ASSESSING THE CONTRIBUTIONS OF REMOTE SENSING DATA IN GEOLOGICAL SITE INVESTIGATIONS

by

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A thesis submitted to the Department of Geological Science and Geological Engineering

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Abstract

Unforeseen ground conditions can have significant impact on the success of any geological project. Therefore, geological site investigation is an essential component of geological field campaigns. Remote sensing techniques have been used extensively for many geological applications, however, their incorporation into geological site investigations have been slow. A framework is required to demonstrate how remote sensing techniques can be incorporated into conventional site investigation practices. Thus, it is the objective of this thesis to assess the contributions of remote sensing datasets and show how to seamlessly integrate these datasets into practical workflows to compliment conventional methods. Case studies using three remote sensing datasets operating at different spatial scales, close-range laser scanning, airborne optical/LiDAR and Synthetic Aperture Radar (SAR), were used.

A literature review revealed that close-range 3D laser scanning was a useful tool for the morphological study of geological hand-samples and had been widely applied in the fields of paleontology, rock mechanics and sedimentology. A case study was completed to digitally calculate the grain-size distribution of ore minerals using laser scanning, which produced comparable results to those generated using a scanning electron microscope, the current state-of-practice.

The utility of LiDAR reflectance data for improved shadow detection in multispectral images was explored. When combined with the spectral bands as input into shadow classification using Support Vector Machines (SVM), the performance of the classification was improved to greater than 95%. To mitigate the effects of these shadows, four methods of colour correction were tested of which Reinhard’s colour transform performed the best. Shadow mitigation substantially improved subsequent vegetation mapping using the Normalized Difference Vegetation Index (NDVI).

It was investigated whether SAR backscatter intensity data could be applied to monitoring temporal changes in northern Canada. Results showed that this data was suitable for monitoring ice cover seasonality, seasonal flooding and seasonal vegetation growth.

These case studies make evident that remote sensing datasets can be used to enhance geological site investigation. Creation of workflows, in which suitable remote sensing techniques are integrated, for each site investigation application is recommended as future work.
Acknowledgements

This thesis would not be possible without the incredible support I have received throughout this process. I would like to thank the NSERC CREATE Grant (Advancing Environmental Assessment) for providing the funding that allowed this research to be possible. I would also like to thank my committee Dr. Vicki Remenda and Professor Rob Harrap.

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<td>LiDAR</td>
<td>Light Detecting and Ranging</td>
</tr>
<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>1D</td>
<td>One-Dimensional</td>
</tr>
<tr>
<td>3D</td>
<td>Three-Dimensional</td>
</tr>
<tr>
<td>CCD</td>
<td>Charge-Coupled Device</td>
</tr>
<tr>
<td>Ma</td>
<td>Million Years Ago</td>
</tr>
<tr>
<td>CT</td>
<td>Commuted Topography</td>
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<tr>
<td>2D</td>
<td>Two-Dimensional</td>
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<tr>
<td>BGS</td>
<td>British Geological Survey</td>
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<tr>
<td>SEM</td>
<td>Scanning Electron Microscope</td>
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<td>RGB</td>
<td>Response in Red-Blue-Green Colour Space</td>
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<tr>
<td>FOV</td>
<td>Field of View</td>
</tr>
<tr>
<td>MLA</td>
<td>Mineral Liberation Analysis</td>
</tr>
<tr>
<td>NIR</td>
<td>Near-Infrared</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
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<td>MLAs</td>
<td>Machine Learning Algorithms</td>
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<td>Support Vector Machines</td>
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<tr>
<td>PCC</td>
<td>Percent Correctly Classified</td>
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<tr>
<td>GAO</td>
<td>United States Government Accountability Office</td>
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<td>GNSS</td>
<td>Global Navigation Satellite System</td>
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</table>
Ka  Thousand Years Ago
TN MPA  Tarium Niryutait Marine Protected Area
HH  Horizontal-Horizontal Polarization
HV  Horizontal-Vertical Polarization
VV  Vertical-Vertical Polarization
VH  Vertical-Horizontal Polarization
DLR  German Aerospace Center
CDEM  Canadian Digital Elevation Model
WGS84  World Geodetic System of 1984
ECR  Earth-centered Rotating Cartesian
GIS  Geographic Information System

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
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<tbody>
<tr>
<td>b</td>
<td>Baseline</td>
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<td>α</td>
<td>Angle of Projection</td>
</tr>
<tr>
<td>β</td>
<td>Angle of Collection</td>
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<td>f</td>
<td>Distance between the camera lens and the CCD in the x-direction</td>
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<td>p</td>
<td>Distance between the camera lens and the CCD in the z-direction</td>
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<td>X</td>
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<td>$\bar{y}$</td>
<td>Mean LiDAR Reflectance Value</td>
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<td>Number of Nearest Neighbours</td>
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<td>Corrected RGB Value</td>
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<td>Original Shadow RGB Value</td>
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<td>LiDAR Reflectance Value</td>
<td>LiDAR Reflectance Value</td>
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<td>Brightness Value</td>
<td>Brightness Value</td>
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<td>$\text{DN}_{\text{restored shade}}$</td>
<td>Linear Correlation Corrected Colour Value</td>
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<tr>
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<td>Linear Correlation Corrected Mean of the Non-Shadow Region</td>
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<td>Linear Correlation Corrected Mean of the Shadow Region</td>
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<td>Linear Correlation Corrected Standard Deviation of the Shadow</td>
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<td>$G_c$</td>
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<td>$B_c$</td>
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<td>Value of R in XYZ Colour Space</td>
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$Y_c$  Value of $G$ in XYZ Colour Space

$Z_c$  Value of $B$ in XYZ Colour Space

$L_c$  Value of $X$ in LMS Colour Space

$M_c$  Value of $Y$ in LMS Colour Space

$S_c$  Value of $Z$ in LMS Colour Space

$L_c$  Value of $L$ in $l\alpha\beta$ Colour Space

$\alpha_c$  Value of $M$ in $l\alpha\beta$ Colour Space

$\beta_c$  Value of $S$ in $l\alpha\beta$ Colour Space

$x'$  Reinhard’s Colour Transfer Corrected Shadow Value

$\sigma_{x'}^2$  Reinhard's Colour Transfer Standard Deviation of the Non-Shadow Values

$\sigma_{x}^2$  Reinhard’s Colour Transfer Standard Deviation of the Shadow Values

$x^*$  Reinhard’s Colour Transfer Original Shadow Value

NIR  Response in the NIR spectrum

Blue  Response in the Blue spectrum

$B_0$  Brightness Values

DN  Digital Numbers

ks  Calibration Factor

$\sigma^\theta$  Normalized Radar Cross Section

NEBN  Noise Equivalent Beta Naught

$\theta$  Local Incidence Angle
Chapter 1

Introduction

Site investigation is an essential component of geological field campaigns. It is integral to the creation of geological models, as well as geological engineering and geoscience design. Site investigation is the process of collecting information about the subsurface for sites that are to be mapped or developed (Fookes, 1997). Geological site investigation is a multistep process composed of four distinct phases. Phase I consists of non-intrusive data collection including desktop studies and walk-over surveys. During a desktop study, all available pre-existing information about a site is collected and reviewed. Important resources for desktop studies include current and historical geologic and topographic maps, borehole records from previous nearby investigations, published information on hazards including earthquakes, landslides, or potential contamination, as well as current land use restrictions, such as protected ecosystems, regions of archaeological significance, or Indigenous Territory. Desktop studies can provide important information at a modest cost and can be completed relatively quickly, especially since most of these data sources can now be accessed online (Clayton and Smith, 2013).

The walk-over study, or site inspection, can provide site specific information not available in published works. A walk-over study can reveal differences between the recorded information of the site and the true ground conditions. During a walk-over study, evidence of high groundwater, contamination, previous developments, slope instability, erosion, permafrost degradation are of interest, to name a few. Structural damage of nearby infrastructure can be an important indication of ground instability in the area. The types of vegetation growing within the study region could be used to indicate the presence of mineral deposits within the subsurface. The health of the vegetation present can also be used to indicate the presence of contamination. Walk-over studies can reveal
whether the site is accessible to heavy equipment such as boring or drilling equipment that will be used during Phase II of the site investigation (Building Research Establishment, 1989).

Phase II of the site investigation process includes in-situ techniques that, unlike Phase I investigation, can be intrusive or destructive. Phase II techniques are relatively expensive and so are applied carefully based on the data collected during Phase I. These techniques include boring to collect geological samples at depth. Bored samples are studied in order to determine the lithology of each geological unit within the site and tested to determine the physical properties (such as strength, porosity, permeability etc.) of the geological units present. Borehole data can be interpolated between sampling locations to develop a cross-section of the geology of the site (Bieniawski and Bieniawski, 1989). In addition to boring, penetration testing and dynamic probing can be performed to get a broader understanding of the subsurface (Schnaid, 2009). Non-intrusive methods of ground investigation, such as geophysical surveys, are not as commonly applied as the intrusive methods above (Clayton and Smith, 2013). There is a great variety of geophysical techniques that can be used in site investigation including seismology, which can be used to detect the depth to the water table or the depth to bedrock, ground penetrating radar, which can be used to map near-surface voids, and electrical resistivity surveys which can be used for the mapping of fractures (Almen et al., 1986; McCann et al., 1997; McDowell et al., 2002). The proliferation of remote sensing datasets can also be accessed for information for both Phase I and Phase II stages of site investigation, although this practice is sporadic to date. Once Phase II of the site investigation is complete, the project can transition to the Phase III.

Unlike Phase I and Phase II, which are largely consistent between all site investigation applications, Phase III and Phase IV site investigations are application specific. For example, in geotechnical site investigation, Phase III includes foundation exploration which occurs during construction and
is used to validate the results of the previous phases of site investigation which is not the case for geoenvironmental assessments (Fookes, 1967). The final phase in site investigation is the monitoring of the site. This is important for a variety of geological applications such as monitoring the stability of infrastructure or monitoring the potential movements of contaminants. Several (5-10) years are commonly required for monitoring sites (Lewis et al., 2013); however geological projects such as nuclear waste storage require monitoring for the next one million years (Ontario Power Generation, 2014). For this, continuous and reliable methods with repeated information may be necessary. Remote sensing techniques have the ability to record information at a variety of spatial scales, which makes their application flexible. Different spatial and temporal scales may also be required for specific monitoring applications.

Unforeseen ground conditions can have significant impact on the success of any geological project. A lack of proper site investigation can result in delayed construction schedules (Clayton and Smith, 2013) negative impacts on the health and safety of workers and end-users (Hagan et al., 1998), damage to archaeological remains (Williams et al., 2007) or contamination to the soil and groundwater (Strange and Langdon, 2008). Figure 1.1 illustrates the relationship between the site investigation budget and how much the project went over budget. From this graph, it is evident that investment in site investigation at the beginning of a project leads to reduced spending in the future of the project (Mott MacDonald and Soil Mechanics, 1994). Therefore, site investigation is necessary for all geological projects. However, there is an optimal investment into site investigation after which point, information gained is not worth the extra cost, as seen in Figure 1.2.
Figure 1.1: Cost of site investigation over construction cost versus total increases in construction than originally planned for road construction in the United Kingdom (Modified from Mott MacDonald and Soil Mechanics, 1994).

Figure 1.2: Cost of site investigation versus the overall robustness of the site investigation with the optimal site investigation spending outline in yellow. (Modified from Gong et al., 2017)
Remote sensing techniques have been used extensively for many geological applications, including remote geological mapping, mineral exploration and geohazard monitoring. However, the field of geological site investigation has been slow to adopt remote sensing into their practices. For site investigation, standards set by professional organizations specify how each site investigation technology should be used. In Canada, airborne and optical satellite images have currently been included in these guidelines (Professional Engineers of Ontario, 1993; Professional Engineers and Geoscientists of British Colombia, 2016). However, these images are usually confined to the visible portions of the electromagnetic spectrum and do not take advantage of other wavelengths. It is also state-of-practice to use digital maps to interpret and present geological spatial data. This technology was first developed in the late 1980’s and since then, there have not been any significant technological advancements in site investigation. ASTM International is an organization that sets technical standards for a wide range of products, systems, and services including site investigation techniques. As of 2018, only one standard, (for oil spill detection), has been published by ASTM International that utilizes remote sensing techniques (Ehlers, 1996). It is evident that remote sensing techniques in geological site investigation are severely underutilized. Therefore, a framework is required to demonstrate how remote sensing techniques can be incorporated into conventional site investigation practices.

Frameworks are not new to the field of site investigation. Standards established by professional organizations and government agencies have long been used by professionals to ensure that the results generated from their investigations are nationally and internationally consistent. However, these frameworks focus on how site investigation methods should be used, as opposed to how to initially select the most relevant site investigation methods. Workflows are common tools to effectively communicate decision making processes. Thus, it is the objective of this thesis to assess the contributions of various remote sensing datasets and show how they can be seamlessly
integrated into practical workflows to compliment conventional methods. This is achieved through the use of three different remote sensing datasets at three different spatial scales. The three remote sensing datasets investigated throughout this thesis include close-range laser scanning for small (<1m) scale analysis (Chapters 2 and 3), airborne optical and LiDAR data for regional (m²) analysis (Chapter 4), and Synthetic Aperture Radar data for larger scale (>km²) analysis (Chapter 5).

1.1 Thesis Objectives

There are three main research objectives of this thesis:

- To identify the advantages and challenges when creating 3D digital models of geological hand samples using a close-range (<1m) laser scanner. A workflow that demonstrates the applicability of close-range laser scanning to the calculation of ore grain size was conducted as a case study. Geological hand samples are integral to the development of an accurate geological model. The morphology of geological hand samples provides geologists data through which they make interpretations of the geological processes and history of their study region (Harvey, 2016). Hand samples are collected during Phase II of site investigation and are subject to visual interpretation or laboratory testing. To date, there are few resources for the digital storage and sharing of geological hand samples. There is a large potential for digital models of hand samples to be stored/shared in online/virtual digital databases. Geologists can incorporate these digital hand samples in Phase I site investigation to further their knowledge and understanding of the area prior to physically visiting the site. It is for this reason that the applicability of close-range laser scanners for the digitization of geological hand-samples will be explored in this thesis.

- To determine the utility of LiDAR reflectance for enhanced shadow detection in multispectral images for improved Normalized Difference Vegetation Index (NDVI) mapping. The extent
and diversity of vegetation can be used to indicate the properties of the soils in which they grow. Each species of plant is adapted to a specific range of porosities, permeabilities and nutrient concentrations in the substrate, which are in part dictated by the soil and the parent rock from which they originate. Therefore, vegetation mapping can have many geological applications including the mapping of soil and rock units, and most significantly, mineral exploration (Shantz, 1938; Kruckeberg, 2004; Cannon 1971). Vegetation mapping is primarily done through the use of multispectral images and indicators such as NDVI. Vegetation mapping is not commonly done for geological site investigation though it has great potential for use in Phase I. One factor may be that shadows can negatively affect the interpretation of multispectral images. Therefore, it is an objective of this thesis to mitigate the effects of shadows in multispectral data for improved NDVI mapping.

To determine how dual-polarization Synthetic Aperture Radar (SAR) backscatter intensity data can be used for monitoring temporal changes in northern Canada. The Canadian Arctic is a region of ecological importance and is one of the many regions expected to be greatly affected by climate change in the coming years (Vaughan et al., 2013). This region is highly remote and difficult to access with weather conditions being harsh and unforgiving. Therefore, current methods of site investigation in the Canadian Arctic are both challenging and expensive. With the development of satellite imaging, remote regions such as the Canadian Arctic can be observed. The ability to study previously inaccessible regions is one of the many advantages of remote sensing techniques. SAR is one such remote sensing technique and thus far, has been widely used for the monitoring of geological hazards such as subsidence (Strozzi et al., 2001) or landslides (Tarchi et al., 2003). It is an objective of this thesis to determine how dual-polarization SAR intensity data can be used for Arctic monitoring for more robust Phase I site investigation.
1.2 Thesis Outline

Chapters 2 – 5 are written in manuscript format with each chapter encompassing one of the three remote sensing datasets. In Chapter 2, a case study in which the advantages and limitations of close-range laser scanning as applied to geological hand-samples for morphological studies and the digitizing, visualizing, sharing and printing of these geological hand samples is investigated. In order to conduct this investigation properly, a detailed literature review is included on close-range laser scanning for various geoscience applications. In Chapter 3, a case study in which close-range laser scanning is applied to the calculation of ore grain-size distribution is presented. In Chapter 4, a case study in which the utility of LiDAR reflectance data for mitigating shadows for improved NDVI mapping is investigated. In Chapter 5, a case study in which the applicability of dual-pol SAR data to monitoring changes in the Mackenzie Delta region of northern Canada is presented. In Chapter 6, the conclusions of each research objective are summarized and recommendations for future work are provided. Two appendices which contain auxiliary information for Chapter 2.
Chapter 2

Three-Dimensional Laser Scanning in Geology: Digitization of Fossils, Rocks Minerals and Sediments

2.1 Introduction

Morphology, the study of structure or form of geological hand samples, including fossils, rocks and sediments, has a variety of applications. The morphology of fossils aids in the identification of species (Lyons et al., 2000; Arakawa et al., 2002; Bethoux et al, 2004) and simulations of locomotion (Rybczynski et al., 2008; Evans and Fortelius, 2008; Polly and MacLeod, 2008). For hand-specimen sized rock samples, the roughness of its surface or joints allow for the calculation of shear strength (resistance of rock joints to shearing) and transmissivity (ability of water to travel through joints) (Lanaro et al., 2000; Fardin et al., 2001; Hong et al., 2006). Centimeter-scale features on the surface of rock samples, such as folds or faults indicate stress conditions (Dunham and Crider, 2012). The morphology of sediment samples is used to assess the suitability of a sediment particle for engineering applications, such as railroad ballast (Komba et al. 2007; Anochie-Boateng et al., 2013; Mvelase et al., 2016). The morphology of a sediment particle also indicates its transport history and paleoenvironment (Roussillon et al., 2009; Rossi and Graham, 2010; Hirmas et al., 2013). Established methods of assessing morphology include measuring the distances between known landmarks on a sample’s surface using rulers or calipers (Atwood and Sumrall, 2012; Mike et al., 2016), using profilometers to create one-dimensional (1D) cross sections of a sample’s surface (Bizjak, 2010), or visually comparing the sample to established shape charts (Hawayaka and Oguchi, 2005).

Lyons et al. (2000) and Lanaro et al. (2000) were among the first to apply three-dimensional (3D) close-range laser scanners to the study of morphology of geological materials, specifically fossils.
and rock joints. Over the past two decades, the spatial resolution and the achievable accuracy of data point locations in 3D space via laser scanning has improved, allowing for the analysis of fine (<mm) details. Features that were too small to be captured with previous scanners can now be studied (Lyons et al., 2000). In addition, 3D information can be displayed, manipulated, archived and shared rather efficiently. Historically, photographs and illustrations were used to communicate and preserve geometric information. These continue to be used in conjunction with 3D digital models providing new ways for sharing morphological data (Bethoux et al., 2004; Petti et al., 2008; Harvey et al., 2017).

The goal of this chapter is to highlight the established literature to date which involves the significant use of digital geological hand samples acquired from 3D close-range (<1m distance between scanner and target) triangulation laser scanners. A discussion on how close-range laser scanners collect point data and the challenges posed in digitizing geological materials is presented. Specifically, their use in the fields of paleontology, rock mechanics, sedimentology, planetary sciences and structural geology is presented. Ultimately, the visualization, sharing and printing of 3D digital models of geological hand samples is discussed as a key enhancement to conventional geological workflows. A case study, in which close-range laser scanning was applied for the calculation of ore grain size distribution was undertaken to further illustrate the utility of close-range laser scanners in the field of geology (see Chapter 3).

2.1.1 Close-Range Laser Scanning
Non-contact laser scanners collect three-dimensional data by measuring distances between the scanner and the target surface using directed laser beams (Kanade and Asada, 1981) most commonly in the 450-1550 nm wavelength range (Angelopoulou and Wright, 1999; Amann et al., 2001). The three primary laser scanning techniques include time-of-flight, phase-shift and
The most common method used for close-range laser scanning is triangulation due to its relatively high resolution (10-100 pt/mm²) (Guidi et al., 2010) and accuracy (2.25 µm - 200µm) (Blais, 2004). For the purposes of this study, “close-range” laser scanners collect point data from a baseline of ≤ 1 meter. Triangulation-based laser scanning systems emit a laser beam, either continuously or as a pulse, directed towards a target surface, as depicted in Figure 2.1. A single beam or a series of striped, gridded or patterned beams can be used (Jarvis, 1983). Upon contact with the target surface, the beam is scattered and the waves that are reflected back to the scanner are focused by a lens within the scanner onto a charge-coupled device (CCD). The position that the beam strikes the CCD is recorded (Rioux, 1984). With this information, the target’s location with respect to the laser source is calculated. The baseline \( b \) is known, as are the angle of projection \( \alpha \) and the angle of collection \( \beta \). The distance between the camera lens and the CCD is also known and represented by \( f \), in the x-direction, and \( p \), in the z-direction (Reid et al., 1988; Beraldin et al., 2009). Eq. (2.1) is used to calculate the distance between the laser source and the object in the x-direction \( X \).

\[
X = \frac{b \cdot f}{p + f \cdot \tan \alpha}
\]  

(2.1)

Basic trigonometric principles are applied to calculate the distance between the laser source and the target in the z-direction \( Z \), as follows:

\[
Z = X \cdot \tan \alpha
\]  

(2.2)

The scanner records this information for each point and creates a point cloud (the collected data points and their local 3D coordinates).
Figure 2.1: Schematic of a close-range triangulation laser scanner layout with a rock hand sample as the target surface (modified from Beraldin et al., 2010)

Sensitivity is defined as the laser scanner’s ability to detect backscattered signals at a low intensity. If the CCD is not sensitive enough to detect the laser beam return, gaps within the data are created, reducing resolution. For instance, reflected beams from translucent geological materials have a low intensity and thus may not be detected (see section 1.2.1). The spatial resolution of a laser scanner is defined by its ability to resolve the position of the backscattered laser beams. If the feature of interest is smaller than the maximum spatial resolution, it would not be visible in the resulting point cloud. The sensitivity and spatial resolution are delineating characteristics of a laser scanner (Blais et al., 2000). The peak detection algorithm determines when to record a return signal by detecting at what point the amplitude of a signal is the strongest. Variations in the internal peak detection
algorithm and the signal-to-noise ratio of the return are also limiting factors in scanning results (Cosarca et al., 2009).

Random errors can be introduced from constructive interference of the reflected laser beam. This creates a high or low intensity signal, called speckle, which the CCD has more difficulty resolving, lowering overall accuracy (Amann et al., 2001; Feng et al., 2001) and affecting the final point cloud of the geological sample. The calibration of each laser scanner can vary depending on the manufacturer (Isheil et al., 2010, Santolaria et al., 2009). Studies have shown that the manufacturer stated accuracy and the achievable accuracy in practice may differ (Boehler et al, 2003, Lichti, 2007, Lichti and Skaloud, 2010). For example, in Polo and Felicisimo (2012), a low cost 3D scanner was found to have an accuracy of 0.80 mm rather than the stated accuracy of 0.13 mm. Recommended calibration steps include scanning objects with known dimensions and comparing the digital results to the physical measurements (i.e. caliper measurements) to look for bias (Mills and Fotopoulos, 2013; Zhang et al., 2014).

Generally, close-range laser scanners take several individual scans in order to capture the complete 3D object (Levoy et al., 2000). Photographs can also be captured simultaneously and registered to the 3D point cloud, creating a “texture map”. The individual scans and corresponding texture are aligned within the same reference frame (Park and DeSouza, 2005). Initial alignment of the individual scans can be calculated automatically by either monitoring the scanning position throughout the scanning process or by using a controllable turntable. The user performs final alignment manually. Alignment is accomplished by selecting three common points between each individual scan to define the transformation of two overlapping scans (Bernardini and Rushmeier, 2002). It can be made easier by using the texture map to select common points rather than the point cloud (Bernardini et al., 2001). However, this step may introduce uncertainty as it is dependent on
the skill of the user. Once alignment is complete, extraneous data, such as the scanning platform, can be trimmed from the point cloud (Axelsson, 1999). Finally, the aligned scans are integrated or fused together into a single point cloud producing a unified, non-redundant surface (Levoy et al., 2000). The fused point cloud and related texture map is defined as a “3D digital model” for the purposes of this study and can be used for further analysis (Platt et al., 2010).

A number of factors need to be considered during the process of laser scanning geological specimens. The quality of the generated point-cloud model is affected by conditions such as lighting as well as set-up of the instrumentation (distance and angle between scanner and object) (Isheil et al., 2011). In general, lower lighting conditions are preferable over high ambient radiation as this creates noise, reducing the signal-to-noise ratio (Boehler and Marbs, 2003; Schaefer and Inkpen, 2010). High incident angles (> 40°) result in both a lower signal-to-noise ratio of the laser beam and the footprint of the beam is elongated; meaning the resolution of the point is lower. The reflected signal is also weaker in intensity (Soudarissanane et al., 2009). Therefore, placing the surface of interest directly parallel to the scanner produces the highest quality results. For larger samples that do not fit within the 40° incident angle range, multiple scans of the object are necessary to accurately capture the complete face.

2.1.2 Digital Geological Samples

Creating a complete, or gap-free, point cloud from geological targets that are either highly reflective or translucent is a challenge. Retro-reflective materials such as minerals with a metallic lustre, for instance galena or pyrite (reflectivity of over 40%; Folinsbee, 1949), are generally not suitable for scanning because they reflect the laser beam signal at an intensity which exceeds the limits of the sensor’s dynamic range. This saturates the receiver, creating a truncated signal which cannot be used to accurately calculate the target’s position. Translucent materials, such as minerals that have
a vitreous lustre, such as cerussite or fluorite, are challenging to scan because the laser beam can interact with the object in a variety of ways, i.e., the laser beam can be absorbed or transmitted rather than reflected by the translucent object resulting in no point measurements. Additionally, the laser beam can be scattered within the translucent object’s volume. Since the measured backscattered beam will not originate from the target’s surface, the position measurements will be inaccurate.

Coating either a retro-reflective or translucent object in a talc powder creates an opaque scattering surface which allows the laser beam to be backscattered to the CCD detector. Figure 2.2A shows the point cloud of a fluorite mineral prior to talc powder application and the results show an approximate 10% data gap. Figure 2.2B shows the same mineral after the talc has been applied which results in only 2% data loss and the surface of the model is smoother, better representing the actual sample. The application of the talc allowed for a higher proportion of the directed laser beams to reflect back to the scanner creating a 3D digital model with 8% fewer data gaps for this sample. During this research it was found that on average, data gaps are reduced by 10-30% after the application of talc powder depending on the samples reflectivity or translucency. Numerous comparisons between talc and no-talc 3D digital models of geological hand samples are provided in Appendix A.
Figure 2.2: Texture map (left) and point cloud (right) of a fluorite sample scanned at 10,540 pts/cm$^2$. (A) fluorite sample without talc coating, (B) fluorite sample with the talc coating. Regions that showed the greatest reduction in data gaps are circled.

Edges on samples are also challenging to scan as a portion of the directed laser beam will strike the adjacent side, elongating the beam and creating a reduced return as seen in (Boehler and Marbs, 2003) and illustrated in Figure 2.3.
Figure 2.3: Example of the elongated reflection created by the laser beam (exaggerated in size) striking the edge of the rock sample. The portion of the beam on the face (yellow) is reflected as expected; the portion of the beam reflected off the adjacent side (red) is distorted.

Geological materials that have features which obstruct parts of the hand sample can also be challenging to scan. This is the case for samples with a vesicular or botryoidal texture. By increasing the scanning resolution, a denser point cloud will be created, increasing the likelihood that the sharp edges or obstructed features will be captured. Increasing the scanning resolution in turn increases scanning time and the size of the point cloud significantly. Figure 2.4 shows a low (295 pt/cm²), medium (5,000 pt/cm²) and high (10,400 pt/cm²) resolution scan of a hand sample of malachite, which has a botryoidal texture. Additional examples which further illustrate the differences between scan time, point cloud size and 3D digital model are summarized in Appendix A.
Figure 2.4: Texture map (left) and point cloud (right) of malachite mineral sample at various resolutions (A) low resolution scan (295 pt/cm²), (B) medium resolution scan (5,000 pt/cm²), (C) high resolution scan (10,400 pt/cm²). Note that with increasing resolution, finer details, such as the botryoidal texture, of the mineral are captured. Regions in which small details become more apparent are circled. This is further illustrated by the in-set outlined in yellow.

The geometry of hand samples can pose challenges during the scanning process. Hand samples that have one dimension that is significantly smaller than the other two, as seen in Figure 2.5, are unstable on this edge. Therefore, stabilizers are required secure the sample. These stabilizers can occlude sections of the sample creating gaps within the target’s point cloud. In addition, if the samples are unstable then the rotation of the scanning platform can cause them to move. Therefore,
the samples need to be manually repositioned which increases scanning time and effort and also introduces human error.

Figure 2.5: 3D model of fossil sample. To scan the face of interest, the sample must be balanced on the short edge

2.2 Application of Close-Range Laser Scanners in the Geosciences

Five geoscience-related fields of research were appraised for the use of 3D laser scans of hand samples, namely paleontology, rock mechanics, sedimentology, structural geology and planetary sciences. Figure 2.6 represents the categorization of 72 peer-reviewed manuscripts where point or multi-stripe triangulation scanners were used for the digitization of hand-specimen sized geological
materials (~10cm$^3$) between 2000 and 2017. These hand samples range from 1mm$^3$ - 8,000cm$^3$ with an average size of 20cm$^3$. Table 2.1 outlines the properties of the various scanners used within the literature.

Figure 2.6: Proportion of peer-reviewed manuscripts that apply close-range laser scanners to geological hand samples per field of study. Other is comprised of structural geology and planetary sciences.
Table 2.1: Close-range laser scanners used in morphology studies within the geosciences and their associated highest available spatial resolution and spatial accuracy

<table>
<thead>
<tr>
<th>Scanner</th>
<th>Spatial Resolution</th>
<th>Spatial Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>NextEngine 3D Scanner</td>
<td>41,540 points/cm²</td>
<td>±0.13 mm</td>
</tr>
<tr>
<td>Minolta Noncontact VIVID 910</td>
<td>307,200 points/scan</td>
<td>±0.1 – ±0.4 mm</td>
</tr>
<tr>
<td>ShapeGrabber SG1002</td>
<td>0.025–0.33 mm</td>
<td>±0.076 mm</td>
</tr>
<tr>
<td>Escan Laser Scanner</td>
<td>0.025 mm</td>
<td>±0.038 mm</td>
</tr>
<tr>
<td>Polhemus FastSCANTM</td>
<td>0.01 mm</td>
<td>±0.18 mm</td>
</tr>
<tr>
<td>Roland Picza LPX-600/LPX-250/LPX-1200</td>
<td>0.1 mm</td>
<td>±0.1 mm</td>
</tr>
<tr>
<td>FARO Arm Laser Scanner</td>
<td>-</td>
<td>± 0.02 mm</td>
</tr>
<tr>
<td>NRC Laser Scanner</td>
<td>0.05 mm</td>
<td>-</td>
</tr>
<tr>
<td>Cyberware 3030 RGB 3D scanner</td>
<td>0.025 mm</td>
<td>-</td>
</tr>
<tr>
<td>Zsnapper portable scanner</td>
<td>0.2 mm</td>
<td>± 40μm</td>
</tr>
<tr>
<td>Arius three-dimensional scanner</td>
<td>0.1 mm</td>
<td>-</td>
</tr>
<tr>
<td>Xyris 3000/4000LT</td>
<td>0.25 μm</td>
<td>-</td>
</tr>
<tr>
<td>Nikon MCA II 7</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Accredited library-based peer reviewed databases were searched to locate papers of interest that met certain criteria, namely close-range laser scanning via triangulation (use of pattern projection and moiré techniques were outside of the scope of this review) and the geological materials analyzed were hand sample sized. This assessment provides an overview of the widespread use of close-range laser scanning in the geosciences. This not a review of state-of-the art laser scanning or 3D models, but rather a review of laser scanning applied to the digitization of geological hand samples.
2.2.1 Close-Range 3D Laser Scanning in the Field of Paleontology

Lyons et al. (2000) were among the first to apply a close-range 3D laser scanner to the digitization of body fossils, or the preserved remains of past species. The objective of this study was to establish whether 3D laser scanning would be a viable option for paleontological studies. Since the physical form of the fossil is one of the most important defining features, an accurate representation is crucial. The basisphenoid and basioccipital bones belong to the braincase of many vertebrates, and are located at the base of the skull. In this study, the basisphenoid and basioccipital bones of a juvenile Tylosaurus (a genus of the Mosasaur family) were scanned using a 3D laser scanner developed by the Institute for Information Technology, a division of the National Research Council of Canada. The basisphenoid and basioccipital bones were selected because they both have complex surfaces with small features indicating the locations of cranial nerves. While this scanner is capable of scanning at a resolution of 0.01mm, it was found that scanning at 0.1mm resolution was sufficient for capturing the structures of interest. It was concluded that laser scanners were appropriate tools for the morphological study of fossil samples.

Higher resolution scanners allow for the morphological study of smaller and/or more morphologically complex fossils. Kullmer et al., (2001) developed a methodology for digitization of hominid teeth, using 3D laser scanning. The morphology of teeth provides information on fossils species and how it ate. This in turn, can provide information on its prey of preference and its environment (Massare, 1987). By digitizing the teeth, structural parameters, which were necessary for morphological analysis (e.g. cusp area or height index), could automatically be calculated. In 2001, Freiss et al. used a Cyberware 3030 RGB 3D scanner (accuracy of 0.25-0.5 mm) to create 3D scans of the skull bones of both modern humans and Neanderthals. The resulting scanned models were used to determine if facial features varied depending on the climate. Motani (2005) applied a Konica-Minolta Noncontact VIVID 910 3D laser scanner to the digitization of the tooth crown of the Ichthyosaur, Mixosaurus. Commonly, ichthyosaur tooth crowns are conical in shape.
with flattened tips. However, through the use of the 3D digital model, it was found that the Mixosaurus tooth does not have a distinct conical crown tip; rather its shape is elongate forming a ridge, which is thinnest at the center. This shape is unique to the Mixosaurus and can thus be used as taxonomical identifier. In addition, due to the wear patterns of the teeth, it was determined that it was likely that the Mixosaurus crushed hard prey items, like shells, with its posterior teeth (molars).

In 2011, Sato et al. scanned the braincase of a plesiosaur, Polycotylidae with an Arius three-dimensional (3D) scanner at a resolution of 0.1 mm to determine whether it was a member of the short-necked plesiosaur family or the long-necked branch. The 3D digital models allowed for distinguishing key identifiers, such as a key-hole shaped foramen magnum (hole in the base of the skull for the spinal cord to pass through). It was determined that the Polycotylidae more closely resembled the long-necked plesiosaurs rather than the short-necked. Scanners have also been used in examining dinosaur bones. Wright and Selden (2011) applied a NextEngine 3D laser scanner to create 3D digital models of two trigonotarbid specimens. These specimens are significant because they were the first of this type of dinosaur to be found in Kansas. Using the 3D digital model, the boundaries between the fossils body segments were more visible allowing for easier study. The same scanner was applied to the digitization of the main bodies, called Thecaes, of blastoids, an extinct marine animal (Atwood and Sumrall, 2012). Blastoids are small, 1-2 cm, in size, and their landmark features are >1mm. To identify the specific species of blastoid, a robust series of geometric landmarks were used. Four known species of blastoid were distinguished using the 3D digital models, and three new species were discovered.

The NextEngine 3D laser scanner was also used in studies by Adams (2013) and Mike et al. (2016). Adams (2013) scanned the skull of a crocodyliform found in the Twin Mountain formation of
north-central Texas. Through studying the morphology of the skull, a new species of crocodyliform, Paluxysuchus newmani, was discovered. Paluxysuchus newmani is distinguishable based on the medial separation between its frontal and orbital margins, an elongated anterolateral process of the postorbital, large and rounded supratemporal fenestra and a narrow posterior ramus of the jugal. Paluxysuchus newmani was placed in the Neosuchia clade based on six synapomorphies. Mike et al. (2016) aimed to develop a quantitative way to discriminate between species of blastoids. The differences between scans of various species were calculated using Discrete Procrustes distance, a standard method for comparing shapes with known landmarks, and three species of blastoid were accurately distinguished.

The use of 3D digital models has resulted in improving our understanding and modeling of chewing motions (Rybczynksi et al., 2008; Evans and Fortelius, 2008; Cuthbertson, 2012; Nabavizadeh, 2014), locomotion (Polly and MacLeaod, 2008; Bechard, 2014), fossil deformation (Boyd and Motani, 2008) and species growth based on the constraints of the fossil morphology (Mitsopoulou, 2015). Evans and Fortelius (2008) used 3D scans to model chewing motions of eight different carnivoran species. A Nextec Hawk 3D laser scanner was used to digitize skull samples in order to model fine-scale movements and relative position of teeth surfaces during chewing. Evidence from the 3D digital models shows that attrition wear facets were the result of tooth-tooth contact during chewing. In addition, the models showed that the amount of horizontal movement in the chewing cycle depended on the number and complexity of the specie’s teeth. Rybcynski et al. (2008) incorporated a 3D digital model of the Hadrosaur skull, scanned using an Arius 3D laser scanner at a resolution of 0.3-0.5 mm, into 3D animation software. Since Hadrosaurs were a highly successful species that lived throughout most of the planet, it is hypothesized that they must have had an evolutionary edge over other species. One possible contributing factor was a transverse chewing stroke, or side-to-side motion during chewing. To determine if this was physically
possible, Rybcynski et al. (2008) simulated various chewing scenarios constrained by the geometry of the skull. It was determined that if the Hadrosaur did indeed use a transverse chewing stroke, there would be large secondary movements to accommodate this type of chewing. Therefore, it was unlikely that a transverse chewing stroke was used. In a follow-up to this study, Cuthbertson et al. (2012) described the morphology of the intracranial joints of both Edmontonosaurus regalis and Brachylophosaurus Canadensis. Based on the morphology of these joints, as well as the observed dental wear, a new chewing hypothesis was developed for Hadrosaurids which involved only rotational movement of the mandibles. Nabavizadeh (2014) were also interested in simulating hadrosauroid chewing motions. Eleven hadrosauroid skulls of varying genera were scanned with a NextEngine 3D Laser Scanner in order to determine the function of the predentary bone. The predentary bone is unique to ornithischian clade dinosaurs, of which hadrosaurs are a member, and its overall significance was not well understood. It was determined that predentary bone acts as an axial point for the dentary bones to simultaneously rotate mediolaterally by studying the morphology of the predentary bone and surrounding jaw bones, as well as the predentary bone’s placement within the skull.

In addition to chewing, full body locomotion can be simulated with the use of 3D digital models. Polly and MacLeod (2008) used 3D scans of ankle bones of four extinct species created using a Konica-Minolta Noncontact VIVID 910 in order to determine how they walked. The principal components of each ankle bone were calculated. These components were used to automatically determine the number of toes, the stance and the locomotor type of each species based on comparisons to existing species. Since these three locomotion parameters were already known through independent studies, the accuracy of this methodology could be assessed. Of the twelve parameters calculated (three parameters for four species), only two were incorrect suggesting that the use of the 3D digital models was a valid methodology. Like Polly and MacLeod (2008), Bechard
et al. (2014) simulated species movement through the use of 3D digital models. Nineteen specimens of the species Bothriolepis Canadensis, a placoderm fish, were scanned with the aim of reconstructing its thoracic armor. A more accurate description of the morphology of this species compared to previous reconstructions was produced, which was used to explore biomechanical aspects and constraints. It was determined that there was likely no mobility between the cephalic (head) and thoracic (middle body) armor and within the thoracic armour there was a previously undiscovered gill opening. In terms of movement, it was likely that the dorsal ridge played an important role while the pectoral fins were restricted.

Fossils are rarely pristine and have been subject to deformations over time including brittle deformation (structural breakage) and plastic deformation (changing of shape without breakage). Brittle deformation is usually overcome by “jigsaw puzzling” which involves placing the pieces back in their presumed original position. Boyd and Motani (2008) sought to determine if the jigsaw puzzling method was viable as samples that have experienced brittle deformation are often subject to plastic deformation as well. A scan of the skull of a Woolly Monkey taken with a Konica-Minolta Noncontact VIVID 910 was digitally “broken”. Simulated plastic deformation was applied to the digital skull and was reconstructed using the jigsaw puzzling method. Both a 3D digital model of the original skull and one that had been subject to simulated plastic deformation to a lesser degree were used. The two reconstructions were very similar, meaning that retrodeformations using the jigsaw method can superficially look correct even if they have been deformed.

Another study involves the skeletal remains of ichnospecies, which are often incomplete and were recreated using proportionally accurate skeletal parts. Mitsopoulou et al. (2015) created 3D digital models of the humerus, ulna and tibia of the species Palaeoloxodon tiliensis, a dwarf elephant that used to live in the Mediterranean during the Pleistocene, using a FARO Platinum Arm Scanner. A
mathematical relationship between adult and juvenile skeletons was developed based on 3D digital models. To recreate the missing bones necessary for a complete skeleton, the mathematical function was applied to the known adult bones in order to model the size of the juvenile bones. In addition, Palaeoloxodon tiliensis is commonly confused with another dwarf elephant, Palaeoloxodon antiquus. In order to determine which morphological characteristics can differentiate them, the scans of the two species was overlaid and the differences identified.

Trace fossils, such as footprints, burrows or feeding marks, also provide important information on the paleoenvironment. Arakawa et al. (2002) were among the first to apply 3D laser scanning to trace fossils. Three sets of therapod footprints and one set of bird footprints collected from China and Japan were scanned using a Konica-Minolta Noncontact VIVID 700 scanner. The aim of this study was to demonstrate laser scanning as an alternative traditional footprint analysis. Results showed that 3D digital models can provide important information on the morphology of trace fossils. Platt et al. (2010) used 3D scanning to quantify the morphology of several trace fossils including ant tunnels, dinosaur tracks, and insect burrows including those of a tiger beetle and a brown scorpion. New measures to quantify the morphology, including surface area index and volume exploited, were developed. Different burrow makers had characteristic surface areas and volumes and thus, these parameters could be used during taxonological identification. Similar to body fossils, the morphology of trace fossils allows for species identification of the track maker. This was done using footprints (Petti, 2008; Fiorillo, 2010; Belvedere, 2011; Fanti, 2013; Marchetti, 2014) or on the imprint of the species itself (Bethoux, 2004; Antcliff and Brasier, 2008; Belvedere, 2011). Petti et al. (2008; 2009; 2011) conducted two studies using a ShapeGrabber SG1002 3D scanner to digitize tracks in the Coste dell’Anglone tracksite in the southern Alps. Based on the depth of various digits within the footprint, interpretations were made on how the dinosaur walked. The newly discovered trackway was scanned and based on the morphology of the
footprint, the fossils could be attributed to an archosaur trackmaker and at least three of the trackways could be assigned to the ichnogenus Brachychothrich. This discovery is significant because this was the first well documented report of this ichnogenus from the Upper Triassic of Northern Italy.

Fiorillo et al. (2010) discovered a footprint in the Nunushuk formation in Alaska. Based on 3D digital models created using a NextEngine 3D Laser Scanner, it was determined that it was likely that of a Neoceratopsian. This would not only be the earliest recorded occurrence of Neoceratopsian species in North America, but would also substantiate the Beringia land bridge theory. The theory was further corroborated by the discovery and identification, using 3D scanning, of a Therizinosaur track found in the in the Lower Cantwell formation, also in Alaska (Fiorillo et al., 2012). In the first of three studies applying laser scanning to footprint analysis, Belvedere and Mietto (2010) scanned footprints from Upper Jurassic Iouaride`ne ichnosite of Morocco using ShapeGrabber SG1002. The prints were assigned to the Stegosaurian ichnogenus Deltapodus based on the analysis of the digital model of the footprints. This was significant as it was the first time that this species has been discovered in Africa and indicated that there was a connection between the northern and southern parts of Tethys. Belvedere et al. (2011a) scanned casts of dinosaur tracks using a NextEngine 3D Laser Scanner. The goal of this study was to determine if the tracks were from avian or small non-avian dinosaurs. These tracks were significant because, if avian, they would be the oldest evidence of birds in Gondwana. This would have significant biogeographic and paleobiological implications. Using the 3D information, they were able to identify new footprints which, along with a more detailed description of the prints, allowed them to conclude that the footprints were from a small non-avian dinosaur rather than a bird. In 2013, Belvedere et al. used laser scanning for footprint analysis at the Kem Kem beds, and identified theropod and turtle tracks (verified in the skeletal record in different proportions). Potential explanations were that the
skeletal fossils and the footprints were found in two different units or that the skeletal remains do not accurately represent the ecology of the area. Many of the skeletons used for analysis of the taxonomy of the area were purchased rather than collected by scientific research groups. Therefore, the results of these studies may be less accurate since the remains exact location within the strata was unknown. Footprints can provide a more accurate account since they are not subject to post-mortem transportation in the way that skeletons are.

In 2012, Contessi and Fanti scanned tracks from the Cenomanian Kerker Member in southern Tunisia using a Zsnapper portable scanner with a resolution of 0.2mm and an accuracy of 40μm. Within these tracks, which are dominated by tridactyl dinosaur tracks, three bird tracks were discovered and based on their morphology were assigned to the ichnogenus Koreananornis. These tracks were significant as they represent the oldest fossil birds from the Cretaceous of continental Africa and it is the first time that this ichnogenus has been found in Africa (previously only known in Asia and North America). The morphology of the tracks was compared to the morphology of tracks of modern birds and it was found that they were most similar to sand pipers. Sand pipers are most commonly found in modern tidal flat environments. Both the tridactyl and Koreananornis tracks indicate the presence of land in southern Tunisia which had been previously thought to be entirely marine. In their first follow-up study, Fanti et al. (2013a) scanned footprints created from silicon molds from tacks in the Wapiti Formation in Alberta, Canada. The tracksite contains a diverse ichnofauna which, in this study, were attributed to mammals, tyrannosaurids, medium-sized theropods, hadrosaurids, ankylosaurs, and amphibians. The presence of amphibian was unexpected as they were not generally found in high-latitude environments. The assemblage of this tracksite was similar to other sites of the same time period throughout western North America. In their second follow-up study, Fanti et al. (2013b) created a 3D digital model by scanning the silicon casts of representative footprints from the Hojapil-Ata tracksite located in Turkmenistan. The
morphological features were run through a statistical program which showed two distinct clusters without overlap. Therefore, could quantitatively determine that there were two distinct species at this tracksite.

Fiorillo et al. (2014a) used a NextEngine 3D laser scanner to create a 3D digital model of a newly discovered track within an unnamed rock unit within the Yukon-Charley Rivers National Preserve, Alaska. The track was attributed to a hadrosaur based on its morphology. The rock unit in which the prints were found was dated from the late Cretaceous. This is the earliest evidence of dinosaurs in the east-central Alaska region. That same year, Fiorillo et al. (2014b) scanned a series of theropod tracks from the Lower Cantwell Formation within Denali National Park, Alaska. Two types of small to medium theropod tracks were scanned and based on their morphologies were assigned to the ichnotaxa Eubrontes and Menglongipus respectively. The findings were significant for two reasons, this was the first time that these two species had been discovered in this region and these results indicated the presence of a multi-tiered predatory dinosaur guild structure, each providing greater detail on the paleonenvironment of the region during the Upper Cretaceous.

The study of small (< 20mm) tetrapod footprints is challenging as they are rarely preserved well and are often deformed. Erpetopus willistoni and Camunipes cassinisi are two such tetrapod species which are commonly mistaken for each other. Marchetti et al. (2014) scanned the footprints of these two species in order to develop a quantitative way to distinguish them. It was discovered that the separation between the two species was justified based on their differing morphology, with Erpetopus willistoni having a short digit V which curved outwards unlike the longer and straighter digit of Camunipes cassinisi.
In addition to footprints, laser scanning can be applied to imprints of the species entire body. Bethoux et al. (2004) scanned the fossils of insect wings using a Xyris 3000 and Xyris 4000LT scanners. These scanners have a laser point size of 30 μm and 2 μm respectively. The wings of an insect are typically the best preserved structures in fossil insects and so are important for identifying taxa. Using the laser scans, the folds and veins within the wings, both important features for identification, were distinguishable. The digital models of a sample from the order Caloneurodea collected using laser scanning indicated that this order is related to the order Orthoptera rather than Cimiciformes, hemipteroid insects, or Protorthoptera. The relationship of this order to other known orders had been a subject of debate. Antcliffe and Brasier (2008) scanned the holotype of Charnia masoni, an important fossil for studying Ediacaran biology. It was concluded that Charnia cannot be related to the modern cnidarian group based on the fact that these two species have opposite growth polarities evident from the species morphology. Brasier and Antcliffe (2009) scanned fossil samples of eight different Ediacaran biota including Charnia Masoni, Bradgatia, Fractofusus, Ivesheadia, Charniodiscus, Charnia wardi, C antecedens, Beothukis mistakensis in order to develop a potential phylogeny. A phylogeny which shows the evolution of these species over time was developed by determining which fossils most closely resembled each other morphologically based on the 3D digital models.

Fish feeding traces are less studied compared to other trace fossils in part because they are quite rare and often confused for different traces. One such example is the trace fossils found in the Lutetian-Bartonian formation. The origin of these fossils has been debated. Belvedere et al. (2011a) aimed to settle this dispute by combining paleoenvironmental data and 3D scanning. The scanned the fossils using a NextEngine 3D Laser Scanner. Since the site was established as an open marine environment, it was unlikely that the traces were from dinosaur footprints as previously thought. The traces were determined to be very similar to those created by various types of sturgeons.
Therefore, the trace maker was likely a common ancestor. An important function of 3D digital models is that they provide a record of the fossil. In-situ casting is expensive and requires high costs in terms of both labour and materials. In addition, casts have a limited life span and need to be physically stored. They can also cause damage to fragile trace fossils. Digitally preserved models is one way to overcome handling and potential damage to specimens (Adams et al., 2010, Fanti et al., 2013, Subsol et al., 2015).

Figure 2.7 shows the scans of two fossils that were collected from the upper Cryogenian of the Mackenzie Mountains of the Northwest Territories, Canada (courtesy of Dr. Guy Narbonne, Queen’s University). The fossils represent the oldest known benthic multicellular communities in the world, predating the Ediacara biota by approximately 50 Ma. The topography of these fossils was of significance but was extremely difficult to measure by hand since these are shallow depressions. Thus, the 3D digital model of the fossils can allow for these to be measured from the digital model. Figure 2.8 shows the scans of a fossilized theropod footprint (Miller Museum of Geology, Queen’s University collection). The footprint was scanned to visualize the morphology of the track and to assist with determining if a second footprint was located at the base of the fossil. Based on the scan, it was readily apparent that only one footprint existed.
Figure 2.7: Texture map (left) and the point cloud (right) of a Cryogenian fossil scanned at a resolution of 10,540 pt/cm². Note the ripple patterns in the sedimentary rocks outlined in blue. Close-ups of the fossils (circular imprints) are outlined in yellow and can be seen in A-C.
Figure 2.8: The texture map (left) and point cloud (right) of a therapod footprint. (A) and (B) show different angles (90° and 50° from parallel respectively) of the scan in order to highlight different features in the morphology. In (A) the texture map best illustrates the outline of the footprint while in (B), the point cloud best illustrates the topography of the surface of the footprint.

2.2.2 Close-Range 3D Laser Scanning in Rock Mechanics

Surface roughness is an important rock joint property as it heavily influences shear strength and transmissivity (Fardin et al., 2001). Lanaro et al (2000) and Fardin et al. (2001) were among the first to apply 3D laser scanners to determine the surface roughness of joints. A 1m x 1m size cast of joint surfaces were scanned and used to explore the validity of fractal models for fracture surface morphology and the scale dependence of rock joint surface roughness. In Tam et al. (2013) the
joints of granite cores at two different sampling lengths (60mm and 8,000mm) were digitized using a Roland LPX-60. The calibrated roughness angles measured by the scans to peak frictional angles which were calculated using established methods. This provides a way to quantify the shearing resistance at multiple scales which is significant as shearing resistance is highly scale dependent. Li et al (2014) used a 3D close-range laser scanner to determine the morphology of the two fracture surfaces of a joint set. A new model was developed to calculate the pressure-saturation relationship and the relative hydraulic conductivity of unsaturated fractures whose hydraulic properties had been not studied extensively. Barton (1973) was the first to propose a Joint Roughness Coefficient (JRC) to allow for the quantification of surface roughness. The use of JRC is now well established, and is calculated through the use of 2D profiles. However, a 3D JRC has not yet been widely recognized. Herda et al. (2006) and Zhang et al. (2017) aimed to resolve this issue and developed a new 3D Joint Rock Coefficient (JRC) based on depth generated by a 3D laser scanner. The results from the new methodologies were compared to those of established methods and concluded that this procedure produced comparable results.

In addition to the characterization of surface morphology, laser scanning can be applied for temporal analysis to assess changes of targets of interest over time, such as studies on weathering (Birgnie and Rivas, 2005; Mohtarami et al., 2017) and deformation (Indraratna et al., 2014; Zhao et al., 2017). Birgnie and Rivas (2005) used a laser scanner to monitor the degradation of limestone when exposed to salt spray. Daily scans showed the four stages of deterioration: sand disaggregation, scaling, appearance of blisters, and sub-efflorescence, and the rate at which they occurred. Areas of degradation can easily be identified by comparing the successive scans. To quantify the rates of degradation, the standard deviation of the topographic relief and laser return intensity can be used. Comparison of degradation between rock types can now be determined. Mohtarami et al. (2017) also studied weathering effects using multi-temporal scans in order to
simulate the acidic chemical solvents that are commonly used in rock engineering projects at heap leaching sites.

To quantify deformation over time, Indraratna et al. (2014) used a Konica-Minolta Noncontact VIVID 910 3D laser scanner in order to measure the asperity damage and gouge accumulation pre- and post- constant normal stiffness shear tests. 3D digital models were used to calculate the difference between scans before and after constant normal stiffness shear tests. The difference between pre- and post-test scans was calculated with negative values indicating regions of asperity damage and positive values regions of gouge accumulation. Results showed that asperity damage and gouge accumulation increase with higher initial normal stress and JRC. Zhao et al. (2017) applied a laser scanning to quantify the morphological changes of fracture surfaces after being subjected to a transient pulse test. By using the 3D digital models, it was discovered that the effect of fracture roughness on the permeability of rock units was related to the confining pressure with rougher fractures having lower permeability at lower confining pressures.

Figure 2.9 shows close-range laser scanned samples of drill core of Cobourg limestone from a quarry near Bowmanville, Ontario (courtesy of Dr. Jenn Day, University of New Brunswick) pre- and post-direct shear tests in order to conduct change detection analysis of the topology of the rough shear test target surface.
Figure 2.9: Shear tests were applied to limestone core samples. Samples were scanned at a resolution of 5,000 pt/cm² before and after testing. (A) shows the texture map of a representative sample pre- (left) and post- (right) shear test (B) shows the point cloud of the sample pre- (left) and post- (right) shear test. Note the topographic changes between each scan.

2.2.3 Close-Range 3D Laser Scanning in Sedimentology

Size and shape of sediments can provide information about the processes of fluvial transport and past environmental conditions, as well as their suitability for engineering applications. Lanaro and
Tolppanen (2002) were among the first to apply 3D laser scanning to quantification of sediment particle shape and size. The objective of this study was to provide a new method for determining established size and shape parameters for aggregates. These parameters determine the particle’s suitability for engineering applications, such as pavement layers or as ballast in railway tracks. Hayakawa and Oguchi (2005) scanned gravel samples with a Roland LPX-250 scanner in order to determine their sphericity and roundness. These are important parameters for determining the processes of fluvial transport and past environmental conditions that sediment experienced as the rounder the particle, the longer distance it has travelled. It was shown that the laser scanner was an effective way to measure surface area, which is used to calculate sphericity. Lee et al. (2007) aimed to further automate the laser scanning by collecting surface morphology data from aggregate particles travelling along a conveyor belt resulting in automatic calculation of shape parameters. From the scan data, the height, width and length of each particle was computed. Angularity was calculated using mathematical morphology where the difference between a standard ellipsoid and the surface of the particles was determined. If the difference is high, the surface is more angular.

Komba et al. (2007) and Anochie-Boateng et al. (2013) tested laser scanning, specifically the Roland LPX-1200 scanner, as a new method to determine the “flakiness” of soil particles. Flakiness is defined as the ratio between the length, width and thickness of a particle. A particle is considered flaky if one of the dimensions is significantly larger than the other two. Flaky particles are not desirable for use as construction material, specifically for railroad ballast. The 3D digital models were compared to those calculated using the traditional slot method and that the results agreed well and that the laser scanner was a more efficient method. Anochie-Boateng et al. (2011) and Mvelase et al. (2016) also used laser scanning data to calculate other shape parameters, such as roundness and sphericity, to determine suitability for railroad ballast. Asahina and Taylor (2011) used a NextEngine 3D Laser Scanner to scan a number of both crushed and naturally rounded rock
particles in order to calculate shape parameters including volume, surface area and density. These values were compared to the results from both commuted topography (CT) scanning and the projected area method. Since the CT scanning had the highest resolution, it was used as truth data and the laser scanning results and the projected area methods results were compared to it. It was found that the laser scanning values showed strong agreement with those generated using the CT scanning.

The morphology of lithic clasts that result from the failure of conduit wall rock provides information on the process that shaped them during eruption. Campbell et al. (2013) scanned lithic clasts from the eruption of Mount Meager, British Columbia, with a NextEngine 3D Laser Scanner to calculate the sphericity and smoothness. The amount of surface modification, such as rounding, is proportional to the time that lithic clast spent in the conduit before eruption. It was proposed that subangular and rough clasts had shorter residence times (<2 min) and rounder, smoother clasts had longer residence times (up to 60 min). The shape can be used to estimate the fragmentation depths and the rates of attrition during volcanic eruptions. Bagheri et al. (2014) also applied laser scanning to the quantification of the shape of irregular volcanic particles. The morphological characteristics of volcanic particles have a large influence on their threat to aviation and public health as well as dispersion and reaction with gases and water vapor during eruption. Existing 1D and 2D shape parameters are used to estimate 3D shape parameters of the particles using caliper measurements, image analysis, the laser scans and results from CT scanning. The existing 1D and 2D shape parameters were compared these shape parameter estimations to 3D parameters calculated using the actual 3D data. The results showed that the 2D variables were more accurate than the 1D variables (2.4-4.6% versus 7.2-20%).
Sediment clasts can also be affected by weathering processes. Bourke et al. (2008) and Ehlmann et al. (2008) were among the first to apply laser scanning to study weathering effects on sedimentary clasts, specifically basalt cobbles. These cobbles were scanned before and after being exposed to weathering processes, specifically wind abrasion. These scans were converted into digital elevation models from which the morphological changes could be quantified and areas of preferential weathering determined. Rossi and Graham (2010) scanned granite fragments from locations within the subsurface at varying depths in order to understand the rate of porosity development in granitic rock. Solid rocks typically have low porosities but due to weathering processes, fractures and microcracks can develop over time thus increasing the porosity. Those closest to the surface were expected to be more weathered than samples from deeper depths. Using the laser scan models, the bulk volumes of these fragments were calculated. The bulk volumes were converted into porosity values by using the bulk density and the particle density and the equation developed by Flint and Flint (2002). Based on their porosity distribution of the particles at various depths, it was determined that clast porosity developed at a rate of 0.1%/thousand years.

Soil structure is of vital importance to understanding the hydrological, environmental, and ecological processes. Bulk density can be used as an indicator of soil quality as it controls the ease of root penetration, water movement and soil strength. Rossi et al., (2008) applied a NextEngine laser scanner to determine the bulk volume of soil samples. The laser scanner results were compared to those generated from a traditional method of calculating bulk density, the paraffin-coated clod method, and showed that the results agreed well. Hirmas et al. (2013) used volume calculations from laser scanning to determine if the relationship between soil mass and soil volume could be described using fractal models on decimeter scales. Soil samples were scanned and sequentially broken between each scan. The corresponding volumes and masses were plotted against each other and fit with a power-log equation in order to determine the fractal dimension. Results showed that
fractal models do in fact represent soil mass and soil volume relationships well but several orders of magnitude should be used when calculating the representative fractal dimension. Falcon-Saurez et al. (2015) scanned compacted samples of granite fines at varying water contents. The objective of this study was to determine the suitability of laser scanners to calculate dry densities of fine grained soils. The compared the laser scanning results to those from the Standard Proctor test, the current method. It was determined that the laser scanning method was applicable until a water content of less than 20% after which the fine grained soil becomes too incohesive for the laser scanner to capture properly.

2.2.4 Close-Range 3D Laser Scanning in the Field of Planetary Sciences
Dufrense et al. (2013) and (Poelchau et al., 2013, 2014) scanned rock samples that had been subjected to impacts from a metal projectile in order to simulate small scale crater impacts. The objectives of this study was to determine the effects of rock type, porosity and saturation on the morphology of impact craters. Results show that while a high porosity decreases the overall size of the crater, by filling the pore space with water, the size increases again. Three rock types tested (sandstone, quartzite and tuff) showed similar crater sizes despite having different strengths (Poelchau et al., 2014). Once these relationships have been determined on a smaller scale, they can be scaled to planetary-sized craters (Poelchau et al., 2014).

Baratoux et al. (2015) scanned a wide set of shatter cones with a Nikon MCA II 7 axis scanner in order to determine the shape term that best describes their morphology. The term “conic” was selected based on the shape of the original samples. These cones were well defined and isolated. Since then, the term has been loosely applied to other impact structures with a range of rounded fractures. It was determined that shatter cones were best described with hyperboloid to paraboloid
shapes rather than conical and that shatter cone shape was not dependent on the type of lithology or impact crater size.

Finally, Macke et al. (2015) applied a NextEngine Laser Scanner, with a resolution of 3,850 pts/cm² and an accuracy of 0.1mm, to determine the volume of lunar samples collected from the Apollo mission. Volume calculations were used in conjunction with the sample mass in order to determine the bulk density, an important parameter for the interpretation of gravimetric data from orbiting satellites. Traditionally, the bulk density is calculated using bead emersion techniques and the laser scanner was found to be equally accurate and more efficient than the bead method.

### 2.2.5 Close-Range 3D Laser Scanning in the Field of Structural Geology

Kink bands are a distinct type of double hinged fold that results from the shearing of rocks. Traditionally, they are described using simple two-dimensional cross sections but this does not capture their full 3D form. In order to quantify these complex structures, 3D laser scanning can be a useful tool. Dunham and Crider (2012) were the first to apply 3D laser scanning to kink bands. The kink bands were scanned with a FARO Arm 3D laser scanner. This was done in order to quantify the geometry of the kink folds in order to quantitatively distinguish the three types of intersections that they can have (crossing, bifurcating and obliquely diverging). This was based on parameters calculated from the 3D data such as gradient and curvature.

Figure 2.10 shows the scan of paragneiss sample which was found in a mylonite zone outcrop north of Kingston, Ontario and is part of the Miller Museum of Geology collection at Queen’s University. The sample shows gneissic banding which is indicative of the regional metamorphism that affected the area during the Grenville orogeny and the geological evolution of North America as a whole based the metamorphic and structural history. This sample was scanned to provide insight into the
formation of the geological units of the Kingston area and for improved visualization (Harvey, 2017).

![Figure 2.10: The texture map (left) and point cloud (right) of a Paragneiss sample from two different angles (A) and (B) to highlight the gneissic banding on the surface of the sample](image)

### 2.3 Three-Dimensional Model Visualization, Data Sharing and Printing

In addition to studying the morphology of physical objects, 3D digital models can be integrated into spatial environments in order to provide greater context. De Poar (2016) visualized 3D rock models in Google Earth™ to show their utility for geoscience education. The 3D digital models were shown to be useful for revealing hidden features on the rock’s surface, preparing for field trips and aiding in the retention of information. In addition, the rock’s evolution overtime could be displayed along with the external forces that had acted upon it, such as weathering, tectonic
deformation or metamorphism. Harvey et al. (2017) integrated 3D digital models of geological hand samples into ArcGIS© for improved visualization and to enhance comprehension of sample context. The 3D digital models were georeferenced within datasets of various spatial scales and accompanying metadata, such as lithology and location of origin. Additional geoscience datasets, such as geological maps or geophysical data, like the total magnetic field or the Bouger anomaly, were incorporated to aid the user in interpreting the geological settings.

Historical context and significance can be provided to museum or other preservation-type rock hand sample collections using 3D digital hand samples. Appendix B outlines a case study undertaken for this thesis in which historical context is provided to the Captain Alan Innes-Taylor collection from the Miller Museum of Geology at Queen’s University. Captain Alan Innes-Taylor, an important figure in Canadian exploration, collected these till samples during the Second Byrd Expedition to Antarctica in 1935. These till samples are displayed within the story of Captain Innes-Taylor’s life through an Esri StoryMap. Since this collection is not currently on physical display, this visual narrative allows for access and sharing of the collection by the broader community.

The 3D geological hand sample models can be shared digitally for efficient communication of morphological data. This has two primary uses. The first is for collaboration between scientists as rare and fragile samples can be analyzed without risk of breakage during transportation or being lost (Lyons et al., 2000; Betts et al., 2011; Smith and Strait, 2008). The second is the hosting of geological hand sample collections online for easier dissemination of scientific information to the public (Carrasco et al., 2005; Rebbert, 2007, Bates et al., 2010). Online databases that host 3D geological hand samples include The Great Britain 3D Project which was created by the British Geological Survey (BGS) and the GeoFabLab which was created by the Iowa State University. The Great Britain 3D Project holds more than more than 1,800 digital fossils created using a close-range
laser scanner with the goal of (BGS, 2018). The GeoFabLab has over 100 3D digital models available for download, specifically for 3D printing (Iowa State University, 2018). Other databases that host 3D digital models of geological hand samples include the Smithsonian X 3D which contains digitized fossils (Smithsonian, 2018), Smorf which contains 3D digital models of crystal shapes (Holtkamp, 2014), African Fossils which contains digitized fossils, although they were created through photogrammetry (African Fossils, 2018) and Digimorph which contains digitized fossils, although they were created through CT scanning (The University of Texas, 2018). The goal for these databases is that users can download the 3D digital models for visualization and 3D printing.

3D printing of geological hand sample models has two main areas of application, the first is for educational purposes (Grant et al., 2017; Hasiuk, 2014; Mitsopoulou et al., 2015; Subsol et al., 2015) and the second is for repeatability in destructive sample testing (Bourke et al., 2008; Vogler et al., 2017). 3D printed specimens can allow students or member of the public to interact with the specimens and appreciate their scale and take measurements. Grant et al. (2017) used 3D printed samples of Megalodon teeth to teach students about how scientists use estimate the size of extinct species based on the size of their teeth. Students were able to make measurements of the teeth and use relevant equations to calculate approximate size. Mitsopoulou et al., 2015 3D printed fossils in order to fill in missing parts of skeletons for museum display.

Many geotechnical tests are destructive. Volger et al. (2017) repeated Brazilian tensile tests on two types of 3D printed synthetic as well as three samples natural sandstone at different strengths (weak, medium and strong). The synthetic samples had smaller range of tensile strengths than the sandstone samples and correlated best with the weak sandstone samples. The samples post-test to compare fracture surfaces. The printed samples again showed a high correlation between the natural
weak sandstone. These findings can help in finding a suitable printing material that can recreate natural rock characteristics. Like geotechnical testing, weathering tests breakdown the rock samples. Bourke et al. (2008) printed samples of vesicular basalt cobbles. These samples were exposed to wind abrasion tests with the idea that the test on each natural sample could be repeated using the 3D printed samples. While the morphology of the real and artificial samples was similar, similar material properties would be necessary for an accurate representation of the weathering process.

2.4 Conclusions
This review chapter highlights literature that utilized 3D close-range laser scanning in the field of geology wherein the primary purpose has been for the improved study of the morphology of hand specimens. For paleontological studies, primary applications are in quantitative analysis of the fossil’s morphology and for integration into 3D animation models to determine the species movement. The field of rock mechanics primarily used 3D digital models of geological models of geological hand samples to determine the surface roughness of the rock sample and to study how their morphology changes over time due to weathering processes. 3D digital models of geological models were also widely used in the field of sedimentology in order to characterize the shape of sediment particles and to calculate bulk density. There is a variety of further geological applications for which 3D digital models may be of use, as outlined in Table 2.2.
Table 2.2: Potential applications for digital hand sample collection at Queen's University

<table>
<thead>
<tr>
<th>3D Digital Sample Type</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Limestone Core</td>
<td>Calculate roughness for geotechnical design</td>
</tr>
<tr>
<td></td>
<td>Calculate changes in joint morphology pre- and post- direction shear test</td>
</tr>
<tr>
<td>Mylonite</td>
<td>Calculate shortening to compute stresses applied to rock during shearing</td>
</tr>
<tr>
<td>Metamorphic Rock with Quartz Inclusions</td>
<td>Calculate direction of stress based on the long and short axis of quartz inclusions</td>
</tr>
<tr>
<td>Dinosaur footprint</td>
<td>Identify dinosaur taxon by comparing scan to scans of known species</td>
</tr>
<tr>
<td>Rock Hand Samples</td>
<td>Use surface characteristics to guide users in identifying the sample’s lithology</td>
</tr>
<tr>
<td>Mineral Hand Samples</td>
<td>Use surface characteristics to guide users in identifying the sample’s mineralogy</td>
</tr>
</tbody>
</table>

The 3D digital models of geological hand samples can be visualized in spatial environments in order to facilitate interpretation of the geological setting, shared digitally for efficient communication of morphological data and three-dimensional printing allows for physical interaction with geological hand samples without the need for the original sample. Global datasets created using collections from multiple institutions can allow for broader scale research. The analysis of geological hand samples is fundamental to the study of geology. The use of digital geology samples for archival purposes as well as global data sharing will become increasingly important as it allows for easier collaboration and communication between not only researchers but between the academic world and the public. In the following chapter a case study that demonstrates the utility of close-range laser scanning to the calculation of ore grain size distribution.
Chapter 3

Calculation of Ore Grain Size Distribution for Mineral Liberation using 3D Close-Range Laser Scanning

3.1 Introduction

Mineral processing, the process to extract the ore minerals from the host rock, is a multi-step process that is highly dependent on the characteristics of the ore rock. The grade, ore mineral type, and grain size can all effect how the ore is processed (Evans and Napier-Munn, 2013). In this case study, we will examine grain size. Comminution, or particle size reduction, is the first step in the mineral processing workflow and is typically composed of crushing and grinding. These steps are done in order to liberate the ore minerals so that a high grade ore concentrate can be created (Houdin et al., 2001). There are two factors to consider when designing the crushing process. First, the particles must be ground to a fine enough size to allow for a high concentrate grade. Second, the particles are not over-ground as the grinding process is very energy intensive, and thus expensive, and particles that are too fine can reduce ore mineral recovery (Lindqvist and Akesson, 2001). Therefore, an optimal grain size must be selected based on the grain distribution of the ore minerals (King, 1979). Current methods of quantitatively assessing grain size distribution use digital images, optical microscope or Scanning Election Microscope (SEM) systems. Each of these methodologies take several small but high resolution samples of the ore and classify them into each mineral type. SEM systems are preferred as they can provide very high resolution results compared to optical systems whose spatial resolution is limited by the wavelengths of visible light (500 nm). In addition, SEM systems are able to identify the elements in the minerals themselves rather than their spectral characteristics, which provides a far more accurate classification (Sutherland and Gottlieb, 1991). Once these classified images have been created, the grain size distribution can be assessed. Line measurements can be taken where the intercepts, or boundaries between the ore grains and gangue
grains, occur. From these measurements, a mean intercept length, surface area or volume can be calculated. The values are then used as an input for grain size distribution models (King, 1979).

In this case study, the goal was to develop a methodology that would allow for the automatic calculation of the grain size distribution using a close-range laser scanner. This was done in order to assess the feasibility of close-range laser scanners for this purpose. The grain size distribution calculated through laser scanning was compared to those collected using the established SEM methodology in order to determine if this technique would add value to the current approach.

3.2 Methodology
A zinc ore sample containing sphalerite ore minerals was selected for this case study. This ore sample also contained gangue minerals, primarily dolomite and tourmaline. This specific ore was selected since there was a high spectral contrast between the ore and gangue minerals within the visible spectrum. This was significant as the texture map of the 3D digital model was collected optical wavelengths. Figure 3.1 illustrates the 3D digital model of the ore sample used. The original ore sample was provided by Andre Tessier of the Ontario Geological Survey.
Figure 3.1: 3D digital model of the zinc ore sample used in the case study. The sphalerite ore minerals are dark in colour while the dolomite/tourmaline gangue minerals are light in colour.

The workflow developed for the calculation of the grain size distribution can be seen in Figure 3.2. The workflow consists of two major steps: first, the creation of a 3D digital model and second, the calculation of the ore grain size. The final output is grain size distribution. The grain size distribution calculated using the 3D digital model can then be compared to the grain size distribution generated using an SEM, the current state-of-practice.
Figure 3.2: Workflow illustrating the steps used to collect the 3D point cloud of the ore and calculate the grain size distribution of the ore grains

The first step in this workflow was to collect a 3D digital model of the ore, which would then be used for the grain size distribution calculations. This was done using the Next Engine 3D scanner, which uses four laser arrays at 650 nm wavelength to collect a 3D point cloud data. The scanner also uses a digital camera to collect RGB data for each point within the point cloud. The 3D digital model of each face used for the calculation of grain size can be seen in Figure 3.3.
Figure 3.3: Five faces of the sphalerite ore were scanned (A-E). The orientation of the faces is shown in the diagram in the lower right corner. These were used in grainsize calculations.

A medium resolution of 5,000 points/cm² was used. For this specific type of laser scanner, this resolution could only be achieved with a field of vision (FOV) of 13.0 x 9.6 cm. The ore scanned was 13.0 x 21.8 cm in size. Therefore, to collect the full face, three overlapping scans were collected, as seen in Figure 3.4.
Figure 3.4: Extent of the individual scans used to collect the entire face of the sphalerite ore. Overlapping regions were used to align the separate scans into a single point cloud.

The scans were then aligned manually using three common locations between each scan, as seen in Figure 3.4. Any overlapping sections that were not used to align the individual scans were trimmed from the point cloud. If these overlapping strips were not removed, this resulted in stripes of misclassified data, as seen in Figure 3.5.
Figure 3.5: Scans were classified to mineral type (gangue minerals in pink and ore minerals in blue). (A) point cloud contains overlapping parts from multiple scans (B) point cloud in which all but one scan in each overlapping region was removed. The point cloud now better represents the real ore.
The spectral signature of the ore and gangue minerals was manually identified by inspecting the RGB triplets between 0-255 of each mineral class. A threshold which separated the ore and gangue minerals in each colour band was developed. The threshold selected for the red band was 150 and the threshold selected for the green and blue bands was 120. These thresholds were then used to classify the point cloud into “ore” and “gangue” minerals. Ore mineral grains were then identified. A contour detection algorithm was used to identify the boundaries between the ore gangue minerals. The contour detection algorithm detects the transition between a gangue class point and an ore class point based on their assigned mineral class. The algorithm then calculates where this change continues in the surrounding points. The algorithm will then record the location of the mid-point between the ore/gangue boundary points and assign it a unique identifier, repeating this until all boundaries have been identified. The contours were visually compared to determine the validity of the results. The grain size was calculated by vertices of the mineral grain boundary and calculating the surface area. This was repeated for each face resulting in a histogram representing the grain size distribution was created.

### 3.3 Results of Ore Grain Size Calculation Using Close-Range Laser Scanning

The grain size distribution generated using the laser scanner can be seen in Figure 3.6. The grain sizes of the sphalerite mineral grains range from 0.5mm² to 2,5000 mm² with 75 mm² being the average grain size. It is evident from Figure 3.6, that the resolution of the scanner limits its ability to detect the smaller (>0.5 mm²) grains. If the small grains are detected by the laser scanner, they will appear as a single point within the point cloud. Thus, when their grain size is calculated, they are all have a grain size value of 0.5mm², creating the large jump seen in the grain distribution.
3.3.1 Comparison of Close-Range Laser Scanning Results with Scanning Electron Microscope Data

To assess the quality of the ore grain size results generated from close-range laser scanning, they were compared to results generated using a Scanning Electron Microscope (SEM). A FEI Quanta 650 FEG ESEM was used to calculate the ore grain size from three thin sections of the Sphalerite Ore sample. These three thin sections were cut at 3 different orientations in order to account for the preferred grain orientation. The SEM calculated the backscatter electron intensity of the three sections, as seen in Figure 3.7.
Figure 3.7: Backscatter intensity data for the three thin sections collected using the SEM. Sphalerite, Dolomite and Tourmaline minerals are identified.
The backscatter intensity was used to create an X-Ray image. The Mineral Liberation Analysis (MLA) software only recorded backscatter data if the backscatter intensity was above a certain threshold. Sphalerite minerals had a higher intensity backscatter value than the host silicates and so this threshold allowed the MLA to focus exclusively on the regions that contained sphalerite minerals. The X-Ray image was then classified into Sphalerite, Dolomite and Other by comparing the backscatter responses in the X-Ray image to a predefined library (Gu and Napier-Munn, 1997; Fandrich et al., 2007). These classified images can be seen in Figure 3.8.
Figure 3.8: Classified mineral data for the three thin sections calculated using the MLA software

The area of the classified Sphalerite grains were calculated using the MLA. The grain distribution generated using the SEM methodology can be seen in Figure 3.9. The grain sizes of the sphalerite ores range from $2 \times 10^{-6}$ mm$^2$ to 8mm$^2$ to with 0.1mm$^2$ being the average grain size.
Figure 3.9: Cumulative grain size distribution of the ore grains within the sphalerite ore as calculated using the SEM

The grain distributions generated using the laser scanner and the SEM overlap between grain sizes 1 mm$^2$ to 8 mm$^2$. Figure 3.10 shows the cumulative grain distribution for both the SEM data and the laser scanning data between 1 mm$^2$ and 8 mm$^2$. From this figure, the overall shape of two grain size distributions match relatively well with a large number of grains (>50%) between 1-2 mm$^2$ in size and then a gradual decrease in the number of grains for the larger grain sizes. There are some discrepancies between the two grain size distributions. One of the contributing factors may be the result of SEM data having fewer points contributing to the shape of the grain size resulting in larger jumps in grain size. Another contributing factor could be the sampling of the minerals at various orientations (for example, long axis versus the short axis of the mineral grains) as laser scanning can sample the minerals at differing orientations unlike the individual SEM measurements.
3.4 Discussion of Case Study Results

Due to greatly different spatial resolutions of SEM and close-range laser scanner used in this experiment, the grainsize results also differ, as expected. The SEM has a spatial resolution of 1-3 nm while the close-range laser scanner has a spatial resolution of 0.5-1 mm. Therefore, when comparing the grain sizes, the SEM is able to detect grains that are much smaller than that of the laser scanner. For the grain sizes that are within both the scanner’s range and the SEM range, the overall shape of the grain distribution matches reasonably well. Both distributions show that at least half of the grains within this range are between 1-2 mm$^2$ in size and 70% of the grains are smaller than 3mm$^2$. There are some differences in grain size distribution with laser scanning results showing a lean toward larger grain sizes. One of the potential advantages to laser scanning is the ability to sample the ore grains at multiple orientations with ease producing a more representative grain-size distribution curve.
The SEM methodology can classify the ore and gangue minerals more accurately than the laser scanner and so can be applied to wider range of ore types. The laser scanner method is limited to those ore whose ore and gangue minerals are spectrally distinct within the RGB wavelengths. The grain size calculated by the laser scanner is also limited by the spatial resolution of the scanner used. Grains that are smaller than the resolution would not be detected. Since the SEM has a significantly higher resolution than that of the scanner (3nm versus 5mm), it is able to detect these small grains better. Therefore, the decision to use laser scanning over SEM analysis would be based on the resolution required for the grain size analysis. This would depend on the range of crushing sizes that are being considered. For instance, if a crushing size greater than 0.5mm$^2$ is being considered than the use of laser scanner is possible. However, if the time and budget allows, an SEM analysis should still be performed as this produces state-of-practice results.

This case study illustrates an area of future work that may involve the combination of SEM and close-range laser scanning for calculating ore grain size distribution for mineral liberation. While this process is still in the development stage, due to the efficiency of laser scanning there seems to be some indication of utility at the larger (>0.5 mm$^2$) ranges.
Chapter 4

Correcting Shadow Regions in Multispectral Images using Airborne LiDAR Reflectance Data for Improved NDVI Mapping

4.1 Introduction

The identification and mapping of surficial entities, such as bodies of water, exposed soil or vegetation, have many geological applications. The type, extent and diversity of vegetation in a region can provide information on soil properties (Shantz, 1938), the geological units from which the soils developed (Kruckeberg, 2004) as well as the occurrence of subsurface mineral deposits (Cannon, 1971). In this study, an improved technique for mapping vegetation is presented which mitigates the effects of shadows originating from cloud cover and physical structures within multispectral images used to calculate the Normalized Difference Vegetation Index (NDVI) for a region. NDVI is an important indicator of the species of vegetation and the health of these species within a multispectral image and is calculated using the ratio of the Near-Infrared (NIR) spectral band (0.7 – 1.3 μm) and the visible spectral bands (0.4 – 0.7 μm) (Rouse et al., 1974). Shadows can hinder land cover classification using NDVI because the spectral signature of the shadow and non-shadow regions of the same material will be measurably different (George, 2011). Current methods of shadow detection, such as examining the spectral brightness of the features within the multispectral image, are ineffective as low reflectance materials, such as asphalt or exposed soil, are often mistaken for regions of shadow (Dare, 2005; Yuan, 2008). Misclassification of shadow regions can also manifest themselves in poor interpretations of wildlife habitat (Wang et al., 1999; Bork and Su, 2007), resource management (Goetz et al., 2003; Sawaya et al., 2003; Ozdemir, 2008; Bolch et al., 2010), urban infrastructure (Rashed et al., 2001; Shackelford and Davis, 2003; Bhaskaran et al., 2010; Lu et al., 2010) and land cover change (Im and Jensen, 2005; Zhu and Woodcock, 2012). Established methods for detecting the extent of shadows within multispectral
images include the use of the spectral properties of the multispectral image (Nagao et al., 1979; Otsu, 1979; Dare, 2005; Chen et al., 2007), the use of a digital elevation model (DEM) (Rau et al., 2002; Li et al., 2005) and the use of a time series of multispectral images (Goodwin et al., 2013; Zhu and Woodcock, 2014). Using the spectral properties of the multispectral image is the most prevalent method and involves the use of thresholds to segregate the image into two classes. This approach assumes that the spectral signature of shadow and non-shadow classes are significantly different (Adeline et al., 2013) and therefore a bimodal or Gaussian mixture mode distribution characterizes the two classes (Otsu, 1979; Dare, 2005; Chen et al., 2007; Yamazaki et al., 2009). Results are typically better with spectral bands of longer wavelengths (i.e., infrared), which are more prone to scattering since they have lower energy leading to significantly lower reflectance values for shadow regions relative to non-shadow regions. Degraded shadow detection results occur when a scene contains targets of low spectral response that can be confused with the low spectral response of the shadow regions (Adeline et al., 2013). For instance, asphalt, which is present in many mixed/urban scenes, has a low spectral response within the visible spectrum and is often misclassified as shadow (Nichol and Lee, 2005; Zhai et al., 2018). Digital Elevation Model (DEM) data and solar illumination data collected at the time of multispectral data acquisition can be used to model the location of shadows within a scene (Giles, 2001; Rau et al., 2002) through ray tracing, (Thirion, 1990, Li et al., 2005; Tolt et al., 2011), the creation of a buffer with regions lower than a predefined elevation classified as shadow (Rau et al., 2002), or the application of a hillshade algorithm which computes the slopes of DEM and classifies those of a certain orientation as shadow (Zhan et al., 2005). The accuracy of the binary shadow mask is primarily dependent on the accuracy of the DEM and the accuracy of the registration between the elevation and the multispectral datasets. The spatial resolution of the shadow mask will be limited by the lowest resolution dataset. The use of a time series of multispectral images for shadow detection is targeted towards cloud shadows within satellite images, which exploits the fact that clouds change position through time.
(Goodwin et al., 2013; Zhu and Woodcock, 2014). To reduce error, other sources of change, such as snow or ice cover, plant growth or urbanization, can be identified and removed (Hagolle et al., 2010; Zhu and Woodcock, 2012).

While each of these aforementioned methods are well established and have been used extensively, there are some practical limitations. As mentioned, when using the multispectral data alone, low reflectance materials are often confused with regions of shadow, reducing the accuracy of the shadow classification. The use of digital elevation models for detecting shadows are limited by the presence of cloud cast shadows as these cannot be modelled using elevation data. When using the time-series shadow detection technique, it is unlikely that no change would occur between campaign dates, especially for airborne images of a high resolution, thus limiting the accuracy of this method. If the images were collected at a similar time in the day, the position of cast shadows would not alter significantly, further limiting this method. There is an opportunity to develop a shadow detection technique which can overcome these limitations. A workflow that would specify under what conditions each shadow detection technique should be applied has yet to be established.

The overall objective of this research is to improve NDVI mapping by detecting and mitigating shadows within multispectral images using multispectral optical images and airborne Light Detecting and Ranging (LiDAR) reflectance data. LiDAR intensity values vary depending on the source energy and the composition of the reflective targets and can be calibrated using targets of known reflectivity to create LiDAR reflectance values. These reflectance values do not vary due to source energy and only represent the reflectivity of the ground (Kaasalainen et al., 2005). A monochrome image can be generated based on these reflectance values and their georeferenced coordinates (Richards, 1993). This allows the multispectral dataset and the LiDAR reflectance dataset to be compared. LiDAR reflectance data is also not affected by shadows from the sun.
because LiDAR is an active system (Zhou et al., 2009; Brell et al., 2017). The difference between
the LiDAR reflectance data and the multispectral data can be used to identify regions of shadow
(George, 2011).

Correcting both satellite and airborne optical data using LiDAR reflectance data is not common
practice (Coren and Starizai, 2006). To convert LiDAR intensity to LiDAR reflectance, it is
necessary to have targets on the ground to calibrate the LiDAR intensity values (Kaasalainen et al.,
2009). The installation of these targets can be time consuming and expensive and not suitable for
regions that are difficult to access. However, a few studies have shown LiDAR reflectance as a
promising tool for shadow detection. In George (2011) two Machine Learning Algorithms (MLAs),
specifically a Linear Classifier and Support Vector Machines (SVM), were used to classify the
multispectral data into shadow and non-shadow classes. For each algorithm, four input parameters
were tested in combination, including the multispectral RGB values, the local LiDAR average
value, the local green average value and the ratio between the LiDAR reflectance and the Green
spectral band. The LiDAR system used wavelengths within the Green spectrum so the Green band
within the multispectral dataset and the LiDAR reflectance data were highly correlated. Regions of
shadow had a large ratio value (>1) since the LiDAR reflectance values would be much greater
than the corresponding Green values. Ten-fold cross validation was applied to assess the
performance of each classification. SVM classification that used all four parameters as input
produced the highest quality results of 89% as calculated from cross validation. In this study, each
input parameter was tested independently to determine the inherent strengths and limitations. This
would also better illustrate LiDAR reflectance’s applicability for shadow detection as the
performance of the classification results generated using LiDAR reflectance as input can be
quantitatively compared to those generated with the multispectral data. In George et al., 2011 four
colour correction algorithms were tested including ratio multiplication, histogram equalization, histogram matching and Reinhard’s colour transfer, three of which are tested in this study.

In Priem and Canters (2016), the ratio between the LiDAR intensity values and the brightness, or average of the three visible spectral bands, was calculated. A ratio value of four was then used as a threshold to classify the multispectral data into shadow and non-shadow classes. Percent Correctly Classified (PCC) was used to assess the quality of this methodology and resulted in a PCC value of 69%. Since the LiDAR reflectance ratio did not perform well using the thresholding methodology, it was examined with varying classification techniques. In addition, shadow detection using the spectral properties of the scene was not one of the shadow detection methods tested by Priem and Canters (2016). Therefore, the results using LiDAR reflectance could not be compared to the use of multispectral properties alone and so no comment on how it improved shadow detection could yet be made. It is the aim of this study to make this comparison.

The effects of the shadows in the multispectral images can be mitigated by correcting the colour values for each spectral band. The quality of further analyses can be improved with the correction of shadow regions, including the calculation of NDVI, as the results from the non-shadow and shadow regions can accurately be compared. There are several techniques that can be used to correct multispectral images including include ratio multiplication, linear correlation correction, histogram matching, and Reinhard’s colour transfer. The linear correlation correction uses first-order statistics of the scene as whole in order to get more representative correction values. The ratio between the standard deviation of the shadow and non-shadow was calculated and multiplied by the difference between the shadow value and the average shadow value. This value was added to the average non-shadow value to calculate the corrected value (Sarabandi et al., 2004; Zhou et al., 2009). The linear correlation correction is a well-established colour correction technique but has
not been widely applied to the correction of shadow regions. One of the aims of this study was to determine how this technique performed relative to standard shadow correction techniques.

The ratio multiplication method is the simplest of the colour correction methods as each RGB value is corrected by multiplying it by the LiDAR reflectance/green value for each point. The green band was used by George (2011) since there was a high correlation between this band and the LiDAR reflectance band as they were collected at similar wavelengths. The ratio between the LiDAR reflectance and multispectral reflectance is high for shadow regions and thus will increase the low RGB values. In this study, instead of using the Green band alone, all three spectral bands were used. The histogram matching method uses the first-order statistics of the entire scene. The cumulative density function of the shadow and non-shadow regions are plotted. Each value of the shadow regions is then mapped to the corresponding non-shadow value (Gonzalez and Fittes, 1975).

Histogram matching is a well-established technique and included for assessment herein as well. Reinhard’s colour transfer decorrelates the red, blue and green bands prior to correction. The correction is applied through a series of matrix multiplications, which translates the RGB to \( \lambda_\alpha \beta \) colour space. Color spaces are mathematical representations of colours with tuples of numbers (usually triplets or quadruplets). Developed by Ruderman et al. (1998) \( \lambda_\alpha \beta \) colour space minimizes the correlation between the three colour channels. For Reinhard’s colour transfer, in \( \lambda_\alpha \beta \) space the shadow value is multiplied by the ratio between the standard deviation of the non-shadow region and the standard deviation of the shadow region. The colour values are then translated back to RGB space (Rienhard et al., 2001). While Reinhard’s colour transfer performed the best in George (2011), it only performed marginally better than the ratio multiplication method (the simplest correction method) for certain regions within the multispectral mosaic. Therefore, it was the goal
of this study to compare the results of these four colour correction methods to determine if the complexity of the technique justified the quality of the corrections.

### 4.2 Description of Data

The study region is located in an industrial region in northwest Calgary, Alberta and is approximately 2300m × 400m as shown in Figure 4.1. The region is primarily composed of vegetated areas with two industrial buildings located in the northwest and northeast corner of the area of interest. Adjacent to the eastern industrial building is a small lake. Of note are five dirt roads that cross the study region traversing east-west and north-south within the northern half of the region.

![Figure 4.1: Optical image of study region in northwest Calgary outlined in the white box with land cover denoted](image)

Multispectral and LiDAR data were collected by SarPoint Engineering. The two datasets simultaneously collected from an airborne platform during two campaigns on May 24th, 2016 and May 11th, 2017. By collecting the two datasets simultaneously, the shadow detection results would not be adversely affected by potential temporal changes allowing for direct comparison between the two datasets. For this study, the airborne multispectral data was collected with a modified Nikon DSLR (D7200) camera equipped with a 45mm lens focused at infinity. Typically, cameras have a
NIR filter which filters out wavelengths between 700-800 nm. With the modified camera, the NIR filter was removed and replaced with a red bandpass filter, which filters out red wavelengths (600-700 nm). Therefore, this camera captured information from the blue (400-500 nm), green (500-600 nm) and NIR bands (700-800 nm). The multispectral images were mosaicked into one dataset and sampled at each point within the LiDAR point cloud resulting in assigned RGB values. The collection of the NIR band, as opposed to the red band, was necessary to capture vegetation. Vegetation has a relatively high response in the green band as the chlorophyll proteins absorb blue and red light-energy for photosynthesis and reflect green wavelengths. This also results in low spectral reflectances in the blue and red wavelengths. Vegetation has a very high spectral response in the NIR band as the internal structure of the leaves strongly reflect energy in these wavelengths. The level of response in the green and NIR spectrum is dependent on the health of plant. This overall spectral signature allows for the identification of vegetation from other classes. Specific plants can be identified based on their spectral response within these four bands (Rouse et al., 1973; Tucker, 1979).

NIR electromagnetic waves behave similarly to the visible wavelengths of light measured as solar radiation reflected from the Earth’s surface. Therefore, filters and cameras with the same design can be applied to imaging data at these wavelengths (Lillesand et al., 2014). Figure 4.2 illustrates the mosaic of multispectral optical images collected during the two data collection campaigns and sampled at each point within the LiDAR point cloud.
Figure 4.2: (A) RGB values sampled for each point within LiDAR point cloud for the 2016 dataset (B) RGB values sampled for each point within LiDAR point cloud for the 2017 dataset

The LiDAR for this study data was collected using a Riegl VMX-450 scanner configured for low-level airborne use and flown at an altitude of 400m. The LiDAR data points were collected at a wavelength of 1450 nm. The Riegl VMX-450 uses time-of-flight measuring the time for the emitted laser beam to reach the object of interest and reflect back to the scanner. In addition to measuring target location in 3D space, the scan angle (the degree from the nadir that the measurement was taken from), return number (a given laser pulse can have multiple returns so this parameter records the place in sequence that this particular return occurred), and the amplitude of the reflected laser beam are known. The LiDAR return amplitude is converted to LiDAR return intensity using eq. 4.1:

\[ I = A^2 \]  

where \( I \) represents the intensity in W/m\(^2\) and \( A \) represents the amplitude in W/m.
The intensity of the returning directed beam characterises the reflectance of the illuminated spot on the ground and records it. Multiple wavelengths can be collected by LiDAR systems, however the system used in this study collected one wavelength 1450 nm. The intensity images produced for this study are panchromatic with white representing high intensity returns and black representing low intensity returns (Vosselman and Maas, 2010). For instance, at 1.064 μm, snow has a reflectance of 70 – 90%, mixed forest has a reflectance of 50 to 60% and black asphalt has a reflectance of 5%. It is this LiDAR reflectance data that is of interest to our study of shadow detection in multispectral images. Figure 4.3 illustrates the LiDAR reflectance data collected during the two data collection campaigns.

Figure 4.3: (A) LiDAR reflectance values for each LiDAR point within the 2016 dataset (B) LiDAR reflectance values for each LiDAR point within the 2017 dataset

Table 4.1 summarizes the details of the multispectral optical data and the LiDAR reflectance data collected for this study.
Table 4.1: Details of the multispectral optical dataset and LiDAR reflectance dataset used in this study

<table>
<thead>
<tr>
<th></th>
<th>Multispectral Optical Dataset</th>
<th>LiDAR Reflectance Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Campaign Dates</td>
<td>May 24\textsuperscript{th} 2016</td>
<td>May 11\textsuperscript{th} 2017</td>
</tr>
<tr>
<td>Platform</td>
<td>Fixed Wing Airplane</td>
<td></td>
</tr>
<tr>
<td>Altitude</td>
<td>400 m</td>
<td></td>
</tr>
<tr>
<td>Wavelength</td>
<td>400-500 nm (Blue)</td>
<td>1450 nm</td>
</tr>
<tr>
<td></td>
<td>500-600 nm (Green)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>700-800 nm (NIR)</td>
<td></td>
</tr>
<tr>
<td>Resolution</td>
<td>5 cm</td>
<td>10 pt/m\textsuperscript{2}</td>
</tr>
<tr>
<td>Number of images/points</td>
<td>2016 – 272 images</td>
<td>2016 – 5,771,732 points</td>
</tr>
<tr>
<td></td>
<td>2017 – 181 images</td>
<td>2017 – 3,619,436 points</td>
</tr>
<tr>
<td>Parameters</td>
<td>Relative local x,y coordinates, blue, green, NIR</td>
<td>Relative local x,y,z, coordinates, reflectance, scan angle return number, time</td>
</tr>
</tbody>
</table>

4.3 Overview of Methodology

The shadow mitigation workflow for this study was comprised of seven main steps, as seen in Figure 4.4. The LiDAR and multispectral data was preprocessed removing excess data and normalized to scale. Five classification techniques were tested in order to determine the highest quality binary shadow mask. The best performing classification technique was used to test five input parameters in order to increase the performance of the classification, quantified through cross-validation. The ‘best’ shadow mask was used to sort the multispectral data into shadow and non-shadow classes for the colour correction of the shadow regions. Four colour correction methods were tested and the best method was used to calculate the NDVI for the study area. Ultimately, the process was designed to determine how much (if at all) the modified shadow mitigation workflow improved NDVI mapping.
4.3.1 Description of Shadow Detection Assessment

In order to determine which classification technique performs the best when creating a binary shadow/non-shadow map and to quantify whether the LiDAR reflectance data can improve the shadow detection workflow, a number of empirical tests were conducted. Specifically, five classification techniques, namely thresholding, Support Vector Machines SVM, naive Bayes, k-nearest neighbour and decision trees and five input parameters, namely NIR band, green band, blue band, brightness and LiDAR reflectance/brightness ratio, were tested. Figure 4.5 outlines the methodology used to test the various classification methods and input parameters.
Figure 4.5: Detailed workflow for shadow detection using multispectral data and LiDAR data
The multispectral data was used to create training and validation polygons for the non-shadow and shadow classes. These polygons were created manually with an equal number of training and validation polygons for each class. The locations of the training and validation polygons were selected to ensure that all different land cover types (grass, trees, exposed soil and industrial buildings) were well represented. While these were collected concurrently, two different instruments were used to collect each dataset, resulting in different extents. The spatial coverage of the LiDAR data was greater than that of the multispectral data and thus was clipped to match the spatial extent of the multispectral data. The RGB values and the LiDAR reflectance values were normalized to a range of 0-65280 (16 bit values) so that similar intensities would be represented by the same value. A non-shadow value is represented as a value of 1 (consistent with previous studies).

In previous studies, the correlation between the spectral bands, average spectral intensity (or brightness) and the LiDAR reflectance values was determined in order to select which spectral information should be used for the calculation of the ratio values. This was done using the Pearson’s correlation coefficient (i.e. the linear correlation coefficient) in order to determine the linear dependence between the two datasets as seen in eq. 4.2 (Press et al., 1992):

\[
 r = \frac{\Sigma_i(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma_i(x_i - \bar{x})^2 \sqrt{(y_i - \bar{y})^2}}}
\]  

(4.2)

where \(i\) is equal to 1,\ldots,N (then number of elements within both datasets), \(r\) represents the Pearson’s correlation coefficient, \(\bar{x}\) represents the mean of the \(x_i\)'s (the multispectral intensity values) and \(\bar{y}\) represents the mean of the \(y_i\)'s (LiDAR reflectance values). Pearson’s correlation coefficient ranges between -1 and 1 with 1 representing a perfect positive correlation, -1 representing a perfect negative correlation and 0 representing no correlation between the datasets. For correlation
coefficients between 0 and 1, a correlation of 0.7 or greater is considered to be a high correlation, between 0.3 and 0.7 a moderate correlation, and less than 0.3 a low correlation (Taylor, 1990; Asuero et al., 2006). This correlation was calculated in order to determine which spectral band should be used for

The Pearson’s correlation coefficient was calculated for the NIR spectral band and the LiDAR reflectance data. The NIR band was selected since it had the closest wavelength to the LiDAR data. These two datasets had a low correlation coefficient of 0.24. The correlation between the “brightness”, or average of the blue, green and NIR spectral bands, and the LiDAR reflectance data was also calculated. These two datasets had a higher correlation coefficient at 0.35. Therefore, the ratio between the spectral brightness and the LiDAR reflectance data was used as one of the parameters to classify the multispectral data into shadow and non-shadow classes.

The ratio of the LiDAR reflectance over the multispectral brightness were calculated for each LiDAR point. These LiDAR/brightness ratio values were compared to the multispectral data and a user-defined threshold was selected. The ratios calculated for each point were overlaid over the original multispectral data. Pre-defined regions of shadow and non-shadow were compared (ratio values) in order to select a ratio value that best separated the two classes. In this study, a threshold value of 3 was selected (similar to other studies, i.e., Priem and Canters, 2016). In an ideal scenario, this threshold value would be close to 1, however, the variance in the two datasets resulted in non-shadow regions having a greater ratio value.

A second threshold of 1.8 was selected to differentiate partial shadow from non-shadow points. By exclusively using a threshold of 3, the strongly cast shadows (e.g. the shadow cast by urban agglomerates such as transmission towers, utility poles or industrial buildings within the scene)
were well represented but weakly cast shadows (e.g. cloud cast shadows) were not included. Both thresholds were selected by overlaying the ratio values over the multispectral data and comparing regions of obvious non-shadow to regions of weakly cast shadows. Figure 4.6 displays the three classes and their associated thresholds.

![Figure 4.6: Three shadow classes and associated LiDAR reflectance/Multispectral brightness ratio thresholds](image)

To create the shadow mask, the multispectral and LiDAR data points were sorted into shadow, partial shadow and non-shadow classes. The performance of the thresholding shadow detection method was assessed via cross validation (using manually created shadow and non-shadow classes) on the assigned classes. The predicted shadow/non-shadow classes and the actual predicted shadow/non-shadow classes were compared through the use of a confusion matrix as seen in Figure 4.7. The user’s accuracy, the proportion of the predicted class that was correctly predicted, and the producer’s accuracy, the proportion of the known class that has been assigned the correct label, was calculated for each class.
Figure 4.7: Confusion matrix used to determine the performance of each classification method

Each Machine Learning Algorithm (MLA) must be trained with the user-defined training data in order to identify the signature of each class. For each point in the training dataset, the value for each input parameter and the class assigned is known. A graphical representation of how each of each classifier operates is illustrated in Figure 4.8. In the case of SVM, the training data is plotted in n-dimensional space, as seen in Figure 4.8A. The number of dimensions in space is defined by “n” which is the number of input parameters. Clusters within the training data are found. The extreme data points in each cluster are used as support vectors. Using these support vectors, a line or hyperplane is created, segregating the data. Each point in the data set to be classified is assigned a class depending on which side of the hyperplane they lie on in n-dimensional space (Stewart and Christmann, 2008).

The Naïve Bayes classifier creates a table of the input parameter values and the assigned class, as seen in Figure 4.8B. The probability that a specific value of each input parameter results in each class is calculated for each input parameter. To classify a new point, the probability that it is a member of each class is determined using its input parameter values.
The k-nearest neighbour plots the training data in n-dimensional space, as seen in Figure 4.8C. Each point of the data to be classified is plotted and a predefined number, represented by k, nearest neighbours are identified. The modal class of the nearest neighbours is assigned. The Decision Trees classifier uses the training data to create a tree-like model of sequential decisions and notes possible outcomes, as seen in Figure 4.8D. To classify a new point, the classifier starts at the left of the tree and follows the sequential decisions until a class is decided upon. The performance of each method was assessed by using the same cross-validation method that was applied to the thresholding classification. Each input parameters were tested individually and in various combinations for a total of nine trials. SVM was used as the classifier for each test to keep the results consistent. The performance of each input parameter was determined using the same cross-validation method as the classification algorithms.
4.3.2 Description of Shadow Colour Correction Assessment

In order to correct the RGB values of the detected shadow regions, four colour correction methods were assessed, namely (i) ratio multiplication, (ii) linear correlation correction, (iii) histogram matching and (iv) Reinhard’s colour transfer. These methods were selected as they had been successfully used for the mitigation of shadows in previous studies (Gonzalez and Fittes, 1975; Shu and Freeman, 1990; Rienhard et al., 2001; George, 2011). While Reinhard’s colour transfer has shown the greatest promise, the best colour correction method varies on a case-by-case basis. Figure 4.9 outlines the workflow used for testing the performance of each colour correction method.
The colour values of each point were normalized to fall between 0 and 1 to allow for a consistent comparison and visualization of all methods. The study region is dominated by four land-cover types, namely grasslands, trees, industrial buildings and exposed soils/dirt roads. The colour correction tested was the LiDAR/brightness ratio multiplication. For this correction technique, eq. 4.3, adapted from George (2011) was applied to each point classified as shadow:

Figure 4.9: Detailed workflow for colour correction of multispectral image to produce corrected NDVI map

The colour values of each point were normalized to fall between 0 and 1 to allow for a consistent comparison and visualization of all methods. The study region is dominated by four land-cover types, namely grasslands, trees, industrial buildings and exposed soils/dirt roads. The colour correction tested was the LiDAR/brightness ratio multiplication. For this correction technique, eq. 4.3, adapted from George (2011) was applied to each point classified as shadow:
Corrected RGB Value = Shadow RGB Value \frac{\text{LiDAR reflectance value}}{\text{Brightness value}} \tag{4.3}

where the Corrected RGB Value is the corrected RGB value, the Shadow RGB value is the original shadow RGB value, LiDAR reflectance value is the LiDAR reflectance value at that point and the Brightness value is the brightness value at that point.

The Linear Correlation Correction, developed by Shu and Freeman (1990), was tested shown in eq. 4.4 and applied to each point classified as shadow:

\[ DN_{\text{restored shade}} = \frac{\sigma_{\text{sun region}}}{\sigma_{\text{shadow region}}} (DN_{\text{shadow region}} - \mu_{\text{shadow region}}) + \mu_{\text{sun region}} \tag{4.4} \]

where \( DN_{\text{restored shade}} \) is the corrected colour value, \( \sigma_{\text{sun region}} \) is the mean of the non-shadow region, \( \sigma_{\text{shadow region}} \) is the mean of the shadow region, \( \mu_{\text{sun region}} \) is the standard deviation of the non-shadow, \( \mu_{\text{shadow region}} \) is the standard deviation of the shadow region, and \( DN_{\text{shadow region}} \), is the original colour value.

The Histogram matching technique is applied by calculating the cumulative distribution function for the non-shadow and shadow colour values. This was done for each material class individually. Each shadow point value on the cumulative distribution curve of the particular land cover class was matched to the equivalent value in the non-shadow cumulative distribution curve (Gonzalez and Fittes, 1975), as seen in Figure 4.10.
The colour correction tested was Reinhard’s Colour Matching whereby the colour values of both the shadow and non-shadow regions were converted from RGB space to lαβ space via eq. 4.5-4.7. Each material class was corrected separately. First the RGB values are converted to XYZ colour space using the following (Rienhard et al., 2001):

\[
\begin{bmatrix}
X_C \\
Y_C \\
Z_C \\
\end{bmatrix} =
\begin{bmatrix}
0.5141 & 0.3239 & 0.1604 \\
0.2651 & 0.6702 & 0.0641 \\
0.0241 & 0.1228 & 0.8444 \\
\end{bmatrix}
\begin{bmatrix}
R \\
G \\
B \\
\end{bmatrix}
\] (4.5)

where \( R \) is the original NIR band value, \( G \) is the original Green band value and \( B \) is the original Blue band value, \( X_C \) is the value of \( R \) in XYZ colour space, \( Y_C \) is the value of \( G \) in XYZ colour space, \( Z_C \) is the value of \( B \) in XYZ colour space. The colour values in XYZ colour space are then converted to LMS space (Rienhard et al., 2001):

Figure 4.10: Diagram illustrating the histogram matching method. The value \( x_i \) within the cumulative probability distribution, \( G(x) \), is matched to the same value in the reference cumulative probability distribution, \( H(x) \), which results in the corrected value \( x_j \).
\[
\begin{bmatrix}
L_c \\
M_c \\
S_c
\end{bmatrix} =
\begin{bmatrix}
0.3897 & 0.6890 & -0.0787 \\
-0.2298 & 1.1834 & 0.0464 \\
0.0000 & 0.0000 & 1.0000
\end{bmatrix}
\begin{bmatrix}
X_c \\
Y_c \\
Z_c
\end{bmatrix}
\] (4.6)

where \( L_c \) is the value of \( X_c \) in LMS colour space, \( M_c \) is the value of \( Y_c \) in LMS colour space, \( S_c \) is the value of \( Z_c \) in LMS colour space.

The log of the LMS values was then calculated. Finally, the colour values are converted to \( l\alpha\beta \) space using the following (Ruderman et al. 1998):

\[
\begin{bmatrix}
l_c \\
\alpha_c \\
\beta_c
\end{bmatrix} =
\begin{bmatrix}
\frac{1}{\sqrt{3}} & 0 & 0 \\
0 & \frac{1}{\sqrt{6}} & 0 \\
0 & 0 & \frac{1}{\sqrt{2}}
\end{bmatrix}
\begin{bmatrix}
1 & 1 & 1 \\
1 & 1 & -2 \\
1 & -1 & 0
\end{bmatrix}
\begin{bmatrix}
L_c \\
M_c \\
S_c
\end{bmatrix}
\] (4.7)

where \( l_c \) is the value of \( L_c \) in \( l\alpha\beta \) colour space, \( \alpha_c \) is the value of \( M_c \) in \( l\alpha\beta \) colour space, \( \beta_c \) is the value of \( S_c \) in \( l\alpha\beta \) colour space.

The colour values are in \( l\alpha\beta \) colour space, the colour correction can be applied to each band separately using the following (Rienhard et al., 2001):

\[
x' = \frac{\sigma_x^t}{\sigma_x^s} x^*
\] (4.8)

where \( x' \) is the corrected value, \( \sigma_x^t \) is the standard deviation of the non-shadow values, \( \sigma_x^s \) is the standard deviation of shadow values and \( x^* \) is the uncorrected shadow value in \( l\alpha\beta \) colour space.

The corrected values were then converted back to RGB colour space.
In order to quantify the performance of each colour correction technique, the range of colour values for the non-shadow, shadow and corrected shadow classes, was calculated. This would indicate whether the shadow values were increased enough to match the non-shadow values. Each material type was assessed individually. The corrected values for each colour correction method were also visualized manually to determine the qualitatively assess the performance of each correction method.

4.3.3 Calculation of Normalized Difference Vegetation Index

Vegetation has a uniquely high response in the green and NIR bands and a low response in the blue and red bands. This signature allows vegetation to be distinguished from other materials. NDVI is a unitless index that indicates the density of vegetation on an area of land. NDVI values range from -1 to 1. Table 4.2 shows NDVI values and their associated ground cover material (Ahern et al., 2013).

<table>
<thead>
<tr>
<th>NDVI</th>
<th>Ground Cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 0</td>
<td>Water, snow, ice</td>
</tr>
<tr>
<td>~ 0</td>
<td>Soil, exposed rock</td>
</tr>
<tr>
<td>&gt; 0</td>
<td>Vegetation</td>
</tr>
<tr>
<td>0.2-0.4</td>
<td>Grass/shrub</td>
</tr>
<tr>
<td>0.6-0.8</td>
<td>Temperate and Tropical Forests</td>
</tr>
</tbody>
</table>

The majority of studies calculate NDVI using the NIR band and the red band since vegetation have a high spectral response in the NIR band and a low spectral response in the red band. However, since the customized camera used for this study removed the red channel and replaced it with a
NIR channel, the blue band was used for the calculation of NDVI instead. Since vegetation also
has a low response in the blue band, this was used to calculate instead of the red band, as seen in
eq. 4.9:
\[
\text{NDVI} = \frac{(NIR - \text{Blue})}{(NIR + \text{Blue})}
\]  

(4.9)

where NIR represents the response in the NIR spectrum and Blue represents the response in the
Blue spectrum.

4.4 Results of Shadow Detection and Colour Correction Trials

4.4.1 Classification Test Results
The overall cross-validation results between classification techniques were compared and their
binary shadow masks visually inspected in order to assess performance. Of the five shadow
classification techniques, SVM produced the highest overall cross-validation performance at 74%.
This was followed by Naïve Bayes and Thresholding, which produced an overall cross-validation
performance of 69% and 71% respectively. Finally, K-nearest neighbour and Decision Trees
produced the lowest overall cross-validation performance of 55% and 60%, respectively. The cross
validation overall performance for the 2016 and 2017 datasets can be seen in Table 4.3. The
performance results are on par with previous studies (thresholding in Priem and Canter, 2016
resulted in 69%; SVM in George, 2011 resulted in 89%).
Table 4.3: Performance of Shadow Detection Classifiers for the 2016 and 2017 datasets computed via Cross-Validation

<table>
<thead>
<tr>
<th>Shadow Detection Classifier</th>
<th>Performance</th>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thresholding</td>
<td>71%</td>
<td>High Producer’s accuracy for shadow regions</td>
<td>Low Producer’s accuracy for non-shadow regions</td>
</tr>
<tr>
<td>Support Vector Machines</td>
<td>74%</td>
<td>High overall accuracy</td>
<td>Medium Producers’ accuracy for non-shadow regions</td>
</tr>
<tr>
<td>K-nearest neighbour</td>
<td>55%</td>
<td>High User’s accuracy for shadow regions</td>
<td>Low User’s accuracy for non-shadow regions</td>
</tr>
<tr>
<td>Decision Trees</td>
<td>60%</td>
<td>High User’s accuracy for shadow regions</td>
<td>Low User’s accuracy for non-shadow regions</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>69%</td>
<td>High User’s accuracy for shadow regions</td>
<td>Misclassifies edge points as shadow</td>
</tr>
</tbody>
</table>

By examining the binary shadow masks produced by each classification, the weaknesses and strengths of each method can be determined. The binary shadow mask produced using k-nearest neighbours demonstrates the poor performance in distinguishing small regions of shadow and often confused non-shadow areas for shadow. Since the algorithm uses the surrounding points to classify the point of interest, it was able to classify continuous regions of shadow moderately well, but misclassified many non-shadow points as shadow. Decision Trees produced a similar binary shadow mask as k-nearest neighbours. This algorithm classified the continuous regions of shadow
well but produced confused many points of non-shadow as shadow. Thresholding distinguished regions of dark shadow as there was a large difference between the intensity values but was poor at identifying regions with lighter coloured shadows or darker LiDAR reflectance values. In addition, many non-shadow points were misclassified as shadow. Naïve Bayes classified the darkest shadows well but misclassified the regions of electrical wires, water and edges of the LiDAR swaths. Support Vector Machines was able to classify the regions of cloud shadows well and was excellent at identifying cast shadows (e.g. utility pole or tree cast shadows) Figure 4.11 and Figure 4.12 shows the binary shadow mask generated using the SVM classification with the LiDAR reflectance/brightness ratio as input.

![Binary mask created for the 2016 dataset using SVM classification with the LiDAR reflectance/brightness ratio as input. Red represents areas classified as shadow and blue represents areas classified as non-shadow.](image)

Figure 4.11: Binary mask created for the 2016 dataset using SVM classification with the LiDAR reflectance/brightness ratio as input. Red represents areas classified as shadow and blue represents areas classified as non-shadow.
Figure 4.12: Close-up of the 2016 binary shadow mask. The shadows generated by trees and utility poles are circled.

Of the five detection algorithms Support Vector Machines had the highest performance. This was consistent with across all input parameters tested.

### 4.4.2 Input Parameter Test Results

Table 4.4 shows the combination of input parameters that were tested and the corresponding performance for the study region. Performance was measured by taking the average overall cross-validation accuracy values for the 2016 and 2017 data sets.
### Table 4.4: Performance of input parameter trials. A checkmark indicates the input parameters that were used in each trial

<table>
<thead>
<tr>
<th>Trail/Inputs</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>LiDAR/ Bright.</td>
<td>✔</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>NIR Band</td>
<td>✔</td>
<td></td>
<td>✔</td>
<td>✔</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Green Band</td>
<td></td>
<td></td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Blue Band</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Brightness</td>
<td></td>
<td>✔</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Performance</td>
<td>74%</td>
<td>78%</td>
<td>61%</td>
<td>50%</td>
<td>65%</td>
<td>79%</td>
<td>79%</td>
<td>78%</td>
<td>89%</td>
<td>89%</td>
</tr>
</tbody>
</table>

The blue band performed the worst as it classified the entire dataset as non-shadow. This was due to its inability to distinguish between vegetation and shadow. In addition, cloud shadows and cast shadows had two different signatures within this band, which complicated classification. The green band also produced low performance results, classifying the 2017 dataset entirely as non-shadow. This was primarily due to the green band’s inability to distinguish between dark coloured soils and shadows. Of the individual input parameters, the NIR band performed the best. However, it could not distinguish between the exposed soil and industrial regions and shadow. Therefore, it misclassified these two material types as shadow. The LiDAR/brightness ratio produced moderately accurate results. This input parameter worked especially well for classifying shadows produced by structures in the region but was most sensitive to errors in the LiDAR data leading to a lower performance. When combining the input parameters together, higher performance results were achieved. The trials that achieved the highest performance results were #9 and #10 which used the RGB values + LiDAR reflectance/brightness and RGB values + LiDAR reflectance/brightness + brightness respectively. Therefore, the RGB values + LiDAR reflectance/brightness was selected as the optimal combination of input parameters. Figure 4.13 and Figure 4.14 shows the binary shadow mask generated using these input parameters.
Figure 4.13: Binary mask for the 2016 data using SVM classification with the RGB values and the LiDAR reflectance/brightness ratio as input. Red represents areas classified as shadow while blue represents areas classified as non-shadow.

Shadows generated by trees and utility poles are clearly seen and represent the morphology of these shadows within the images well. In addition, the cloud shadow is better represented.

Figure 4.14: Close-up of the 2016 binary shadow mask with source of shadows identified

Within the 2016 data, the south-west corner of the study region is primarily misclassified. Here, a large section of cloud shadow was misclassified as non-shadow. This was due to the errors within the LiDAR point cloud making the reflectance much lower than it should be despite being the same.
material as the surrounding brighter reflectance regions. This created a LiDAR reflectance/brightness ratio closer to 1. Therefore, to improve the classification, this region was isolated and classified using just the RGB values instead. Figure 4.15 shows the results from this classification.

Figure 4.15: Binary mask of anomalous region with low LiDAR reflectance values created using RGB values

With this anomalous area removed from the rest of the classification, the overall accuracy of the RGB + LiDAR reflectance/brightness increases to 95%, making it significantly better than solely relying on RGB values. By integrating the two classifications, the final shadow mask was produced, as seen in Figure 4.16.
Figure 4.16: Final binary mask created by combining the RGB classification for the anomalous region and the RGB + LiDAR reflectance/brightness classification

4.4.3 Colour Correction and Shadow Mitigation

The colour corrections were applied to the shadow regions defined by the best performing shadow classification. Table 4.5 shows the comparison between the four methods in terms of the percent increase the shadow regions experienced and the quality of the correction.

Table 4.5: Results from colour correction trials showing the amount of increase in the multispectral values and the quality of the correction method

<table>
<thead>
<tr>
<th>Color Correction Method</th>
<th>% RGB Increase</th>
<th>Quality of Correction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio multiplication</td>
<td>20</td>
<td>Maintained hue at a sufficient level</td>
</tr>
<tr>
<td>Linear correlation correction</td>
<td>40</td>
<td>Increased bands at different rates</td>
</tr>
<tr>
<td>Histogram matching</td>
<td>40</td>
<td>Increased bands at different rates, regions whitened out</td>
</tr>
<tr>
<td>Reinhard’s colour transfer</td>
<td>40</td>
<td>Maintained hue at a sufficient level</td>
</tr>
</tbody>
</table>

Figure 4.17 illustrates the original and colour corrected 2016 data set to highlight the differences between each colour correction method.
Figure 4.17: (A) the original false-colour multispectral data in 2016 scene, (B) the binary mask used to separate the shadow (red) and non-shadow (blue) values used for each correction method, (C) the multispectral data after the ratio multiplication method, (D) the multispectral data after the linear correlation correction method, (E) the multispectral data after the histogram matching method, and (F) the multispectral data after the colour transfer method.
Of the four correction methods, the ratio multiplication method increased the RGB values the least, average of 20%. The linear correlation correction, the histogram matching and Reinhard’s colour transfer methods all increased the RGB values by an average of 40%. However, the rate at which each band was corrected differed for the linear correlation correction and histogram matching corrections. For these corrections, the blue band was increased the most, followed by the green band and then the NIR band. Thus the corrected regions appear bluer than their corresponding non-shadow regions. The Reinhard’s colour transfer method produced the best results as it increased the shadow values to a similar range to the non-shadow regions while maintaining the hue (results agree with previous studies, i.e., George, 2011).

Table 4.6 shows the range of NDVI values for each material type for the non-shadow, shadow and corrected shadow regions. These results show that correcting the shadow regions makes a significant improvement when calculating the NDVI. The grass material showed the best improvement as the range of NDVI values for the non-shadow and corrected now overlap well. The tree, industrial and exposed soil regions are all corrected to values slightly higher than the non-shadow values. For the purposes of identifying vegetation types and vegetation versus no vegetation, the corrected NDVI are distinct with no overlap and so perform well for classification.

<table>
<thead>
<tr>
<th>Range of NDVI values</th>
<th>Grass</th>
<th>Tree</th>
<th>Industrial</th>
<th>Exposed Soil</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-shadow</td>
<td>0.15-0.4</td>
<td>0.5-0.8</td>
<td>-0.1-0.1</td>
<td>0-0.1</td>
</tr>
<tr>
<td>Shadow</td>
<td>0-0.1</td>
<td>0.4-1.0</td>
<td>-0.05-0</td>
<td>0-0.05</td>
</tr>
<tr>
<td>Corrected Shadow</td>
<td>0.1-0.4</td>
<td>0.6-0.85</td>
<td>0-0.1</td>
<td>0.05-0.15</td>
</tr>
</tbody>
</table>
4.5 Shadow Detection Workflow

Figure 4.18 and Figure 4.19 show the developed workflow for determining which method of shadow classification would be most suitable depending on the available data. If multispectral data is available then the workflow in Figure 4.18 should be followed. Depending on the number of scenes, either the spectral responses of a single scene or change detection between scenes for multiple images, can be used. For a single scene, radiance (in lieu of reflectance) is preferable because it better represents the material properties of the ground surface (Lu et al., 2010). A threshold determined from the lowest wavelength spectral band (this has the highest difference between shadow and non-shadow responses) can be applied or SVM using all spectral bands as input (as this study has shown, this creates a higher performance classification). Given multiple spectral scenes, the location of the shadows must be determined as well as any apparent changes. Constant presence of shadows indicates poor performance for change detection as evidenced with the case study and the utility poles and trees between the 2016 and 2017 images. Cloud shadows will change over time and if the images are taken at different times during the day then the cast shadows will also move position. In these cases, change detection can be used to detect shadows, hindered by other significant changes such as snow cover or leaf-on versus leaf-off conditions.

Given the availability of LiDAR data, the recommended workflow is shown in Figure 4.19. If elevation data is provided then solar illumination data can be used, along with the DEM from the LiDAR data, to simulate the location of shadows. If this is not the case, then the “multispectral” branch of the workflow should serve as a guide. If the data is collected from an airborne platform then the location of cast shadows can be simulated, while satellite-based multispectral data may be affected by clouds along the signals path from the platform to the target. A cloud cover model for the region of interest should be used and if not available then the “multispectral” branch of the workflow can serve as a guide. Provided only LiDAR reflectance data is available the workflow
outlined in section 2.2 can be followed, whereby the correlation between each spectral band and the LiDAR reflectance data is calculated. If this correlation is high then the most correlated band provides input for the ratio with the LiDAR reflectance data. Either the threshold or SVM using all spectral bands and the ration can be used as input. If, however, the correlation is low, the brightness should be incorporated to calculate the LiDAR reflectance ratio. Given both elevation and reflectance data, both workflows (Figure 4.18 and Figure 4.19) should be applied for a combined shadow classification.
Figure 4.18: Shadow detection workflow based on multispectral data
Figure 4.19: Shadow detection workflow based on multispectral data and LiDAR reflectance data

4.6 Discussion of Results

The results from the shadow detection show that the incorporation of LiDAR reflectance is beneficial for increasing the performance of the non-shadow/shadow classification. By
incorporating this data into classification with the NIR, green and blue bands the overall performance increases to greater than 86%. This is primarily due to the fact that regions of low multispectral response, like the exposed soil regions, are not classified as shadow and therefore the LiDAR reflectance data becomes increasingly useful in scene populated with low reflectance targets. When classifying exclusively with the LiDAR/brightness ratio, the regions of strong shadow are classified well. Therefore, if the scene was composed exclusively of object cast shadows or other strong shadow types, then classification can be sufficiently performed by using this parameter alone. When examining the strongly cast shadow within the scene alone (i.e. the transmission tower or utility poles), the LiDAR/brightness performs as well, if not better than when using the NIR band, green band, blue band and the LiDAR/brightness ratio.

The results of this study also show that the identification and correction of the shadow regions improved NDVI mapping up to 90%. For regions in shadow, the NDVI is significantly lower than the non-shadow regions (up to 80%). By correcting these regions, the NDVI values now fall within the range of the non-shadow regions. This worked especially well for the grass and tree classes. However, corrected NDVI values can be higher than the original non-shadow values, as was the case for the exposed soil and industry regions. For the purposes of identifying specific vegetation types and vegetation versus non-vegetation, the range of NDVI values for the grass and tree classes were still distinguishable. The increase of the shadow values is limited since methods such as applying the colour correction twice, mean shifting the corrected shadow histogram to the non-shadow histogram or simply increasing the values through multiplication or addition, do not increase the colour corrected values and thus the NDVI values any further. In this study, the colour corrected values are still 30% lower than the non-shadow values. Therefore, NDVI mapping may still be influenced by shadows post-correction since the corrected and the non-shadow values are
still different. The more sensitive the classification is to the NDVI values, the more likely this will be an issue.

4.7 Conclusions

Overall, the incorporation of LiDAR reflectance into shadow detection methods improves the performance of shadow classification. This study has shown that the use of LiDAR reflectance data can improve the shadow/non-shadow classification by greater than 86%. When combined with the NIR band, the green band and the blue band, the LiDAR/brightness ratio produces the most accurate results. This study has also shown the Support Vector Machine produces the most accurate results when compared to decision tree, k-nearest neighbour and naïve Bayes machine learning algorithms. The use of LiDAR reflectance data into the established shadow detection workflow was determined. An accurate binary shadow mask can be used to correct the colour of the shadow regions, which in turn can be used for improved NDVI mapping. The calculation of NDVI was possible through the replacement of the NIR filter with a red filter in order to collect NIR data. The results shown here indicate that the corrected NDVI values allow for improved differentiation between the vegetation (grass and trees) classes and between vegetation (grass and trees) and non-vegetation (exposed soil and industrial buildings) classes.

The corrected multispectral and NDVI maps can be used in the Phase I site investigation process. For instance, vegetation mapping with NDVI can be used in the Phase I site investigation for mineral exploration as an initial indicator for the presence of ore bodies. For mixed-use urban areas specifically, information on the location and extent on existing developments, water bodies or soil properties can all be learned from multispectral data. This can be important for both geotechnical engineers who may have to design future developments as cities continue to expand. Geoenvironmental engineers can use multispectral data of mixed-use urban areas to determine
vegetation health and to locate and monitor regions of contamination. Therefore, correcting shadow regions in multispectral images has the potential to dramatically improve these types of site investigations.
Chapter 5

Application of Dual-Pol Synthetic Aperture Radar Intensity Data for Monitoring Changes in Northern Canada

5.1 Introduction

Since 1901, the average temperature of the Canadian Arctic has increased by 1-1.5°C and since 1950, the amount of precipitation has increased by 1-5mm/year (Vaughan et al., 2013; Hartmann and Ceppi., 2014). This trend is expected to continue as mean temperatures are predicted to increase by an additional 1-3.5°C and precipitation is predicted to increase by 10% by 2036 (Kirtman et al., 2014). A number of important changes that affect northern regions such as Canada include, but are not limited to, shoreline erosion (Brown et al., 2003; Soloman et al., 2005; Hinzman et al., 2005; Jones et al., 2009a,b; Gunther et al., 2013; Radosavljevic et al., 2016), ice cover seasonality (Markus, et al., 2009; Grebmeier et al., 2010; Comiso, 2010; Massom and Stammerjohn, 2010; Stammerjohn et al., 2012; Vaughan et al., 2013) and seasonal flooding and vegetation changes (Watson et al., 1997; Ford and Smit, 2004; Ford et al., 2006; Prowse et al., 2006; Chapin et al., 2012). In this research, Synthetic Aperture Radar (SAR) is evaluated as a means for monitoring shoreline erosion, ice cover seasonality and seasonal flooding in northern Canada (Mackenzie Delta, NWT). The overall goal is to establish workflows that incorporate this observational dataset (specifically dual-polarization SAR scenes) as part of monitoring process, which would contribute to both desktop (Phase I) and monitoring phases of larger-scale site investigations.

Increasing sea levels, combined with increasing wave run-up, higher intensity storm events and permafrost degradation along coasts, are expected to contribute to higher rates of shoreline erosion (Hinzman et al., 2005). The window for shoreline erosion to occur is limited to the summer months (3-4 months annually) as open, moving water is necessary for erosion (Overduin et al., 2014). Rates
of erosion in the Arctic are on average 2-6 m/year and can be as high as 10 m/year (Brown et al., 2003). These high rates of erosion can have many effects including threatening archeological sites (Shaw, 1998), reducing shoreline habitat (Feagin et al., 2005; Airoldi and Beck, 2007) and damaging infrastructure (Mittal, 2009; Prowse, 2009a). For example, the town of Tuktoyaktuk, NWT, which is located on the coast of the Beaufort Sea, has experienced high rates of shoreline erosion, which destroyed town infrastructure (Shaw et al., 1998). Shoreline erosion is currently monitored globally with the use of cartographic mapping (Thieler and Danforth, 1994; Genz et al., 2007; Dornbusch et al., 2008; Brooks and Spencer, 2010), aerial photogrammetry (Catalao et al., 2002; Moore and Griggs, 2002; Costa et al., 2004; Pierre and Lahousse, 2006; Mancini et al., 2013; Gibbs et al., 2015; Warrick et al., 2016), airborne and satellite optical images (Brown et al., 2003; Soloman et al., 2005; Jones et al., 2008, Pardo-Pascual et al., 2012), Global Navigation Satellite System (GNSS) measurements (Mills et al., 2005; Baptista et al., 2011), as well as airborne and terrestrial LiDAR (Rosser et al., 2005; Poulton et al., 2006; Jones et al., 2013; Montreuil et al., 2013; Obu et al., 2017). For regions in the Arctic, optical airborne and satellite data is by far the most commonly used technique (Brown et al., 2003; Jorgenson and Brown, 2005; Soloman et al., 2005; Mars and Houseknecht, 2007; Lantuit and Pollard, 2008, Lantuit et al., 2009, 2012; Jones et al., 2008, 2009a, 2009b; Karsli et al., 2011; Wobus et al., 2011; Gunther et al., 2013; Radosavljevic et al., 2016). Georeferenced optical images are used to create either shoreline control points or to digitize the entire location of the shoreline and a time series of optical images is used to determine how the shoreline changes temporally. Aerial photographs can provide centimeter-level spatial resolution while optical satellite data can achieve a spatial resolution of 0.25-5 meters. Typical temporal resolutions are 5-10 years and 3-8 days for airborne and satellite data, respectively. There is a large record of aerial photographs of Canadian coastlines dating back as early as the 1950’s (Mars and Houseknecht, 2007). Therefore, long term studies of shoreline erosion spanning multiple decades can be conducted by comparing a time-series of aerial photographs detecting change.
an ideal scenario, water, land and ice have distinct spectral signatures which can aid in mapping shorelines (Soloman, 2005). However, complications can arise due to inconsistencies from manual visual inspections (Gens, 2010). The coverage for airborne images is much greater than that of in-situ techniques such as time-lapse photography or traditional cartographic mapping surveys (Solomon et al., 2005; Jones et al., 2013). SAR has also been used for the detection of coastal erosion primarily through the use of interferometric synthetic aperture radar (InSAR), which uses the changes in the phase of backscattered radar signals (Buckely et al., 2002; Aly et al., 2012; Klemas, 2012; Joyce et al., 2014). However, InSAR techniques are not well-suited to natural landscapes, like the Canadian Arctic, as they have low coherence. Therefore, one of the objectives of this study is to determine the suitability of SAR backscatter intensity for monitoring shoreline erosion in The Mackenzie Delta, Northwest Territories, Canada. The SAR results will be compared to those generated using optical satellite images, which operate on different spatial scales and pose a number of challenges.

The times at which sea ice advancement (freeze-up) and retreat (melt) and duration between these two dates (melt period) is collectively called seasonality. The seasonality of ice cover has changed dramatically in the past four decades with an estimate of overall increases in melt period between 5.3-5.7 days per decade since 1979 (Smith, 1998; Vaughan et al., 2013). Changes in melt period seasonality is spatially dependent; for instance, the melt period for regions in the East Siberian Sea have increased by 3 months since 1979 (Belchansky et al., 2004; Stammerjohn et al., 2012). Longer melt periods can have serious ecological effects such as extended summer ranges for species of zooplankton and fish, including Wall-eye Pollock, Pacific Cod and Bering Flounder, and loss of sea ice habitat for larger marine mammals, most notably polar bears (Nelson et al., 2009; Fischbach et al., 2007; Grebmeier, 2010). Albedo, or the Earth’s ability to reflect solar radiation, is also affected by lengthening melt seasons (Vaughan et al., 2013). Ice is an important reflector of solar
radiation which reduces warming. Between 1979 and 2005, there was an increase in the amount of solar energy absorbed by the Arctic Ocean by approximately 4% per year due to decreased ice extent and shorter ice cover conditions (Perovich et al., 2007). This in turn has resulted in higher ocean temperatures as these waters absorb the solar energy rather than reflecting it away exacerbating the effects of global warming (Vaughan et al., 2013).

Three established techniques for monitoring the onset of melt, the onset of freeze-up and the melt period season are the use of satellite passive microwave emission data (Comiso et al., 1997; Smith, 1998; Drobot and Anderson, 2001; Parkinson, 2002; Belchansky et al., 2004; Stammerjohn et al., 2008; Comiso, 2010; Stammerjohn et al., 2012), satellite active microwave data (e.g. scatterometers and SAR data) (Winebrenner et al., 1994; Drinkwater and Liu, 2000; Forster et al., 2001; Kwok et al., 2003), and temperature data from a network of buoys (Colony et al. 1992; Martin and Munoz, 1997; Lindsay, 1998; Rigor et al., 2000) (see Table 5.1).
Passive microwave emission techniques are most commonly used for monitoring ice melt seasonality. It is advantageous because of the very high temporal resolution (daily) and continuous data record starting in 1978 until present day (Parkinson and Comiso, 2013). However, the spatial resolution is very low (25–55 km spatial resolution) so these techniques are typically applied to a larger region (i.e., the Arctic) as a whole rather than smaller areas. The ice temperature data also

Table 5.1: Overview of methods for monitoring ice cover seasonality for water bodies

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Methodology Overview</th>
<th>Typical Spatial Resolution</th>
<th>Typical Temporal Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passive Microwave Emission Data</td>
<td>Difference between channels calculated, thresholds set to separate frozen and melt conditions (ex. difference between 18.0 GHz and 37.0 GHz channel commonly used, if difference is &gt; 4000, then winter conditions, if difference is ≤ 10000, then melt onset conditions (Anderson, 1987))</td>
<td>25 – 55 km resolution</td>
<td>Daily or quasi-daily</td>
</tr>
<tr>
<td>Active Microwave Data</td>
<td>The beginning of melt is characterized by a significant drop in backscatter coefficient (≈5-10 dB in the C band)</td>
<td>10 – 30 m resolution</td>
<td>8 to 24 days</td>
</tr>
<tr>
<td>Buoy Temperature Measurements</td>
<td>Calculate daily averages and apply a 2-week running mean filter with a threshold of -0.1°C to −1.0°C to the time series of each grid point, melt defined when averages surpass this threshold and freeze defined when averages become less than this threshold</td>
<td>N/A (point data)</td>
<td>Daily</td>
</tr>
</tbody>
</table>
has very high temporal resolution (daily) but no spatial resolution. Therefore, it is commonly used as validation data for the other two methods (Forster et al., 2001). Unlike passive microwave data, active microwave has a high spatial resolution (10-30-meter resolution) but a lower temporal resolution (8-24 days). The Canadian Ice Service provides daily and weekly ice charts for important shipping routes in the region by using a combination of satellite and in-situ measurements including SAR (Tivy et al., 2011). Full-polarization SAR has been a useful tool for the identification of ice extent and type (Gill and Yackel, 2011; Geldsetzer and Yackel, 2014). RadarSAT-1 and RadarSAT-2 are Canadian SAR satellites and have been used in a number of these studies due to their ability to collect quad-pol data (Yackel and Barber, 2000; Daboor and Geldsetzer, 2014).

Passive microwave data is not suitable for regional scale (<10 km²) studies of ice seasonality due to its low spatial resolution so dual-polarization SAR may be able to allow for the study of smaller scale changes in ice melt (Agnew and Howell, 2003). Another objective of this study is to determine how SAR backscatter data can be utilized for monitoring ice cover seasonality, specifically the spring ice melt for the Mackenzie Delta study region.

Closely related to this topic is ice road operations, which are dependent on the thickness of the ice and are limited by how long the ice is present and strong enough to support vehicles. Therefore, their operation is likely to be affected by the warming climate. SAR data is explored herein as a monitoring tool for these roads. In addition, it may be possible to use their operation as indicators for ice extent, thickness and season. For example, ice roads require >5m of ice to operate (Masterson, 2009) so if the road is not usable then it can be concluded that the ice is no longer as suitable as it was in the past. The Tuktoyaktuk Ice Road, which passes through the Mackenzie Delta study region, is resolvable using SAR backscatter intensity so its presence can be used as a proxy for ice thickness.
Increasing temperatures and precipitation will contribute to higher levels of seasonal flooding and changes in the type and extent of vegetation in Arctic regions (Vaughn et al., 2013). The monitoring of flooding with SAR data has been well established (Ramsey, 1995; Kasischke and Bourgeau-Chavez, 1997; Townsend, 2001; Kussulet al., 2011; Matgen et al., 2011; Irwin et al., 2017; Irwin et al., 2018). For SAR backscatter intensity data, the response of SAR backscatter is dependent on the dielectric constant and geometric structure of the target. Thus saturated soils and vegetation have a lower intensity response due to their moisture content with very high dielectric permittivity. In addition, open water bodies can act as specular reflectors which results in a very low intensity response. Thus, SAR backscatter can be used to identify regions of water based on its unique signature and low backscatter. This makes it an ideal tool for the monitoring of seasonal flooding.

SAR has also been used for the monitoring of vegetation as the geometric structure of targets effects the intensity of the SAR backscatter. Vegetation scatters the emitted SAR wave in one of two ways. Vegetation can create a double-bounce signature as the emitted wave will bounce of the ground and then the base of the vegetation resulting in a high intensity response. Vegetation can also create a volume scattering signature as the emitted wave can get reflected from the leaves and branches of the vegetation. This results in creating a weak backscatter response (White et al., 2015). (Moran et al., 2002; Martinez and Le Toan, 2007; Minchella et al., 2009; Salas et al., 2010). Another objective of this study is to establish baselines of vegetation changes and seasonal flooding in the Mackenzie Delta study region.

5.2 Description of the Study Region

The study region is located in the north-western part of the Northwest Territories of Canada, east of the Mackenzie Delta where the East Channel of the Mackenzie River meets the Beaufort Sea, as seen in Figure 5.1.
The Mackenzie Delta study area is primarily made up of sedimentary deposits from the Quaternary period. There are six geological units present within this study region, as seen in Figure 5.1. The Moraine Veneer glacial deposits, outlined in green in the geologic map, are the oldest in the region and were deposited during the last ice age (30 Ka) (Duk-Rodkin and Lemmen, 2000). These deposits are composed of <2m thick till layers which overlie sandy or silty moraine deltaic sequences (Aylsworth et al., 2000). Glaciofluvial deposits, which are primarily composed of sand and gravel, were deposited during the retreat of the Laurentide Ice Sheet between 13-10 Ka (Duk-Rodkin and Lemmen, 2000). The Ice Contact deposits, outlined in red in the geological map, are composed of gravel and sand. These deposits commonly occur as hummocks or ridges, and are 2-30 m thick. Outwash plains and terraces, outlined in orange in the geological map, are composed of sand and gravel with some silt and peat. These deposits occur either flat or gently sloping and are 2-30 m thick (Aylsworth et al., 2000). Lacustrine plain deposits, outline in purple in the
geological map, were deposited in thermokarst lakes that formed and infilled during the Holocene. The deposits within the study area are composed of fine-grained sediment, primarily silt and clay, are typically 1-25 m thick. Eolian ridges, outlined in light pink in the geologic map, were formed by erosional process and primarily composed of sand with minor silt. The youngest deposits in the region are the Alluvial Plain deposits were composed of suspended sediments in the Mackenzie River. These sediments are deposited when the velocity of the river decreases when it meets the Beaufort Sea (Aylsworth et al., 2000).

![Geological map of study region outlining the extent of the five types of Quaternary sedimentary deposits within the area (modified from Dyke and Brooks, 2000)](image)

**Figure 5.2: Geological map of study region outlining the extent of the five types of Quaternary sedimentary deposits within the area (modified from Dyke and Brooks, 2000)**

This region is classified as an Arctic tundra region (Furgal and Prowse, 2008) and lies within the continuous permafrost (90-100%) zone and experiences snow/ice cover for the majority of the year (September to May). This region specifically experienced 1.75°C increase in yearly mean temperature and 3°C increase in mean temperature during the winter months between 1950 and 1998. Precipitation increased by 25% annually during this same time period, specifically 45% in the winter and 15% in the summer (Zhang et al., 2000). It is predicted that these trends will continue
as temperatures are expected to increase by 5-10°C and precipitation is expected to increase by an additional 40-80% by 2090 (von Salzen et al., 2013). The Mackenzie Delta has already been experiencing changes due to climate change, most prominently in permafrost degradation. Since 1970, the ground temperature has increased between 1.5-2.5°C (Burn and Kokelj, 2009) which has led to an increase retrogressive thaw slumps by a factor of 1.4 (Lantz and Kokelj, 2008).

The Mackenzie Delta study is ecologically significant as it is home to endangered species including the polar bear and wolverine (Environment Canada, 2018). The opening bay of the Mackenzie River, located within the study site, belongs to the Tarium Niryutait Marine Protected Area (TN MPA). The mixing of the Mackenzie River with the Beaufort Sea created brackish water with a high nutrient content attracting a great variety of fish. During the ice-free summer months, groups of the Eastern Beaufort Sea beluga whales enter the TN MPA. Their motivation for doing so is yet unknown but current theories suggest mating, calving or protection from predators (Harwood et al., 2014). The study region is located proximally to the Kendall Migratory Bird Sanctuary. This sanctuary provides safe nesting ground to 60,000 migratory birds including the Lesser Snow Goose, the White-fronted Goose, the Canada Goose, the Tundra Swan, the Black Brant and the Sandhill Crane (Fenge, 1982). The location of the Tarium Niryutait Marine Protected Area and the Kendall Migratory Bird Sanctuary can be seen in Figure 5.3.

The archaeological site of Kittigazuit is located in the south-west region of the study area. In the past, this site was used as the largest seasonal meeting place known in the Canadian Arctic between 1400-1900 and was used as a beluga hunting station by the Kitigaaryungmiut peoples. Today, the remains of six large winter houses and a number of traditional aboriginal graves are located here (Government of Northwest Territories, 2018). This location was designated an official National Historic Site of Canada and thus, its preservation in the face of climate change is significant.
Shoreline erosion could potentially affect this site since it is located proximally (<1 km) to the coast. Therefore, assessing the rates of erosion in this region can be used to understand the risk of shoreline erosion impacting this archeological site.

The Mackenzie Delta is also an important region in Canada economically. Reserves of oil have been found in the Beaufort Sea adjacent to the Mackenzie Delta study region. While it is not currently exploited due to the challenges in accessing the site and transporting oil from this location, it may become important in the future. It is estimated that approximately 206 million m$^3$ of oil and 350 billion m$^3$ of gas is located within the Kugmallit Bay region at the mouth of the Mackenzie River (Osadetz et al., 1998). Figure 5.3 shows the location of the wells and exploration permits for oil exploration in the Mackenzie Delta Region as of 2014.
Figure 5.3: The location of the Tuktoyaktuk Winter Road, the Tarium Niryutait Marine Protected Area and Kendall Migratory Bird Sanctuary, the location of oil and gas exploration wells, significant discovery licenses, production licenses within the Mackenzie Delta are also outlined (modified from Government of Northwest Territories, 2014)

Increased rates of shoreline erosion and flooding, and reduced ice cover can threaten the regions in the Mackenzie Delta study regions that have archeological, economic and ecological significance.
5.3 Description of Datasets

Synthetic Aperture Radar is a remote sensing technique that uses radio wavelengths (mm to cm) to sense the environment. SAR is an active system which means that it generates the signals that it uses to image the Earth. One of the advantages to this is that it is able to collect data in both day and night conditions, something that passive systems are unable to do. Radar reflections are able to provide a different view of the world since there is a low correlation to visible or thermal portions of the electromagnetic spectrum (Harger, 1970). The SAR satellite mission configuration can be seen in Figure 5.4.

Figure 5.4: Geometry of side looking radar where (A) is the flight path, (B) is the incidence angle, (C) is the swath width, (D) is the ground range direction and (E) is the azimuth
direction. The system scans from the near range (closest to the aircraft) to the far range (farthest from the aircraft) (modified from European Space Agency, 2014).

During the early development of radio monitoring systems, specific wavelengths of the radio waves were assigned arbitrary letters (e.g. C band represents wavelengths between 3.75 and 7.5 cm) (Lillesand et al., 2004). The bands with longer wavelengths (e.g. P and L) are able to penetrate through vegetation, dry soils and dry snow/ice better than bands of shorter wavelengths (e.g. X and K) (Henderson and Herrig, 1996). However, smaller wavelengths are able to produce SAR images of higher resolution. Therefore, different bands are appropriate for different applications (D’Iorio et al. 1995). The satellite mission data used in this study, TerraSAR-X and TanDEM-X both use X-band radar of 2.4 to 3.75 cm wavelengths.

Wavelength is the first of the primary factors influencing SAR transmission signals; the second is polarization (Henderson and Herrig, 1996). Non-polarized electromagnetic waves propagate in all directions perpendicular to the direction of propagation. Polarized waves are filtered so that they are transmitted and received as a single plane oriented parallel to propagation. Linear polarization is the most common in SAR applications, specifically horizontal linear (H) and vertical linear (V) polarizations. SAR systems that are able to transmit and receive in both horizontal and vertical planes have the ability to collect data in four possible combinations: HH, HV, VV and VH (Lillesand et al., 2004). TerraSAR-X and TanDEM-X are able to collect data in single polarization, dual-polarization or quad-polarization. TerraSAR-X and TanDEM-X are virtually identical satellites with near polar orbits at an altitude of 514 km, and an inclination angle of 97.44° and repeat period of 11 days (return to the same location every 11 days). The nominal acquisition direction is right-looking and data is collected at a look angle between X and Y. These satellites collect data in the X-band with a center frequency of 9.65 GHz (0.031m). Three different imaging modes are available which allow for the selection of resolution and scene size depending on the
application. For this study, the imaging mode StripMap was selected, which uses a fixed antenna beam and imaging illuminates the ground swath with a continuous sequence of pulses. The resulting strip scene has a continuous image quality in the flight direction. A series of 35 Synthetic Aperture Radar (SAR) scenes collected by TerraSAR-X and TanDEM-X between December 1, 2011 and August 28, 2014. Table 5.2 illustrates the characteristics of the SAR data used in this study.

Table 5.2: Specification of TerraSAR-X and TanDEM-X data used in the Mackenzie Delta Region

<table>
<thead>
<tr>
<th>Specification</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Band (m)</td>
<td>X (0.031 m)</td>
</tr>
<tr>
<td>Polarization</td>
<td>HH/VV</td>
</tr>
<tr>
<td>Beam Mode</td>
<td>StripMap</td>
</tr>
<tr>
<td>Ground Range Resolution (m)</td>
<td>1.2</td>
</tr>
<tr>
<td>Azimuth Resolution (m)</td>
<td>6.6</td>
</tr>
<tr>
<td>Scene Size (east-west x north-south)</td>
<td>15 km x 50 km</td>
</tr>
<tr>
<td>Repeat Period</td>
<td>11 days</td>
</tr>
</tbody>
</table>

Figure 5.5 outlines the data collection timeline of the SAR data. Since the scenes were primarily collected during the winter months (November to May), the majority of the SAR scenes are ice-covered. The three SAR scenes collected between late-May to June show the ice melting. The SAR scenes collected during the summer months (June to September) are ice-free.
Figure 5.5: Timeline of SAR data collection between December 1, 2011 and August 28, 2014. Blue circles represent scenes collected by TerraSAR-X and purple circles represent scenes collected using TanDEM-X.

5.4 Description of Methodology to Determine SAR’s applicability to Monitoring

5.4.1 Synthetic Aperture Radar Data Processing and Change Detection

SAR systems measure the backscatter of the transmitted radio wave, which is the portion of the reflected wave that is scattered back in the direction that it was transmitted from. Two components of this backscatter can be measured: the wave’s phase and its intensity (amplitude\(^2\)), as seen in Figure 5.4. These values are stored as a two-dimensional matrix of complex numbers with the intensity component stored as a real value and the phase component stored as an imaginary value. The exact value recorded within the pixel of the scene is a vector sum of each of the individual scatterers contained with the resolution cell (Moriera et al. 2013). Figure 5.6 outlines the SAR processing workflow used to detect changes over time in the SAR intensity data.

Prior to the interpretation of SAR data, a radiometric correction, which corrects for decreasing backscatter intensity in the range direction, must be applied. Due to the side-looking nature of SAR, the intensity of the image changes across the range direction. Pixels that are farther from the satellite
will appear darker than those closest to the satellite for the same radar cross section as demonstrated in Figure 5.7. This is principally caused by two geometric factors: (1) the size of the ground resolution cell decreases from near range to far range (as seen in Figure 5.7), reducing the strength of the return signal and (2) more significantly, backscatter is inversely related to the local incidence angle (as the local incident angle increases, the backscatter which is in turn related to the distance in the range direction. As a result, radar images will tend to become darker with increasing range (Ulander, 1996), hence the need for the radiometric correction.
The normalized radar cross section is a proxy for the size and ability of a target to reflect radar energy assuming that all of the radar energy is reflected equally in all directions. This normalized value allows for the comparison of SAR images taken at different times since the same intensity value should be consistent across all scenes. The radiometric correction ensures that the collected intensity values actually represent the radar cross section (Freeman, 1993).
Figure 5.7: Schematic demonstrating the backscatter intensity decreases and the range resolution increases as the incidence angle in the range direction increases

To convert the raw values, also called digital number, collected by the satellite into brightness values, the following equation is applied:

$$\beta_0 = ks \cdot |DN| \cdot 2$$  \hspace{1cm} (5.1)

where $\beta_0$ represents brightness values, $DN$ represents digital numbers, and $ks$ is a calibration factor. The factor is determined by the SAR satellite manufacturers by using targets in the field with a known brightness and measuring their brightness and calculating the difference between the true and recorded values (DLR, 2014). To calculate the normalized radar cross section, the following equation is applied:

$$\sigma^0 = (\beta_0 - NEBN) \cdot \sin \theta$$  \hspace{1cm} (5.2)
where $\sigma^0$ represents the normalized radar cross section, $\beta_0$ represents brightness calculated using equation 7, $NEBN$ represents the Noise Equivalent Beta Naught (the influence of various noise contributors), and $\theta$ represents the local incidence angle.

The shape and orientation of the structures within these areas must also be considered when evaluating radar returns. For example, two adjacent smooth surfaces will create a corner reflector which will have a very high response. This is especially true for vertical structures, i.e. mountains. “Layover” is a phenomenon that is caused by radar pulses that are reflected from the top of a vertical structure to arrive back to the antenna before those from the base of the structure. This causes the feature to appear as if it’s leaning towards the satellite. The opposite of this is “foreshortening” when the pulses reflected from the base of the slope arrive back to the antenna before those from the top. This makes it appear as if the surface of the vertical structure facing the satellite is much smaller in the range direction than it actually is. Layover effects occur when the terrain slope facing the satellite is steeper than the look angle, while foreshortening occurs when this slope is shallower than the look angle. The areas on the slope that face away from the satellite will return weak to no return signals and so will appear dark in the SAR image (Lillesand et al., 2004). The Range-Doppler Terrain Correction corrects for the effects of foreshortening and layover, as well as the varying ground resolution caused by the different slopes of the terrain. The Range-Doppler Terrain Correction uses the position of the satellite in orbit during data acquisition and a reference digital elevation model (DEM) to correct the pixel-coordinates and the pixel backscatter intensity values of the backscatter intensity image (Bayer, 1991). For this study, the Canadian Digital Model (CDEM) was used as the reference DEM for the Range-Doppler Terrain Correction. The CEDM used had a resolution of 20m, a horizontal accuracy of 10-25m and a vertical accuracy of 2-15m. This DEM was selected as it had the least number of data gaps of the DEMs for this region. To
correct for the varying ground resolution, the image was re-sampled from Slant-Range/Azimuth coordinates to Ground-Range/Azimuth coordinates using bilinear interpolation (Small, 2011).

To aid in the interpretation of changes over time, the intensity values of each SAR scene was normalized by taking the mean intensity of each scene and subtracting it from the intensity values of each pixel. This simplified change classification as all no change values across each 34 change maps were represented by zero, as represented in Figure 5.8.

Figure 5.8: Normalization methodology (1) original values which are not centered around zero, (2) the mean is then subtracted from each image, (3) normalized values which are now centered on zero.
A “master scene” is selected from which all other scenes would be compared. For this study, the June 28th, 2012 scene was selected as it was one of three “ice-free” scenes and had a high contrast between the water and vegetation classes of the scene allowing for easy differentiation. Each scene was overlaid onto the master scene and any regions that did not overlap between datasets were removed. The spatial resolution of both the master scene and the scene that was being subtracted was reduced by a factor of three for computational purposes. To ensure that this reduction of spatial resolution would not affect the results, the same scenes were compared pre- and post-resolution reduction and no significant differences were found. The 19 scenes that were collected prior to June 28th, 2012, were subtracted from the master scene while those that occurred afterwards had the master scene subtracted from them. This was done to ensure that all increases in dB over time were represented as positive changes and all decreases in dB over time were represented as negative changes, resulting in 34 difference scenes. The difference maps were classified as positive change, negative change and no change using the thresholds seen in Figure 5.9. A threshold of -2 to 2 dB was selected to represent regions of no change and was found by comparing regions where no significant changes occurred (e.g. still water remained still water) and selecting a threshold that fully represented the amount of noise in this class. Values greater than 2 dB were considered positive changes while values less than -2 dB were considered negative changes. The two change classes were further broken down into “small” and “large” change classes. A value of 6 dB was selected to separate the small and large positive changes and a value of -6 dB was selected to separate the small and large negative changes. These threshold values were selected by manually examining the scenes and determining the change values that represented significant changes within the same land cover type (e.g. changes in backscatter from vegetation growth) and the change values that represented significant changes between land covers (e.g. from water to vegetation). It was found that changes within land cover types were represented by values between 2 dB and 6 dB while changes between land cover types were represented by values greater 6 dB.
This range of change values is consistent with previous studies on change detection (Rignot and van Zyl, 1993; Villasensor et al., 1993).

Figure 5.9: Thresholds selected to segregate the change maps into five change classes

5.5 Optical Satellite Data, In-Situ Water Level and Temperature Datasets and Processing

In addition to SAR data, 5 Landsat-7 and 3 Landsat-8 true colour scenes were used. There is no relationship between the visible and radio portions of the electromagnetic spectrum and therefore different information about the environment within the scene is acquired. Since SAR emits signals at a much longer wavelength than optical wavelengths which is able to penetrate, clouds, vegetation, dry soils and dry snow/ice depending on the wavelength used (Henderson and Herrig, 1996). It is because of these different wavelengths that SAR methods and optical methods are able to detect different land cover features. The response of SAR backscatter is dependent on the dielectric constant and the roughness of the target while the response of optical measurements is dependent on pigmentation and saturation of the target. In addition to providing a different perspective on the study region, the use of optical data is an established method for the detection shoreline erosion and so can provide valuable validation information for our attempt to detect
shoreline erosion with SAR. Landsat-7 was launched in 1999 and Landsat-8 was launched in 2013 and both missions collect multispectral data within the visible, infrared and thermal portions of the electromagnetic spectrums (Landsat-7 collecting eight spectral bands and Landsat-8 collecting eleven). For this study, we were interested in information from the red, blue and green portions of the electromagnetic spectrum, as summarized in Table 5.3.

Table 5.3: Specifications of Landsat-7 and Landsat-8 multispectral scenes

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bands Used</td>
<td>Landsat-7: 1 (0.45-0.52 µm), 2 (0.52-0.60 µm), 3 (0.63-0.69 µm)</td>
</tr>
<tr>
<td></td>
<td>Landsat-8: 2 (0.452 - 0.512 µm), 3 (0.533 - 0.590 µm), 4 (0.636 - 0.673 µm)</td>
</tr>
<tr>
<td>Resolution (m)</td>
<td>30</td>
</tr>
<tr>
<td>Scene Size (east-west x north-south)</td>
<td>183 km x 170 km</td>
</tr>
<tr>
<td>Repeat Period</td>
<td>16 days (Landsat-7 and Landsat-8 offset by 8 days)</td>
</tr>
</tbody>
</table>

In 2003, the Scan Line Corrector in Landsat-7 failed which has affected all Landsat-7 scenes collected since this date, including the three used for this study. The errors in the Scan Line Corrector result in linear data gaps that extend from the center of the image out to the sides. This has created some difficulty in the interpretation of three of the Landsat-7 scenes since portions of the study region are missing.

In-situ water level data collected from a single tide gauge located on the eastern shore of the East Channel of the Mackenzie River was acquired from the Government of Canada. This data was used to determine the baseline for changes in water level over the course of the SAR data collection time period. Temperature data from an in-situ weather station located in Tuktoyaktuk was also acquired.
from the Government of Canada. Figure 5.10 outlines the data collection timeline for these three datasets.

![Data acquisition periods for Landsat (green), in situ water level data (blue dashed line) and in situ temperature data (red dashed line)](image)

**Figure 5.10: Data acquisition periods for Landsat (green), in situ water level data (blue dashed line) and in situ temperature data (red dashed line)**

### 5.6 Results of Change Detection Analysis using Multi-temporal SAR

This section will discuss the applicability of SAR when applied to shoreline erosion, ice cover seasonality and vegetation/flooding monitoring.

#### 5.6.1 Shoreline Erosion

To establish a baseline for shoreline erosion in the Mackenzie Delta study region, a time series of Landsat data over this region was compared. Figure 5.11 shows Landsat-7 and Landsat-8 data taken two years apart on June 20, 2012 and July 13, 2014 respectively. Summer scenes were also used as the shoreline is not visible in the winter due to ice cover. To determine how SAR would perform when applied to shoreline erosion monitoring, differences in the shoreline of the Mackenzie River were analyzed by comparing multi-temporal SAR intensity data and associated change maps. Figure 5.12 illustrates five intensity scenes approximately evenly distributed throughout the study period taking into account satellite data acquisition periods and seasonal variations. These scenes were selected to illustrate the location of the shoreline over time.
Figure 5.11: Landsat-7 natural colour image taken on June 20, 2012 (top) and Landsat-8 natural colour image taken on July 13, 2014 (bottom). Note that in the top image, the scan-line oscillator was broken and so stripes of no data (black) are found in the image.
Figure 5.12: Time series of the southern shoreline (left) and overall changes between December 1, 2011 and March 14, 2015.

In Figure 5.12, the location of the shoreline seemingly remains constant over time. From these results it is evident that both the Landsat and the SAR datasets cannot resolve the shoreline erosion for this study region. Previous shoreline erosion studies for the Mackenzie Delta study region have
been completed by Soloman et al. (2005) and O’Rouke et al. (2010) through the use of air photos over a 30 and 60-year period, respectively, to calculate changes in the shoreline. The results from these two air photo studies indicate that the shoreline in the Mackenzie Delta study region was eroding at a rate of 1m or less per year. The resolution of StripMap TerraSAR-X data used in this study is between 1 to 6 meters, therefore a longer time series would be required to resolve shoreline erosion. Alternatively, a higher resolution imaging mode for SAR data collection (e.g. Staring Spotlight which has a resolution of 0.25 to 0.6 meters) could be used. In addition, the identification of the shoreline in the backscatter intensity can be challenging as the water-land boundary may not necessarily represent the location of the coast. Fluctuations in the daily tides or seasonal water levels will change the location of the water-land boundary without changing the location of the shoreline. For this region, the daily tides fluctuate on a scale of 20-50 cm while seasonal fluctuations occur on a scale of 1m. Therefore, from this study we cannot make conclusions concerning the applicability of SAR backscatter intensity to the monitoring of shoreline erosion in Canadian Arctic regions.

5.6.2 Monitoring of Ice-Melt Period in the Mackenzie Delta between 2012 and 2014

As water and ice have distinct radar backscatter intensity signatures, these two land cover types are distinguishable in SAR intensity data. Therefore, their extents can be monitored to detect changes over time. Figure 5.13 shows the progression of ice melt for 2012 and 2014 for the Mackenzie Delta Study region.
Figure 5.13: SAR intensity data for the initiation of ice melt over time for 2012 (A) displaying data before the initiation of melt, (B) displaying the initiation of melt and (C) displaying the initial exposed water during melt.

As seen in Figure 5.13A, on May 3, 2012 the scene is completely ice covered. Figure 5.13B shows that on May 14, 2012 the river ice is now covered with water, which decreases the intensity signal. Figure 5.13C shows that on May 25, 2012 there are regions located adjacent to the islands within the south-west portion of the Mackenzie River that are exposed water.
Figure 5.14: SAR intensity data for the end of ice melt period over time for 2012 with (D) displaying the midpoint of the melt period and (E) displaying the end of melt season and (I) displaying post-melt season.

Figure 5.14D shows that on June 5, 2012 that the south-west portion of the river is now totally exposed while the north-west portion is still ice-covered. This was taken during the highest water levels and highest water turbidity which is most likely the reason why the water appears higher in dB than the ice, which would have been covered by a layer of melt water. Figure 5.14E shows that
on June 16, 2012, the river is now completely devoid of ice while the lakes are some lakes still ice-covered. Finally, Figure 5.14F shows that on June 27, 2012 all ice has melted by this point.

Figure 5.15: SAR intensity data of ice melt over time for 2014 with (G) displaying the midpoint of ice melt and (H) displaying the end of melt season and (I) displaying post-melt season

Figure 5.15G – Figure 5.15I show the period of ice melt that overlapped with the satellite collection dates for 2014. Figure 5.15G shows that on June 12, 2014 most of the ice from the river has melted
with exception of the northern most section of the river. On this date the rivers are still ice covered. Figure 5.15H shows that on June 23, 2014 all of the river ice is gone but some of the ice within the rivers has remained. Finally, Figure 5.15I shows that on July 15, 2014 the ice from the all the rivers and the lakes have now melted. In order to validate the ice melt results, the Landsat-7 and Landsat-8 natural colour scenes were compared to the SAR scenes of a similar collection date. Figure 5.16- Figure 5.18 illustrates the multi-temporal Landsat data which was used to compare to the SAR data.

Figure 5.16: Landsat 7 natural colour image for the initiation of ice melt over time for 2012 with (A) displaying data before the initiation of melt, (B) displaying the initial exposed water during melt and (C) displaying the retreat of ice in the Mackenzie River
Figure 5.16A shows that on May 12, 2012 cracks in the ice indicate the beginning of the melt process. This is similar to the May 14, 2012 SAR scene which shows flooded ice indicating the beginning of the melt process. Figure 5.16B shows that on May 28, 2012 ice around the islands has melted, exposing the water underneath. This is similar to the May 25, 2012 results which also show melting around the islands. Figure 5.16C shows that on June 6, 2012 the ice in the river has retreated to the northeast corner of the scene while the lakes remain ice covered.

Figure 5.17D shows that on June 13, 2012 the ice on the river have almost entirely melted with the exception of the northern most part of the river. This differs slightly from the June 16, 2012 SAR scene which shows that there is no ice in the river. However, this can most likely be attributed to the possibility that the ice here melted in the three days between the Landsat and SAR scene collection dates. Both Landsat and SAR scenes show ice remaining the lakes. Finally, Figure 5.17E shows that on June 27, 2012 that all ice has melted in the region. This is consistent with the June 27, 2012 SAR scene.
Figure 5.17: Landsat 7 natural colour image for the end of ice melt over time for 2012 with (D) retreat of ice from the study region in the Mackenzie River but ice located in lakes and (E) displaying post-melt season.
Figure 5.18: Landsat-8 natural colour image data of ice melt over time for 2014 with (F) ice retreat in the Mackenzie River but not in the lakes (G) displaying the end of melt season and (H) displaying post-melt season.

Figure 5.18F shows that on June 11, 2014 the river ice has almost completed retreated with the exception of the northern most part of the river and the lakes remain frozen. This is consistent with the June 12, 2014 SAR scene which also shows river ice in the northern most section of the river and ice on the lakes. Figure 5.18G shows that on June 27, 2014 the river ice has completely melted, as has the ice on the lakes. This is different than the SAR scene collected on June 23, 2014 but this is again most likely due to the ice melting over the four days between collection dates. Finally, Figure 5.18H shows that on July 15th, there is also no ice cover which is consistent with the July
15, 2014 SAR scene. As passive microwave data lacks the resolution necessary to monitor our study region and buoy temperature data is not available, the correlation between Landsat and SAR was used for validation.

Ice road operation is closely linked to ice seasonality as their operation is limited by the thickness of the ice. The Tuktoyaktuk Winter Road was an ice road that passed through the study region during the winter travelling from Inuvik to Tuktoyaktuk. This is clearly visible in the SAR intensity data and even more so in the change maps. Figure 5.19 shows SAR intensity taken before and after the ice roads construction in 2011/2012. At the end of the season, the road melts away with the melting of the ice cover, as illustrated in Figure 5.20. By looking at the SAR data collection it can be determined when the road is constructed and decommissioned. These dates can be seen in Table 5.4. Such information would be of use for site investigations in the region as the main route for transporting materials onto potential sites for further investigation.

Figure 5.19: (A) December 1, 2011 SAR scene prior to construction of road; (B) Difference image between December 1 and December 12 scenes with the road showing as a positive change; (C) December 12, 2011 SAR scene after construction of the road
Figure 5.20: (A) SAR intensity data collected on June 5, 2012. On this date the ice road passes through the entire scene. (B) SAR intensity data collected on June 16, 2012. On this date the ice road is limited to the ice cover in the northeast section of the scene.

Table 5.4: Dates of construction and melting of ice road for the 2011-2012, 2012-2013 and 2013-2014 seasons. N/A represents no data collected for this period.

<table>
<thead>
<tr>
<th>Season</th>
<th>Ice Road Construction</th>
<th>Ice Road Melt</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011-2012</td>
<td>Between December 1, 2011 and December 12, 2011</td>
<td>Between June 5, 2012 and June 16, 2012</td>
</tr>
<tr>
<td>2012-2013</td>
<td>Between November 28, 2012 and December 9, 2012</td>
<td>N/A</td>
</tr>
<tr>
<td>2013-2014</td>
<td>N/A</td>
<td>Between June 1, 2014 and June 12, 2014</td>
</tr>
</tbody>
</table>

5.6.3 Seasonal Flooding and Vegetation Changes
Seasonal flooding within the low lying-deltaic regions can be seen within the June 27th 2012 SAR scene. Figure 5.21 shows the locations of two such flooded areas represented in Figure 5.22 and Figure 5.23.
Figure 5.21: June 27, 2012 SAR scene with flooding locations outlined. (A) The location of the flooding shows in Figure 5.22 (B) the location of the flooding shown in Figure 5.23.

Figure 5.22: (A) SAR intensity data collected on June 16, 2012 prior to flooding, (B) change map June 16 2012 scene and June 27 2012 scene, (C) SAR intensity data collected on June 16, 2012 during flooding (D) change map between June 27, 2012 scene and June 23, 2014 scene, (E) SAR intensity data collected on June 23^rd, 2014 post flooding.
As seen in Figure 5.22 and Figure 5.23, on June 16, 2012 the rivers are at their normal width. On June 27, 2012 these rivers become significantly wider due to flooding which shows up in the change maps as a strong negative change in intensity. In addition, the scene taken on June 23, 2014 was shown as no SAR data was collected immediately after June 27, 2012. This scene was selected since it is a year after the flooding and so can be used to determine if the flooding is seasonal. Since this flooding is small (magnitude of meters), it is not captured well by the Landsat data. The water level data available for this region on this date showed that the water level was not significantly greater (on the order of cm) than previous collection dates. Tidal data was also checked. While tidal data was not available for this date, the tides in this area range between 0.2 to 1.0m. Therefore, tidal changes would not be resolvable by the SAR data.
Vegetation in-growth can be seen within the August 28, 2014 SAR scene. Figure 5.24 shows the locations of two such vegetated areas represented in Figure 5.25 Figure 5.25 and Figure 5.26 Figure 5.26.

Figure 5.24: August 28, 2014 SAR scene with flooding locations outlined. (A) The location of the flooding shows in Figure 5.25 (B) the location of the flooding shown in Figure 5.26.
Figure 5.25: (A) SAR intensity data taken on June 23, 2014 prior to vegetation in growth, (B) SAR intensity data taken on August 28, 2014, during vegetation in growth, (C) Landsat-8 natural colour image taken on June 27, 2014, (D) Landsat-8 natural colour image taken on September 8, 2014. Locations of vegetation growth are highlighted in orange.
Figure 5.26: (A) SAR intensity data taken on June 23, 2014 prior to vegetation in growth, (B) SAR intensity data taken on August 28, 2014, during vegetation in growth, (C) Landsat-8 natural colour image taken on June 27, 2014, (D) Landsat-8 natural colour image taken on September 8, 2014. Locations of vegetation growth are highlighted in orange. In addition, (A) shows examples of layover (blue) and shadow (pink).
One of the challenges of SAR backscatter intensity data is the complexity of the interaction between the emitted radar signal and the target. In Figure 5.26, layover is seen as bright backscatter intensity on the eastern shore of the lake, which is the result of the vegetation located along this bank. This high backscatter intensity changes between the two SAR collection dates and so could be misinterpreted as changes in vegetation. For the June 23, 2014 image, a region of low backscatter is found on the western shore. This is likely the result of shadows cast by the adjacent vegetation.

To improve the identification of flooding and vegetation, the SAR scenes can be classified into specific land covers using quad-polarization SAR data (Wdowinski et al., 2004; Hong et al., 2015). For instance, Banks et al. (2012) have successfully applied quad-pol TerraSAR-X data to the land cover classification of the Mackenzie Delta region. However, the resolution of SAR backscatter images is reduced when all four polarizations are collected. The flooding and vegetation changes detected using the dual-pol SAR backscatter intensity data are very fine, between 10’s-100’s meters in size. Therefore, these may go undetected by quad-polarization scenes as they typically have resolutions of ≥15m.

5.7 Arctic Monitoring Workflows
The overall objective of this chapter focused on determining how SAR datasets can be incorporated into various monitoring applications in northern Canada with the aim of improving overall site investigation. To demonstrate how SAR backscatter intensity data can be integrated into the current Arctic monitoring workflows, the use of SAR data for ice cover seasonality is described here. Figure 5.27 outlines the integration of SAR intensity data as part of the workflow for the monitoring of ice over seasonality. It is expected that such a process will become more relevant and sought after as the changes in the Arctic become more pronounced in the (near) future.
Figure 5.27: Workflow used to determine which ice over seasonality monitoring technique should be used to monitor past changes for geological site investigation. For the >100km² spatial scale, different paths should be followed to monitor past changes for Phase I of geological site investigation (outlined in blue) and to monitor future changes for Phase III of geological site investigation (outlined in green).

As shown in Figure 5.27, the spatial scale of the study region is of utmost importance. For both Phase I and Phase II site investigation, passive microwave data is best for studies of regions that are greater than 100 km² as it has very high coverage and low resolution. Phase I and Phase III differ at this point as passive microwave data has a very long data collection history over sea ice which would only be relevant for Phase I investigation. For Phase I site investigation, a decision
on whether sea ice or land ice is being studied should be made. If sea ice is the topic of site investigation, then as mentioned there is historical passive microwave data. If, however, land ice is the topic of site investigation, then the user must check to see if passive microwave data has been collected over the region in the past. For Phase III site investigation at the 100 km² study region scale, passive microwave data should be ordered for the monitoring of ice cover seasonality.

If the study region is smaller, then active microwave data or localized in-situ buoy temperature data may be available. As can be seen from the figure, both the spatial and temporal resolution requirements will dictate the type of datasets that can be used. Active microwave data, which includes SAR, is suitable for smaller studies that focus on specific regions, usually 10 – 100km² in size. If, however, the study region is very small, less than 10 km², then the user can either use high resolution SAR data, such as that captured using Staring Spotlight Mode by TerraSAR-X, or if daily measurements are required, buoy temperature data can be used. It should be noted that buoy temperature data are in-situ measurements and consequently localized.

5.8 Conclusions
It was the aim of this study to determine the suitability of dual-polarization SAR data for the monitoring various processes in northern Canada, specifically shoreline erosion, ice cover seasonality and seasonal flooding/vegetation changes. The results from the shoreline erosion study demonstrated that SAR backscatter intensity data was not able to resolve changes in the shoreline. Based on the spatial resolution of the SAR data used, a significantly longer study period would be required for the detection of shoreline erosion (estimated at approximately ≤1m/year). Higher resolution SAR data could also be applied to the Mackenzie Delta which would be able to capture fine scale shoreline erosion. This could be significant for the Mackenzie Delta study region both for archaeological and economic factors. The Kittigazuit is located proximal to the shoreline and
may be damaged in future years due to erosion. In addition, shoreline erosion can threaten large-scale infrastructure projects (such as the construction of pipelines). Thus, detailed site investigation in this area involving higher spatial and temporal resolution SAR datasets is recommended. It should be further noted, that this investigation demonstrates the complexity of incorporating observations as various scales to complex shorelines where the target surface varies with the seasons.

The results of the ice cover seasonality study were more conclusive. The backscatter intensity data was able to detect the spring ice melt for the 2012 and 2014 seasons. The spatial resolution of the SAR backscatter images is on the order of 1-6m and so can provide detailed spatial information on how the ice retreats. For instance, it can be seen from the results that the ice within the Mackenzie River melts ≥11 days before the ice within the lakes. When compared to the established methods, the spatial resolution of SAR is finer than that of passive microwave intensity and the spatial coverage is greater than that of in-situ techniques like buoy temperature data making SAR data preferable for regional analyses (10-100km²). SAR data can be used for the monitoring of sea ice cover changes which can be useful for a variety of applications related to climate change including studying its ecological affects in the Mackenzie Delta region. For instance, the changes in the ice cover period can affect a number of the endangered animals that live in the Mackenzie Delta region, most notably the polar bears whose populations are already diminishing due to the reduction in sea ice (Regehr et al., 2010; Bromaghin et al., 2015). SAR was also able to detect the construction and destruction Tuktoyaktuk Winter Road. This has site investigation implications as the presence of the winter road can be used to assess the accessibility of northern regions and can also be used as a proxy for ice thickness. One possible way to improve on this methodology is to collect full polarization data to classify regions of water and ice, in order to provide a more detailed time series of melting. Therefore, it can be concluded that SAR can be utilized for the Phase I and Phase III
portions of geological site investigation to determine the past changes in ice cover seasonality, as well as the monitoring of future changes.

The SAR backscatter intensity data also showed fine-scale seasonal flooding and vegetation growth on the scale of 10-100m. This has implications for Phase I and Phase III of geological site investigation. Flooding patterns would be useful to determine during the Phase I of site investigation as this could affect decisions such as site selection for geotechnical engineering projects. Seasonal flooding is also a component of geoenvironmental hazard assessment and the use of SAR could compliment other data sources to provide a wider breadth of information when making this assessment. In addition, the monitoring of flooding and vegetation changes once the geological engineering project has been completed would be useful to determine either if the presence of the engineering project is affecting the surrounding environment or if there are changes in the surrounding environment that could affect the stability of the project. Therefore, the incorporation of SAR into site investigation procedures can be very beneficial.
Chapter 6

Conclusions

It was the objective of this thesis to investigate the use of remote sensing datasets acquired at various spatial (and temporal) scales from three different platforms (desktop, airborne and satellite) for improved phased site investigation in geological applications. In particular, established workflows were re-conceptualized in order to incorporate these new datasets.

The smallest scale (<m) examined the advantages and challenges of close-range 3D laser scanning when applied to the digitization of geological hand-samples, namely rocks, minerals, fossils, and sediments. Through a detailed literature review it is evident that close-range 3D laser scanning is a useful tool for the morphological study of the geological hand-samples and has been widely applied in the fields of paleontology, rock mechanics and sedimentology. The most promising aspect of this process is the use of 3D datasets in digital sharing environments (and 3D printing) to be used as educational tools in academic environments, for repeat testing for destructive tests and as an additional database for desktop studies of geological site investigations. Challenges in scanning arise if the hand-sample target is retro-reflective or translucent, which can be mitigated through the use of talc powder which creates a scattering surface which increases the amount and intensity of backscattered waves. A case study was completed to digitally calculate the grain-size distribution of ore minerals, with results compared to those generated from an SEM (current state-of-practice). It was found that the laser scanner and SEM produced comparable results in the range 1-10 mm². Due to greatly different resolution of the laser scanner and the SEM (mm vs nm) there significant differences in the grain sizes the two instruments are able to detect. Therefore, the decision to use laser scanning over SEM analysis would be based on the resolution required for the grain size analysis, for a typical desktop laser scanner a grain size of >0.5mm².
The regional scale (>\text{m}^2) application involved determining the utility of LiDAR reflectance data for improved shadow detection in multispectral images. It was found that the addition of LiDAR reflectance when combined with the spectral bands as input into shadow classification using Support Vector Machines increased the performance of the classification to greater than 95%. To mitigate the effects of shadows in multispectral images for improved NDVI mapping, four methods of colour correction were tested. It was found that Reinhard’s colour transform performed the best and was able to increase the colour values of the shadow regions by 40%. The mitigation of shadows within the multispectral images improved subsequent vegetation mapping using NDVI by 90%. Vegetation mapping has been employed for a variety of geological applications but has been underutilized for geological site investigation. The incorporation of vegetation mapping into Phase I site investigation can provide valuable information on the soil properties in their region of interest, and can be used as an indicator for the presence of mineral deposits.

The large scale (>\text{km}^2) application in this thesis evaluated how SAR backscatter intensity data can be utilized for the monitoring of temporal changes within northern regions of Canada, specifically the Mackenzie Delta, Northwest Territories. It was found that SAR backscatter intensity data was suitable for the monitoring of ice cover seasonality, seasonal flooding and seasonal vegetation growth. SAR backscatter intensity was also applied to the monitoring of shoreline erosion. The SAR backscatter results showed no evidence of shoreline erosion but this was consistent with the results generated using optical data, the current state-of-practice, and previous studies of the region. SAR backscatter intensity was then integrated into the workflows of ice cover seasonality. Compared to the established techniques of ice cover seasonality, SAR backscatter intensity is able to provide higher spatial resolution than passive microwave techniques and high spatial coverage than in-situ buoy measurements and so is best suited for regional studies. The incorporation of SAR into Phase I site investigation enables geologists to make an assessment on the geological hazards.
of shoreline erosion and establish a baseline of ice cover seasonality. SAR can also be used for Phase III site investigation for the monitor of ice cover changes due to the changing arctic climate. This can have a wide range of applications from the monitoring of land cover and wildlife habitat to the geotechnical monitoring of ice roads.

6.1 Future Work

There is still much work to be done for the seamless integration of remote sensing datasets into geological site investigation. Digital models of geological hand samples have significant potential for enhancing site investigation. Online databases containing thousands of downloadable models of geological samples could be an important source of information for the Phase 1 portion of site investigation. The 3D digital models of samples can be shared, downloaded and hand sample interpretation could be made directly from the digital models. Shape parameters, like angularity or roughness, can be automatically calculated using morphology of the digital hand samples providing initial estimates for geotechnical or geoenvironmental design. The 3D digital models can also be 3D printed and subjected to physical testing to calculate geotechnical design parameters such as shear strength. To accomplish this, relevant metadata like the coordinates of hand sample’s location, orientation, mass attributes, unit of origin, mineralogy etc. must be made available.

Airborne data is no longer limited to just photographs. Currently, airborne platforms can carry a variety of sensors including Side-Looking Airborne Radar (SLAR), radiometers, or hyperspectral cameras. SLAR and LiDAR measurements can be used to create high-resolution DEMs of the site of interest. This can be important for a variety of geological applications such modeling water flow in hydrological studies or assessing slope stability in geotechnical studies. Radiometric datasets can be used in Phase I of geoenvironmental or mineral exploration studies to identify locations of high uranium concentrations. Images created using hyperspectral cameras can be used to for Phase
I of geological mapping investigations as different minerals will have varying spectral responses and the high spectral resolution of hyperspectral cameras can better distinguish between mineral types. In addition to remote geological mapping, hyperspectral data can be used in Phase I site investigation for mineral exploration to identify mineral deposits and their associated alteration. There is great potential for the incorporation of a wider variety of airborne remote sensing data into geological site investigation as was shown through the incorporation of LiDAR reflectance data to enhance NDVI mapping.

Satellite data can achieve very high spatial coverage, as well as high temporal resolution. SAR data in particular can be further exploited for the geological site investigation process. Repeat passes of SAR data can be used in both the Phase I and Phase III portion of geological site investigation to assess geological hazards such as landslide or ground subsidence for a particular site. Land cover classification using SAR data can be map the location and extent of water bodies, vegetation, ice etc. for Phase I site investigations. The full applicability of SAR for geological site investigation has yet to be determined.

Three vastly different applications at various scales were evaluated for the integration of remote sensing datasets for enhanced geological site investigation. For the Phase I portion of site investigation, remote sensing can provide a wealth of information. This can be especially important for sites that are remote or otherwise difficult to access. Because the use of these datasets is in fact an area of intense interest, it must be evaluated on a case-by-case basis. An understanding of the strengths and limitations of each technique should be conducted prior to incorporating the datasets into the conventional workflows. Finally, no remote sensing dataset can be properly acquired (from any platform) without careful consideration of the physical and technical limitations of the sensors as well as a holistic understanding of the complicated data processing strategies.
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doi: [10.1016/j.rse.2014.06.012](https://doi.org/10.1016/j.rse.2014.06.012)
Appendix A

Scanning Geological Hand-Sized Samples: Lessons Learned

The application of talc powder on the surface of natural targets increases the number of laser returns for retro-reflective or translucent minerals. Talc powder creates an opaque scattering surface reducing the area with data gaps in the resulting point cloud. Figure A.1 illustrates the texture map and point cloud of a pyrite sample with and without the coating of talc. The percent data loss between the two scans is approximately 17% without the talc coating. While the percent data loss is decreased using the talc, the colours displayed in the texture map are greyed out due to the talc and do not accurately represent the true colour of the sample. Figure A.2 illustrates the texture map and point cloud of a galena sample with and without the coating of talc. The percent data loss between the two scans is approximately 30% without the talc coating. The samples show in A1 and A2 were scanned by Fouad Faraj.

Figure A.1: Texture map (left) and point cloud (right) of a pyrite sample scanned at 1,084 pt/cm². Scans of the pyrite sample without (A) and with talc coating (B). Regions that showed the greatest reduction in gaps are outlined.
Figure A.2: Texture map (left) and point cloud (right) of galena sample scanned at 1,084 pt/cm². (A) side view with talc, (B) without. (C) bottom view with talc, (D) without
As the resolution of the sample increases so does the scanning time and resulting file size. Figure A.3 illustrates the relationship between resolution and scan time for the digitization of a single face. Figure A.4 illustrates the relationship between the resolution and resultant file size for the original scan file size and a common output file format, OBJ, for three representative samples.

**Figure A.3: Scanning time required to capture a single face vs scanning resolution**

**Figure A.4: File size of the original scan file and the output OBJ file of the 3D digital model for three different mineral samples vs scanning resolution**
Figure A.5 illustrates the texture map and point cloud of a gneiss at three different resolutions to illustrate how the level of detail increases with increasing resolution.

Figure 6: Texture map (left) and point cloud (right) of a gneiss sample (A) low resolution scan (295 pt/cm²), (B) medium resolution scan (5,000 pt/cm²), (C) high resolution scan (10,400 pt/cm²). Note that with increasing resolution, the topography of the sample’s surface becomes more visible.
Figure A.6 illustrates the texture map and point cloud of a opal at three different resolutions to illustrate how the level of detail increases with increasing resolution.

Figure A.6: Texture map (left) and point cloud (right) of a scan of an opal mineral sample (A) low resolution scan (295 pt/cm²), (B) medium resolution scan (5,000 pt/cm²), (C) high resolution scan (10,400 pt/cm²). Note that with increasing resolution, the edges of the conchoidal fractures on the surface of the mineral, outlined in black, are captured more completely.
Appendix B

Visual Narrative of the Captain Charles Alan Innes-Taylor Collection

The Captain Charles Alan Innes-Taylor collection was donated to the Miller Museum of Geology (special thanks to Mark Badham) by Captain Innes-Taylor himself in 1935. These samples were collected during the Byrd Expedition II in 1934. This collection consists of 15 till samples of varying lithologies, as outlined in Table B.1. All samples from the collection were scanned using a Next Engine Laser scanner with a spatial resolution of 5,000 point/cm².

Table B.1: The rock ID, the lithology and collection location for each of the 15 till samples within the Captain Charles Alan Innes-Taylor collection.

<table>
<thead>
<tr>
<th>Rock ID</th>
<th>Type</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>X-173</td>
<td>Granite</td>
<td>152° 30' W, 86° 58' S</td>
</tr>
<tr>
<td>X-174</td>
<td>Tourmaline Granite</td>
<td>152° 30' W, 86° 58' 2'' S</td>
</tr>
<tr>
<td>X-175</td>
<td>Mica Granite</td>
<td>152° 30' W, 86° 58' 2'' S</td>
</tr>
<tr>
<td>X-176</td>
<td>Biotite Granitic Gneiss</td>
<td>152° 30' W, 86° 58' S</td>
</tr>
<tr>
<td>X-177</td>
<td>Quartz Vein</td>
<td>152° 30' W, 86° 58' S</td>
</tr>
<tr>
<td>X-178</td>
<td>Quartz Vein</td>
<td>152° 30' W, 86° 58' 2'' S</td>
</tr>
<tr>
<td>X-179</td>
<td>Drusy Quartz</td>
<td>152° 30' W, 86° 58' 2'' S</td>
</tr>
<tr>
<td>X-180</td>
<td>Quartzite</td>
<td>153° W, 76° 40' S</td>
</tr>
<tr>
<td>X-181</td>
<td>Felsite</td>
<td>152° 30' W, 86° 58' 2'' S</td>
</tr>
<tr>
<td>X-182</td>
<td>Felsite</td>
<td>152° 30' W, 86° 58' 2'' S</td>
</tr>
<tr>
<td>X-184</td>
<td>Drift from a Moraine</td>
<td>152° 30' W, 86° 58' 2'' S</td>
</tr>
<tr>
<td>X-185</td>
<td>Chert</td>
<td>152° 30' W, 86° 58' S</td>
</tr>
<tr>
<td>X-187</td>
<td>Gneiss</td>
<td>150° 00' W, 80° 04' S</td>
</tr>
<tr>
<td>X-188</td>
<td>Lignite Coal</td>
<td>152° 30' W, 86° 58' S</td>
</tr>
<tr>
<td>X-189</td>
<td>Banded chert</td>
<td>152° 30' W, 86° 58' 2'' S</td>
</tr>
</tbody>
</table>
In addition to the till samples, the hand-drawn routes and notable landmarks on the original maps of the geological surveys Captain Innes-Taylor conducted was also donated, as seen in Figure B.1.

Figure B.1: Hand-drawn survey route vs maps map of surveys conducted by the member of the Boyd Expedition II between 1933-1935.

The 3D digital models the donated till-samples and hand-drawn survey routes map were combined with archival newspaper stories and historical documents in order to create a visual narrative illustrating Captain Innes-Taylor’s life and his journey to the Arctic. The purpose of this project was to provide the collection with historical context and make this significant collection available to the community. The visual narrative was created through the use of a StoryMap (ESRI). Three of the most significant till samples were displayed including sample X-185, sample X-188 and sample X-187. Table B.2 outlines the details of each sample.
Table B.2: Details of the significance of the three samples selected to be displayed in the StoryMap.

<table>
<thead>
<tr>
<th>Rock ID</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>X-185</td>
<td>This sample was found within glacial till and the leaf imprint is of importance as the species of plant can provide information on the paleoclimate and the paleogeographic setting.</td>
</tr>
<tr>
<td>X-188</td>
<td>The sample of Lignite Coal contains layers of coal within a sedimentary host rock. This is sample is particularly interesting as it could indicate coal deposits in Antarctica, which could hold potential economic interest.</td>
</tr>
<tr>
<td>X-187</td>
<td>This sample of granite was found at Mt. Grace McKinley which is located close to Little America. The size of the mineral grains, as well as their relative percentages can indicate the environment in which the granite formed. This can add to our understanding of the geology of Antarctica.</td>
</tr>
</tbody>
</table>

Figure B.2 – Figure B.5 show examples of the pages from the Captain Innes-Taylor StoryMap. By displaying the incredible story of the explorer himself and the importance of the expeditions that the samples were collected in, greater interest for this collection can be generated. Figure B.2 illustrates Captain Innes-Taylor’s time in the RCMP where we was stationed in Whitehorse, Yukon.
Figure B.2: Captain Innes-Taylor (right) was stationed in Whitehorse, Yukon in the early 1900’s (left).

Captain Innes-Taylor held many positions on the expeditions including chief of field operations, as seen in Figure B.3. As part of this role, he planned geophysical surveys, meteorological studies and two geologic surveys in which the samples of this collection were collected.

Figure B.3: The location of the base of the Byrd Expeditions as seen on the original maps (left) and the "dog department" of BAE II (right), Captain Innes-Taylor can be seen second from the right.
Figure B.4: The main image displays the location where the Chert hand samples were collected, as well as the 3D digital scan of the Chert sample.

Figure B.5: Captain Innes-Taylor’s visited Queen’s University in 1935 (left) to discuss the necessary qualities of an explorer (right) and at this time donated the Antarctic till samples to the Miller Museum of Geology.

The digital StoryMap can be viewed on Esri Canada’s StoryMap webpage.