015). This is due to the narrow bandwidth and high spectral contiguity of hyperspectral data (Figure 1.8). These contiguous bands have also allowed for characterisation of the atmospheric windows, to the level required for removal from the measured spectrum (e.g. Goetz, 2009). This is not a capability of multispectral sensors which are limited to acquiring data from between the atmospheric windows. Furthermore, a higher number of spectral bands results in finer details (e.g. the shape of absorption), which can be quantified (Clark et al., 2003; van der Meer, 2004). Thus, the spectral resolution is fine enough to identify and quantify the presence of specific mineral signatures.
1.6.2 Identification of alteration mineralogy through hyperspectral imaging

Hyperspectral reflectance data can be used to identify chemical compositions of individual minerals and mineral groups with molecular or cation-hydroxyl bonds, based on their absorption features in the VNIR and SWIR regions of the electromagnetic spectrum (Kereszturi et al., 2018; Simpson & Rae, 2018). The crystal and chemical structure of minerals controls the position, shape, depth, and width of these absorption features (van der Meer, 2001). There are two main chemical processes that cause these absorptions: electronic and vibrational (Hunt & Ashley, 1979; Clark, 1999; van der Meer, 2001).

Electronic transfers involving iron (Fe) shows absorption bands at wavelengths shorter than 1200 nm (Figure 1.9; Hunt & Ashley, 1979). This electronic transition may occur in two ways. The first is an intervalence charge transfer which involves a transfer of an electron between the ions of two different elements or between different ions of the same element (Clark, 1999). These band positions generally occur in the ultraviolet and extend into the visible spectrum, which is why iron oxides and hydroxides have a red colour. The second type is caused by crystal field transitions where the presence of ligands changes the energy levels of an ion. These processes largely affect transition elements such as iron (Fe$^{2+}$ and Fe$^{3+}$), as they have unfilled electron shells (Clark, 1999). Therefore, the VNIR region is useful for detecting iron oxide minerals such as hematite (Fe$_2$O$_3$), goethite (FeO(OH)), and jarosite (KFe$_3$H$_2$(OH)$_6$(SO$_4$)$_2$); Hunt & Ashley, 1979; Kruse et al., 1993a; Clark, 1999; Ben-Dor, 2001; Murphy & Monteiro, 2013; Magendra & Sanjeevi, 2014; van der Meer, 2018). There are three main broad absorption features that occur in oxides due to electronic transfer: 450 nm, 550 – 650 nm which usually appears as a shoulder (a small absorption off of a larger absorption peak), and 750 – 950 nm. The sharp absorption band at 430 nm has been identified as jarosite (Hunt & Ashley, 1979), however, a double absorption at 450 nm is a result of goethite (Kokaly et al., 2017). The shoulder near 650 nm occurs in hematite, goethite, and jarosite however, it is most apparent in goethite (Figure 1.9). Hematite typically has an absorption that is centred around 850 nm, whereas goethite and jarosite is generally centred at 940 nm (Hunt & Ashley, 1979).
Vibrational absorptions occur when the bonds within a group of atoms jumps from a ground state to an excited state (Bishop, 2019). This change occurs when the wavelength of incident radiation corresponds to the vibrational energy of the bond within the mineral structure, causing the photon of equal amount of energy to the vibrational frequency, to be absorbed from the reflectance spectrum (Bishop, 2019). This produces an absorption band at the wavelength that corresponds to that energy level. When the energy provided corresponds to the first excitation level, fundamental vibration occurs (van der Meer, 2001). Furthermore, if the energy provided matches that of the second or third (etc) excitational level, overtone vibrations occur. This process causes hydroxyl (OH) bearing minerals to absorb light into their atomic structure in the SWIR region (Figure 1.10; Hunt & Ashley, 1979; McKeown et al., 2011; Bishop, 2019). These minerals include kaolinite, montmorillonite, illite, alunite, pyrophyllite, chlorite, and many sulfides (Figure 1.10). Most of these minerals have an absorption feature near 1400 nm due either to a combination of two different fundamental OH stretching modes or to the first overtone of the fundamental OH-stretching vibration. The location and appearance of

![Figure 1.9: Minerals that produce absorption features in between 350 – 1350 nm due to electronic transfers; hematite, goethite, and jarosite. Spectral profile of minerals sourced from Kokaly et al. (2017) and positions of ferrous and ferric ions from Hunt & Ashley (1979) and Clark et al. (1990).](image-url)
this absorption feature can be used to discriminate between minerals. For example, a broad single feature may indicate montmorillonite, a sharp single feature may indicate pyrophyllite, or a sharp double absorption feature may indicate either kaolinite or alunite (Hunt & Ashley, 1979; Clark et al., 1990). The majority of these minerals also show an absorption feature near 2200 nm due to OH bond fundamental stretch with Al-O-H fundamental bending mode. As before, the absorption feature can appear different for the minerals, which allows for identification. Montmorillonite has a broad single absorption at 2215 nm which is asymmetric towards longer wavelengths, whereas kaolinite has a narrow doublet at 2170 nm and 2205 nm (McKeown et al., 2011). Alunite also has an absorption feature at 2170 nm; however, it can be distinguished from kaolinite as it is only a single absorption and has a broad single absorption feature at 1760 nm (Bishop & Murad, 2005), which kaolinite does not contain. Illite has a similar broad single band as montmorillonite near 2200 nm, however, it contains additional absorptions at 2350 nm and 2450 nm (Clark et al., 1990). Pyrophyllite has multiple absorptions near 2200 nm due to the presence of Al-O-H bands. The absorption features of these minerals can be used to identify them in their respective environments.
singular, sharp absorption at wavelengths such as 2086 nm, 2166 nm, 2314 nm, and 2504 nm (Clark et al., 1990). Jarosite does not have an absorption feature near 2200 nm but instead shows an intense absorption feature at 2269 nm due to the combination of OH stretches with an Fe-OH bend (Clark et al., 1990). Chlorite has a diagnostic triple absorption feature centred near 2330 - 2350 nm, which varies depending on the relative abundance of Fe:Mg bonded to OH (King & Clark, 1989; Bishop, 2019).

Another feature that is worth a note is the absorption band near 1900 nm, which is due to the combination of OH with the H-O-H bending fundamental (Hunt & Ashley, 1979). Hydrothermal minerals can have this feature, as it is a result of the hydroxyl group in the form of molecular water. Montmorillonite is the only mineral group that readily absorbs water from the air, as it is an expanding clay. Therefore, the absorption feature for this mineral is commonly deep and narrow.

1.6.3 Reflectance and absorption influences
A few of the processes that affect the reflectance and absorption of solar radiation in the VNIR and SWIR regions are atmospheric interaction, grain size effects, topographic effects, and the continuum spectra, as discussed below.

1.6.3.1 Atmospheric effects
Incident radiation, or irradiation from the Sun, can interact with the Earth’s atmosphere, including gasses and aerosols, and clouds before it can be measured with airborne or space-based sensors (Rani et al., 2017). The amount of scattering or absorption of the atmosphere varies spatially and temporally, depending on the concentrations of various atmospheric constituents, such as water vapor (H₂O), carbon monoxide (CO), carbon dioxide (CO₂), nitrous oxide (N₂O), methane (CH₄), ozone (O₃), and oxygen (O₂; Gao et al., 1993; Rani et al., 2017). Major water vapor absorption band positions are approximately 940, 1140, 1380, and 1880 nm (Gao & Goetz, 1990), the carbon dioxide bands are near 2010 and 2080 nm, and oxygen has several bands between 600 – 1300 nm (Figure 1.11; Gao et al., 1993; Gao et al., 2006). Ozone has a band near 600 nm, methane has a band near 2350 nm, and nitrous oxide and carbon monoxide have weak bands between 2000 – 2500 nm (Figure 1.11; Gao et al., 1993). In the VNIR region, radiation can also be affected by molecular and aerosol scattering (Gao...
et al., 2006). Based on these band positions, approximately half of the spectral range of 300 – 2500 nm is affected by atmospheric gases. Corrections of these atmospheric gas effects is required if data is to be compared to a spectral library or laboratory spectral measurements (Clark, 1993).

1.6.3.2 Grain size effects
It is well documented that grain or particle size affects the spectral characteristics of minerals (Lyon, 1965; Hunt & Vincent, 1968; Vincent & Hunt, 1968; Pieters, 1983; Salisbury & Eastes, 1985; Crown & Pieters, 1987; Clark et al., 1990; Salisbury & Wald, 1992; Clark, 1999; Cooper & Mustard, 1999; van der Meer et al., 2012; Bishop, 2019). There are two ways that grain size affects the strength of the absorption. The first is due to the surface/volume ratio affecting the amount of light that is reflected or absorbed by a mineral. For large grains, the internal path where photons may be absorbed is greater, whereas for smaller grains there is proportionally more surface area for reflection than internal area for absorption (Clark, 1999; Cooper & Mustard, 1999). Therefore, absorption increases as grain size increases (Figure 1.15). The second is that some properties that are affected by grain size can also impact the absorption strength, such as porosity and the degree of crystallinity (Cooper & Mustard, 1999). It has been proven that increasing porosity with decreasing grain size reduces the height of the reflectance peaks in powdered samples compared to coarser samples (Salisbury & Eastes, 1985). The reflectance will be reduced due to multiple reflections caused by the cavities in the sample (Aronson et al., 1966). These effects are important to understand when comparing laboratory to aerial datasets (Cooper & Mustard, 1999), as grain size will proportionally change with resolution capabilities of sensors and porosity will change depending on lithology and/or alteration within samples (Mordensky et al., 2018a).

1.6.3.3 Topographic effects
Incident radiation can be received by a horizontal target in three ways; direct solar beam, diffuse radiation, and the interaction between the atmosphere and the ground. However, in a mountainous environment, the position of the sun in relation to the topography and the location of the sensor can influence the spectral signature of a ground surface (Figure 1.12; Proy et al., 1989). The topography influences the incident radiation in two ways: (1) the direct (E_s) and diffuse (E_d) radiation can vary according to the angle between the solar beam and the surface (Figure 1.12a); and (2) the topography can either cast shadows on a pixel so that it receives little to no radiation (Figure 1.12b) or it can reflect the radiation towards the target area (E_t; Figure 1.12a), providing it with additional irradiation. Therefore, care needs to be taken when interpreting aerial or satellite reflectance data of mountainous terrain, as these irregular topographies effect can create noise within the hyperspectral dataset.
1.6.3.4 Continuum spectra

An absorption in the spectrum has two components; individual features and a continuum (Clark, 1999; van der Meer, 2004). The continuum is the background albedo of the reflectance curve which the individual absorption features are superimposed (Figure 1.13; Clark, 1999; van der Meer, 2004). The continuum can cause shifts to the local reflectance minimum, which is the tip of the absorption peak. Correction of the continuum can remove the effects on the peak band location (Clark et al., 2003). An example by Clark (1999) shows the effect of the continuum shifting the local minimum towards shorter wavelengths, however, once the continuum is corrected the local minimums line up (Figure 1.14).

When the continuum is removed from the reflectance across the spectrum, it isolates the spectral features and scales the spectrum to 100% when the spectral curve reaches the continuum, effectively normalising the data (Figure 1.14). Therefore, spectral features from different datasets (field dataset vs spectral library dataset) or different scales (aerial hyperspectral data vs satellite hyperspectral data or laboratory vs library data) can be compared for a more accurate spectral-based mineral identification.

Removing the continuum from the reflectance spectra can also reduce the effects of grain size on the band depth and shape (Clark et al., 2003). For example, Figure 1.15 shows a series of reflectance spectra for the mineral hypersthene from the pyroxene mineral group, with increasing grain size. Given the large range of grain sizes, the absorption features are very similar. As the grain size becomes larger, the absorption increases until it starts to flatten out at the peak (Figure 1.15b). When the continuum is removed from the spectra (Figure 1.15a), the similarity of the shape of the absorption peak is more apparent. For clay minerals such as hematite and goethite, their absorptions are so intense that they become saturated and the widths of their absorption change with grain size, typically at wavelengths near 900 nm (Clark et al., 2003).
Figure 1.13: Example of kaolinite spectrum with and without the continuum reflectance. Sourced from van der Meer (2004).

Figure 1.14: Example of how the local minimum can shift due to continuum reflectance; a) spectra with continuum reflectance and b) spectra with continuum reflectance removed. Sourced from Clark (1999).
1.6.4 Spectral libraries

A common method of interpreting components of spectral data from laboratory, field, airborne, and orbital sensors, is to compare them to pure and well-characterised reference samples within spectral libraries (e.g. Kokaly et al., 2017). The concept of spectral libraries was pioneered by Roger Clark and associates at U.S Geological Survey (UGSG) in the 1990s when it became apparent that a knowledge base for the spectroscopy of minerals and other materials was needed for remote identification and mapping purposes. The first version of the digital library was published in 1993 which included 498 spectra of 444 samples measured between 200 – 3000 nm (Clark et al., 1993). The latest version of this library, version 7, was published in 2017 which has laboratory and field spectral measurements spanning the last 30 years (Kokaly et al., 2017). Each sample within the library has associated metadata which describes what was measured and how it was measured, the grain size, impurities, and photographs of the sample, as well as other information on the composition and characteristics of the material which can include x-ray diffraction (XRD), electron microprobe (EM), X-ray fluorescence (XRF), and petrographic microscope analyses (Kokaly et al., 2017). The sensors used to gather the library data are: (1) Beckman™ 5270, spectral range of 200 – 3000 nm, (2) ASD field portable spectrometers, spectral range of 350 – 2500 nm, (3) Nicolet™ Fourier Transform Infra-Red (FTIR) interferometer spectrometers with a range of 1120 – 216000 nm, and (4) the NASA Airborne Visible/Infra-red Imaging Spectrometer (AVIRIS), spectral range of 370 – 2500 nm. The majority of the pure mineral laboratory samples are in a powdered form, and the resulting very small grain size produces high absorptions of the incident radiation. This must be taken into consideration when comparing library spectra with

Figure 1.15: Spectra for pyroxene with increasing grain size for a) reflectance spectra, and b) reflectance spectra with the continuum removed. Sourced from Clark et al. (2003).
laboratory data collected from whole-rock field samples or aerial/satellite data, as these will effectively have a larger grain size and smaller absorptions (Clark et al., 2003). Other spectral libraries that have been developed include the NASA ECOSTRESS spectral library managed by Simon Hook at Jet Propulsion Laboratory (Baldrige et al., 2009; Meerdink et al., 2019), which contains data from the John Hopkins University spectral library developed by Salisbury et al. (1991a; 1991b). However, for the purposes of this thesis, the USGS spectral library will be used for mineral identification.

1.6.5 Image analysis techniques

1.6.5.1 Principal Component Analysis (PCA)

Hyperspectral datasets naturally have high dimensionality due to the large number of narrow, contiguous bands providing a wealth of spectral information per pixel (Bruce et al., 2002). Moreover, some bands can be highly correlated which leads to high redundancy within the dataset (Gao et al., 2015). Reducing the dimensionality of the dataset decreases the redundancy and allows for hyperspectral feature extraction (Bruce et al., 2002; Gao et al., 2015). One method that achieves this while preserving the original information is a Principal Component Analysis (PCA; Clevers & Jongshcaap, 2001; Prasad & Bruce, 2008; Chen et al., 2018). PCA is a multivariate statistical analysis that uses an orthogonal transformation to convert an original set of correlated variables into a new set of linearly uncorrelated variables, called Principal Components (PC; Yéou et al., 1993; Tangestani & Moore, 2000; Rodarmel & Shan, 2002). A PCA classifies these PC’s by calculating the eigenvectors and eigenvalues within the dataset. Eigenvectors represent the direction the data is dispersed, and eigenvalues represent the variance of each eigenvector direction (Eismann, 2012). The first PC band consists of the maximum direction of variance in the dataset, with each successive PC band decreasing in variance (Clevers & Jongshcaap, 2001; Rodarmel & Shan, 2002). Therefore, the first few PC bands (up to ~10) have the highest chance of identifying a significant spectral change associated with hydrothermal alteration within the hyperspectral dataset. The PC bands after band 10 only show noise (Rodarmel & Shan, 2002).

1.6.5.2 Image classification

Unsupervised and supervised classifications are popular methods to convert continuous observations (e.g. surface reflectance) into thermal maps (e.g. lithological classes). For unsupervised classification, the user can only pick the number of classes the classifier will spectrally cluster, therefore it does not require prior knowledge of the study area (Foody, 2002; Farrand et al., 2019). Supervised classification requires prior knowledge of the study area to create training sites that represent different classes of interest that have been characterised spectrally (Foody, 2002; Joevivek & Chandrasekar, 2010). Supervised image classification is preferred in this study due to the abundance of prior knowledge on alteration types and their spatial distribution. The image classification can highlight the ability of the hyperspectral imagery to discriminate the alteration types.

To have an efficient supervised classification, challenges that need to be addressed are: (1) mitigating the Hughes phenomenon; (2) dealing with non-linearity of variables; (3) dealing with imbalanced
training samples and noise in both training samples and unlabelled data; and (4) reducing computational time (e.g. Belgiu & Drăgut, 2016). Hughes phenomenon is also referred to as the “curse of dimensionality”, which occurs when the number of spectral bands or dimensions become larger than the fixed number of training samples. Therefore, redundant data and noisy wavebands need to be removed from the hyperspectral data to prevent misclassifications. As explained above, a PCA is often used to mitigate these issues.

Spectral Angle Mapper (SAM) is a supervised classification algorithm that recognises the spectral similarity of image spectra to reference spectra, by calculating an ‘angle’ between the two spectra (Eismann, 2012). The spectra are treated as vectors in a space with dimensionality equal to the number of bands, therefore, the angle between the image and reference spectra can be determined (Kruse et al., 1993b; van der Meer et al., 2001). Smaller angles signify a higher similarity between the pixel and reference spectra (Crosta et al., 1998). If the angle exceeds the maximum angle threshold for that class, the pixel will not be classified. Each class can be assigned different maximum angle thresholds by the user. Illumination of pixels in the image will affect the length of the vectors in the classification, however, the algorithm only uses vector direction, not vector length (Girouard et al., 2004). Therefore, the SAM classifier is insensitive to gain factors such as solar illumination (Kruse et al., 1993b; Crosta et al., 1998; Girouard et al., 2004). This classification has been successfully used in the past for geological mapping (e.g. van der Meer, 1997; Crosta et al., 1998; Girouard et al., 2004; Jevivek & Chandrasekar, 2010; Honarmand et al., 2012; Hasan et al., 2016; Mishra et al., 2019; Xu et al., 2019).

1.7 Previous studies

Utilising hyperspectral imaging for surface geological mapping and mineral identification has largely been applied in geothermal and mineral exploration geology with sensors such as Hyperion, HyMap, and AVIRIS (e.g. Goetz et al., 1985; Kruse et al., 1993a; Bedini et al., 2009; Kruse, 2012; Murphy & Monteiro, 2013; Magendran & Sanjeevi, 2014; Swayze et al., 2014; Gabr et al., 2015; Raj et al., 2015; Hasan et al., 2016; van der Meer, 2018; Xu et al., 2019). Multispectral imaging has been used considerably for volcano and geothermal research through Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Landsat satellites (Pieri & Abrams, 2004; Mia & Fujimitsu, 2012). Light Detection and Ranging (LiDAR) technology and digital elevation models have widely been used to study volcanic terrains and related hazards (Crowley et al., 2003; Kereszturi et al., 2018). However, hyperspectral imaging has rarely been used for mineral and geological mapping in volcanic environments. These include:

(1) Crowley and Zimbelman (1997) describes remote sensing methods to support ground-based mapping of the hydrothermal alteration on Mount Rainier using ARVIS reflectance data. This analysis was done using spectral band fitting to identify the alteration minerals in the spectra and linear spectral unmixing to classify the pixels into alteration zones.

(2) Crowley et al. (2003) explored the utility of hyperspectral data from Hyperion and AVIRIS sensors, with digital elevation data for mapping hydrothermally altered rocks and other volcanic features that
could lead to debris flow hazards. The study was based on Mount Shasta in the Cascade Volcanic Arc, US.

(3) Guinness et al. (2007) used AVIRIS reflectance data to map the distribution of ferric oxide, sulfate, and phyllosilicate minerals that were exposed on the summit of Mauna Kea Volcano, Hawaii. They used their research to signify the importance of high spatial resolution hyperspectral observations on Mars.

(4) Spinetti et al. (2008) demonstrated how AVIRIS hyperspectral data from the 1900-2100 nm region was able to identify carbon dioxide absorption over the Pu‘u ‘O‘o Vent at the Kilauea East Rift zone, Hawaii.

(5) Bedini et al. (2009) utilised the HyMap imaging system to map the surface mineralogy in the epithermal gold alunite deposit that occurs within the Rodalquilar caldera complex, in the Cabo de Gata volcanic field.

(6) Lombardo et al. (2009) employed the multispectral infrared and visible imaging spectrometer (MIVIS) to map the thermal structure and effusive rates of Mt Etna lava flows that were erupted in July 2001, in Italy.

(7) Kereszturi et al. (2018) combined airborne hyperspectral data with Light Detection and Ranging (LiDAR) topographic data to map and identify volcanic deposits of the Te Maari craters in the Tongariro Volcanic Complex. From this they were able to generate a workflow to create geological maps using remote sensing applications such as image classification and image stacking.

(8) Yant et al. (2018) details the spectral characterisation, in the VNIR and MIR (mid-infrared) regions, of a hydrothermal solfatara site situated on the Kilauea caldera, adjacent to the December 1974 flow. The Hawaiian volcanic deposits have been studied as Mars analogues, due to the range of potentially Mars-relevant environments. Similar references include Bishop et al. (2007), Minitti et al. (2007), and Hamilton et al. (2008), among many others.

1.8 Summary

Pinnacle Ridge is an old (<205 ± 27 ka), eroded eruption centre of thinly bedded lava flows and massive breccia deposits, blocky magma intrusions, dikes, and associated hydrothermal alteration. Identifying and mapping the spatial distribution of the hydrothermal alteration on the ridge is critical for understanding the stability of the units as well as its eruptive and post-eruptive history. Previous research indicates that hyperspectral imaging is an excellent tool for identifying and mapping alteration products remotely, due to strong vibrational absorptions of hydroxyl bonds in phyllosilicates in the SWIR region and Fe^{2+}/Fe^{3+} electronic transfers in iron oxides causing absorptions in the VNIR region. Therefore, thin sections of hand samples, laboratory, and aerial hyperspectral imagery are utilised to explore the aims of this thesis. This includes investigating methods of identification and quantification of the abundance of secondary alteration minerals, defining the spatial scales that are required to verify alteration mineral signatures in hyperspectral data, determining the best method to deconvolute the aerial hyperspectral data to map alteration mineral intensities and assemblages, and increasing our current understanding of the alteration history on Pinnacle Ridge. This chapter
described several approaches that are used in this study, such as manual identification of mineral absorption features using spectral libraries, Principal Component Analysis (PCA) and Spectral Angle Mapper (SAM) classification, as well as some of the influences that may affect hyperspectral image data, such as grain size, topography, atmospheric, and the continuum. The different types of alteration on Pinnacle Ridge will also be considered, and how this may affect the hyperspectral image data.
Chapter 2: Methods

2.1 Introduction

This chapter will provide insight into the methods used to analyse the three main datasets in this thesis: thin sections, laboratory spectroscopic data, and aerial hyperspectral imagery (Figure 2.1).

Figure 2.1: The process of geological and hyperspectral analyses to produce alteration maps of Pinnacle Ridge. Yellow box indicates the dataset, blue box represents ArcGIS tools, green box represents ENVI tools, orange box represents other software, and the grey boxes indicate the output of a tool or product.
2.2 Samples and datasets

2.2.1 Field work and sample collection

Field work was completed in early 2019 for sampling of 13 locations on Pinnacle Ridge (Figure 2.2), across a range of hydrothermally altered deposits and intrusions, in the Te Herenga Formation. The locations of the samples were largely dictated by the accessibility of the outcrops; therefore, majority of the samples are low on the west slopes or on the top of the ridge. The sample locations were recorded using a handheld Garmin GPSMAP 64 unit. Sample locations were chosen based on accessibility and the map of the seven geotechnical units created by Mordensky et al. (2018a; 2018b).

![Figure 2.2: Location of collected samples on Pinnacle Ridge with the orthophoto of high-resolution digital RGB photos.](image)
Thin sections were cut from the exterior to the interior of each hand sample, to aid in quantifying the full range of alteration within the samples, as previous studies illustrated that the interior of samples showed a different degree of alteration than the exterior (Mordensky et al., 2019a). Supplementary thin sections, XRD, and SEM data was obtained from Mordensky (2019). A list of these samples and their corresponding sample names from Mordensky’s work is available in Appendix A (Table A1). The SEM and XRD analyses were conducted on three samples; R14, R19a and R19b. Samples collected in the field and supplementary samples from Mordensky (2019) were analysed using laboratory-based spectroscopy.

2.2.2 Laboratory spectroscopic data collection
The hand samples were analysed in laboratory conditions using a FieldSpec 4 Hi-Res spectroradiometer at Massey University. To prepare the samples, they were dried in an oven for 12 hours at 40°C. Before the analysis, the spectroradiometer readings were calibrated using a white Diffuse Reflectance Standard. In total, 3-6 spot measurements were collected per sample, using a contact probe with a 1 cm diameter sampling footprint. These measurements were splice corrected to minimize the offset of the transition wavelengths between the VNIR and two SWIR detectors (at 1000 and 1800 nm, following Danner et al., 2015). They were subsequently averaged, using View Spec Pro software, to represent the spectral reflectance of the whole sample. Most of the samples were homogeneous in composition, however, some samples (R5, R10, R4, and R9) had a visible difference in the exterior and interior of the sample. For these samples, spectral readings for the interior and exterior were measured.

2.2.3 Aerial hyperspectral data collection
The airborne hyperspectral data for Pinnacle Ridge was part of a survey of Mt Ruapehu carried out on the 1st April 2018 between 10:45-12:00 using a push-broom, full spectrum AisaFENIX hyperspectral sensor (370-2500 nm), along with an Oxford Survey + GPS/Inertia Measurement Unit (IMU) in a Cessna 185 aircraft. On this survey aircraft, a Nikon D810 DSLR camera was also operated to cover the ground with high-resolution digital photos. These photos were used to reconstruct digital topography models and an orthophoto for orthorectification. The AisaFENIX sensor has a total Field of View of 32.2° and an instantaneous Field of View of 0.084°. The study area was surveyed at solar elevations ≥40°, in cloud free conditions. The flight height was 3300 m above ground level, resulting in pixel resolution of 1.5 m. The aircraft was flown at speeds of 105–115 knots to maximise the exposure time of the outcrops at the study site. The resulting aerial image has 448 spectral bands as the VNIR signal strength was enhanced by a spectral binning setting of 4x2. This process was not applied to the SWIR region. The spectral sampling intervals are 3.3-5.7 nm for the VNIR bands and 11 nm for the SWIR bands. The image is oriented from N (350-10°) to S (170-190°), to reduce the Bidirectional Reflectance Distribution Function (BRDF) effects. However, the image used in this thesis is a single strip. A calibrated flight before the survey meant boresight corrections could be applied to the imagery to reduce the misalignment between the Oxford Survey + GPS/IMU unit and the AisaFENIX sensor. The AisaFENIX
sensor has some (≤1%) malfunctioning detectors in the SWIR region. This caused vertical lines in the data that have constant Digital Number (DN) values. This is a common issue for AisaFENIX sensors due to the push-broom imaging geometry (e.g. Pullanagari et al., 2016).

The raw imagery with digital numbers (DN) was converted to radiance using a sensor-specific calibration. The radiance was converted to surface reflectance using ATCOR-4 (Richter & Schläpfer, 2002), in the raw imaging geometry. As a last step, the image strip was geocoded using a parametric approach, implemented in PARGE (Richter & Schläpfer, 2002). The hyperspectral imagery was registered using a high-resolution Digital Surface Model, created from close-range photogrammetry (Fonstad et al., 2013). The workflow of aerial hyperspectral data collection and post-processing is similar to Kereszturi et al. (2018).

2.3 Analytical methods
2.3.1 Quantifying alteration in samples
The thin sections of the samples were analysed under a Meiji Techno MT9420 Binocular Polarizing Microscope to identify primary and alteration minerals and textures in the samples. Thin sections images in Chapter 3 (Figure 3.2, 3.3, 3.4, 3.5, 3.6, and 3.7) were captured on a Leica DM2500P Modular Polarization Microscope equipped with a Nikon DS-L4 Microscope Camera and Control Unit. To quantify the alteration identified in the thin sections, a point count analysis was tested. Several images of the thin sections captured through a Meiji Techno Binocular Stereo Microscope with a plane polarising filter and a Lumenera’s INFINITY1 digital camera were mosaicked using an app called AutoStitch. These stitched images were point counted in JMicroVision, where 250 points were automatically selected in a random grid across the thin section. The number of points per thin section was selected based on when the percentages became constant, which was verified using an evolution plot (Appendix B, Table B1). There were two classes used to point count the thin sections; altered and unaltered. An issue arose as to how the altered class was defined, due to the range of primary and secondary disequilibrium textures in the plagioclase and pyroxene phenocrysts in majority of the samples. Due to the semi-qualitative approach of this method, an example of how the altered and unaltered classes were defined is shown in Figure 2.3. Crystals that only show slight sieve texture or rims of alteration are considered unaltered, whereas crystals nearly completely replaced with secondary clays are considered altered. If the point count selected an area of the groundmass that was altered to clay minerals or recrystallised to silica polymorphs, they were classified as altered.

The image point count method was initially tested on three Pinnacle Ridge samples R14, R19a, and R19b (Mordensky, 2019; Appendix A, Table A2). These samples had previously published XRD results therefore the alteration mineral percentages were summed to calculate the amount of alteration for the three samples from the XRD (Mordensky, 2019; Table 2.1). These summed percentages were plotted with the point count percent to determine the accuracy of the point counting method (Figure 2.4). The results show that the alteration percent from the point counts fall within the uncertainty of
the XRD percent. Therefore, the point counting method was considered reliable and used for quantifying the alteration in the rest of the samples.

Table 2.1: Composition of samples R14, R19a, and R19b from x-ray diffraction analysis. Secondary alteration minerals used to calculate the percent of alteration have been identified in the table with an asterisks (*). Data sourced from Mordensky (2019).

<table>
<thead>
<tr>
<th>Minerals</th>
<th>R19a</th>
<th>R19b</th>
<th>R14</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plagioclase</td>
<td>36 ± 2</td>
<td>48 ± 2</td>
<td>37 ± 2</td>
</tr>
<tr>
<td>Orthopyroxene</td>
<td>&lt;1</td>
<td>10 ± 1</td>
<td></td>
</tr>
<tr>
<td>Clinopyroxene</td>
<td>2 ± 1</td>
<td>1 ± 1</td>
<td></td>
</tr>
<tr>
<td>Magnetite</td>
<td>&lt;1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amorphous Phases (Glass)</td>
<td>16 ± 2</td>
<td>11 ± 2</td>
<td></td>
</tr>
<tr>
<td>Opal-C (Cristobalite)*</td>
<td>8 ± 1</td>
<td>11 ± 2</td>
<td>2 ± 1</td>
</tr>
<tr>
<td>Quartz</td>
<td>3 ± 1</td>
<td>2 ± 1</td>
<td></td>
</tr>
<tr>
<td>Iilit*</td>
<td>1 ± 0.5</td>
<td>2 ± 1</td>
<td></td>
</tr>
<tr>
<td>Talc</td>
<td>&lt;1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smectite*</td>
<td>27 ± 4</td>
<td>12 ± 2</td>
<td>25 ± 3</td>
</tr>
<tr>
<td>Pyrite</td>
<td>&lt;1</td>
<td>7 ± 1</td>
<td></td>
</tr>
<tr>
<td>Kaolinite*</td>
<td>18 ± 4</td>
<td></td>
<td>14 ± 3</td>
</tr>
<tr>
<td>Jarosite*</td>
<td>1 ± 0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ferrihydrite</td>
<td>4 ± 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barite</td>
<td>&lt;1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anatase</td>
<td>&lt;1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Alteration</td>
<td>55</td>
<td>25</td>
<td>41</td>
</tr>
</tbody>
</table>
Classifying the image into altered and unaltered classes was a limitation as the percent was generalised across all alteration types. However, due to the difficulty of identifying different types of alteration minerals in thin section (i.e. clay minerals), this generalisation was necessary for the consistency of the point count. While XRD analysis of the samples is preferred, this is a time and resource intensive process and therefore was beyond the scope of this study. However, the point count method described here proved to be an efficient way to quickly quantify sample alteration with minimum resources.

2.3.2 Geological mapping of alteration

A geological map of alteration zones was created for Pinnacle Ridge, based on the location and point count alteration percent of the samples. This was mapped in ArcGIS ArcMap by digitising the polygon zones of alteration on the ridge. The extent of the Te Herenga Formation and the surrounding units on Pinnacle Ridge, and the location of known fault lines, were sourced from the recent geological mapping of the Tongariro National Park by GNS Science (Townsend et al., 2017). The Te Herenga Formation was then divided into zones, based on the location of the samples and their alteration percent from the point count. Geological structures, such as lava flows and intrusions, were mapped from high-resolution aerial RGB photos and photos taken from the field. Mordensky (2019) found that the alteration zones surrounding the intrusions on Pinnacle Ridge do not systematically decrease in alteration intensity away from the intrusions. Hillshade and contour lines were created from the digital surface model from section 3.2.2, which aided in understanding the general topography of the study area, and how this could affect the alteration zones.
2.3.3 Alteration mineral identification in hyperspectral data

The laboratory data was analysed first to identify the alteration minerals in the samples. The aerial data was then compared to the laboratory data to assess for similarities in the mineralogy and spectral signatures. The hyperspectral data (lab and aerial) was correlated to the point count data to attempt to quantify the alteration minerals in the laboratory and aerial datasets. Finally, an image classification of the aerial dataset produced a map of the alteration zones, based only on the hyperspectral data. The process is detailed below and visualised in Figure 2.4.

2.3.3.1 Laboratory hyperspectral data and unmixing

To identify mineral absorption features in the laboratory dataset, samples were compared to mineral spectra from the USGS Spectral Library in ENVI Classic (USGS Spectral Library Version 7; Kokaly et al., 2017). The XRD data was used to provide a baseline insight into the bulk rock mineral composition in the samples. The reference spectra from the USGS Spectral Library was compared to the lab sample spectra manually to find similarities in the location and shape of the absorption peaks. Mineral samples chosen for reference spectra from the USGS Spectral Library were based on the match of their available geochemistry to published Pinnacle Ridge data (Hackett, 1985). The relevant alteration minerals and the reference sample names from the USGS Spectral Library are listed in Table 2.2. The samples and reference library spectra were normalised in a continuum removed format to ease the comparison of individual absorption features. Continuum removed lab data was exported as .ascii files to be graphed in Microsoft Excel. To further identify the alteration assemblages in the laboratory data, the abundance of alteration minerals in the XRD was correlated to the spectral features. Because XRD data is only available for three samples, the findings were applied to the other samples to infer the relative importance of certain alteration minerals.

<table>
<thead>
<tr>
<th>Alteration Minerals</th>
<th>USGS Spectral Library Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alunite</td>
<td>Gds83 Na63</td>
</tr>
<tr>
<td>Chlorite</td>
<td>SMR-13.a 104-150</td>
</tr>
<tr>
<td>Goethite</td>
<td>WS219</td>
</tr>
<tr>
<td>Hematite</td>
<td>GDS76 2%+98%Qtz</td>
</tr>
<tr>
<td>Illite</td>
<td>IMt-1.a</td>
</tr>
<tr>
<td>Jarosite</td>
<td>GDS24 Na</td>
</tr>
<tr>
<td>Kaolinite</td>
<td>KGa-1 (wxyl)</td>
</tr>
<tr>
<td>Magnetite</td>
<td>HS78.38</td>
</tr>
<tr>
<td>Montmorillonite</td>
<td>SAz-1</td>
</tr>
<tr>
<td>Pyrite</td>
<td>S26-8</td>
</tr>
<tr>
<td>Pyrophyllite</td>
<td>SU1421</td>
</tr>
</tbody>
</table>

A representative spectral profile was created from the sum of the spectral library data, weighted by the XRD percent of samples R14, R19a, and R19b. Spectral data from the USGS spectral library was exported in continuum removed format for all the minerals identified in the XRD analysis. Hackett (1985) identified the plagioclase minerals on Pinnacle Ridge to be bytownite, therefore, the library
spectra of bytownite was used to represent the plagioclase identified in the XRD analysis. Diopside and enstatite were used to represent clinopyroxene and orthopyroxene respectively, and montmorillonite was used to represent smectite in the XRD data. An example of the process can be seen in Equation 2.1, which was applied to each band within the library spectra to gain a spectral profile for each sample.

\[ RV_{band,x} = (\alpha A_{band,x}) + (\beta B_{band,x}) + (\gamma C_{band,x}) + \cdots \]

*Equation 2.1: Reflectance value (RV) calculation for each band (band x) where, A, B, and C represent reflectance value of minerals identified by XRD, and \( \alpha \), \( \beta \), and \( \gamma \) represent XRD percent of respective minerals.*

The resulting spectral profiles for the three samples with XRD data were compared to the laboratory data of these samples, to identify any similarities in the spectral profiles. Similarities in absorption features validate the laboratory hyperspectral dataset to the XRD results.

### 2.3.3.2 Aerial hyperspectral data

The aerial hyperspectral data had to undergo co-registration, smoothing, and band reduction before any analysis could be run to remove noise in the dataset. The aerial image was co-registered to the RGB orthophoto using the ‘image to image’ tool in ENVI Classic, with a bilinear convolution resampling and polynomial warping method. The spectral polishing and smoothing were completed in ATCOR (atmospheric correction software) using the Savitzky-Golay (3x3) filter. For band reduction, the first and last 10 bands were removed, as well as the bands between 1960 – 2047 nm as this is the region where carbon dioxide is absorbed from the atmosphere. This left the aerial hyperspectral dataset with 419 bands between 401 – 2459 nm wavelengths.

To compare the aerial reflectance data to the laboratory data, spectral profiles of pixels near the location of the samples were selected in ENVI. The topography of the ridge and the position of the sun on the east side of the ridge when the airborne data was collected resulted in poor illumination of the west side of Pinnacle Ridge (Figure 2.5), which created a lot of noise in the spectra. Unfortunately, the west side of Pinnacle Ridge is more assessible, therefore almost half the sample locations are affected by poor illumination (Figure 2.5). This is the largest limitation for comparison of laboratory to aerial hyperspectral data, however nearby aerial data was able to be extracted for some samples (R14, R19a and b, and R18). Therefore, only samples R1b, R6, R7, R8b, R9, R11, R12a, R12b, R13, R14, R18, R19a and R19b were used in the following aerial hyperspectral analysis. To extract the spectra for each sample location from the aerial image, the ‘Region of Interest (ROI)’ tool was used to average spectral data over a 2x2 pixel area. The spectra were then converted to a continuum removed format in ENVI Classic and exported to excel. Once the aerial and lab data were graphed together, similar absorption peaks were able to be identified.

To validate the use of aerial imagery for mapping the alteration percent on Pinnacle Ridge, the reflectance data was correlated to the point count alteration percent. This was achieved by plotting
the alteration percent per sample against the laboratory and aerial reflectance values at 2207 nm. This band was selected as it is within the range of the main absorption feature of the Al-OH bond in phyllosilicates (Clark et al., 1990; McKeown et al., 2011; Bishop, 2019) and majority of the samples had an absorption features at this wavelength. To check the correlation of alteration reflectance between the aerial and lab data, the reflectance values at 2207 nm were plotted for the 12 samples.

![Figure 2.5: True colour image of the aerial hyperspectral imagery with the location of the fault, vein, and samples.](image-url)
2.3.4 Mapping using hyperspectral data

To gain further insight into the alteration abundance on Pinnacle Ridge, and to reduce the high redundancy in the data (e.g. co-linearity between neighbouring spectral bands), a Principal Component Analysis (PCA) was run on the aerial imagery in ENVI. The Principal Components (PC) were calculated using a covariance matrix on the full band hyperspectral data (419 bands).

There were three main analyses completed on the PCA output:

(1) The ROI’s used to extract the aerial hyperspectral data, in section 3.3.3.2, were used on the PCA output to gain the variance values per PC band in those locations. These values were plotted against the point count alteration abundances for each sample to determine if there was a correlation between the variance in the aerial data and the abundance of alteration from the thin sections. If there was a positive or negative correlation, it shows that the variance in those PC bands is somehow related to the alteration on the ridge.

(2) The PC bands identified as being related to the alteration were then loaded as greyscale images, as the variance from the PC band mean is displayed as light and dark pixels. ROI’s were created in the light and dark pixel areas per PC band, to extract the spectral data from the aerial image in these locations. The ROIs were a 2x2 pixel shape, so the spectral data was averaged across four pixels. Four to five ROIs were created for both the light and dark pixel areas per PC band, to capture intra-class variation of the spectral profiles in the dark and light zones. From the spectral profiles of these areas, an interpretation could be drawn as to the type and abundance of the alteration affecting these variance zones in the PC bands.

(3) An RGB composite image was created from three PC bands to show the variation in alteration across the ridge. Only one PC band was selected to represent the alteration across the ridge while the other two PC bands represent the other surface classes such as vegetation. ROIs were again created in the locations of the different colours in the composite output, as per step 2, to extract the spectral data in these locations. The spectral data for these colours showed an order of alteration intensity across the ridge which helped train the classes for the supervised classification.

Spectral Angle Mapper classification (SAM; e.g. Kruse et al., 1993b; Girouard et al., 2004; Eismann, 2012; Savitri et al., 2020) was used to map the alteration mineral assemblages on the ridge, based on the mineral identification of the absorptions in the laboratory and aerial hyperspectral data (section 3.3.3) and the interpretation of the alteration intensity from the PCA (section 3.3.4). A supervised image classification technique was chosen based on the considerable knowledge of the study area from previous studies (e.g. Hackett, 1985; Hackett & Houghton, 1989; Townsend et al., 2017; Mordensky et al., 2018a, 2018b), as well as analyses (PCA and laboratory analysis), aerial imagery, and field work from this thesis. SAM classification was selected because it is relatively insensitive to illumination and albedo effects (when used on calibrated reflectance data; Rani et al., 2017), which are prevalent in the aerial hyperspectral data from topographic effects. Therefore, this classifier was chosen to reduce the effects of illumination during the classification. The previous PCA analysis and
mineral identification of the aerial and laboratory data helped define the classes used in the supervised classification to develop training and validation datasets. These feature class datasets were created in ArcGIS ArcMap using the ‘create features’ tool to draw polygons around the pixels that represent the different intensities of alteration across the ridge. The training data was used in the classification to categorise the pixels into the different classes. Each class had different maximum angle thresholds based on the number of mis-classified pixels. The validation dataset was used in the ‘confusion matrix’ tool with the output classification to calculate the accuracy of the classification against a ‘ground truthed’ dataset (Congalton, 2001; Foody, 2002). The confusion matrix also identified how many pixels were being mis-classified which in turn, helped guide the selection of the maximum angle thresholds per class (Foody, 2002). Therefore, this was a process of trial and error until the accuracy of the classification was higher than 90%. The kappa coefficient was not considered in this study as a measure of accuracy (c.f. Foody, 2020). The classification resulted in a map of the alteration intensity on the ridge, based on the airborne hyperspectral image. This map was compared with the independent geological map (section 3.3.2), to evaluate the use of hyperspectral remote sensing in mapping alteration zones in volcanic environments.

2.4 Summary
The methodological framework used in this study is displayed in Figure 2.6. The hand samples and thin sections were used to quantify alteration products in the samples. This in turn, facilitated the categorisation of the samples into alteration groups based on percent altered minerals to generate a geological map of the alteration distribution across the ridge. A manual spectral matching technique was used for the laboratory and aerial hyperspectral datasets to identify the composition of the altered minerals in the samples. Identifying the alteration minerals led to defining the classes for the classification (SAM) of the aerial hyperspectral imagery, to generate a second alteration distribution map of Pinnacle Ridge. The results chapter follows the general format in Figure 2.6, which will lead to the discussion of the accuracy and implication of aerial hyperspectral imaging for generating geological maps in Chapter 4.
Figure 2.6: Simplified flow chart of the general methods used to analyse the hand samples, laboratory, and aerial hyperspectral data from Pinnacle Ridge.
Chapter 3: Results and Interpretations

3.1 Introduction
The first section of this chapter displays the results of quantifying the abundance of alteration in the samples using a point counting method and the generation of a geological map of the alteration distribution across the ridge, based on the location of samples and their alteration percent. The second part focuses on the mineral identification of the alteration in the laboratory and aerial hyperspectral data and the correlation of this data to the alteration percent determined in the first section. The last section of this chapter focuses on the results of the Principal Component Analysis (PCA) and Spectral Angle Mapper (SAM) classification of the aerial hyperspectral data, as another technique for creating a geological map of the alteration spatial distribution in the study area.

3.2 Quantifying alteration in samples
3.2.1 Assessment of alteration in thin sections
Based on the point count analysis of the thin sections, alteration across the ridge ranges between 7.6 – 84.5% (Figure 3.1). The data was grouped into different alteration groups as: <10%, 10-20%, 20-40%, 50-65%, 70-75%, and >85% (Figure 3.1). Examples of the thin sections for each alteration group are shown in Figures 3.2, 3.3, 3.4, 3.5, 3.6, and 3.7. The composition of the samples is largely the same throughout the different rock types (breccia, lava, and intrusions) of the Te Herenga Formation, which contained phenocrysts of clinopyroxene, minor orthopyroxene, and plagioclase with a groundmass of plagioclase and volcanic glass. In most samples, pyroxene altered preferentially over plagioclase to form iron oxides and clay minerals (Figure 3.3, 3.4, 3.5, 3.6, and 3.7). The alteration of plagioclase

![Figure 3.1: Point count alteration percent for 20 samples from Pinnacle Ridge.](image-url)
either occurred in the core of the crystals or in rims within the crystals, forming clay minerals. Within
the groundmass, alteration was either in veins or patches where it had replaced volcanic glass with
recrystallised silica polymorphs and/or clay minerals. For detailed unit descriptions and mineralogical
identification, refer to Hackett et al. (1985).

3.2.1.1 <10% alteration group
The <10% alteration group contains two samples: R6 (7.6% alteration) and R4 (8.4% alteration; Figure
3.2). Both samples are from andesitic lava flows with very low alteration. The alteration within these
samples are largely in the fractures within the rock and in micro-fractures in the phenocrysts of
plagioclase, which has caused the middle of the crystal to alter (Figure 3.2a and b). The main fracture
within the thin section in Figure 3.2a is in the middle to bottom right corner, which has clay alteration
associated within the margins. The sporadic orange dots of the point count indicate the alteration
within the phenocrysts (Figure 3.2a). Some plagioclase phenocrysts display sieve texture and

![Figure 3.2: Example of a lava flow on Pinnacle Ridge from the <10% alteration group, R4, as a) full thin section image in plain polarised light from the point count analysis to show the location of b) close up of thin section to display the types of alteration in the sample in plain polarised light (PPL) and crossed polarised light (CPL).]
embayments which suggests disequilibrium conditions when this sample formed. Other phenocrysts within the samples are clinopyroxene and orthopyroxene, and the groundmass has a high content of volcanic glass.

3.2.1.2 10–20% alteration group
The 10–20% alteration group contains four samples: R2 (16%; Figure 3.3), R15 (17.2%), R18 (20.4%), and R16 (20.4%). The samples in this alteration group range from lavas, breccia, and intrusions. The alteration in R2 is largely concentrated around the edges of the sample and has formed in veins and replaced crystals. These veins have caused clay alteration in both clinopyroxene and plagioclase, and iron oxide alteration of clinopyroxene to form poikilitic opaques. The plagioclase alteration is the same as <10% alteration group, formed through microfractures in the crystal structure, whereas the clinopyroxene alteration is either large rims around the crystals or alteration of the whole crystal.

Figure 3.3: Example of a lava flow on Pinnacle Ridge from the 10–20% alteration group, R2, as a) full thin section image in plain polarised light from the point count analysis to show the location of b) close up of thin section to display the types of alteration in the sample in plain polarised light (PPL) and crossed polarised light (CPL).
(Figure 3.3b). The low amount of alteration in the middle of the thin section only occurs along microfractures (Figure 3.3a). Glomerocrysts of plagioclase, clinopyroxene and opaques are present.

3.2.1.3 20 - 40% alteration group
The 20 – 40% alteration group contains four samples: R9 (29.2%), R7 (30.0%, Figure 3.4), R19b (30.8), and R14 (38.4%). The samples in this alteration group are lavas, breccias and intrusions. Intrusion sample R7 has alteration that predominantly occurs along a fracture through the middle of the sample (Figure 3.4). There are also smaller and narrower subsequent veins that propagate away from the main vein. The array of veins has altered both the groundmass plus clinopyroxene and plagioclase phenocrysts surrounding it, to clay minerals. R7 has a phaneritic texture that is typical of intrusive rocks and similar clinopyroxene and plagioclase alteration as the 10 – 20% alteration group, where clinopyroxene altered to both iron oxide and clay minerals and plagioclase altered to clay minerals.

Figure 3.4: Example of an intrusion on Pinnacle Ridge from the 20 - 40% alteration group, R7, as a) full thin section image in plain polarised light (ppl) from the point analysis to show the location of b) close up of thin section to display the types of alteration in the sample in plain polarised light (PPL) and crossed polarised light (CPL).
The euhedral to subhedral opaques are a result of iron oxide alteration and are most likely magnetite (Figure 3.4b). The other samples in this alteration group have predominant phenocryst alteration.

### 3.2.1.4 50 - 65% alteration group

The 50 – 65% alteration group contains six samples: R3a (50.8%), R19a (56.8%), R1b (57.2%), R8b (59.2%; Figure 3.5), R11 (60.8%), and R12b (62.8%). These samples are of lava, breccia and intrusions (Appendix B, Table B1). Breccia sample R8b has block clasts of lava and intrusion, within a dominantly clay altered, silica recrystallised and volcanic glass groundmass. The lava clasts have recrystallised silica patches of volcanic glass and clay alteration of plagioclase and clinopyroxene phenocrysts (Figure 3.5). Iron oxide alteration of clinopyroxene phenocrysts is present throughout the thin section. The

![Figure 3.5: Example of a brecciated lava margin on Pinnacle Ridge from the 50 - 65% alteration group, R8b, as a) full thin section image in plain polarised light from the point analysis to show the location of b) close up of thin section to display the types of alteration in the sample in plain polarised light (PPL) and crossed polarised light (CPL).](image-url)
intrusion clasts are identified by the phaneritic texture and predominantly plagioclase composition. These clasts can have clay alteration of the plagioclase crystals and opaques from iron oxide alteration of clinopyroxene crystals, comparable to R7 (Figure 3.4).

3.2.1.5 70 – 75% alteration group
The 70 – 75% alteration group has three samples: R20 (70.8%), R13 (71.6%), and R12a (74.0%; Figure 3.6). Sample R12a has patches of dense alteration where both the crystals and the groundmass are almost completely altered predominantly to clay minerals (Figure 3.6b), and patches where there is only phenocryst alteration (e.g. top left corner of Figure 3.6a). Iron oxide alteration has formed opaques in some areas however, clay alteration is dominant. Remnant crystal structures of clinopyroxene can be seen throughout the thin section (Figure 3.6b).

**Figure 3.6:** Example of an lava on Pinnacle Ridge from the 70 - 75% alteration group, R12a, as **a)** full thin section image in plain polarised light from the point count analysis to show the location of **b)** close up of thin section to display the types of alteration in the sample in plain polarised light (PPL) and crossed polarised light (CPL).
3.2.1.6 >85% alteration group

This alteration group only has one sample, which is R17 (85.2%; Figure 3.7). This sample is from a hydrothermal vein deposit on the ridge that is ~1m long (Mordensky, 2019). Almost all the phenocrysts have been altered in this sample to clay minerals or recrystallised silica polymorphs, however, there are remnant crystal structures of plagioclase and clinopyroxene phenocrysts. The groundmass has generally been completely altered to clay minerals.

![Figure 3.7: Example of a hydrothermal vein on Pinnacle Ridge from the >85% alteration group, R17, as a) full thin section image in plain polarised light from the point count analysis to show the location of b) close up of thin section to display the types of alteration in the sample in plain polarised light (PPL) and crossed polarised light (CPL).](image)

3.2.2 Mapping the alteration on Pinnacle Ridge

The alteration groups were applied to the sample locations to develop a map of the alteration percent at the surface using field notes, high-resolution aerial RGB photos, and hyperspectral imaging (Figure
The ridge is divided into three alteration zones: <10% alteration to the north (blue unit), 20-40% alteration in the middle (yellow unit), and 50-65% alteration to the south (orange unit). The yellow unit in Figure 3.8: Geological map of the alteration groups on Pinnacle Ridge adapted from Mordensky et al. (2018a) and the Ruapehu geological map (Townsend et al., 2017) using the point count analysis and field survey from this study.
3.8. The ridge is divided into three alteration zones: <10% alteration to the north (blue unit), 20 – 40% alteration in the middle (yellow unit), and 50 – 65% alteration to the south (orange unit). The yellow unit is cut off by the active fault (red dashed line), which follows the general NNE trend of the TVZ, however, the type of fault is unknown (Townsend et al., 2017). This zone also has lava flows of <10% (blue unit) and 10-20% (green unit) alteration. The intrusions on the ridge (light blue unit) are mainly situated in the south of the orange unit. The intrusions have a range of alteration from 0 – 30%, based on the thin section analysis. The area surrounding some of the intrusions in the 20 – 40% zone has a higher alteration percent of 50-65% (orange unit) or 70-75% (red unit). Localised alteration of 70 – 75% can be seen near the top of Pinnacle Ridge as the red unit. The alteration does not systematically decrease in intensity away from the intrusions, which is supported by mapping completed by Mordensky et al., (2018a, 2018b).

3.3 Alteration mineral identification

3.3.1 Laboratory hyperspectral data

The thin section analysis was limited in identifying the exact type of alteration minerals due to the fine-grained nature of the alteration minerals. It was therefore necessary to perform complementary laboratory analysis. Absorption features in the laboratory hyperspectral data are described and the mineralogy interpreted for each alteration group (Figure 3.9) and the interior and exterior of select samples (Figure 3.10). Then the laboratory data is verified to the XRD data (Figure 3.11).

3.3.1.1 Description for alteration groups

Figure 3.9 shows the laboratory hyperspectral data between 300 – 2500 nm for six representative samples, ordered from high to low alteration. For the laboratory spectra of all samples, refer to Appendix B (Table B1). The following results will have the wavelengths of the significant absorption features listed, with their corresponding continuum removed values in brackets. All samples have a broad double absorption feature at 430 nm (0.794, 0.703, 0.926, 0.581, 0.465, and 0.852, from R6 to R17 respectively) and 490 nm (0.782, 0.690, 0.901, 0.545, 0.448, 0.846, from R6 to R17 respectively), a small single absorption at 670 nm (bar 12a, 0.979, 0.923, 0.992, 0.933, and 0.984, respectively), and a broad single absorption at 932 nm for R2 (0.869), 953 nm for R14 (0.891), and 966 nm for R6, R1b, R12a, and R17 (0.876, 0.702, 0.778, and 0.911, respectively). Sample R17 has a sharp double absorption feature at 1401 nm (0.653) and 1415 nm (0.624), and a broader doublet at 2172 nm (0.715) and 2205 nm (0.619). R17 also has a broad triple absorption feature in the SWIR at 2324 nm (0.916), 2361 nm (0.934), and 2378 nm (0.911). Sample R12a, R1b and R14 have single absorption features at 1415 nm (0.851, 0.808, and 0.884, respectively) and 2205 nm (0.918, 0.920, and 0.878 respectively). However, for samples R12a and R14 a shoulder near 1460 nm and 2172 nm is evident, and R1b has a shoulder at 1460 nm and 2241 nm. Sample R2 and R6 has a broad single absorption features around 1440 nm (0.946 and 0.903, respectively) that is asymmetric towards longer wavelengths and R2 has a broad absorption feature at ~2205 nm (0.983). R6 has a sharp double absorption feature at 2205 nm (0.945) and 2269 nm (0.947). R12a, R14, R2, and R6 show some features from the triple absorption at
2324 nm, 2361 nm, and 2378 nm (Figure 3.9). All samples show an asymmetrical absorption feature towards longer wavelengths at 1924 nm for R6 and R2 (0.799 and 0.812, respectively), 1910 nm for R14 and R17 (0.709 and 0.717, respectively), and 1914 for R1b and R12a (0.597 and 0.617, respectively).

Figure 3.9: Samples R6, R2, R14, R1b, R12a and R17 of laboratory hyperspectral data for each alteration percent group from Figure 4.1, for a) iron bearing minerals (300-1400 nm) and b) hydroxyl-bearing minerals (1300-2500 nm). The data is displayed in a continuum removed format. Spectral profiles are offset for clarity.
3.3.1.2 Mineralogical Interpretation for alteration groups

The double absorption at 430/490 nm and shoulder at 670 nm is indicative of goethite present in all the samples. All samples have a broad shallow absorption that varies between 900 – 950 nm that is asymmetric towards longer wavelengths, which is caused by absorption of Fe$^{3+}$ (Clark et al., 1990). Therefore, all samples have a form of iron oxide alteration.

The absorption feature between 1415 – 1440 nm in all samples is a result of OH absorptions, however, the number and symmetry of the peaks can be indicative of minerals. The double absorption at 1401/1415 nm for R17 is consistent with kaolinite absorption (Hunt & Ashley, 1979). The single absorption at 1415 nm for R12a, R1b, and R14, or at 1440 nm for R2 and R6, is either a result of montmorillonite due to the broad feature or it could be poorly-crystallised kaolinite (Clark et al., 1990). The absorption between 1910 – 1920 nm for all samples is a result of H$_2$O absorptions, which commonly occurs in montmorillonite minerals (Hunt & Ashley, 1979). For the absorption at 2205 nm, the double feature for R17 and R12a is characteristic of kaolinite and the single feature for R1b, R14, R2, and R6 could be a result of poorly crystalline kaolinite, montmorillonite, or illite (therefore, it is labelled as phyllosilicate; Figure 3.9). However, no absorption features at 2350 nm or 2450 nm reduces the likelihood of the 2205 nm feature being a result of illite. The absorption peak at 2269 nm for R6 is a result of Fe-OH in jarosite and the triple absorption at 2324/2361/2378 nm is characteristic of kaolinite (Clark et al., 1990).

3.3.1.3 Correlation of XRD to laboratory hyperspectral data

The analysis of Figure 3.9 identifies the absorption feature at 2205 nm for alteration groups <10% (R6), 10 – 20% (R2), 30 – 40% (R14), and 50 – 65% broadly as phyllosilicate. This feature could not be identified as a specific mineral since it could be indicative of poorly crystalline kaolinite (Yang et al., 2001), montmorillonite (Bishop et al., 1994), or a mixture of both (McKeown et al., 2011). The XRD data for R14 identifies the presence of both kaolinite (14%) and montmorillonite (25%) in the sample (Ch 2, Table 2.1). To correlate this to the laboratory spectra (Figure 3.10), the position of the absorption at 2205 nm and the slight shoulder at ~2170 are indicators of kaolinite (Clark et al., 1990). Montmorillonite can form an absorption at 2205 nm (Shi et al., 2014), however, this absorption typically occurs at 2210 nm for a pure montmorillonite sample (Figure 3.10a; Kokaly et al., 2017). The inflection point on the longward side of the 2205 nm absorption is at 2270 nm which is typical of montmorillonite, as an inflection point closer to 2230 nm is more indicative of kaolinite (Figure 3.10b; McKeown et al., 2011). The broad absorption at 1415 nm with the shoulder at 1460 nm and the broad single absorption at 1915 nm, that is asymmetrical towards the longer wavelengths, is indicative of montmorillonite also (Figure 3.10a; Hunt & Ashley., 1979; Clark et al., 1990). Therefore, R14 absorption features and inflection points signify a higher abundance of montmorillonite to kaolinite, which is verified by XRD. Therefore, when comparing these findings to the other alteration groups, we can determine relative importance of kaolinite and montmorillonite in the samples.
Figure 3.10: Laboratory hyperspectral data of representative samples for the alteration percent groups, ordered to show relative abundance of montmorillonite (bottom) to kaolinite (top), based on the XRD data of R14 (30 – 40% alteration group). 

a) Key absorption feature wavelengths, and b) inflection wavelengths. The bold values at the bottom correlate to montmorillonite and the bold values at the top correlate to kaolinite. Spectral profiles are offset for clarity.
Figure 3.10 (a and b) show the samples ordered based on their montmorillonite and kaolinite ratio, determined from the spectral interpretation of R14’s XRD percent. R1b and R14 (50 – 65% and 30 – 40% alteration groups, Figure 3.10) have more montmorillonite than kaolinite in their samples due to the inflection points matching at 1350 nm, 1815 nm, and 2270 nm, and the presence of 1415 nm with shoulder at 1460 nm, the 1915 nm absorption with shoulder at 1960 nm, and shape of the absorption at 2205 nm. Kaolinite is evident in these samples as well but to a lesser extent by the position of the 2205 nm peak, and the inflection point of the shortward side of 2205 nm shifting towards the kaolinite inflection at 2115 nm. For R17 (>85% alteration group), the absorption at 1915 nm, the inflection point on the longward side of the 2205 nm absorption at 2270 nm, and the shallow gradient of the longward side of the 1415 nm double absorption is more typical of montmorillonite. However, R17 has a double absorption at 1415 nm and 2205 nm, a triple absorption between 2321 – 2384 nm, and the inflection points line up for both absorptions at 1415 nm and 2205 nm (Figure 3.10b), which strongly indicates the presence of kaolinite in the sample (Figure 3.10a; Clark et al., 1990). R12a has less kaolinite than R17 as the absorption at 1415 has a shoulder at 1460 nm which indicates montmorillonite, and the double absorption at 2205 nm is significantly smaller than for R17 (Figure 3.10a). The spectra for R6 and R2 are less pronounced at 2205 nm therefore, it is possible that there is kaolinite and montmorillonite in both these sample, just to a lesser extent compared to R14. Or that the kaolinite and montmorillonite in these samples are less crystalline. Therefore, all six alteration groups show key features for goethite, montmorillonite and kaolinite, with minor jarosite for some samples. However, the absorption features for samples from lower absorption groups are less defined. The 2205 nm peak will be identified as phyllosilicate for the rest of the results as it represents both montmorillonite and kaolinite in the samples.

3.3.1.4 Description for interior and exterior of laboratory samples

Figure 3.11 shows the 300 – 2500 nm spectrum for the interior (solid black line) and exterior (dashed black line) hyperspectral data of samples R10, R5, R4, R6, R2, and R9. There are four main absorption features in the 300-1350 nm region; 430 nm, 489-501 nm, 680 nm and 980-1001 nm (Figure 3.11a). The doublet at 430/489-501 nm can be seen in both the interior and exterior regions of all samples except for R9, where it is only visible in the exterior of the sample. This doublet absorption feature is asymmetrical towards the left for both the interior and exterior of R5, however, for R6, R10, R4, and R2 the peak is asymmetrical towards the left for the interior but is asymmetrical towards the right for the exterior of the samples. R6, R5 and R2 have an absorption feature at ~660 nm in the interior and exterior of the sample whereas sample R10, R4 and R9 only have this feature in the exterior of the sample. All samples, bar R5, have an absorption feature near 950 nm in the exterior, however, only R4 and R10 have the same feature in the interior of the sample. There are four main absorption features in the 1350 – 2500 nm region; 1415-1430 nm, 1915-1950 nm, 2205 nm, and 2269 nm (Figure 3.11b). All samples have the broad absorption features at 1415-1430 nm and 1915-1930 nm in the interior and exterior. The sharp absorption feature at 2205 nm is present in the exterior of samples R5, R4, R6, and R2, and in the interior of R6. The interior and exterior of R6 have similar continuum
removed reflectance values at this feature of 0.945. The sharp absorption at 2269 nm is present in the exterior of R10 and R4, and the interior of R6.

3.3.1.5 Mineralogical interpretation of interior and exterior of samples

The double absorption at 430/489-501 nm for all the samples, except for the interior of R9, is a result of goethite. The absorption at ~660 nm in the interior of samples R6, R5, and R2 and the exterior of
samples R6, R5, R10, R4, and R9 is either jarosite or goethite. All samples except R5 have an absorption at ~950 nm in the exterior and R4 and R10 have it in the interior also, which is a result of Fe$^{3+}$ absorption. Therefore, all samples in the exterior and samples R6, R5, R2, R4, and R10 in the interior, have an extent of iron oxide alteration as either goethite or jarosite.

The double absorption at 1430 nm/1440 nm for R10 in the exterior and R6 in the interior could be a result of kaolinite or alunite absorption. Samples R5, R4, R6, and R2 in the exterior and R2, R4, and R5 in the interior have a singular absorption at ~1430 nm which is asymmetric to longer wavelengths, which is either montmorillonite due to the broad feature or it could be poorly-crystallised kaolinite (Clark et al., 1990). The singular broad absorption at 1915 – 1950 nm in the interior and exterior of all samples is caused by H$_2$O, which commonly occurs in montmorillonite minerals (Hunt & Ashley, 1979). The single absorption at 2205 nm for the interior and exterior of sample R6 is a result of Al-OH absorption that could be a few hydroxyl minerals, e.g. illite, montmorillonite, or poorly-crystallised kaolinite. However, there are no absorption features at 2350 nm therefore, it is unlikely to be illite (Clark et al., 1990). For the exterior of R5, R4, and R2 the absorption shifts to 2213 nm, which is more indicative of Al-OH absorption in montmorillonite (McKeown et al., 2011). The interior of R5 and R4 also have an absorption feature at 2213 nm however, it is a broader absorption that is asymmetric towards longer wavelengths, which is typically indicative of Al-OH absorption in montmorillonite (McKeown et al., 2011). The sharp absorption at 2269 nm in the exterior of R10 and R4 and the interior of R6 is due to the absorption of Fe-OH in jarosite.

3.3.1.6 Laboratory validation

The linear mix of USGS Spectral Library data focuses on the minerals identified in previous XRD for samples R19a, R19b, and R14 (Mordensky, 2019) and is shown in Table 3.1. These spectra were then compared to measured laboratory spectra, to determine the accuracy of the lab-based dataset (Figure 3.12). The laboratory spectra in the SWIR (1900 – 2500 nm) are near identical to the linearly mixed data for samples R19a and R14. The similar absorption features for these samples are at wavelengths 475 nm, 650 nm, 950 nm, 1400 nm, 1900 nm, 2205 nm, 2300 nm, and 2350 nm. Some absorption peaks have similar symmetry and continuum removed reflectance values, e.g. 2205 nm for sample R19a. For sample R19b the similar absorption features are at wavelengths 1100 nm, 1400 nm, and 1900 nm. However, the absorption feature of the lab data at 2205 nm is offset towards the shorter wavelengths compared to the linear mix at wavelength 2214 nm. Since there is no kaolinite in the XRD for this sample (Table 3.1; Mix 2), the absorption feature at 2205 nm for the lab data could be a result of a mixture of montmorillonite and illite. The similarity of the absorption peaks for all three samples shows that the laboratory data is consistent with the XRD dataset.
Figures 3.13, 3.14, 3.15, 3.16, and 3.17 show the difference between the aerial and laboratory hyperspectral datasets from each alteration group identified in section 4.2.1. The other aerial and laboratory plots are in Appendix B (Table B1). There is significantly more noise in the aerial dataset which is represented by the insignificant clusters of absorption peaks throughout the wavelengths. However, the major absorption peaks mirror the laboratory data, largely at wavelengths 500 nm, 950

### Table 3.1: USGS sample names utilised in the linear calculations with x-ray diffraction (XRD) weightings for mix 1 (R19a), 2 (R19b), and 3 (R14).

<table>
<thead>
<tr>
<th>USGS Mineral Samples</th>
<th>Mix 1 (%)</th>
<th>Mix 2 (%)</th>
<th>Mix 3 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bytownite (HS106.3B)</td>
<td>37</td>
<td>48</td>
<td>36</td>
</tr>
<tr>
<td>Kaolinite (KGa-1 (wxy))</td>
<td>14</td>
<td>-</td>
<td>18</td>
</tr>
<tr>
<td>Montmorillonite (SAz-1)</td>
<td>25</td>
<td>12</td>
<td>27</td>
</tr>
<tr>
<td>Opal (TM8896)</td>
<td>13</td>
<td>27</td>
<td>11</td>
</tr>
<tr>
<td>Pyrite (S26-8)</td>
<td>-</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>Illite (Imt-1.a)</td>
<td>-</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Talc (WS659)</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Jarosite (GDS24 Na)</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Goethite (WS219)</td>
<td>-</td>
<td>-</td>
<td>4</td>
</tr>
<tr>
<td>Barite (HS79.3B)</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Magnetite (HS78.3B)</td>
<td>-</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>Enstatite (NMNH128288)</td>
<td>10</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>Diopside (HS317.3B (Cr))</td>
<td>1</td>
<td>2</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 3.12: Weighted percentage of USGS Spectral Library data (Kokaly et al., 2017), using XRD data from Mordensky (2019), plotted with corresponding laboratory data for those samples in a continuum removed format. Spectral profiles are offset for clarity.

#### 3.3.2 Aerial hyperspectral data

Figures 3.13, 3.14, 3.15, 3.16, and 3.17 show the difference between the aerial and laboratory hyperspectral datasets from each alteration group identified in section 4.2.1. The other aerial and laboratory plots are in Appendix B (Table B1). There is significantly more noise in the aerial dataset which is represented by the insignificant clusters of absorption peaks throughout the wavelengths. However, the major absorption peaks mirror the laboratory data, largely at wavelengths 500 nm, 950.
nm, 1400 nm, 1900 nm, and 2207 nm for majority of the samples (Figure 3.13, 3.15, 3.16, and 3.17). For the aerial data, all samples have the absorption feature that has been identified as goethite and all samples, bar R18, have the phyllosilicate absorption at 2207 nm. This feature is also not present in the laboratory data for R18. For sample R6, the jarosite absorption at 2269 nm in the laboratory data is also present in the aerial dataset. The goethite absorption peak gets deeper in the more altered samples for the lab data, but this trend is not evident in the aerial imagery.

**Figure 3.13:** Continuum removed reflectance of aerial (line) and laboratory (dotted) data for <10% alteration group (sample R6) between 300 – 2400 nm wavelengths. Arrows indicate the main alteration absorption features for the aerial data. Aerial hyperspectral data was averaged over 2x2 pixel area.

**Figure 3.14:** Continuum removed reflectance of aerial (line) and laboratory (dotted) data for 10 – 20% alteration group (sample R18) between 300 – 2400 nm wavelengths. Arrows indicate the main alteration absorption features for the aerial data. Aerial hyperspectral data was averaged over 2x2 pixel area.
Figure 3.15: Continuum removed reflectance of aerial (line) and laboratory (dotted) data for 20 – 40% alteration group (sample R7) between 300 – 2400 nm wavelengths. Arrows indicate the main alteration absorption features for the aerial data. Aerial hyperspectral data was averaged over 2x2 pixel area.

Figure 3.16: Continuum removed reflectance of aerial (line) and laboratory (dotted) data for 50 – 65% alteration group (sample R8b) between 300 – 2400 nm wavelengths. Arrows indicate the main alteration absorption features for the aerial data. Aerial hyperspectral data was averaged over 2x2 pixel area.

Figure 3.17: Continuum removed reflectance of aerial (line) and laboratory (dotted) data for 70 – 75% alteration group (sample R12a) between 300 – 2400 nm wavelengths. Arrows indicate the main alteration absorption features for the aerial data. Aerial hyperspectral data was averaged over 2x2 pixel area.
3.3.3 Quantifying hydrothermal alteration using hyperspectral imaging

The aerial and laboratory hyperspectral data was plotted against the point count percentage to determine if there were any correlations between the different datasets. The laboratory reflectance at 2207 nm has a strong positive correlation with the alteration percent from the point count analysis (Figure 3.18). The aerial data at 2207 nm does not show a clear trend using this wavelength alone (Figure 3.19). When the reflectance of the lab data is plotted against the aerial data, there are only two samples that plot near the 1:1 trend line, samples R18 and R8b (Figure 3.20). This might be due to the different sensor’s footprint at the surface (e.g. 1 cm for lab-based and 1.5 m for airborne data). Therefore, further analysis was required on the aerial data to be able to utilise it for geological mapping of the alteration minerals on Pinnacle Ridge.

![Figure 3.18: Point count alteration percent against the reflectance laboratory data at 2207 nm.](image)

![Figure 3.19: Point count alteration percent against the averaged reflectance aerial data at 2207 nm. Aerial hyperspectral data was averaged over 2x2 pixel area.](image)
3.4 Mapping using hyperspectral data

3.4.1 Principal Component Analysis (PCA)

The shade area in the hyperspectral imagery, identified in Chapter 2 Figure 2.4, demonstrates the number of samples that could not be used to correlate the point count alteration percent to the airborne imagery. Therefore, a Principal Component Analysis (PCA) was performed on the aerial imagery in an attempt to find significant patterns in the data that correlated to the alteration intensity along Pinnacle Ridge. Locations on the east side of the ridge were identified as potential zones of alteration from analysis of individual Principal Components (PC). The PCA values of the first 11 PC bands are listed in Appendix B (Table B2). The first 4 PC bands explain 99.7% of the variance in the dataset. Each PC is expressed as a greyscale image with the light and dark pixels indicating the pixel values that are furthest away from the PC band mean. Therefore, these dark and light zones show the most variance in each PC. PC1 highlights the illumination effects on the ridge as the west side is dark and the east side is light, while PC2 shows the vegetation and scree deposits at the top of the ridge (Appendix B, Figure B1). PC bands 4, 6, 7, and 11 highlight the difference between the scree deposits and the in-situ rocks (Appendix B, Figure B1). PC 3, 5, 8, and 9 show potential for identifying the alteration intensity on Pinnacle Ridge due to the strong correlation to the alteration percent (Figures 3.21, 3.22, 3.24, and 3.25). The correlation of the other PC bands with the point count alteration percent are in Appendix B (Figure B2).

3.4.1.1 Content analysis of Principal Components (PC) 3, 5, 8, and 9

Figure 3.21 shows the results of the analysis of Principal Component 3 (PC 3). The more altered areas in this band, based on the point count percent and the eigenvalues, are the negative values (Figure 3.21a) represented by black pixels. The black pixels have high phyllosilicate (2207 nm) and goethite (~480 nm) scaled reflectance values (Figure 3.21b; 0.7 and 0.64 respectively; B3), but also covers an

![Figure 3.20: Averaged laboratory reflectance against averaged aerial reflectance data at 2207 nm.](image-url)
area that has both low phyllosilicate and low goethite (Figure 3.21b; B1 and B2), and an area with strong vegetation absorptions (Figure 3.20b; B4 and B5, can see red edge at 674-750 nm wavelengths). The white pixels show a variation in goethite (Figure 3.21c; 0.69-0.93) reflectance values but very similar low phyllosilicate absorptions (between 0.83-0.85; Figure 3.21c).

Figure 3.22 shows the results of the analysis of Principal Component 5 (PC 5). This band has the same negative correlation between the eigenvalues and the point count percent as band 3 (Figure 3.21a), therefore, the more altered areas in this band are the negative values (Figure 3.22a) and the black pixels. The black pixels all have very similar high goethite (Figure 3.22b; 0.71-0.78) and medium phyllosilicate (Figure 3.22b; 0.81-0.85) reflectance values. The white pixels show two distinct groups of absorptions for goethite as W2 and W5 absorption peaks are shorter (~0.93) than for W1, W3, and
W4 which are deeper (0.76-0.80; Figure 3.22c). There is a similar trend for the phyllosilicate peak except the W3 absorption is closer to samples W5 and W2 peaks (0.80-0.81), whereas W1 and W4 have quite high absorptions (0.71-0.74; Figure 3.22c). The white pixels seem to correspond well to the location and geometry of the intrusion outcrops. On average, the black pixels have more goethite and less phyllosilicate than the white pixels.

On the largest dike on the eastern side of the ridge (Fig 3.23a), the black and white pixels have similar phyllosilicate signatures between (0.78-0.85), however, the black pixels surrounding the intrusion have a deeper goethite reflectance than the white pixels (0.72-0.78 and 0.83-0.93 respectively; Figure 3.23 b and c). Therefore, the surrounding units may have a higher goethite abundance which suggests the units surrounding the intrusion were exposed at the surface before the dike intruded. The
absorption feature at ~2207 nm for the surrounding units (orange) shifts towards longer wavelengths which could suggest formation of hydrothermal minerals such as montmorillonite (Clark et al., 1990). Therefore, the surrounding units were hydrothermally altered as the dike intruded.

Figure 3.24 shows the results of the analysis of Principal Component 8 (PC 8). This band has a weak positive correlation between the eigenvalues and the point count percent; therefore, the more altered areas are the white pixel values which are positive (Figure 3.24a). This is interesting because majority of the white pixels show a strong vegetation signature (W1, W2, and W3; Figure 3.24d), as seen by the red edge at 677-760 nm (Figure 3.24c). The other two white pixel samples, W4 and W5, are scree deposits which show the same phyllosilicate absorption (0.79) but varying goethite absorptions (0.86
and 0.78 respectively; Figure 3.24 c and d). The black pixels vary in both goethite and phyllosilicate reflectance values (Figure 3.24b). B5 has the deepest absorption feature for both phyllosilicate (0.69) and goethite (0.72). Not including B5, there are two distinct groups for both the goethite (0.79-0.81) and phyllosilicate (0.76-0.84) absorptions (Figure 3.24b).

Figure 3.24: Analysis for Principal Component band 8 showing, a) positive correlation between the eigenvalues and point count percent, b) spectral profile of the reflectance in continuum removed format for the black pixels, c) spectral profile of the reflectance in continuum removed format for the white pixels, and d) PC band 8 with a standard deviation stretch, along with the location of the pixels used for b) and c). B=black pixels, W=white pixels and the colours and numbers of the points in d) correlate to the colours and numbers in the spectral profiles of b) and c). Aerial hyperspectral and PCA data was extracted in a 2x2 pixel area.

Figure 3.25 shows the results of the analysis of Principal Component 9 (PC 9). This band has a negative correlation between the eigenvalues and the point count percent; therefore, the more altered areas are the black pixel values which are negative (Figure 3.25a). The black pixels show a variation in goethite absorptions from 0.71-0.83, whereas the absorption peaks are very similar for phyllosilicate at 0.81-0.84 (Figure 3.25b). For the white pixels, there are two distinct groups for goethite at 0.74-
0.78 (W3, W4, and W5) and 0.91 (W1 and W2), whereas phyllosilicate absorptions range between 0.79-0.82 (Figure 3.25c).

**Figure 3.25:** Analysis for Principal Component band 9 showing, **a)** negative correlation between the eigenvalues and point count percent, **b)** spectral profile of the reflectance in continuum removed format for the black pixels, **c)** spectral profile of the reflectance in continuum removed format for the white pixels, and **d)** PC band 9 with a standard deviation stretch, along with the location of the pixels used for b) and c). B=black pixels, W=white pixels and the colours and numbers of the points in d) correlate to the colours and numbers in the spectral profiles of b) and c). Aerial hyperspectral and PCA data was extracted in a 2x2 pixel area.

### 3.4.1.2 PCA composite map

From the Principal Component interpretation, only one PC band was used in a PCA composite map to represent alteration variation across Pinnacle Ridge, with the other two bands representing vegetation and shade. PC 3 was selected for the composite, as it displayed a range of goethite and phyllosilicate absorption depths. Therefore, the PC bands used to create the composite were PC2, PC3, PC4 (RGB), which is shown in Figure 3.27. Spectral profiles of averaged aerial hyperspectral data from each of the eight main colours of the PCA helped identify why these colours are spectrally different (Figure 3.26). The pink class represents vegetation due to the red edge at 678 – 759 nm.
wavelengths (Figure 3.26a; e.g. Kooistra et al., 2004; and Shafri et al., 2006), the grey class represents shade/noise (Figure 3.26a), and the other six colours represent different levels of goethite (Figure 3.26b) and phyllosilicate alteration (Figure 3.26c). The order of absorption features marginally changes between the goethite and phyllosilicate features, due to the high goethite absorption relative to the phyllosilicate absorption for the light green spectra. The average order of alteration is as follows, from least to most altered: light blue, dark blue, light green, dark green, orange, and red. Therefore, this created the class names for the alteration zones in the classification, as: primary (unaltered) mineralogy (light blue), low phyllosilicate and goethite (dark blue), low phyllosilicate and high goethite (light green), moderate phyllosilicate and goethite (dark green), high phyllosilicate and goethite (orange), and very high phyllosilicate and goethite (red).

Figure 3.26: Continuum removed reflectance for a) vegetation and shade/noise classes, b) the six dominant colours from the PCA composite in Figure 3.27, between 400 – 600 nm wavelengths, to show the order of goethite absorption, and c) the six dominant colours from the PCA composite in Figure 3.27, between 2000 – 2400 nm wavelengths, to show the order of phyllosilicate absorption. Aerial hyperspectral data was extracted in a 2x2 pixel area.
Figure 3.27: PCA band composite using PC band 2, 3, 4 with the locations that the aerial image data was averaged from for the eight main colours of the PC composite, to create the profiles in Figure 3.26: vegetation, shade/noise, primary (unaltered) mineralogy, low phyllosilicate and goethite, low phyllosilicate and high goethite, moderate phyllosilicate and goethite, high phyllosilicate and goethite, and very high phyllosilicate and goethite.
3.4.2 Spectral Angle Mapper (SAM) image classification

The PCA analysis was utilised to develop the class names for the Spectral Angle Mapper (SAM) classification, which were: vegetation (pink), shade/noise (grey), primary (unaltered) mineralogy (light blue), low phyllosilicate and goethite (dark blue), low phyllosilicate and high goethite (light green), moderate phyllosilicate and goethite (dark green), high phyllosilicate and goethite (orange), and very high phyllosilicate and goethite (red; Figure 3.27, 3.28, and Figure 3.29). The training and validation datasets used for the classification and accuracy assessment can be seen in Figure 3.28a and b. They were created in ArcGIS Pro as a polygon feature class, based on the interpretation of the coloured zones of the PCA composite (Figure 3.26 and 3.27). The training dataset categorised 8378 pixels into the eight classes, which was 1.3% of the overall pixels in the aerial imagery (634800 pixels; Table 3.3 and 3.4).

![Training and validation data created in ArcGIS Pro, based on the PCA composite analysis in section 3.4.1, used in SAM classification in ENVI. Base image is the aerial orthophoto.](image)
The SAM classification was run using the training dataset with multiple maximum angle thresholds (Table 3.2). These thresholds determine the maximum acceptable angle between the training data spectrum and the pixel vector (Petropoulos et al., 2010). The output of the classification is in Figure 3.29 and the rule images for each class are in Appendix B (Figure B3). All three alteration maps (geologic, PCA composite, and SAM classification) are compared in Figure 3.30. The accuracy of the classification was first analysed by comparing the classification output to the geological map (Figure 3.30a and c). The overall shape of the alteration zones on Pinnacle Ridge is similar between the geological alteration map and the classification map. The least altered section of the ridge in both maps is to the north and the most altered area is the central section surrounding the fault. Some of the detail in the geology map can be seen in the classification such as the less altered lava flows identified in the geology map as the <10% stripes in the 50 – 65% altered zone (blue stripes in orange zone) which can be seen in the classification as the low P/high G stripes in the moderate P/G unit (light green in dark green zone, circled in Figure 3.29). The intrusions in the geological map are also identified by the primary (unaltered) mineralogy class in the classification. In places, the classification is more detailed than the alteration map, for example in the 50 – 65% alteration zone on the west side of the ride. The geology map indicates the whole upper section of the ridge is 50 – 65% altered however, the classification map shows areas within this zone that are more altered than others. This is due to the limited geological mapping that could be completed using only aerial imagery. The shade in the classification means the units on the west side of the ridge in the geology map cannot be compared. An area of misclassification was identified surrounding samples R11, R12a and b, and R13. The classification classed this area as low P/G with zones of moderate P/G, whereas the geological map classes this area as 50 – 75% alteration.

Further analysis of the accuracy of the classification map was measured using a confusion matrix and a validation dataset (Table 3.3 and Figure 3.28b). This matrix shows the accuracy of the overall classification to be 92.1%, as the correctly classified pixels from the validation dataset was 7714 pixels (sum of yellow pixel values in Table 3.3), out of a total of 8378 pixels highlighted in the training and validation datasets. The user’s and producer’s accuracies can be calculated from the confusion matrix to quantify the accuracy of the individual classes (Table 3.4; Congalton, 1991; Congalton, 2001; and Foody, 2002). The producer’s accuracy is derived from the total number of pixels of a class divided by the total number of pixels of that class from the validation data (i.e. the column total). This accuracy indicates the probability of a reference pixel being correctly classified. The user’s accuracy is derived by the total number of correct pixels in a class divided by the total number of pixels classified in that class (i.e. the row total) and measures the probability that a pixel classified in the image represents that category on the ground.
Table 3.2: Maximum angle thresholds used in the SAM classification for each class.

<table>
<thead>
<tr>
<th>Class</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shade/noise</td>
<td>0.3</td>
</tr>
<tr>
<td>Vegetation</td>
<td>0.2</td>
</tr>
<tr>
<td>Primary (unaltered) mineralogy</td>
<td>0.1</td>
</tr>
<tr>
<td>Low phyllosilicate and goethite</td>
<td>0.2</td>
</tr>
<tr>
<td>Low phyllosilicate and high goethite</td>
<td>0.3</td>
</tr>
<tr>
<td>Moderate phyllosilicate and goethite</td>
<td>0.1</td>
</tr>
<tr>
<td>High phyllosilicate and goethite</td>
<td>0.1</td>
</tr>
<tr>
<td>Very high phyllosilicate and goethite</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 3.3: Confusion matrix showing the accuracy of the classification by comparing the validation dataset to the training dataset. Highlighted in yellow are the pixels that were classified in the correct class in the validation dataset. The other white values are the pixels incorrectly classified and the orange values highlight the classes with incorrectly classified pixel values higher than 50. For the class names, G = goethite and P = phyllosilicate.

<table>
<thead>
<tr>
<th>Confusion Matrix</th>
<th>Shade/noise</th>
<th>Vegetation</th>
<th>Primary</th>
<th>Low P/G</th>
<th>Low P/High G</th>
<th>Moderate P/G</th>
<th>High P/G</th>
<th>Very high P/G</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unclassified</td>
<td>101</td>
<td>54</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>155</td>
</tr>
<tr>
<td>Shade/noise</td>
<td>2922</td>
<td>4</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2931</td>
</tr>
<tr>
<td>Vegetation</td>
<td>8</td>
<td>1658</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1667</td>
</tr>
<tr>
<td>Low P/G</td>
<td>125</td>
<td>10</td>
<td>46</td>
<td>1669</td>
<td>0</td>
<td>19</td>
<td>0</td>
<td>0</td>
<td>1869</td>
</tr>
<tr>
<td>Low P/High G</td>
<td>13</td>
<td>8</td>
<td>35</td>
<td>0</td>
<td>395</td>
<td>18</td>
<td>1</td>
<td>0</td>
<td>470</td>
</tr>
<tr>
<td>Moderate P/G</td>
<td>20</td>
<td>3</td>
<td>8</td>
<td>57</td>
<td>13</td>
<td>399</td>
<td>7</td>
<td>0</td>
<td>507</td>
</tr>
<tr>
<td>High P/G</td>
<td>10</td>
<td>22</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>23</td>
<td>4</td>
<td>193</td>
</tr>
<tr>
<td>Very high P/G</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>4</td>
<td>128</td>
<td>133</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>3200</td>
<td>1760</td>
<td>504</td>
<td>1767</td>
<td>408</td>
<td>447</td>
<td>141</td>
<td>151</td>
<td>8378</td>
</tr>
</tbody>
</table>

Table 3.4: This table shows the percent of producer’s and user’s accuracy of each class in the classification, the pixel count and percent per class across the whole hyperspectral image, and the area of each class from the classification. The overall pixel count, kappa coefficient, and overall classification accuracy are also included. Accuracy below the recommended 85% (Foody, 2002) are highlighted in orange.

<table>
<thead>
<tr>
<th>Class</th>
<th>Producer’s Accuracy (%)</th>
<th>User’s Accuracy (%)</th>
<th>Pixel Count</th>
<th>Pixel Percent (%)</th>
<th>Area (m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unclassified</td>
<td>-</td>
<td>-</td>
<td>1357</td>
<td>0.2</td>
<td>3053.3</td>
</tr>
<tr>
<td>Shade/noise</td>
<td>91.3</td>
<td>99.7</td>
<td>79918</td>
<td>12.6</td>
<td>179815.5</td>
</tr>
<tr>
<td>Vegetation</td>
<td>94.2</td>
<td>99.5</td>
<td>64449</td>
<td>10.2</td>
<td>145010.3</td>
</tr>
<tr>
<td>Primary (unaltered) mineralogy</td>
<td>82.3</td>
<td>91.6</td>
<td>64568</td>
<td>10.2</td>
<td>145278.0</td>
</tr>
<tr>
<td>Low phyllosilicate and goethite</td>
<td>94.5</td>
<td>89.3</td>
<td>289638</td>
<td>45.6</td>
<td>651685.5</td>
</tr>
<tr>
<td>Low phyllosilicate and high goethite</td>
<td>96.8</td>
<td>84.0</td>
<td>275645</td>
<td>4.3</td>
<td>62021.3</td>
</tr>
<tr>
<td>Moderate phyllosilicate and goethite</td>
<td>89.3</td>
<td>78.7</td>
<td>96964</td>
<td>15.3</td>
<td>218169.0</td>
</tr>
<tr>
<td>High phyllosilicate and goethite</td>
<td>90.8</td>
<td>66.3</td>
<td>8232</td>
<td>1.3</td>
<td>18726.8</td>
</tr>
<tr>
<td>Very high phyllosilicate and goethite</td>
<td>84.8</td>
<td>96.2</td>
<td>2018</td>
<td>0.3</td>
<td>4540.5</td>
</tr>
</tbody>
</table>

Pixel Count of Whole Aerial Image: 634800
Overall Classification Accuracy: 92.1%
Focussing on the high P/G class, the producer’s accuracy for this class is 90.8% (128/141) and the user’s accuracy is 66.3% (128/193). Therefore, even though 90.8% of the high P/G areas have been correctly identified as this class, only 66.3% of the areas called high P/G are actually this class. This is supported by the error matrix as there is confusion in discriminating high P/G from shade/noise, vegetation, moderate P/G, and very high P/G. This is the case for the classes low P/high G and moderate P/G, as the producer’s percent is higher than 85% for both classes (96.8% and 89.3%, respectively), however the user’s percent is lower than 85% (84.0% and 78.7%, respectively). Therefore, a lower percentage of pixels in these classes are actually moderate P/G and low P/high G. The opposite is true for the primary (unaltered) mineralogy class as the producer’s accuracy is lower than the user’s accuracy (82.3% and 91.6%, respectively). Therefore, less pixels were classified correctly in this class, but of the pixels that were classified, 91.6% are actually primary (unaltered) mineralogy. This is due to 46 pixels being mis-classified as low P/G and 35 pixels being mis-classified as low P/high G (Table 3.3). This trend is also observed for the very high P/G class.

From the pixel count per class, the percent of pixels and area per class could be calculated (Table 3.4). This shows that the low phyllosilicate and goethite class to covers the largest area on Pinnacle Ridge at 651685.5 m², which is 45.6% of the study area. The most altered zones on Pinnacle Ridge covers 4540.5 m² (0.3%) for the very high phyllosilicate class, and 18726.8 m² (1.3%) for the high phyllosilicate and goethite class (Table 3.4). These areas are pre-dominantly on the east side of the ridge; however, this is somewhat bias as the shade/noise class covers 179815.5 m² of the west side of the ridge.
Figure 3.29: Spectral Angle Mapper (SAM) classification output from the training data in Figure 3.28a and the aerial hyperspectral data. The classes include vegetation, shade/noise, primary (unaltered) mineralogy, low phyllosilicate and goethite, low phyllosilicate and high goethite, moderate phyllosilicate and goethite, high phyllosilicate and goethite, and very high phyllosilicate and goethite. White circle indicates where lava flows match in the classification and geological map.
Figure 3.30: Comparison of three alteration maps: a) geological map, b) PCA composite, and c) SAM classification.
3.5 Summary

- Petrographic and point counting analysis of 20 samples from pinnacle ridge were categorised into six groups, defined by the percent of altered material. A geological map was created based on the location of these samples, their alteration percent, aerial photos and field observations.

- Phyllosilicates (montmorillonite and kaolinite), goethite, and jarosite assemblages were identified in the laboratory and aerial hyperspectral datasets.

- Mineral identification of laboratory data for the interior and exterior of samples indicates different compositions. The exterior of samples contained iron oxide, OH and H$_2$O absorptions that are typical of weathering and surface processes, whereas the interior of samples displayed OH absorptions, and OH-metal bonding as a characteristic of phyllosilicates, a pathfinder mineral group for hydrothermal alteration processes.

- The laboratory data correlated to the point count alteration percent, but the aerial data correlated poorly to the point count alteration percent and showed no correlation to the laboratory data.

- Principal Component Analysis (PCA) was used to explore the data variability before performing image classification. This maximized the classification accuracy by excluding PC bands that carried less important information on the hydrothermal alteration history of the Pinnacle Ridge.

- The outcome of the classification map shares similarities with the geological alteration map. The airborne image derived classification indicates similar alteration abundances as the ground sample lithologies. However, there was one exception to this which was the area surrounding samples R11, R12, and R13. This area was classified as low phyllosilicate and goethite, whereas the petrographic studies identified these three samples as having alteration between 50 – 75%.

- The overall accuracy of the classification (92.1%) suggests it’s a good thematic map of the alteration distribution. However, by analysing individual class accuracies, a low producer’s and user’s percent for some classes highlights issues within the classification process.
Chapter 4: Discussion

4.1 Introduction

This chapter will review the alteration history of Pinnacle Ridge based on the mineral identification in Chapter 3 and past research. The utility of hyperspectral imagery for alteration assemblage identification and mapping will be explored. Understanding the influence of scale on the aerial and hyperspectral data will aid in understanding the poor correlation between the microscopy and laboratory spectroscopy with the aerial hyperspectral data. The classification accuracy will be discussed to understand why there was a misclassification between the geological map and the classification. The implications of hyperspectral remote sensing analysis for hazard identification and mapping will be touched on, followed by the possible future work on Pinnacle Ridge.

4.2 Pinnacle Ridge alteration history

The Spectral Angle Mapper (SAM) method of supervised classification was successfully applied to the aerial hyperspectral image of Pinnacle Ridge (Figure 3.30c). The alteration zone identified by Mordensky et al. (2018a) on the west slope was not able to be verified by this study due to the influence of the shadow (Zone A in Figure 4.1). However, the alteration was mapped on the east side which could be an extension of this alteration zone (Figure 4.1). The classification results show two other alteration zones: 1) surrounding one of the larger dikes on the east side of the ridge (Zone B in Figure 4.1), and 2) around the intrusions near the top of the ridge (Zone C in Figure 4.1). Deeper phyllosilicate and goethite absorptions were identified along the fault line, through the middle of the ridge (L1 in Figure 4.1). It is possible that this fault was a pathway for hydrothermal fluid flow when the hydrothermal system was active, resulting in higher alteration abundance (very high P/G and high P/G) than the units surrounding the intrusions (low P/high G and moderate P/G).

The hydrothermal system on Pinnacle Ridge was first described by Hackett (1985) as highly jointed and shattered intrusive bodies which are crosscut by altered breccia dikes and surrounded by an aureole of hydrothermal alteration (Zone A; Figure 4.1). Plagioclase within the intrusive complex is commonly replaced or veined by montmorillonite, mixed layered illite/montmorillonite, and minor pyrophyllite (Hackett, 1985). The inner zone of the halo can be identified by intensely oxidised breccias and thin lava flows that have been permeated by finely disseminated sulfides and cut varying by veins of clay. The outer zone of the halo is defined by veins of colloform silica with associated kaolinite (Hackett, 1985). Mordensky et al. (2018a, 2018b, 2019a, 2019b) expands on this work by identifying the hydrothermal alteration within the halo as advanced argillic alteration (AAA), with XRD and SEM data confirming the presence of montmorillonite (smectite, <27 wt%), kaolinite (<18 wt%), silica (cristobalite of <11 wt% and quartz of <3 wt%), and illite in the samples (<2 wt%; Figure 4.2). The presence of jarosite (1 wt%), magnetite (<1 wt%), pyrite (7 wt%), and barite (<1 wt%) were also
identified. The majority of these latter minerals can be associated with advanced argillic alteration (Pirajno, 2009).

Our laboratory hyperspectral results show mixes of iron oxide, clay minerals, and to a minor extent sulphates in the samples collected on Pinnacle Ridge. The identified minerals that agree with past
studies include jarosite in two samples in <10% alteration group, and the kaolinite and montmorillonite features in alteration groups <10% (R6), 10 – 20% (R2), 30 – 40% (R14), and 50 – 65%. Montmorillonite was the dominant phyllosilicate in the spectra for the majority of the samples, present in both the interior and exterior, based on the position and geometry of the absorptions and inflection points (Figure 3.10). Strong kaolinite absorption features were identified for the hydrothermal vein sample (R17; >85% alteration group), with minor montmorillonite. The illite and pyrophyllite established in previous studies was not identified in the hyperspectral data due to the lack of diagnostic features at 2165 nm for pyrophyllite (John et al., 2010) or 2340 nm for illite (Clark et al., 1990). It is common for the features of one phyllosilicate mineral to dominate the spectra in the region between 1200 – 2500 nm (Hunt & Ashley, 1979). Therefore, illite or pyrophyllite may not be present in the hyperspectral data if it is a minor component of the bulk composition, due to the dominance (Vol%) of montmorillonite ± kaolinite between 2201 – 2212 nm in the samples (e.g. Yang et al., 1999). Ferrihydrite was identified in the XRD (sample R19a), however, goethite was the dominant iron-bearing mineral identified in the laboratory and aerial hyperspectral data between 350 – 1200 nm, for all samples. Detection of pyrite in the VNIR region is hindered if iron oxide minerals are present, due to the its low reflectance level and broad Fe-absorption (Swayze et al., 1996). Therefore, the dominant goethite absorptions mask the identification of pyrite. Barite and silica polymorphs (cristobalite and quartz) were not detected in the hyperspectral data either, as they only have diagnostic features in the LWIR region (Table 4.1; Clark, 1999; Baldridge et al., 2009).

An alteration assemblage of kaolinite, ± barite, ± pyrite, ± silica polymorphs can be indicative of advanced argillic alteration following Carrillo- Rosúa et al., 2009 and Mordensky et al. (2018a, 2018b, 2019a, 2019b), or intermediate argillic alteration (often used synonymously with argillic alteration, e.g. Heald et al., 1987; Corbet & Leach, 1998; Hedenquist et al., 2000) following Meyer & Hemley (1967), Reed (1997), Eaton & Setterfield (1993), Robb (2005), Pirajno (2009), John et al. (2010), and Corbett (2018). Alunite is commonly used as an identifying mineral of advanced argillic alteration (e.g. Brimhall & Ghiorso, 1983; Henley & Ellis, 1983; Eaton & Setterfield, 1993; Hedenquist et al., 2000; Stoffregen et al., 2000; Simmons et al., 2005; Ece et al., 2008; Richards, 2011; Hedenquist & Taran, 2013). However, alunite was not identified in the laboratory or aerial hyperspectral data due to the absence of the diagnostic double absorption feature at 1433/1475 nm (Kokaly et al., 2017) and a single absorption at both 1760 nm and 2170 nm (Hunt & Ashley, 1979; Bishop, 2019; Figure 1.10). Furthermore, neither Hackett (1985) or Mordensky (2019) identified alunite on the ridge. Corbett & Leach (1998), Carrillo-Rosúa et al. (2009), Galán & Ferrell (2013), and Corbett (2018) describe some phases of advanced argillic alteration that do not contain alunite group minerals; however, they typically include higher temperature pyrophyllite and kaolin group minerals such as dickite. Minor pyrophyllite was identified by Hackett (1985), but this was not identified in this study or Mordensky et al. (2018a, 2018b, 2019a, 2019b). Moreover, smectite minerals such as montmorillonite, can form with kaolinite in intermediate argillic zones (Eaton & Setterfield, 1993; Robb, 2005; Pirajno, 2009). Therefore, based on the lack of alunite at the broader scale of the hyperspectral data in this study, this alteration assemblage is identified as intermediate argillic alteration (Table 4.1).
There is also evidence of dominant argillic montmorillonite ± illite alteration that is interspersed with areas of intermediate argillic alteration. Typically, these alteration assemblages are zoned so that the intermediate kaolinite alteration appears closer to the intrusions (i.e. source of acidic fluid), which grades into more dominant argillic montmorillonite ± illite away from the intrusion, due to mixing with meteoric water and wall-rock interaction neutralising the acidity of the fluid (Reed, 1997; Corbett, 2018). Although higher altered zones are apparent on Pinnacle Ridge surrounding the intrusions (Figure 4.1, Zones A, B, and C), montmorillonite and kaolinite appear throughout these altered zones, irrespective of the distance to the intrusions. This is most likely due to a focussed hot acidic fluid flow close to the intrusions and along specific pathways overprinted by the lower acidity lower temperature alteration.

Mordensky et al. (2018a) found that smectite-group alteration (e.g. montmorillonite) in the lava and intrusions typically increased the porosity and permeability of these units. Furthermore, the SEM data shows an initial phase of smectite alteration, with a secondary phase of barite and kaolinite infilling pore space (Figure 4.2), suggesting a change in fluid chemistry (Dekov et al., 2005; McKeown et al.,

\[\text{Figure 4.2: Field-emission scanning electron microscope (FE-SEM) data of sample R19a showing two stage clay alteration from Mordensky (2019). a) first stage of intermediate argillic alteration displaying smectite (montmorillonite) with white shrinkage cracks and euhedral pyrite, and b) second stage of advanced argillic alteration displaying long prismatic barite and blocky, infill of kaolinite.}\]
Therefore, it is inferred that the argillic alteration of montmorillonite increased the hydrothermal fluid flow in the lava units (e.g. R19a and b), which enabled the flow of more acidic, higher temperature fluids to permeate and create secondary alteration of kaolinite and barite, which in turn precipitate and reduce the permeability as seen in the hydrothermal breccias.

Three hypotheses that could explain the alteration assemblages on Pinnacle Ridge, and the lack of alunite, are: 1) overprinting of advanced argillic alteration with supergene alteration; 2) the hydrothermal system did not produce advanced argillic alteration; or 3) the samples collected from the ridge thus far, do not encompass the full range of alteration.

1) It is possible that advanced argillic alteration formed when the hydrothermal system was active on Pinnacle Ridge to produce alunite and kaolinite mineral phases. However, when exposed to a supergene environment the alunite could have been altered to amorphous phases (Hedenquist & Taran, 2013; Madden et al., 2015; Miller et al., 2016). Alunite has been identified in other locations on Ruapehu, for example within and surrounding the conduit (Miller et al., 2020) and on the northern slopes (Graham & Robinson, 1986), therefore, the formation of alunite on Pinnacle Ridge is conceivable. In the laboratory hyperspectral data, the presence of montmorillonite ± kaolinite features in samples R5, R4, R6, and R2, jarosite on the exterior of R10 and possibly R4, and the prominent goethite absorptions in all samples supports an overprint of supergene alteration (Hedenquist et al., 2000; Galán, 2006). This hampered the identification of hydrothermal alteration in the laboratory and aerial hyperspectral imagery. What can be deduced from the interior and exterior data (Figure 3.11) is that hypogene montmorillonite and kaolinite are most likely contributing to the stronger, more defined absorption features evident in the more altered samples (e.g. R1b, R14, and R12a; Figure 3.10).

2) If the hydrothermal system on Pinnacle Ridge did only produce argillic to intermediate argillic assemblages (i.e. no advanced argillic alteration formed at the surface or at depth), this would suggest that the system was not as deep or high in temperature as previously hypothesised. If this is true, then the shallow system would not have sustained degassing or high temperature fluids to produce the more acidic mineral phases such as alunite or dickite. There are two ways this could have occurred: A) the hydrothermal system was only supported by the series of dikes that intruded at shallow depths, so there was no eruptive centre to sustain the heat and acidity in the system, or B) the intrusions were more of a cryptodome at the top of the Te Herenga edifice, rather than dikes. Therefore, this magma could have been intruded into possible hyaloclastites (breccias erupted under ice caps has been proposed to have formed some units in the Te Herenga Formation; Townsend et al., 2017), but did not erupt through this layer which would have also produced a short-lived hydrothermal system. A similar model was presented by Cole et al. (2020) to explain the formation of the hydroclastic breccias (a non-glassy version of hyaloclastite, e.g. Honnorez & Kirst, 1975) and lobes in the Whangaehu and Wahianoa valleys on the south-eastern flank of Ruapehu.
3) The samples collected on Pinnacle Ridge so far are largely from the west side due to accessibility (Hackett, 1985; Mordensky, 2019; this study, Figure 2.2). However, the classification of the aerial hyperspectral data has indicated high alteration in locations on the east side of the ridge near an active fault, that have not previously been sampled. It is possible that alunite could be at these locations in low abundance and thus would not show up in the low spatial resolution aerial data. Therefore, the samples that have been collected from Pinnacle Ridge may not encompass the full range of alteration.

Based on the methods (e.g. spectroscopy) and the spatial scale of the data in this thesis, an alteration assemblage of montmorillonite, kaolinite, ± illite, ± quartz, ± pyrite is more likely to be intermediate argillic alteration as the dominant alteration assemblage at the surface, with zones of argillic alteration (Eaton & Setterfield, 1993; Pirajno, 2009), which has been overprinted with supergene alteration to form goethite, ± jarosite, ± montmorillonite, and ± kaolinite.

4.3 The utility of spectroscopy in a volcanic environment

4.3.1 Identifying alteration assemblages

Visible/near infrared (VNIR; 350 – 1000 nm) and shortwave infrared (SWIR; 1000 – 2500 nm) remote sensing techniques have become well established for mapping alteration assemblages in a range of environments. The VNIR region can be used to identify iron oxide minerals, such as goethite, hematite, ferrihydrite, and magnetite (Table 4.1; Clark et al., 1990). This region is often used in the mining industry to map and monitor the iron oxide alteration products from pyrite and chalcopyrite oxidation in acid mine drainage of active and abandoned mining sites (e.g. Farrand & Harsanyi, 1995; Clark et al., 1998; Swayze et al., 2000; Mars & Crowley, 2003).

The minerals that can be detected in the SWIR region are summarised in Table 4.1 (refer to references within Table 4.1 herein), which include phyllosilicates such as kaolin-, smectite-, illite-, and mica-groups; carbonates such as calcite; sulfates such as jarosite or alunite; and silicates such as pyrophyllite. Therefore, assemblages of potassic, propylitic, argillic, intermediate argillic, and advanced argillic alteration can be mapped using the SWIR region (Table 4.1; Sabine, 1999). However, some silicate, sulfate, and sulfide minerals are poorly represented in the SWIR region due to the lack of hydroxyl bonds. The longwave infrared (LWIR; 8000 – 14000 nm; John et al., 2010) region shows strong spectral features for silicate minerals due to fundamental vibrational frequencies of Si-O bond between 8000 – 11500 nm (Clark, 1999; Kopačková & Koucká, 2017). These minerals include quartz (9100 nm), k-feldspar (12500 – 13500 nm), albite (9345 nm), andalusite (9090 – 25000 nm), anhydrite (4200 – 4920 nm), and epidote (9569 and 10256 nm). Epidote does have diagnostic features in the SWIR region at 2254 nm and 2339 nm, however, it can be difficult to differentiate from chlorite (2330 – 2350 nm), and calcite (2340 nm), and possibly illite (2340 nm; Clark et al., 1990) and sericite (2350 nm; John et al., 2010) in the absence of other diagnostic features, e.g. 2200 nm. The integration of hyperspectral LWIR imaging with VNIR and SWIR imagery has started to be explored within the remote sensing community, for more accurate alteration assemblage identification and hydrothermal mineral
mapping (e.g. Notesco et al., 2014; Kruse, 2015; McDowell & Kruse, 2016; Kopačková & Koucká, 2017; Kirsch et al., 2018; Lorenz et al., 2018).

Table 4.1: This table combines minerals that are commonly cited in alteration assemblages and their characteristic spectral features in the visible/near infrared (VNIR; 300 – 1000 nm), shortwave infrared (SWIR; 1000 – 3000 nm), mid-wave infrared (MWIR; 3000 – 5500 nm), and longwave infrared (LWIR; 8000 – 14000 nm) regions of the electromagnetic spectrum. The references refer to the papers where the spectral features were sourced. Some minerals had very sparse information within the literature, therefore their spectral features were derived from spectral profiles in the Jet Propulsion Laboratory (JPL) Spectral Library (Baldridge et al., 2009). The light grey rows differentiate minerals that have diagnostic absorption features in the MWIR – LWIR region, which are mostly silicate minerals. The bold values are the more characteristic absorption features for each mineral. Characterisation of alteration assemblages were amalgamated from Guilbert & Park, 1986; Sabine, 1999; Hedenquist et al., 2000; Giftkins et al., 2005; Payot et al., 2005; Khashgerel et al., 2008; Pirajno, 2009; John et al., 2010; Change et al., 2011; Swayze et al., 2014; and John et al., 2019. IA: intermediate argillic alteration & AA: advanced argillic alteration.

<table>
<thead>
<tr>
<th>Alteration type</th>
<th>Minerals</th>
<th>Characteristic Absorption (nm)</th>
<th>Wavelength Range</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Montmorillonite</td>
<td>1410, 1910, 2215, 2750, 5356, 10900, 11900</td>
<td>SWIR/MWIR/LWIR</td>
<td>Bishop et al., 1994; Baldridge et al., 2009; Laukamp, 2011</td>
<td></td>
</tr>
<tr>
<td>Illite</td>
<td>2220, 2340</td>
<td>SWIR</td>
<td>Clark et al., 1990; Laukamp, 2011</td>
<td></td>
</tr>
<tr>
<td>Illite/smectite</td>
<td>2760, 2933, 9726, 12492</td>
<td>SWIR/LWIR</td>
<td>Baldridge et al., 2009</td>
<td></td>
</tr>
<tr>
<td>Kaolinite</td>
<td>1400, 2165, 2205, 2326-2356, 2707-2762</td>
<td>SWIR</td>
<td>Hunt &amp; Ashley, 1979; John et al., 2010</td>
<td></td>
</tr>
<tr>
<td>Halloysite</td>
<td>1400, 2200</td>
<td>SWIR</td>
<td>Clark et al., 1990</td>
<td></td>
</tr>
<tr>
<td>Dickite</td>
<td>1380, 2180, 2200</td>
<td>SWIR</td>
<td>Kerr et al., 2011</td>
<td></td>
</tr>
<tr>
<td>Chlorite</td>
<td>700, 900, 1100, 1390, 2330-2350, 2817, 2924, 9745</td>
<td>SWIR/LWIR</td>
<td>King &amp; Clark, 1989; Baldridge et al., 2009; Bishop, 2019</td>
<td></td>
</tr>
<tr>
<td>Sericite</td>
<td>2200, 2350</td>
<td>SWIR</td>
<td>John et al., 2010</td>
<td></td>
</tr>
<tr>
<td>Calcite</td>
<td>1870, 1990, 2340, 11200</td>
<td>SWIR; LWIR</td>
<td>Salisbury &amp; Wald, 1992; Laukamp, 2011</td>
<td></td>
</tr>
<tr>
<td>Epidote</td>
<td>366, 616, 1548, 2254, 2339, 9569, 10256</td>
<td>VNIR/SWIR/LWIR</td>
<td>Clark et al., 1990; Laukamp, 2011</td>
<td></td>
</tr>
<tr>
<td>Biotite</td>
<td>2750, 2850, 10000</td>
<td>SWIR</td>
<td>Clark et al., 1990; Land &amp; Bishop, 2019</td>
<td></td>
</tr>
<tr>
<td>Jarosite</td>
<td>430, 650, 950, 1475, 2269</td>
<td>VNIR/SWIR</td>
<td>Hunt and Ashley, 1979; Clark et al., 1990</td>
<td></td>
</tr>
<tr>
<td>Pyrophyllite</td>
<td>1400, 2086, 2166, 2314, 2500</td>
<td>SWIR</td>
<td>Clark et al., 1990</td>
<td></td>
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<tr>
<td>Quartz</td>
<td>1436, 2914, 9159, 12522-12832</td>
<td>SWIR/LWIR</td>
<td>Clark, 1999; Baldridge et al., 2009; John et al., 2010</td>
<td></td>
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<tr>
<td>Alunite</td>
<td>1475, 1770, 2170</td>
<td>SWIR</td>
<td>Clark et al., 1990; Bishop &amp; Murad, 2005</td>
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<tr>
<td>Opal-TC</td>
<td>1390, 1910, 2210, 3000, 12500</td>
<td>SWIR/MWIR/LWIR</td>
<td>Guatame-Garcia &amp; Buton, 2017; Bishop, 2019</td>
<td></td>
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<tr>
<td>Diaspore</td>
<td>1400, 2200</td>
<td>SWIR</td>
<td>Hunt &amp; Ashley, 1979</td>
<td></td>
</tr>
<tr>
<td>Topaz</td>
<td>1404, 2750</td>
<td>SWIR</td>
<td>Clark et al., 1990</td>
<td></td>
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<tr>
<td>Andalusite</td>
<td>10000, 11100, 13300</td>
<td>LWIR</td>
<td>Land &amp; Bishop, 2019</td>
<td></td>
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<tr>
<td>Barite</td>
<td>2925, 4845, 10100, 10868, 12300-12600</td>
<td>SWIR/MWIR/LWIR</td>
<td>Baldridge et al., 2009</td>
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<td>Tourmaline</td>
<td>2750, 2820, 9015-10185, 12768, 13326, 14164</td>
<td>SWIR/LWIR</td>
<td>Clark et al., 1990; Baldridge et al., 2009</td>
<td></td>
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<tr>
<td>Hematite</td>
<td>530, 650, 850</td>
<td>VNIR</td>
<td>Hunt &amp; Ashley, 1979; Baldridge et al., 2009</td>
<td></td>
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<tr>
<td>Albite</td>
<td>2753, 2929, 9342</td>
<td>SWIR/LWIR</td>
<td>Baldridge et al., 2009</td>
<td></td>
</tr>
<tr>
<td>Actinolite</td>
<td>1392, 1398</td>
<td>SWIR</td>
<td>Clark et al., 1990</td>
<td></td>
</tr>
<tr>
<td>Apatite</td>
<td>9090, 9520</td>
<td>LWIR</td>
<td>Land &amp; Bishop, 2019</td>
<td></td>
</tr>
<tr>
<td>Anhydrite</td>
<td>1750, 4200, 4290, 3450, 4470, 4670, 4690, 4920</td>
<td>SWIR/MWIR</td>
<td>Baldridge et al., 2009; Bishop, 2019</td>
<td></td>
</tr>
<tr>
<td>Chalcopyrite</td>
<td>698, 26700</td>
<td>VNIR/MWIR</td>
<td>Baldridge et al., 2009; Land &amp; Bishop, 2019</td>
<td></td>
</tr>
<tr>
<td>Magnetite</td>
<td>1100</td>
<td>SWIR</td>
<td>Clark, 1999; Bishop, 2019</td>
<td></td>
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<tr>
<td>Goethite</td>
<td>450, 650, 950</td>
<td>VNIR</td>
<td>Hunt &amp; Ashley, 1979; Baldridge et al., 2009</td>
<td></td>
</tr>
<tr>
<td>Ferrhydrite</td>
<td>920, 1420, 1930, 2300, 2900-3000</td>
<td>VNIR/SWIR</td>
<td>Bishop &amp; Murad, 2002</td>
<td></td>
</tr>
<tr>
<td>Carbonates</td>
<td>2300, 2340, 2500-2550, 3500, 4000, 4600</td>
<td>SWIR/MWIR</td>
<td>Bishop, 2019</td>
<td></td>
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<tr>
<td>K-feldspar</td>
<td>12500-15500</td>
<td>LWIR</td>
<td>Becker et al., 2010</td>
<td></td>
</tr>
</tbody>
</table>
4.3.2 Benefits of hyperspectral imaging for alteration mapping

Traditional methods of geological mapping in the field only allow for spot measurements at discrete accessible points, which often requires considerable time and resources depending on the topography and size of the study area. The ability to gather data in locations that are inaccessible and over large areas is a major advantage of hyperspectral imaging in particular, airborne high-resolution hyperspectral imaging. For example, the east side of Pinnacle Ridge is inaccessible and dangerous due to the steep topography and rock fall hazard. However, hyperspectral image analysis enabled more detailed mapping and the identification of alteration zones on the east side of the ridge. Some field verification of the hyperspectral data is still necessary; however, an initial hyperspectral analysis could assist in focussing field mapping and sampling activities, to increase efficiency in time and resources and to assure sampling representability. Furthermore, the sampling would be less extensive compared to creating a detailed geological map from ground surveys alone.

X-ray diffraction (XRD) has become the industry standard for qualitative and quantitative mineral analysis for geological samples (Bish & Post, 1993; Jozanikohan et al., 2016; Craddock et al., 2017). However, the identification and quantification of clay minerals is an ongoing challenge caused by their preferred orientation, differing chemical compositions, and structural diversity (Craddock et al., 2017; Zhou et al., 2018). Furthermore, the success of XRD quantification depends highly on sample preparation and method of interpretation (Kleeberg et al., 2008; Raven et al., 2017). The sample preparation process is time consuming and includes initial crushing, grinding, and separation of clay sized fractions for filling of oriented and random powder mounts, glycolation, and dehydration by heating (e.g. Kleeberg et al., 2008; Hansford et al., 2017). In comparison, visible to shortwave infrared spectroscopy is an efficient, cost-effective, and non-destructive method to analyse rock samples (Fang et al., 2018). The little to no preparation of the samples was demonstrated by this study, as the hand samples were only kept consistently dry before spectral measurements to reduce the effects of atmospheric H₂O on the spectral readings. Furthermore, the availability of airborne hyperspectral imaging systems can provide seamless coverage of potentially large areas, while also providing mineralogical information at much higher resolution than before with satellite remote sensing. Hence, these developments can make hyperspectral imaging very effective for volcano geological mapping and hydrothermal mineral mapping. The sensitivity of hyperspectral imaging enables identification of intra-layer variations within phyllosilicates, which are not easily recognised by XRD (Oluwadebi, 2015).

4.3.3 Challenges of hyperspectral imaging for alteration mapping

Challenges remain in utilising hyperspectral imaging for alteration mapping. For example, the sensor will only obtain surface measurements, as light does not penetrate the substrate (Kereszteri et al., 2018). Where surface covers occur, including supergene weathering, vegetation, glacier/snow and tephra mantling, the spectral response of these surfaces will dominate the measurement. This was an issue we encountered with the aerial hyperspectral data, as the dominant vegetation signature in the north of the study area resulted in the classification of this area as vegetation (Figures 3.26a and 3.29).
Therefore, hydrothermal alteration extent is potentially underestimated in a study area, if it is covered by vegetation or snow. Conversely, the overall hydrothermal alteration could be overestimated through hyperspectral mapping due to surficial weathering/hydrothermal alteration in the samples. This was identified by Kereszturi et al. (2018) which showed the surface of samples as highly altered whereas the interior of the sample was unaltered. One method developed to reduce the over or under-estimation of alteration zones is by pairing hyperspectral data with high resolution aeromagnetic data, to correlate internal geologic structure identified by magnetic flux within the volcano to hydrothermal deposits identified from the aerial hyperspectral imagery, at the surface (e.g. Finn et al., 2007; Finn et al., 2018; Jackisch et al., 2019; Miller et al., 2020).

Past studies (e.g. Hunt & Ashley, 1979; Clark et al., 1990; Bishop et al., 1993; McKeown et al., 2011; Awad et al., 2018; Bishop, 2019; Miller et al., 2020, etc.) and this study have shown that clay alteration minerals are able to be distinguished with SWIR spectroscopy. However, it can be challenging when mapping alteration zones, to differentiate between clay minerals formed by hydrothermal activity (hypogene) and clay minerals formed by lower temperature less acidic processes (e.g. supergene; Sabine, 1999), as they appear spectrally similar (e.g. Kereszturi et al., 2018). Past studies have suggested that supergene and hypogene deposits can be identified based on the degree of disorder within the structure of the crystal (crystallinity), i.e. high crystallinity indicates hypogene origin whereas low crystallinity indicates supergene origin (Yang et al., 1999; Oluwadebi et al., 2013; Oluwadebi, 2015). It has been proven that the degree of disorder in kaolinite, most likely due to the amount of structural iron (e.g. Brindley et al., 1986, and references therein), can affect the reflectance in the SWIR region (e.g. Crowley & Vergo, 1988; Yang et al., 1999; Zhang et al., 2001; Awad et al., 2018). For example, well ordered kaolinite will display more defined spectral features at 1401/1415 and 2172/2205 nm (e.g. R17) whereas, less ordered kaolinite will display less defined features (e.g. exterior of R4 has single features). However, these disordered kaolinite features can also look like mineral mixtures of kaolinite with opal or montmorillonite when kaolinite is present at <25 wt%, as the absorption at 2205 nm is reduced to a single feature and the reflectance value decreases (e.g. McKeown et al., 2011). Therefore, in a hydrothermal deposit of kaolinite (<25 wt%), montmorillonite, and opal (e.g. R19a, Table 2.1), the absorption feature at 2205 nm could look similar to disordered kaolinite of supergene origin. Similarly, Bishop et al. (1993) found that mixtures of montmorillonite and ferrihydrite or goethite can reduce or eliminate the absorption at 2215 nm for montmorillonite. Supplementary XRD analysis or LWIR data can help distinguish the minerals in mixtures of natural samples (Hunt & Ashley, 1979; Bishop et al., 2007; Bishop et al., 2013; Lane et al., 2015). Other methods to distinguish between supergene and hypogene clays include stable isotope geochemistry (Sevari & Hezarkhani, 2014) e.g. hydrogen and oxygen ratios (Sheppard et al., 1969; Sheppard & Gilg, 1996; Gilg et al., 1999; Brathwaite et al., 2014), mineral associations and zoning (Oliveira et al., 2007), structural and general geological setting (Sillitoe, 2005), element ratios (Dill et al., 1997), and fluid inclusions (Gilg et al., 1999; Sevari & Hezarkhani, 2014). Using a range of geological and hyperspectral analyses can help increase the accuracy of the mineral identification and interpretation of deposits that have once been hydrothermal altered, with subsequent weathering at the surface.
A significant challenge for hyperspectral remote sensing is the effects of atmospheric gases and water vapor on the spectral measurement at airborne and satellite scale, as the atmospheric molecules scatter the solar radiation. There are several different methods of removing/decreasing the atmospheric absorption and scattering in hyperspectral data (e.g. Gao et al., 2006), of which the Airborne Atmospheric and Topographic Correction Model (ATCOR) was used in this thesis. Even with atmospheric correction the narrow bandwidth of the hyperspectral data enabled the detection of the specific absorptions for different gases and water vapor in the atmosphere (Clark, 1999; e.g. Figure 4.3). Water vapor tends to decrease rapidly with altitude (Gao et al., 1993), however, Ruapehu is a high-altitude volcano which is evident in the prominent water absorptions (Figure 4.3). Atmospheric interference effects the aerial hyperspectral data more than the laboratory data as the absorption features are broader and less defined. For example, the H$_2$O peak at ~1900 nm in the aerial data is broad and shallow, whereas in the laboratory data it is sharp and deep which is more indicative of montmorillonite. Therefore, atmospheric effects reduce the identification of alteration minerals in the aerial hyperspectral data, as they will increase the noisiness of the image data.

![Figure 4.3: Atmospheric absorption features for sample R14 in the aerial hyperspectral data (black line) compared to the laboratory hyperspectral data (grey line) with little to no atmospheric absorptions.](image)

4.4 The influence of scale

4.4.1 Correlating microscopy, laboratory spectroscopy, and aerial hyperspectral imaging

Our results show that the laboratory reflectance values at 2207 nm is dependent on the alteration percent in the samples, as the reflectance values increase as the alteration percent increases (Figure 3.18). Thus, the homogeneity of the alteration at cm-scale reflects largely the scale that we can quantify using lab-based hyperspectral measurements. This trend was not well defined in the aerial reflectance data (Figure 3.19), which can indicate potential conflict between the airborne and lab-based spectroscopy. This conflict was also confirmed in Figure 3.20, as the ratio between the aerial and laboratory reflectance was not 1:1 (Figure 3.20). This means the airborne data is good for the detection of clay, however, the scale is not sufficient for further quantification of the clay abundance at this specific wavelength. The wavelength at which the data was plotted in Figures 3.18, 3.19, and
3.20 was selected based on the common absorption peaks for kaolinite and montmorillonite at 2207 nm, however, the data actually plots similarly across the 2201 – 2212 nm range (Appendix B, Figure B4). This might mean that the airborne data has a broad feature that is much wider than the lab-based data, possibly due to improper atmospheric corrections, different scattering properties of the ground and topographic effects, smile and keystone effects, etc. Other reasons for the poor correlation between the aerial and laboratory data can be due to: 1) the hand sampling is not statistically representative as the hydrothermal alteration is heterogeneous at m-scale due to surface supergene alteration overprinting; 2) differences in the scanning geometry and spectral footprint of the measurements (micron for thin sections, vs centimetre for spectroscopy, vs metre for airborne data); and 3) the signal to noise ratio and atmospheric influences affect the airborne data but have minimal influence on the laboratory data.

1) The samples have a variety of weathered and fresh surfaces (e.g. sample R2, Appendix B, Table B1). When the laboratory data was measured, the spot measurements were taken from around the whole sample and averaged. For the supplementary samples obtained from Mordensky (2019; Appendix A, Table A1), the laboratory data was collected on core cuttings from the samples. Therefore, it is possible that the laboratory data has some influence of ‘fresh’ rock (primary mineralogy or hypogene alteration without the overprint of supergene processes) in the measurement. The aerial data only measured the exterior of the units, and therefore, the airborne data is biased towards supergene alteration minerals.

2) The spatial and spectral resolution of the two hyperspectral datasets and the spatial scale of the thin sections could also be contributing to the differences in correlation to the point count percent. The laboratory data has a sampling footprint of 1 cm and a spectral resolution of 1 nm while the spatial resolution of the aerial data was 1.5 m and the spectral resolution was 3 – 10 nm. The major influences on the alteration abundance in the samples was the frequency of microfractures and their interconnection between the groundmass and the phenocrysits within the samples (Mordensky et al., 2018a). Since these features were visible in thin section scale (mm), they were included in the point count percent of alteration. Some microfractures would have been within the scale of the laboratory sensor, for example the clay alteration filling the micro-fracture in R7 was >40 mm long and ~1 mm wide. The smaller scaled alteration, such as the sieve texture with secondary clay alteration within individual crystals, could also have been picked up by the laboratory spectroscopy. The lower spatial resolution of the aerial data restricts the detection of alteration minerals on the surface, causing spectral mixing of multiple minerals per pixel (per 1.5 m). The spectral mixing is the average reflectance of the minerals within the pixel area, weighted based on the abundance of each mineral. This removes the sharp contrast between the alteration groups identified using thin section analysis. Therefore, this could have caused the similar reflectance values for the aerial data across the alteration groups (Figure 3.19), as it was unable to detect the micro-scale alteration that was defining the alteration groups of the samples.
3) The atmospheric influences on the laboratory and aerial hyperspectral data are discussed in section 4.3.3, where the aerial data is more affected than the laboratory data (Figure 4.3), due to the increased distance or altitude from the sensor to the target area. Atmospheric effects and instrumental (sensor) noise can cause a low signal to noise ratio. This can be a significant source of error in the quantification of constituent abundances (Moses et al., 2012).

One of our main objectives for the hyperspectral data was to determine what alteration percent is required to detect alteration minerals in the laboratory or aerial data. Our results show that phyllosilicate minerals at less than 10 wt% will still produce a relatively strong absorption feature in the 2200-2213 nm range for both the laboratory and aerial hyperspectral data (R6; Figure 3.9 and 3.13). This strong absorption feature is rather an indicator of presence, while its depth is not necessarily proportional to the abundance of the alteration phase, especially when two or more phyllosilicates are present (e.g. kaolinite and montmorillonite). However, the strong correlation of the alteration percent and lab-based spectral data indicates that the alteration phases do occur and are relatively homogeneous at cm-scale. This breaks down at m-scale (e.g. large-scale veins and hydrothermal breccias). This agrees with past studies that have shown that SWIR spectroscopy is able to detect clay minerals at abundances as low as 1 wt% in samples containing a single clay mineral, or at <5 wt% for samples containing more than one clay mineral (Zhang et al., 2001).

These findings indicate that lab-based data (e.g. thin section studies) should be used to improve and ground truth alteration types, while airborne hyperspectral data can be used to map the distribution of hydrothermal mineral associations instead. This approach to the image classification indicates the spatial-spectral changes associated with different proportions of alteration phases (e.g. alteration map of Pinnacle Ridge; Figure 3.29), however, the abundance remains unconstrained using image classification and/or band-based approaches. Alternatively, traditional linear unmixing or synthetically mixed training data of spectral library measurements (e.g. Okujeni et al., 2013) combined with a machine learning approach could be used to recognise alteration phases, and ultimately alteration percent. This must be explored in the future.

The image classification based geological map created here was ground truthed and captures the spatial variation of associated minerals. It successfully delineates the dominantly argillic alteration with ground truthed and hypothesized evidence of local more developed advanced argillic alteration, but the airborne data is hampered by the overprinting supergene processes.

4.4.2 Classification accuracy
The classification accuracy was measured using a confusion matrix (Table 3.3). The producer’s accuracy (error of omission, i.e. underestimation) was always higher than the user’s accuracy (error of commission, i.e. overestimation) for classes that related to the range of phyllosilicate and goethite abundance, e.g. low P/G, low P/high G, moderate P/G, and high P/G. This means that such classes are
spectrally easy to discriminate. The opposite trend was observed for classes with unique spectral features, such as primary (unaltered) mineralogy, vegetation, and shade/noise.

The classification was also compared to the geological alteration map from an independent source (Figure 3.30a), where one location of misclassification was identified (L4 in Figure 4.1). In this location, the samples R11, R12a and b, and R13 have alteration abundances between 60.8 – 74.0 %. However, the classification identified this area as low P/G with zones of moderate P/G. There are three options why this could be: 1) a scaling issue of the petrographic alteration analysis to regional-scale mapping (Figure 3.8), as discussed above; 2) the collected field samples represent more alteration than what occurs on a larger m-scale (i.e. sampling bias); or 3) the field validation (e.g. Figure 4.4) and sampling represent a lithological change between lava dominated to breccia-dominated domains. This “textural” change (e.g. surface roughness) can contribute to the failure of the SAM image classification. These textural changes have recently been mapped out using a combination of LiDAR and hyperspectral data (Kereszturi et al., 2018). Moreover, more sophisticated image classification approaches, such as machine learning, might be able to pick up such subtle changes (Kereszturi et al., 2018).

The classification of the aerial data was based on the relative intensities of phyllosilicate and goethite absorption peaks; thus, the classification does not directly relate to the lava flows, breccias, and intrusions on the ridge. However, based on the connection between the relative abundance of alteration and the porosity and permeability of the units established by Mordensky et al. (2018a, 2018b), some site-specific inferences can be made. The low phyllosilicate (P)/high goethite (G) class is interpreted to predominantly represent the lava flows on the ridge, as they match the mapped lava flows in the geological map (Figure 3.30; L2 in Figure 4.1). The low phyllosilicate alteration of the lava flows is a result of the low connected porosity and thus, low permeability (Mordensky et al., 2018a), with the higher goethite abundance a result of weathering (supergene) processes. The low P/G class makes up the majority of the scree deposits on the ridge and some lava flows in location 2 (L2 in Figure 4.1), as well as the other units surrounding the Te Herenga Formation (e.g. Whakapapa Formation, undifferentiated lava and various quaternary deposits; Figure 3.8; Townsend et al., 2017). This class also most likely classifies the low altered lava and breccia units to the north of the Te Herenga Formation (L3 in Figure 4.1). The last three P/G classes (moderate, high, and very high) are interpreted to represent the porous breccia deposits due to the higher abundance of phyllosilicates. Mordensky et al. (2018a) identified these units as the likely host for the hydrothermal fluid due to the decrease of porosity and permeability closer to the largest intrusion on the west side of the ridge (Int in Figure 4.1), indicating a filling of pore space with hydrothermal alteration of montmorillonite and later kaolinite closer to the intrusions. It is unlikely that any of the hydrothermal veins (<1 m; Mordensky, 2019) or dike intrusions <1.5 m would be identified in the classification due to the low spatial resolution of the aerial data (1.5 m). The larger stocky intrusions and dikes were identified in the classification as the primary (unaltered) mineralogy class, along with unaltered lava and breccia deposits to the north of the study area (L3 in Figure 4.1).
An increase in satellite multi/hyperspectral imagery over the last 20 years has provided global coverage of remote sensing data, with some satellites enabling real-time monitoring of volcanic activity globally (e.g. MODIS; Wright et al., 2002). However, the spatial resolution of these spaceborne sensors are typically 30 m or higher (e.g. ASTER; Pieri & Abrams, 2004; Mars & Rowan, 2011), which is too coarse to account for the heterogeneity of alteration minerals in mapping hydrothermal systems in detail. Some studies have demonstrated accurate mapping of geological materials associated with hydrothermal systems using satellite data (Kruse et al., 2011a, 2011b), however low signal to noise ratios (SNR) due to cloud cover can drastically decrease the amount of mineralogical information acquired (Kruse et al., 2002). Mapping and modelling of smaller (e.g. <10^6 m^3) but more frequent hazards such as rock falls or debris flows cannot rely on regional-scale mapping units that make broad assumptions and do not account for local variability. Therefore, higher spatial and spectral resolution hyperspectral imagery can provide finer detection, such as that of intrusions. This study has demonstrated the ability of high spatial and spectral resolution imagery with PCA-based data exploration and SAM-based classification analyses to map local variation of alteration minerals within a fossil hydrothermal system. Intrusions were identified in the classification, although features smaller than 1.5 m were only detected indirectly (i.e. as a spectral mixture).

**Figure 4.4:** The location of the misclassified region in Figure 4.1 (L4), from the SAM classification of the aerial hyperspectral data (Figure 3.30c or Figure 3.29). The sample locations and the alteration zones are approximately identified from Figure 4.1 for reference (R13 is located behind the cliff).

**4.5 Implications for volcanic mapping and hazards**

An increase in satellite multi/hyperspectral imagery over the last 20 years has provided global coverage of remote sensing data, with some satellites enabling real-time monitoring of volcanic activity globally (e.g. MODIS; Wright et al., 2002). However, the spatial resolution of these spaceborne sensors are typically 30 m or higher (e.g. ASTER; Pieri & Abrams, 2004; Mars & Rowan, 2011), which is too coarse to account for the heterogeneity of alteration minerals in mapping hydrothermal systems in detail. Some studies have demonstrated accurate mapping of geological materials associated with hydrothermal systems using satellite data (Kruse et al., 2011a, 2011b), however low signal to noise ratios (SNR) due to cloud cover can drastically decrease the amount of mineralogical information acquired (Kruse et al., 2002). Mapping and modelling of smaller (e.g. <10^6 m^3) but more frequent hazards such as rock falls or debris flows cannot rely on regional-scale mapping units that make broad assumptions and do not account for local variability. Therefore, higher spatial and spectral resolution hyperspectral imagery can provide finer detection, such as that of intrusions. This study has demonstrated the ability of high spatial and spectral resolution imagery with PCA-based data exploration and SAM-based classification analyses to map local variation of alteration minerals within a fossil hydrothermal system. Intrusions were identified in the classification, although features smaller than 1.5 m were only detected indirectly (i.e. as a spectral mixture).
The effect of hydrothermal alteration on the porosity, permeability, and strength of volcanic deposits has been studied on Pinnacle Ridge (Mordensky et al., 2018a, 2018b, 2019a, 2019b). These studies found that brecciated units decreased in porosity and permeability and increased in strength with montmorillonite alteration. Whereas, the coherent lava units increased in porosity and permeability and decreased in strength with montmorillonite and kaolinite alteration. Therefore, mineral mapping using aerial hyperspectral imagery can give an indication of the mechanical properties of the different units by identifying and quantifying the abundance of montmorillonite and kaolinite. Thus, mapping the spatial distribution of these alteration minerals can give an indication of fluid flow in the hydrothermal system. These alteration maps can also be used to quantify the spatial extent of alteration (e.g. Table 3.4), and when it is combined with depth constraints it can be used to assess 3D volume of hydrothermal alteration (Miller et al., 2020). This has implications on how flank instability hazards are assessed on composite volcanoes.

4.6 Future work

The classification highlighted a few areas that potentially have high phyllosilicate abundances, that have yet to be sampled. Gathering more data in these areas will help constrain the range of alteration and verify the classification. These areas are located in the steeper parts of Pinnacle Ridge, making it dangerous to access for further sampling. The airborne data had spatial resolution that was too coarse to capture the microscale alteration within the deposits, limiting the alteration identified in these areas. The recent development of hyperspectral UAS (unmanned aerial system)-based imaging could help solve the spatial resolution gap between m-scale airborne imagery and cm-scale laboratory hand-held sensors, without the need for further sampling (e.g. Jakob et al., 2017; Jackisch et al., 2018; Kirsch et al., 2018; Jackisch et al., 2019). This would be ideal for the altered zones near the fault on Pinnacle Ridge and the halo surrounding the dike on the east side of the ride, as the spatial resolution would be within cm-scale (Jackisch et al., 2019). UAS are flexible for the logistics of aerial surveys, compared to traditional airborne surveys (Jackisch et al., 2019). They could be deployed throughout the day to consider the solar illumination and topographic effects on the hyperspectral data. The ability to fly autonomously with pre-planned flight paths in open-sourced autopilot apps and with flight controllers, makes the operation of UAS require less personnel with adequate training and flight permissions (Jackisch et al., 2019). The reduction of flight altitude from 1300 m to 30 – 60 m would reduce the effect of cloud cover and would decrease the influence of the atmosphere on the measured data (Jakob et al., 2017). Using UAS to collect targeted hyperspectral data on Pinnacle Ridge would enable verification of alteration abundance on the east side of the ridge and would verify the work on the west side of the ridge that this study was unable to do. This method would also be a cost-effective way to continuously monitor of the stability of the ridge, by tracking the change of alteration across the units (e.g. section 4.5).

The poor correlation of the aerial data to the alteration percent at 2207 nm indicates an inability to quantify alteration abundance at this scale. However, the analysis of a combination of bands after
band reduction and/or band selection methods was proven to be more effective than fitting one band’s values against our observations (PCA Analysis; Section 3.4.1). In this study we successfully used a Principal Component Analysis (PCA) method to reduce the spectral redundancy for the image classification. However, this is an unsupervised dimensionality reduction (DR) technique that does not consider class-specific information provided by labelled samples and thus, does not optimise the accuracy for classification (Ghamisi et al., 2017). A few other DR techniques for image classification should be explored in the future including unsupervised DR methods such as the orthogonal total variation component analysis (OTVCA; Rasti et al., 2016), locality preserving projections (LPP; Wang & He, 2011) or modified locality preserving projections (MLPP; Zhai et al., 2016); supervised DR method such as nonparametric weighted feature extraction (NWFE; Kuo & Landgrebe, 2004); and semi-supervised DR techniques such as semi-supervised discriminant analysis (SDA; Cai et al., 2007), semi-supervised local fishers discriminant analysis (SELF; Sugiyama et al., 2010), semi-supervised local discriminant (SELD; Liao et al., 2013), or semi-supervised graph learning (SEGL; Luo et al., 2016). Fusion-based DR methods are also optimised for image classification which include graph-based methods that couple data fusion and DR in a framework (Debes et al., 2014; Liao et al., 2016), and a kernel-based method that incorporates spatial and spectral information simultaneously (Borhani & Ghassemian, 2015).

There are a few options to explore to improve the classification. Due to the extensive shadow on the west side of the ridge, another airborne survey or a UAS survey focussing on this side would help train the classification based on the laboratory and sample data. More sampling and analyses in Location 4 (Figure 4.1) could help identify whether the misclassification between the geological map and the classification map was due to field sampling bias or the classification process. Different classification methods may also produce more accurate results to the sample alteration percent. For example, machine learning algorithms are becoming more widely used and they can also detect and remove outliers in the training samples (Belgiu & Drăgut, 2016). Kereszturi et al. (2018) and Radford et al. (2018) have demonstrated the accuracy of using machine learning for image classification with the Random Forest Classifier for geological applications. Since the classes were selected based on the alteration percent, the use of LWIR could help classify Pinnacle Ridge based on the units (i.e. lava, breccia, intrusion), as the primary mineralogy (silicates) could be identified.

4.7 Summary

The data presented and discussed here shows that the hydrothermal system on Pinnacle Ridge produced zones of lower temperature argillic alteration of montmorillonite ± illite interspersed with higher temperature and more acidic intermediate argillic alteration of kaolinite, ± pyrite, ± barite at the surface. The resolution was not sufficient enough to identify the advanced argillic alteration hypothesized in previous studies. These alteration zones that surround the intrusions are locally focussed on faults and fractures which suggests an uneven distribution of fluid flow in the system. Supergene alteration has replaced primary and alteration mineralogy to produce assemblages of
montmorillonite, goethite, ± kaolinite, and ± jarosite on the exterior of samples, which hampered the identification of hydrothermal alteration in the laboratory and aerial data. Hypogene alteration associated with intermediate argillic alteration was identified in the interior of samples with the presence of montmorillonite and kaolinite. It is inferred that the hypogene alteration is most likely contributing to the stronger, more defined absorption features evident in the more altered samples. Alunite has not been identified in any of the samples on the ridge or in the aerial data and hence the lack of mappable advanced argillic alteration zones. Three hypotheses are proposed to explain the low temperature and acidic alteration assemblage identified in the hyperspectral data: 1) overprinting of advanced argillic alteration with supergene alteration; 2) the hydrothermal system did not produce advanced argillic alteration; or 3) the samples collected from the ridge thus far, do not encompass the full range of alteration. The classification of the aerial hyperspectral data identified three main zones of predominantly moderate phyllosilicate (P)/goethite (G) and low P/high G abundance surrounding the majority of intrusions (Zone A, B, and C, Figure 4.1) and zones of high to very high P/G abundance along and near an active fault on the east side of the ridge (L1, Figure 4.1).

Shortwave infrared (SWIR) data can identify the majority of minerals in alteration assemblages of potassic, propylitic, argillic, intermediate argillic, and advanced argillic alteration. The addition of midwave or longwave infrared (MWIR or LWIR) data can help identify and map primary mineralogy or silicate alteration minerals in silicic, propylitic, phyllic, and potassic alteration assemblages, leading to more accurate alteration mapping. The benefits of hyperspectral imaging for alteration mapping are: 1) the ability to gather data in inaccessible, hazardous, or large areas; 2) less sampling for field work; 3) could be used to identify key locations for field analysis; and 4) is an efficient, cost-effective, and non-destructive methods to accurately identify minerals in rock samples, especially in the identification of intra-layered variations within the crystal structure. Some challenges that remain are: 1) can only obtain surface measurements with hyperspectral data; 2) the differentiation of hypogene and supergene alteration; 3) the challenge of mineral mixtures on the spectral response; and 4) atmospheric effects on the airborne measurements.

The laboratory hyperspectral data correlates to the thin-section based alteration abundance which shows that the homogeneity of alteration at cm-scale can be quantified by laboratory spectroscopy. This is not true for the aerial hyperspectral dataset that has an image resolution of 1 – 2 m. The airborne data is able to identify whether alteration is present at the surface, as phyllosilicate minerals at less than 10 wt% still produced a relatively strong absorption feature in the 2200-2213 nm range for aerial hyperspectral data, as well as the laboratory data (R6; Figure 3.9 and 3.13). However, the aerial data is unable to quantify the alteration with a single band. The poor correlation between the laboratory and aerial data could be a result of: 1) the hand sampling is not statistically representative of the heterogeneous alteration at metre scale, 2) differences in the scanning geometry and spectral footprint of the measurements, and 3) the signal to noise ratio and atmospheric influences affect the airborne data but have minimal influence on the laboratory data. These are similar reasons why the classification does not align with the geologically derived alteration map in Location 4 (Figure 4.1).
This study has shown the need of higher spatial resolution imagery to detect finer details, such as intrusions or the heterogeneous nature of hydrothermal systems (active and inactive). A combination of PCA and SAM classification can accurately map the abundance of alteration across a hydrothermal system. This method can be used with repeat measurements of aerial hyperspectral data to track changes in the alteration over time. It can also give an indication of the mechanical properties of the different units by identifying and quantifying the abundance of montmorillonite and kaolinite. The spatial distribution of these minerals can map the fluid flow of the system, which is controlled by porosity and permeability of units.
Chapter 5: Conclusions

The overall aim of this study was to identify the alteration on Pinnacle Ridge, on the north-western flank of Mt Ruapehu, using petrographic techniques complemented with hyperspectral lab measurements and aerial imagery. The related objectives, results, discussions, and conclusions are displayed in Table 5.1.

The first objective of this thesis was to quantify the alteration in the collected samples and determine the ability of the hyperspectral data to accurately identify key alteration minerals. A point count analysis was shown to be accurate in quantifying the alteration in thin sections of collected samples to XRD percentages. A geological map of the alteration distribution on Pinnacle Ridge was developed through field mapping and petrographic analysis. The laboratory hyperspectral data successfully identified a dominant argillic to intermediate argillic alteration assemblage of montmorillonite and kaolinite. There was evidence for supergene alteration overprinting the hydrothermal alteration due to the presence of goethite and jarosite on the exterior of hand samples.

The second objective was to determine what resolution is required to verify and quantify the presence of minerals in the hyperspectral data. The methods used for the different scales were optical mineralogy (micron to mm scale), laboratory hyperspectral (cm-scale), and aerial hyperspectral data (m-scale). Both the aerial and laboratory data show that phyllosilicate minerals at less than 10 wt% will still produce a relatively strong absorption feature in the 2200-2213 nm range. Therefore, the absorption feature is generally only an indicator of mineral presence. However, the strong correlation of the laboratory data at 2207 nm wavelength with the alteration percent indicates that the cm-scale of the laboratory data is important to resolve the degree of alteration in samples and, therefore, can be used to quantify the alteration phases at this scale (cm). It also implies that the instrument signal to noise ratio and the spectral sampling intervals might play a big role in this strong correlation. The poor correlation between the aerial data and alteration percent is most likely caused by poor representation in hand samples of alteration at metre scale, the inability to detect microscale alteration that defined the alteration percent, or low signal to noise ratio and atmospheric influences.

The third objective of this thesis was to determine the feasibility and accuracy of mapping alteration zones using hyperspectral remote sensing techniques. The hyperspectral alteration map was created using a Principal Component Analysis (PCA) and a Spectral Angle Mapper (SAM) classification. When compared to the geologically derived alteration map, the image classification produced a map with greater detail in the distribution of the alteration, which is a better representation of the heterogeneity of the alteration at m-scale. There was an inconsistency between the two alteration maps which is either a result of a scaling issue or sample bias.
The fourth objective was using the alteration assemblage and classification map to contribute towards understanding the alteration history on Pinnacle Ridge. Three hypotheses are proposed to explain why the data presented here implies lower temperature, near neutral alteration assemblage compared to the advanced argillic alteration of previous studies: 1) advanced argillic alteration was produced in the system but has been overprinted with supergene alteration at the surface; 2) the shallow system did not sustain degassing or high temperature fluids for sufficient timescales to achieve advanced argillic alteration; or 3) the samples collected from the ridge thus far, do not encompass the highest areas of alteration. Therefore, more sampling and analyses are required to constrain the alteration history on Pinnacle Ridge. The classification-based alteration map verifies that the alteration was controlled by both the fluid migration from the intrusions and large dikes, and regional faulting from the high alteration intensity along the fault through the centre of the ridge.

The fifth objective concerns the utility of hyperspectral mapping in volcanic environments. The methods presented here provides the ability to gather data in locations that are inaccessible and dangerous. Repeat measurements coupled with the methods demonstrated in this study can be used to track changes in the alteration extent and composition over time. Mapping the spatial distribution of the alteration can also give an indication of the mechanical properties of the different units by the abundance of montmorillonite and kaolinite. Therefore, the fluid flow of an active or inactive hydrothermal system, which is controlled by porosity and permeability of units, can be mapped. When the spatial extent of hydrothermal alteration is quantified and combined with depth constraints, it can be used to assess the 3D volume of hydrothermal alteration. This has implications on how flank instability hazards are assessed on composite volcanoes. Defining the composition and extent of the fossil hydrothermal system on Pinnacle can provide insights into current systems on Ruapehu, associated hazards, and ongoing eruptive activity.
**Table 5.1: Overview of the objectives of this study and how they relate to the results, discussion, and conclusions.**

<table>
<thead>
<tr>
<th>Objectives</th>
<th>Results</th>
<th>Discussion</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1.2.1 Alteration mineral identification and Quantification</strong></td>
<td>Point count analysis was shown to be accurate to XRD percentages. Six alteration zones were identified from 20 thin section samples. A geological map of the alteration was created, based on the location of the hand samples and their alteration percent. Phyllosilicates (mixtures of kaolinite, illite, or montmorillonite), goethite, and jarosite assemblages were identified in the lab and aerial hyperspectral data.</td>
<td>4.2 Pinnacle Ridge History</td>
<td>Were able to identify minerals in the lab data that suggested a different take on the alteration assemblage and processes. The lab data was able to identify alteration signatures from both hypogene and supergene origin whereas the aerial data was hampered by the overprinting of supergene processes at the surface. The point count method was accurate to the XRD percentage for alteration abundance in thin sections.</td>
</tr>
<tr>
<td><strong>1.2.2 Spatial scales</strong></td>
<td>The lab data correlated well to the alteration percent, but the aerial data did not. The laboratory and aerial data were poorly correlated to each other. Alteration signatures were identified in all samples, independent of alteration percent.</td>
<td>4.4 The influence of scale – 4.4.1</td>
<td>The laboratory data was able to quantify the alteration abundance in the samples – can be used to quantify alteration. The aerial data could not be used due to a poor correlation. Both the aerial and laboratory data show that phyllosilicate minerals at less than 10 wt% will still produce a relatively strong absorption feature in the 2200-2213 nm range.</td>
</tr>
<tr>
<td><strong>1.2.3 Image analysis</strong></td>
<td>PCA results identified zones of variable alteration assemblages. Image classification accurately identified zones of alteration that were similar to the geological map but provided more detail in areas that were inaccessible in the field.</td>
<td>4.4 The influence of scale – 4.4.2</td>
<td>The laboratory data was able to quantify the alteration abundance in the samples – can be used to quantify alteration. The aerial data could not be used due to a poor correlation. Both the aerial and laboratory data show that phyllosilicate minerals at less than 10 wt% will still produce a relatively strong absorption feature in the 2200-2213 nm range.</td>
</tr>
<tr>
<td><strong>1.2.4 Alteration History</strong></td>
<td>Mineral identification of laboratory data taken from the interior and exterior of samples verified surface weathering imprint on hydrothermal outcrops. Alteration assemblage of montmorillonite, kaolinite, goethite and jarosite.</td>
<td>4.2 Pinnacle ridge alteration history</td>
<td>The porosity and permeability controlled the alteration abundance in the samples. This was influenced by the microfracture density and connectivity at mm to cm scale which controlled the fluid migration from the intrusions. However, the aerial classification indicates that the alteration was also controlled by regional faulting.</td>
</tr>
<tr>
<td><strong>1.2.5 Implications for mapping</strong></td>
<td>The final output from the methods workflow (Figure 2.6): Hyperspectral image classification provided a more detailed map compared to the geologically derived alteration map for the heterogeneity of alteration.</td>
<td>4.3 Utility of spectroscopy in volcanic environments</td>
<td>Hyperspectral mapping can provide a means to track changes over time, indicate mechanical properties of units, map fluid flow in hydrothermal systems, and has implications of how flank instability hazards are assessed on volcanoes. Alteration mapping can also provide insights into current systems on Ruapehu, associated hazards, and ongoing eruptive activity.</td>
</tr>
</tbody>
</table>

**Conclusion**

- Hematite and goethite were more likely to be present in the alteration zones.
- The effect of high alteration on the mechanical properties of the units was studied.
- Identification and quantification of alteration assemblages was achieved.
- Spectral purity or abundance of intermediate alteration signatures were also identified in the lab data that suggested a different take on the alteration assemblage and processes.
- The lab data was able to identify alteration signatures from both hypogene and supergene origin whereas the aerial data was hampered by the overprinting of supergene processes at the surface.
- The point count method was accurate to the XRD percentage for alteration abundance in thin sections.
References


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Appendix A: Methods

Appendix A shows the corresponding sample names from Mordensky (2019; Table A1) and the samples with XRD analyses (asterisk in Table A1). The preliminary results from the validation of the point count percent to the XRD data for samples R14, R19a, and R19b are shown in Table A1 (also shown in Figure 2.4).

Table A1: Samples used from Mordensky, 2019 with their corresponding names from both theses. Samples with asterisk (*) have XRD data (Table 2.1).

<table>
<thead>
<tr>
<th>Douglas Sample Names</th>
<th>Mordensky Sample Names</th>
</tr>
</thead>
<tbody>
<tr>
<td>R14</td>
<td>018*</td>
</tr>
<tr>
<td>R15</td>
<td>024</td>
</tr>
<tr>
<td>R16</td>
<td>025</td>
</tr>
<tr>
<td>R17</td>
<td>027</td>
</tr>
<tr>
<td>R18</td>
<td>003</td>
</tr>
<tr>
<td>R19a</td>
<td>031a*</td>
</tr>
<tr>
<td>R19b</td>
<td>031b*</td>
</tr>
<tr>
<td>R20</td>
<td>005c</td>
</tr>
</tbody>
</table>

Table A2: Comparison of the percentage of alteration for each analysis for the samples R14, R19a, and R19b.

<table>
<thead>
<tr>
<th>Alteration Percentage Samples</th>
<th>Point Counting Analysis</th>
<th>XRD Analysis</th>
<th>Uncertainty for XRD</th>
</tr>
</thead>
<tbody>
<tr>
<td>R14</td>
<td>38.4</td>
<td>41.0</td>
<td>7.0</td>
</tr>
<tr>
<td>R19a</td>
<td>56.8</td>
<td>55.0</td>
<td>10.0</td>
</tr>
<tr>
<td>R19b</td>
<td>30.8</td>
<td>25.0</td>
<td>5.0</td>
</tr>
</tbody>
</table>
Appendix B: Results

Appendix B displays all the data for each sample in Table B1, which includes the hand sample, thin section with point count dot locations, point count alteration percent, the evolution plot from the point count (to show that all point counts were consistently flat at 250 points), and the laboratory ± aerial reflectance data. This appendix also shows the interpretation of the Principal Component bands that were not presented in Chapter 3 which include: PC 1, 2, 4, 6, 7, 10, and 11 (Figures B1a, b, c, d, e, f, and g). Uncertainty is shown using question marks where further analysis is required to verify what is causing the variation in the PC band. Some of these PC bands highlight zones (as either dark or light pixels) that could be due to alteration patterns, however, they didn’t not show a clear correlation with the alteration percent (Figure B2 a, b, c, d, e, f, and g). They are possibly showing a change in lithology instead of alteration at the surface. The percent of variation per PC band and the cumulative percent of variance in the first 11 PC bands is shown in Table B2. The rule images from the SAM image classification are shown in Figure B3 for each class: shade/noise (a), vegetation (b), primary (unaltered) mineralogy (c), low phyllosilicate and goethite (d), low phyllosilicate and high goethite (e), moderate phyllosilicate and goethite (f), high phyllosilicate and goethite (g), and very high phyllosilicate and goethite (h). Finally, the reflectance values for the aerial and laboratory hyperspectral data against the alteration percent are compared across the 2201, 2207, and 2212 nm wavelengths (Figure B4). The data shows a very similar correlation across the three wavelengths.
Table B1: Hand sample, thin section, alteration percent from point count, evolution plot from point count, and laboratory ± aerial hyperspectral data for each sample.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Hand Sample</th>
<th>Thin Section</th>
<th>Alteration Percent</th>
<th>Evolution Plot from Point Count</th>
<th>Laboratory ± Aerial Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>R6 UDCL</td>
<td><img src="image1" alt="Image" /></td>
<td><img src="image2" alt="Image" /></td>
<td>7.6</td>
<td><img src="image3" alt="Image" /></td>
<td><img src="image4" alt="Image" /></td>
</tr>
<tr>
<td>R4 UDCL</td>
<td><img src="image5" alt="Image" /></td>
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Table B1 cont.
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<th>Sample</th>
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<th>Wavelength (nm)</th>
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<td>R9 UI</td>
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Table B1 cont.
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### Table B1 cont.

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**Table B1 cont.**

Scaled Reflectance vs Wavelength (nm)

![Scaled Reflectance vs Wavelength](image)
Figure B1: Grey scale image of each PC band not presented in the thesis. **a)** PC band 1. The dark pixels represent poorly illuminated zones and the light pixels represent the well illuminated areas. **b)** PC band 2. The light pixels represent vegetation while the dark pixels represent scree possibly (?).
Figure B1 (cont): c) PC band 4. This band shows a very clear distinction between the dark and light pixels. The dark pixels appear to represent the alteration halo while the light pixels highlight the unaltered units and the surrounding Whakapapa lavas. This band was used in the PCA composite map but was not included in the thesis as it did not correlate well to the point count percent (Figure B10). d) PC band 6 shows dark pixels of scree and light pixels of majority of the ridge, possibly relating to vegetation cover (?).
Figure B1 (cont): e) PC band 7. This band has some noise, but is similar to PC 6 except opposite, the light pixels represent scree and the dark pixels may represent some form of alteration or a change in lithology. f) PC band 10. This band contains a high quantity of noise, but the light pixels are similar to PC 7.
Figure B1 (cont): g) PC band 11 shows some signs of noise. The light pixels show the drainage paths to the north of the image as well as the intrusions and some scree deposits. The dark pixels highlight the alteration along and surrounding the fault line.
Figure B2: Principal component values against point count percent for: a) PC 1, b) PC 2, and c) PC 4.
Figure B2 (cont): Principal component values against point count percent for: d) PC 6, e) PC 7, and f) PC 10.
**Table B2**: The variance in the first 11 Principal Component bands. This table shows that 99.912% of the total variance in the PCA from the aerial hyperspectral image is within the first 11 PC bands.

<table>
<thead>
<tr>
<th>Principal Components</th>
<th>Variance (eigenvalues)</th>
<th>Percent of total variance (%)</th>
<th>Cumulative percent (%)</th>
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<td>96.4424</td>
<td>96.4424</td>
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<td>1.700461</td>
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<td>950170.6</td>
<td>1.100264</td>
<td>99.24297</td>
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<td>PC 4</td>
<td>357682</td>
<td>0.414183</td>
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<td>PC 5</td>
<td>72386.78</td>
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<td>PC 6</td>
<td>55352.5</td>
<td>0.064096</td>
<td>99.80507</td>
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<td>PC 7</td>
<td>37528.02</td>
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<td>99.87131</td>
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<td>PC 9</td>
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<td>99.88871</td>
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<td>PC 10</td>
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<td>0.013234</td>
<td>99.90194</td>
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<td>8684.94</td>
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<td><strong>Total Variance</strong></td>
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Figure B3: Rule images from the spectral angle mapper (SAM) classification for classes: a) shade and b) vegetation.
Figure B3 (cont): Rule images from the spectral angle mapper (SAM) classification for classes: c) primary (unaltered) mineralogy and d) low phyllosilicate and goethite.
Figure B3 (cont): Rule images from the spectral angle mapper (SAM) classification for classes: e) low phyllosilicate, high goethite and f) moderate phyllosilicate and goethite.
Figure B3 (cont): Rule images from the spectral angle mapper (SAM) classification for classes: g) high phyllosilicate and goethite and h) very high phyllosilicate and goethite.
Figure B4: Reflectance values for: a) laboratory vs alteration percent, b) aerial vs alteration percent, and c) laboratory vs aerial values for each sample. The light grey circles represent values at 2201 nm wavelength, the dark grey circles are values at 2212 nm wavelength, and the alteration group values (coloured circles) are at 2207 nm wavelength (same data that is displayed in thesis for Figures 3.18, 3.19, and 3.20).