DIGITAL ROCKFALL DATABASES: DEVELOPING BEST PRACTICES
FOR SEMI-AUTOMATIC EXTRACTION OF ROCKFALL FROM LIDAR

by

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Abstract

In the digital age, the ability to collect and store information of phenomena in our world has become ever more useful, considering the vast improvements of predictive models and simulations. Geohazards are no different; acquiring data in order to characterize, forecast, and simulate geohazards requires the monitoring and documentation of their occurrences, with as much accuracy and detail as possible. Over the previous decade, advancements in remote sensing has resulted in platforms for capturing detailed 3-Dimensional surficial information of our surrounding world, providing opportunities to monitor geohazards with high levels of detail. Systems with oblique views are able to capture near vertical surfaces of rock cliffs, allowing for the monitoring and characterization of rockfall. Much research has thus focused on characterizing and understanding the failure mechanisms of rock slopes, by developing and applying tools for extracting information key to the rockfall phenomenon.

Observing rockfall allows for an understanding of its magnitude-frequency distribution, its spatial distribution, its geological and environmental triggering factors, as well as its chaotic interaction with the terrain. The potential power of digital rockfall databases is therefore limited by our ability to extract rockfall from our data – this is the focus of this thesis. Over the past 8 years, semi-automated methods have been developed and improved for extracting rockfall from laser scanning data. Although it is simple in theory, many sequential subprocesses are required, and thus, any errors introduced are capable of propagating, significantly impacting a rockfall database. In this thesis, I aim to build some best practices considering the common tools that have become utilized across different examples of semi-automated rockfall extraction methodologies.

I cover my variation of a semi-automatic method for assembling rockfall databases, and refer to its useful application in the domain of quantitative hazard and risk analyses. I discuss a heavily utilized change detection algorithm (multiscale model-to-model cloud comparison, or M3C2) used for isolating changing features in sequential spatial datasets, and discuss its spatial averaging component that has a substantial effect of rockfall extraction. I provide detailed insight into the estimation of rockfall point cloud volumes
in 3D using computational geometry-based surface reconstruction methods. I recommend a hybrid surface reconstruction methodology comprised of two methods, the Alpha Solid, and the Power Crust. Together, the hybrid methodology is robust in achieving the correct topology of the rockfalls, while optimally considering prominent concave geometrical features and detailed surficial information. I finish my thesis by discussing the applications of digital rockfall databases into modern quantitative hazard and risk analyses, and I provide recommendations for future work.
Co-Authorship

The thesis titled “Digital Rockfall Databases: Developing Best Practices for Semi-Automatic Extraction of Rockfall from LiDAR” is a product of work completed by Paul-Mark DiFrancesco. Through collaborative research, ideas and guidance were contributed by Dr. D. Jean Hutchinson, David Bonneau, and other members of the Geohazards Research Group.

This thesis was written in manuscript format according to the School of Graduate studies regulations. Manuscript chapters use first person “we” to indicate co-author contributions. The following two chapters were published in International Journals:


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<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>2D</td>
<td>2-Dimensional</td>
</tr>
<tr>
<td>2.5D</td>
<td>2.5-Dimensional</td>
</tr>
<tr>
<td>3D</td>
<td>3-Dimensional</td>
</tr>
<tr>
<td>ALS</td>
<td>Airborne Laser Scanning</td>
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<tr>
<td>BC</td>
<td>British Columbia</td>
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<tr>
<td>C2C</td>
<td>Cloud-to-Cloud</td>
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<tr>
<td>C2M</td>
<td>Cloud-to-Model</td>
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<tr>
<td>CN</td>
<td>Canadian National Rail</td>
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<tr>
<td>CNRHRA</td>
<td>CN Rockfall Hazard and Risk Assessment</td>
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<tr>
<td>CP</td>
<td>Canadian Pacific Rail</td>
</tr>
<tr>
<td>DBSCAN</td>
<td>Density-Based Spatial Clustering of Applications with Noise</td>
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<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>DMD</td>
<td>Dominant Movement Direction</td>
</tr>
<tr>
<td>DoD</td>
<td>Difference of DEMs</td>
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<tr>
<td>FNEA</td>
<td>Fractal Net Evolution Approach</td>
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<tr>
<td>GIS</td>
<td>Geographical Information System</td>
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<tr>
<td>GPU</td>
<td>Graphics Processing Unit</td>
</tr>
<tr>
<td>ICP</td>
<td>Iterative Closest Point</td>
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<tr>
<td>LiDAR</td>
<td>Light Detection and Ranging</td>
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<tr>
<td>LoD</td>
<td>Limit of Detection</td>
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<tr>
<td>M3C2</td>
<td>Multiscale Model-to-Model Cloud Comparison</td>
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<tr>
<td>MLE</td>
<td>Maximum Likelihood Estimation</td>
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<tr>
<td>MLS</td>
<td>Mobile Laser Scanning</td>
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<tr>
<td>MOTH</td>
<td>BC Ministry of Transportation and Highways</td>
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<tr>
<td>Acronym</td>
<td>Description</td>
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<tr>
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<tr>
<td>MVS</td>
<td>Multi-View Stereo</td>
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<tr>
<td>NSERC</td>
<td>National Sciences and Engineering Research Council of Canada</td>
</tr>
<tr>
<td>NURBS</td>
<td>Non-Uniform Rational Basis-Splines</td>
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<tr>
<td>OAP-H</td>
<td>Oblique Aerial Photogrammetry via Helicopter</td>
</tr>
<tr>
<td>PDF</td>
<td>Probability Density Function</td>
</tr>
<tr>
<td>RGHRP</td>
<td>Railway Ground Hazard Research Program</td>
</tr>
<tr>
<td>SfM</td>
<td>Structure from Motion</td>
</tr>
<tr>
<td>TLS</td>
<td>Terrestrial Laser Scanning</td>
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Chapter 1

Introduction

1.1 Rock Slope Hazard and Risk Management

Mountainous terrains across the world are associated with the presence of geohazards, often related to rock slope instability. Linear infrastructure systems traversing through mountainous river valleys are thus exposed to a variety of rock slope hazards. The spatial and temporal distribution of rock slope hazards across the length of linear infrastructure challenges managers, as they aim to reduce the threat of rock slope hazards to human safety and operational objectives. Rockfall is the smallest volume class of rock slope failures, and is characterized as fragment(s) of rock which detach from a cliff face, and subsequently fall, bounce, and roll as the fragment(s) propagate downslope (Hungr et al. 2014). Rockfall poses a threat to the safety of humans traversing mountainous transportation corridors, due to the potentially high amount of kinetic energy released by rockfall fragments at impact, in addition to the inherently higher spatial and temporal frequency of rockfall in comparison to larger rock slope failures, such as rockslide or rock avalanche (Volkwein et al. 2011). Rock slope failure events follow a magnitude-frequency distribution, which can be described by a power-law, where there is a higher proportion of smaller-magnitude rockfall occurrences in the distribution (Malamud et al. 2004).

Quantitative hazard and risk analysis strategies are utilized to overcome the challenge in reducing the threat of rockfall to human safety and operational objectives. These quantitative analysis strategies are effective for optimizing the usage of risk mitigation resources across large spans of corridor subjected to rock slope hazards, where it may be infeasible to allocate enough resources to completely reduce the risk. Quantifying the risk posed by rockfall involves the analysis of each of the uncertainties involved with its occurrence and dynamics, to the uncertainty of its impact on a human life or an asset. Risk is thus expressed as an annual likelihood of fatality or in dollars per year. Quantifying risk requires assumptions which consider a particular risk scenario, representing the chain of uncertain events that must occur for a human
or asset to be impacted. Bunce et al. (1997) show these different types of risk scenarios for vehicles traversing a corridor subjected to rockfall; (1) a stationary vehicle being impacted by a rockfall; (2) a travelling vehicle being impacted by a rockfall; (3) a travelling vehicle striking rockfall fragments that have fallen. Bunce et al. apply the binomial theorem to evaluate the risk of rockfall on traversing vehicles. Hungr et al. (1999) suggest that the multiplication of the conditional probabilities in the risk chain yields equally accurate results, provided that the resulting risk is relatively low. In the Canadian Technical Guidelines and Best Practices Related to Landslides, Porter and Morgenstern (2013) generalize the risk posed by all landslides to the multiplication of conditional probabilities. The risk equation is given below:

\[
R = f_H \cdot P_{S:H} \cdot P_{T:S} \cdot V \cdot E
\]

Eq. 1-1

The rockfall hazard portion of the risk chain is expressed in the first two parts. The temporal component of rockfall hazard is expressed as an annual frequency of occurrence, \( f_H \), considering a range of rockfall magnitudes. The spatial component of rockfall hazard, \( P_{S:H} \), is expressed as a probability that the rockfall will reach the individual. An understanding of (1) the magnitude-frequency distribution of rockfall and (2) the rockfall sourcing areas and their respective propagation dynamics given their magnitude, is therefore required in order to have an accurate assessment of rockfall hazard. Access to an inventory containing a record of rockfall occurrences is critical in order to have a confident estimate of rockfall hazard. However, these inventories are commonly incomplete and impacted by data censoring (Bunce et al. 1997, Hungr et al. 1999). Data censoring may be resulted from inaccurate documentation, lack of documentation, lack of rockfall evidence at the observation point, or obstruction of evidence.

The other components of the risk estimation equation are more related to an individual and the potential impact of the hazard on them. “Individuals” in this context could also be an asset which is threatened by rockfall. \( P_{T:S} \) is the probability that an individual will be present when the rockfall occurs, \( V \) is the vulnerability or probability of loss of life if the individual is impacted, and \( E \) is the scale factor which considers the number of lives impacted or the value of an asset. Choosing an appropriate mitigation strategy involves a practitioner deciding where to interfere with the risk chain in Equation 1-1. On the left-hand side
of Equation 1-1, they can aim change the physics of the rockfall phenomenon, by altering the probability of its occurrence or the extents of its runout. They can also interfere with the right-hand side of the Equation 1-1, by making logistical changes to prevent the individual from being in the hazardous area, or to reduce the number of allowable people in the area. The vulnerability of an asset could be improved, such as retrofitting a structure to withstand the impact of rockfall fragments. It should be noted that factors within the risk equation can be further decomposed into a multiplication of more detailed factors. For instance, Pratt et al. (2019) analyze the correlation between the occurrence of rockfall with rainfall and freeze-thaw cycles. If sufficiently accurate models are determined, a risk analysis can incorporate weather triggering into its quantification, provided that the additional information would aid in further optimizing the solution for risk reduction. Considering triggering in rockfall hazard quantification would also allow for an estimate of the hazard through a changing climate.

Guzzetti et al. (2004) show a great example of a risk analysis along a transportation corridor in Italy, considering the spatial-temporal and dynamic components of rockfall hazard. The authors utilized a detailed inventory of rockfall events to measure the magnitude-frequency behaviour of rockfall occurrence. Guzzetti et al. then utilized GIS-based rockfall modeling to measure the spatial hazard component of rockfall, considering the magnitude-frequency distribution of rockfall and its spatial distribution across the corridor. The authors also conducted a case study demonstrating how the present mitigation infrastructure sufficiently reduces the risk. The authors expressed that much of the uncertainty involved in the quantification of rockfall hazard surrounds the access to a detailed rockfall inventory. Key to their strategy as well, was the usage of a physical modeling tool to understand the propagation path and energy of the rockfalls. Further understanding the chaotic interaction with rockfall and complex terrain can improve the calibration of physical models, and thus the quantification of the spatial hazard component of rockfall ($P_{S:H}$). Lastly, the Guzzetti et al. noted an importance in any assumptions made throughout the quantification of risk scenarios.
1.2 Thesis Motivation and Objectives

The motivation for this thesis comes from the difficulty in accurately quantifying rockfall hazard, considering how valuable it is in risk analysis frameworks and subsequent mitigation design. The opportunity to make detailed observations of rockfall occurrences has been enhanced by the development of remote sensing techniques, which are capable of acquiring dense, detailed information of near vertical rock slopes and cliffs. This information is stored in point clouds, a collection of points in 3-dimensional (3D) space. These datasets may also be projected onto a plane of a given orientation, and converted into a raster image, where the value of each pixel corresponds to its height normal to the projection.

Light Detection And Ranging (LiDAR) and photogrammetry, are tools for acquiring detailed spatial information of near vertical rock slopes. The development of Terrestrial Laser Scanning (TLS) systems has provided lower cost data acquisition systems in comparison to the widely used commercial Airborne Laser Scanning (ALS) systems (Telling et al. 2017). Additionally, TLS systems are capable of gaining vantages of near-vertical rock slopes, while downward-looking ALS systems are unable to. Merging ALS and TLS surveys as shown by Lato et al. (2015), can provide a more complete view of the slope. Software for data processing has also evolved, allowing for detailed rock slope data to be captured with oblique photogrammetry surveys. Software supporting Structure from Motion (SfM) and Multi-View Stereo (MVS) photogrammetry, such as Metashape (Agisoft 2017), has allowed for these photogrammetric rock slope models to be built.

Advancements in rock slope data capture includes automated TLS processing pipelines (Kromer et al. 2017, Williams et al. 2018), automated photogrammetry surveys and processing pipelines (Anderson et al. 2019, Kromer et al. 2019), as well as increased survey lengths utilizing oblique helicopter-mounted laser scanners (Benjamin et al. 2020).

Advancements in computer graphics hardware, modern 3D software, and developments in oblique surveying methods, are accompanied with the opportunity to record the detailed occurrence of rock slope hazards in a digital fashion. This in turn, requires the development of best practices concerning the
methodologies utilized to extract rockfall information from the spatial datasets. Considering the great importance that the quantification of rockfall hazard has within quantified risk assessment frameworks, it is imperative that we build methods that do not create error in the resulting rockfall databases. A further motivation for this work, is that detailed rockfall information may go far beyond the risk analysis application. In recent years, large datasets and machine learning approaches have become increasingly used within the arsenal of scientific methodology. There is thus much motivation to collected detailed datasets of complex naturally occurring phenomenon, considering their potential in aiding the development modern simulations and predictive tools. Developing detailed geohazard database systems across different geological environments, and across different scales, may also provide us with sufficient data to further understand earth surface processes, as they relate to dynamic earth systems.

1.3 Automated Developments in Rockfall Extraction from LiDAR

Now that I have expressed why automated extraction of geohazard information from remote sensing data has an importance, I give a quick synopsis of some of recent the developments in creating these systems for rockfall. Research in the recent years has been interested in developing tools to extract information from remote sensing datasets, in order to help facilitate an understanding of rockfall and the degradation of rock masses.

Rosser et al. (2007) first demonstrated the usage of rasterized change detection on sequential TLS scans to observe the detailed progressive failure of coastal rock cliffs in England. In 2014, Tonini and Abellán demonstrated that clustering algorithms can be utilized to group proximal data points in the change detection signature corresponding to rockfall. Carrea et al. (2015) furthered the methodology with the usage of cloud-to-mesh change detection in 3-dimensions (3D), and a computational geometry-based surface reconstruction method to determine the 3D volume of clustered rockfall point clouds. Olsen et al. (2015) demonstrated a robust workflow utilizing triangulated models and hole filling, rasterized change detection, region-growing clustering, and 2.5D volume computation. Benjamin et al. (2016) investigated the differences in magnitude-frequency relations determined from utilizing different change detection
algorithms, proving the importance of fully 3D methods. Van Veen et al. (2017) followed a similar workflow to Carrea et al., using an oriented cloud-based change detection method, with the addition of a volume filter and a change detection signature filter, to remove erroneous rockfalls. Van Veen et al. also used a rasterized bedrock classification model to separate movements of bedrock from movements of talus/debris. Williams et al. (2018) further improved automated components for an hourly TLS processing system, by removing data points with high error using a LiDAR waveform filter, geometry-based edge filter, and a change detection noise mask. Williams et al. use an oriented cloud-based change detection method with a single surface searching query, and used rasterized change detection signature to compute volumes in 2.5D.

Research in this domain has continued, to help build tools to semi-automatically extract rockfall information, in order to facilitate the understanding of rockfall hazard. Collaborative work undertaken throughout the thesis has resulted in new additions to the developments in automatic rockfall extraction tools. In the study of Bonneau et al. (2019b), we demonstrated the use of algorithms to compute the shape of extracted rockfalls in 3D, and discussed errors. In the study of DiFrancesco et al. (2020), we demonstrated the importance of local querying in cloud-based change detection, and discussed its impacts of semi-automated rockfall extraction. In the study of Bonneau et al. (2019a), we presented the application of surface reconstruction in 3D rockfall volume estimation for four rockfall point clouds, and discussed errors realized between four different computational geometry-based algorithms. In the study of DiFrancesco et al. (2021), we extended the study of computational-geometry based surface reconstruction methods, to the application on magnitude-frequency power-law relations of rockfall, using a detailed LiDAR-derived database of over 3,000 rockfall events. Lastly in Bonneau et al. (2020), we created a method for extracting trees from LiDAR point clouds during the generation of bare-earth models, from which the protection of forests was incorporated into raster-based rockfall modelling.

Additions to rockfall extraction studies have been made throughout our contributions. Williams et al. (2019) demonstrated the importance of monitoring frequency for magnitude-frequency estimation, by
creating differing rockfall inventories with hourly to monthly change detection intervals. Benjamin et al. (2020) demonstrated the application of corridor-scale monitoring, using a mobile helicopter laser scanning system. Benjamin et al. were able to monitor over 20 km of English coastal cliffs, using automated rockfall extraction methodologies. Williams et al. (2021) determined improved methods for determining the vectors using in the fully point cloud-based change detection algorithms, showcasing its application for delineating the location of rockfalls. Recent studies have also shown the further usage of semi-automated rockfall extraction workflows in measuring rockfall activity (Guerin et al. 2020a, 2020b, Westoby et al. 2020, Hartmeyer et al. 2020b, 2020a). Recently, Carrea et al. (2021) have created and demonstrated a toolset for the extraction rockfalls and determination of their volume, implemented within MATLAB (Mathworks 2020).

1.4 Railway Ground Hazard Research Program

The thesis research was conducted as part of the Railway Ground Hazard Research Program (RGHRP). The RGHRP is a collaborative project including Canadian Pacific (CP) Rail, Canadian National (CN) Rail, Transport Canada, Queen’s University, and the University of Alberta. The RGHRP was created in 2003 to understand the various natural ground hazards that threaten Canadian rail transportation, across its over 45,000 km of rail track. In 2012, the Queen’s Geomechanics research group began to use remote sensing techniques at active rock slopes and river terraces within the Thompson and Fraser River valleys, in interior British Columbia (BC), Canada. Evidence of landslide occurrence in the Thompson-Fraser River valleys is detailed by widespread landslide deposits distributed throughout the valleys (Piteau 1977) and the documentation of significant landslide events in recent history (Evans and Savigny 1994). RGHRP sites were selected with accessibility to areas with vantages suitable for TLS, as well in correspondence with the sites’ elevated activity, historical challenges, high threat, or interesting erosion mechanisms. Field campaigns were conducted by current and previous members of the RGHRP group to collect TLS data and high-resolution panoramic photos. The thesis focuses on the rockfall activity at the CN Ashcroft Mile 109.4 site, outlined in Figure 1-1, across a 5-year time period.
1.5 Thesis Format

The thesis has been prepared in the manuscript format in accordance with the School of Graduate studies guidelines. Each of the manuscripts cover detailed reviews of the literature, and therefore, there is not an extensive literature review provided in an independent chapter. Chapter 2 is a manuscript that has been published in the International Journal, Remote Sensing, and contains a detailed review of the workflow for extracting rockfall from LiDAR data. Chapter 3 is a manuscript that has been accepted to the International Society for Photogrammetry and Remote Sensing’s (ISPRS) International Journal of Geo-Information, and contains a detailed review on surface reconstruction and computational geometry techniques utilized to determine 3D volume estimates of extracted rockfalls. Chapters 4 discusses and
concludes the broader scope ideas regarding the best practices for assembling digital rockfall databases, the future improvements that should be considered, and the application of the rockfall inventories in modern hazard and risk quantifications. Appendix A presents the methodology utilized to fit magnitude-frequency power-law probability distribution models to the rockfall databases, and Appendix B presents all of the change detection datasets utilized and discussed throughout the thesis.

References


Mathworks. 2020. MATLAB. Natick, Massachusetts.


Chapter 2

The Implications of M3C2 Projection Diameter on 3D Semi-Automated Rockfall Extraction from Sequential Terrestrial Laser Scanning Point Clouds

Abstract

Rockfall inventories are essential to quantify a rockfall activity and characterize the hazard. Terrestrial laser scanning and advancements in processing algorithms have resulted in three-dimensional (3D) semi-automatic extraction of rockfall events, permitting detailed observations of evolving rock masses. Currently, multiscale model-to-model cloud comparison (M3C2) is the most widely used distance computation method used in the geosciences to evaluate 3D changing features, considering the time-sequential spatial information contained in point clouds. M3C2 operates by computing distances using points that are captured within a projected search cylinder, which is locally oriented. In this work, we evaluated the effect of M3C2 projection diameter on the extraction of 3D rockfalls and the resulting implications on rockfall volume and shape. Six rockfall inventories were developed for a highly active rock slope, each utilizing a different projection diameter which ranged from two to ten times the point spacing. The results indicate that the greatest amount of change is extracted using an M3C2 projection diameter equal to, or slightly larger than, the point spacing, depending on the variation in point spacing. When the M3C2 projection diameter becomes larger than the changing area on the rock slope, the change cannot be identified and extracted. Inventory summaries and illustrations depict the influence of spatial averaging on the semi-automated rockfall extraction, and suggestions are made for selecting the optimal projection diameter. Recommendations are made to improve the methods used to semi-automatically extract rockfall from sequential point clouds.
2.1 Introduction

2.1.1 Rockfall Hazard in Mountainous Terrain

Linear infrastructure systems which traverse rugged mountainous terrain can be exposed to various landslide hazards, including rockfall. Rockfall is characterized by fragment(s) of rock which detach from a cliff face and, subsequently, fall, bounce, and roll as the fragment(s) propagate downslope (Hungr et al. 2014). Although smaller in magnitude than other classes of landslides such as rockslides, rockfalls pose a significant threat to humans due to their intensity (kinetic energy) and their frequency, both temporally and spatially (Volkwein et al. 2011). Rockfalls further challenge the safe operation of transportation corridors because it is difficult to prioritize the allocation of resources to be utilized to mitigate rockfall hazard across long transportation routes (Hungr et al. 1999). This task is particularly challenging in Canada, where there is over 45,000 km of rail track (Government of Canada 2011) which is susceptible to various geohazards. Rockfall hazard can be quantified along transportation corridors by conducting a rockfall hazard assessment (Guzzetti et al. 2004). As part of a quantitative hazard assessment, developing frequency-magnitude relationships from an inventory of events has become a common procedure (Corominas and Moya 2008). These are power law relations; for rockfall, they are expressed as cumulative frequency-magnitude relationships. Cumulative frequency-magnitude relationships are derived by accessing inventories of known rockfall events, although spatial and temporal censoring of events can result in an inaccurate measurement of the hazard (Hungr et al. 1999). Censoring is caused by underreporting or inaccurate documentation of events, the lack of sufficient time to adequately capture high magnitude and low frequency events, or systematic censoring as a result of mitigation efforts obscuring or removing rockfall evidence (Hungr et al. 1999). Additional factors which can contribute to rockfall censoring include difficulties associated with observing rockfall source zones from infrastructure-level vantage points, heavy alteration of a rock mass preventing observation of fresh surfaces (an indicator of recent rockfall), and propagation of rockfall material well beyond the area of interest which, subsequently, eliminates evidence of a rockfall occurring.
2.1.2 Terrestrial Laser Scanning for Rockfall Monitoring

Terrestrial laser scanning (TLS) is a ground-based light detection and ranging (LiDAR) method. LiDAR is a remote sensing method used to acquire terrain information in the form of point clouds; a collection of data points in three-dimensional (3D) space. LiDAR rapidly measures the reflected energy from an emitted laser (Lemmens 2011, Telling et al. 2017), thus, acquiring detailed terrain point clouds with highly accurate measurements of the surface geometry. Over the last decade, TLS has become a routinely used data source for the characterization and monitoring of rock slopes, particularly, because the terrestrial platform is effective for capturing oblique views of vertical rock slopes (Abellán et al. 2014). TLS technology continues to advance, and as a result, practitioners have been able to capture data faster, at higher densities, and higher levels of accuracy (Telling et al. 2017). Automated workflows have been developed to process these datasets, and therefore practitioners can spend more time analyzing and interpreting the data. Readers are referred to Lemmens (2011) for a practical overview of TLS in the realm of remote sensing and geomatics, and to Telling et al. (2017) for a review of the earth sciences research conducted with TLS.

With sequential datasets, practitioners can monitor active geomorphic processes occurring on rock slopes. Change detection between sequential TLS point clouds delineates rockfall source zones, from which volume is estimated and frequency-magnitude relationships can be derived (Rosser et al. 2007). A degree of automation has been added to the extraction of discrete rockfall events by utilizing clutter removal and density-based clustering algorithms (Tonini and Abellán 2014). Further improvements have been made in the accuracy of rockfall analysis, particularly for volume and shape calculations. Surface reconstruction algorithms have been used to construct 3D triangular meshes from rockfall point clouds, for estimating 3D volume (Carrea et al. 2015, Benjamin et al. 2016, van Veen et al. 2017). There is, however, difficulty estimating 3D volumes because surface reconstruction algorithms are not always robust enough to consistently produce triangular meshes which are fully watertight (i.e., free of holes) and manifold (i.e., no overlapping facets and consistent normal orientation), while also effectively reconstructing and approximating the geometry of the object (Berger et al. 2014). Bonneau et al. (2019a) showed that 3D
computation of rockfall volume was highly sensitive to the surface reconstruction algorithm being utilized, and the authors provided recommendations for improved 3D rockfall volume calculations. Rockfall shape has also been quantified using 3D methods (Bonneau et al. 2019b). The shape of a rockfall is known to have a significant effect on its passage down the slope and its runout (Glover 2015, Sala 2018). Detailed 3D rockfall shape has been carried forward into a new generation of rockfall models, which have incorporated custom rockfall objects and detailed terrain models (Caviezel et al. 2019, Harrap et al. 2019, Sala et al. 2019).

Rockfall volume computation is commonly simplified using 2.5D raster methods (Olsen et al. 2015, Williams et al. 2018). A 2.5D approach considers a detected rockfall as a region of raster cells exceeding the limit of detection. The 2.5D volume is thus the summation of each raster cell area, multiplied by their corresponding change value. While rasterized methods are robust, their output is highly sensitive to the selection of cell size and the affine transformation used to project the data onto the raster. Therefore, rockfall extraction and computation using the 2.5D method is, generally, less accurate as compared with the 3D method, as shown by Benjamin et al. (2016).

2.1.3 Recent Developments for Rockfall Monitoring Using Laser Scanning

In addition to the research on rockfall extraction and analysis, recent studies have looked at upscaling monitoring programs with respect to spatial extents and data acquisition frequency. For the improvement of spatial extents, Benjamin (2018) showed that a mobile laser scanning (MLS) system mounted onto a helicopter was capable of capturing detailed point clouds, and demonstrated the extraction of rockfall events along a 20 km length of coastal cliffs in England. A study of this size would not have been feasible using TLS. Furthermore, the helicopter mounted mobile platform resulted in an oblique view of the cliffs. Therefore, the system was capable of capturing topographic information on near vertical surfaces, which could not have been achieved with downward looking airborne laser scanning (ALS) surveys. Continuous terrestrial laser scanning systems have been investigated for improving acquisition frequency (Kromer et al. 2015a, 2017a, Williams 2017). Williams et al. (2018) established a workflow for
automated rockfall extraction from hourly TLS datasets from an automated, fixed position TLS system. They found that increasing the time interval between data acquisitions resulted in a significant reduction in the number of small rockfall events captured (Williams et al. 2019). The reduction in small magnitude events was due to the coalescence and overprinting of multiple small rockfalls over the monitoring time interval (Williams et al. 2019). However, there are limitations with regard to the spatial extent of the rock slopes that can be monitored with the use of fixed-position continuous TLS systems. Further research in (1) rockfall extraction methodologies, (2) systems for large extent data capture, and (3) frequent data capture or correction factors for infrequent data, would improve our ability to accurately measure rockfall hazard using laser scanning over large regions. This study focuses on the first research area outlined; improving rockfall extraction methodologies, specifically, through appropriate parameter selection in a commonly utilized change detection method.

2.1.4 Methods of Change Detection

Change detection between two datasets taken at different times can delineate active rockfall areas, from which information related to the rockfall events can be extracted and analyzed. There are several common change detection methods which have been used to capture surficial changes as a result of geomorphic processes, each with their respective advantages and disadvantages. These methods include the following: digital elevation model of difference (DoD), cloud-to-cloud (C2C), cloud-to-model (C2M), and multiscale model-to-model cloud comparison (M3C2).

Point clouds can be oriented and projected onto the x-y plane and rasterized into digital elevation models (DEMs). The subtraction of two DEMs produces a DEM of difference (DoD), which highlights change in one direction along the z-axis (Abellán et al. 2009, Wheaton et al. 2010). This method results in simple and fast computations, although for accuracy, it relies on the DEMs being capable of accurately modelling the terrain geometry; oriented terrain surfaces should be relatively orthogonal to the z-axis. An additional consideration is that DEMs cannot model overhanging features in the terrain, and the grid size can diminish the level of detail that can be captured from the DoD change detection (Benjamin et al. 2016).
Therefore, the DoD method is not very suitable for change detections on geometrically complex terrain with overhanging features and wide arrays of surface orientations. In order to improve the DoD accuracy across a challenging site, segments with similar orientations can be grouped together for separate analysis, although this can complicate processing and data interpretation (Barnhart and Crosby 2013).

Cloud-to-cloud (C2C) change detection computes the distance from each point in the second cloud to the closest point in the reference cloud (Girardeau-Montaut et al. 2005). Therefore, the direction along which the distance is computed is somewhat arbitrary, as it is based on whichever neighboring point is the closest. The measured C2C distance is sensitive to point spacing and surface roughness, and it is best suited for quickly computing distances between dense point clouds (Girardeau-Montaut et al. 2005, Barnhart and Crosby 2013). Given the primary usage of C2C distance computations in the optimization point cloud registration, C2C distance computations do not provide directionally signed results (Girardeau-Montaut et al. 2005, Lague et al. 2013). The C2C distances, however, can be signed with reference to point normal vectors. Signed distances are not an option within the industry standard CloudCompare software (Girardeau-Montaut 2019), and therefore, few geomorphology studies have made use of C2C, where the ability to identify areas of loss and areas of deposition is desired (Nourbakhshbeidokhti et al. 2019).

Cloud-to-model (C2M) change detection computes the distance from each point in the second cloud to the closest point on a facet of a triangulated surface model of the reference cloud. Triangular facets allow interpolation between the reference point cloud, and thus result in distance calculation vectors which are less arbitrary as compared with the C2C method. Implementations of C2M have been used for semi-automated rockfall extraction (Tonini and Abellán 2014, Carrea et al. 2015, Olsen et al. 2015), and for manual extraction using 3D software (Guerin et al. 2014, Kromer et al. 2015b, D’Amato et al. 2016). The accuracy of C2M depends on how well the surface mesh is able to model the terrain without over-interpolating the original geometry of the input point cloud.

The multiscale model-to-model cloud comparison (M3C2) algorithm created by Lague et al. (2013) measures the distance along a local normal vector estimated from each point’s neighborhood, and thus
considers local surface orientation in the distance computations. The algorithm projects search cylinders along the local normal vectors to find the locally averaged change between the two clouds. The M3C2 algorithm operates directly on the point clouds, and therefore requires no meshing or gridding, which can induce geometry errors in the terrain model as noted earlier. As a result, M3C2 has become a widely used and preferred method for change detection in various fields, including the monitoring of rock slopes and cliffs with TLS (Kromer et al. 2015a, Benjamin et al. 2016, van Veen et al. 2017, Benjamin 2018, Williams et al. 2018, 2019, Bonneau and Hutchinson 2019), landslide deformation (Kromer et al. 2017a), retrogressive thaw slump monitoring (Barnhart and Crosby 2013), rockfall model calibration (Sala et al. 2019), archaeological monitoring and preservation (Zimmer et al. 2018, Lercari 2019), structure from motion (SfM) photogrammetry monitoring and error analysis (James et al. 2017, Warrick et al. 2017, Cook 2017), and various other monitoring applications in the geosciences (Esposito et al. 2017, Crawford et al. 2018b, Nourbakhshbeidokhti et al. 2019, Anders et al. 2020). The M3C2 method is also widely used because it is freely available as a plugin within the open-source software CloudCompare (Girardeau-Montaut 2019). Direct operations on the point cloud and locally oriented distance computations make the M3C2 algorithm ideal for identifying change on structured rock masses with laser scanning data. Because it is a commonly used change detection method, M3C2 was chosen to be the focus of this study as we evaluated the influence of a key M3C2 parameter on the outcome of semi-automated rockfall extraction from sequential TLS datasets. An explanation of the M3C2 algorithm and its input parameters is provided in the following section.

2.1.5 Multiscale Model-to-Model Cloud Comparison (M3C2)

The M3C2 algorithm calculates a local average cloud-to-cloud distance for a point in the reference cloud, termed the core point, through the use of a search cylinder projected along a locally oriented normal vector (Figure 2-1) (Lague et al. 2013). Then, the distance is assigned as an attribute of the core point. The entire reference cloud can be defined as core points, or a subsampled set of the reference cloud. The original
resolution of both point clouds is used in the M3C2 computations regardless of whether the data is subsampled in the process.

**Figure 2-1: A depiction of the steps involved in multiscale model-to-model cloud comparison (M3C2) distance computation.** (a) In Step 1, the local normal vector, N, is estimated from Cloud 1 by fitting a plane to the points within a radius of D/2 from P<sub>core</sub>; (b) In Step 2, a cylinder is projected from P<sub>core</sub> along the normal vector. The average position is computed for each cloud, along the normal vector, using the points encompassed within the search cylinder. The difference in the average positions is the M3C2 distance. The projection diameter d<sub>a</sub> and the maximum search length L<sub>a</sub> are defined by the user; (c) Step 2 is shown with a larger projection diameter d<sub>b</sub>, resulting in more spatial averaging in the distance computation. A larger search length, L<sub>b</sub>, is also shown. Modified from Crawford et al. (Crawford et al. 2018a). In reality, the search cylinder is projected in both directions, looking for Cloud 2.

The core point’s normal vector is estimated from its surrounding neighborhood, which should be of a scale such that it captures the surface geometry without being sensitive to local surface roughness (Lague et al. 2013). Points encompassed by the search cylinder are used to compute the average position of Cloud 1 and Cloud 2. The distance between the average positions (along the normal vector) is the M3C2 distance (Figure 2-1). The search cylinder geometry is defined by the user, which controls the degree of spatial averaging that occurs, as shown in Figure 2-1, where two different projection diameter sizes are depicted. If there are no Cloud 2 points captured within the cylinder, no distance is computed. The projection diameter size is chosen based on the application, point spacing, and surface complexity (Lague et al. 2013). Readers are referred to Lague et al. (2013) for further details on the M3C2 algorithm.
2.1.6 Study Objectives

Although there has been much research utilizing M3C2 to monitor and extract changes in terrain, there is little guidance on the optimal parameters to be used. Furthermore, there is a lack of reporting of the M3C2 parameters used in various studies. M3C2 parameters should be chosen as a function of the type and magnitude of the process that is being investigated, the density of data, and the complexity of the terrain (Lague et al. 2013). This study aims to help users select appropriate M3C2 parameters for effective extraction of rockfall. The impact of the M3C2 projection diameter on semi-automated rockfall inventory results is investigated. Included in this study are the following:

- An overview of a five-year TLS monitoring campaign for an active rock slope along the Fraser River, in the interior of British Columbia, Canada;
- The full presentation of the semi-automated workflow used in this work for extracting rockfall and computing 3D volume and shape;
- The creation of six different rockfall inventories using different M3C2 projection diameters ranging from two times the average point spacing to ten times the average point spacing;
- An analysis of the impact that the M3C2 projection diameter has on automated rockfall extraction;
- A discussion on the considerations that should be made when selecting appropriate M3C2 parameters for future work;
- Recommendations for improvements on automated rockfall extraction.

2.1.7 Study Site

The study site, Canadian National (CN) Ashcroft Mile 109.4, is a rock slope located along the Fraser River in the interior of British Columbia (BC), Canada, approximately 150 km northeast of Vancouver, BC. The study site spans roughly 250 m of the CN track, which traverses the base of the slope (Figure 2-2). The Trans-Canada Highway lies above the top of the rock slope.
The slope morphology largely consists of exposed bedrock with areas of talus, scattered vegetation, and an overlying layer of soil on the upper reach of the slope. The bedrock is part of the Jackass Mountain Group, a thick succession of Cretaceous shallow-water deltaic sedimentary rock (MacLaurin et al. 2011), with bedding that dips at moderate angles into the slope (Sturzenegger et al. 2015).

The slope is comprised of the following five units: a highly fractured greyish brown argillite, a sandy siltstone, a thin black shale layer, a sandstone, and a thick bedded pebble conglomerate. The five units and a bedrock geology model are presented in Figure 2-3. The mean slope angle ranges from 45 to 55° (Kromer et al. 2017b). There are four major joint sets which contribute to sliding, wedge, and toppling failures (Sturzenegger et al. 2015, Kromer et al. 2017b) plotted in Figure 2-4.
Figure 2-3: Overview of the five lithological units of the CN Ashcroft Mile 109.4, depicted in a photogrammetry point cloud, high-resolution photographs, and a mapped bedrock model. The photogrammetry point cloud was generated from a series of photographs taken from a helicopter. Further information involving the construction of the photogrammetry dataset and subsequent geological mapping is presented in Sections 2.1.3 and 2.2.7, respectively.

Figure 2-4: A stereonet plot of the four major joint sets present at CN Ashcroft Mile 109.4. Modified from Sturzenegger et al. (2015).
Mile 109.4 has been of particular interest due to the high activity of slope movements, most notably a 53,000 m$^3$ rockslide occurring in November 2012 (Figure 2-5a,b). The rockslide was bounded by two local faults which crosscut the slope (Sturzenegger et al. 2015). The rockslide covered the track with more than 15 m$^3$ of debris and destroyed the pre-existing rock shed (Lato et al. 2015). An 80 m long rock shed was designed and completed in the fall of 2014. The design allows for a talus cone to build on top of the structure, which then guides future failures over top of the track (Figure 2-5). For more information on the geological units and the 2012 rockslide, readers are referred to Sturzenegger et al. (2015).

Figure 2-5: Site photos showing major natural and engineered slope changes at CN Ashcroft Mile 109.4 in the previous number of years. (a) 36 h before the 53,000 m$^3$ rockslide; (b) 12 h following the rockslide which buried the track, destroyed a protective structure, and put the track out of service for 4 days (Sturzenegger et al. 2015) photos courtesy of Tom Edwards; (c) The construction of the rock shed. A drape mesh can be seen above the structure which was installed to protect the construction area; (d) The eventual talus cone buildup over the shed allowing for rockfall fragments to traverse overtop of the track.
2.2 Materials and Methods

2.2.1 Data Collection

2.2.1.1 Terrestrial Laser Scanning

Terrestrial laser scanning was conducted at CN Ashcroft Mile 109.4 at weekly to seasonal intervals from November 2013 to December 2018. The survey consisted of a singular scan position approximately 400 m from the study slope across the Fraser River, on a soil slope above the CP track (Figure 2-2 and Figure 2-6). Additional scan positions with a suitable viewpoint of the slope were not possible due to site accessibility and obstruction by dense vegetation. Two time-of-flight TLS systems were used to collect data at the site throughout the 5-year monitoring period. A timeline of the TLS data acquisitions is outlined in Figure 2-6.

Figure 2-6: Data acquisition timeline. (a) The Optech ILRIS 3D-ER system; (b) The RIEGL VZ-400i system; (c) Hillshade site map colorized to show the monitoring duration with respect to slope extents. Warmer colors indicate areas that have been scanned more frequently and through longer time intervals.

Monitoring began in November of 2013 using an Optech Ilris 3D time-of-flight system (Figure 2-6a). The Optech Ilris 3D system has a manufacturer-specified accuracy of 7 mm in range, and 8 mm in vertical and horizontal directions from a distance of 100 m (Teledyne Optech 2014). The maximum range at 20% target reflectivity is approximately 800 m (Pesci et al. 2011). A total of 23 scans were taken from
November 2013 to late August 2017 with the Optech system. Monitoring with the Riegl VZ-400i time-of-flight system (Figure 2-6b) commenced in early September 2017. Laser scanning hardware influences the error in the spatial terrain information captured; the wavelength the systems are operating at, the precision and accuracy of the systems, beam divergence at range, the minimum angular increment both in vertical and horizontal, the maximum range at select target reflectivity, in addition to the environmental sensitivities of the systems (Jaboyedoff et al. 2012). Therefore, a separate Riegl baseline scan was taken after the last Optech scan, to avoid comparing datasets from different scanners. The Riegl VZ-400i scanner has a manufacturer-specified accuracy of 5 mm and precision of 3 mm from a distance of 100 m (Riegl Laser Measurement Systems 2019a). The maximum range with a 100 Hz pulse rate and 20% target reflectivity is approximately 400 m (Riegl Laser Measurement Systems 2019a). A total of 8 scans were taken with the Riegl system from early September 2017 to December 2018. Figure 2-6c shows the total number of days on which various portions of the slope were monitored. The extents of the scan area generally increased over time. Additional variations were due to the fact that the scan extents were uniquely defined during each site visit by different personnel.

With each TLS scan, the associated intensity of the reflected laser pulse was dependent on surface characteristics (color, roughness, and moisture), the beam wavelength, and the presence of atmospheric particles such as dust and water (Jaboyedoff et al. 2012, Abellán et al. 2014), as well as ash and smoke from forest fires. Conducting TLS surveys when there was no moisture on the slope was not possible through late fall and winter months due to higher amounts of precipitation in the region. As a result, scans taken during less optimal weather conditions have poor returns and holes in the data. A total of 4 scanning dates were omitted from the study in order to optimize the spatial resolution of datasets without overly increasing the time intervals between scans.

Optech Ilris scans were parsed using Optech Parsing software. Vegetation and non-stable infrastructure (i.e., slide detector fences and metal mesh installed on the slope surface) were manually removed from the raw point clouds using the Polyworks PIFEdit module (Innovmetric 2016). Then, the
cleaned point clouds were aligned to the November 2013 baseline using the Polyworks IMAlign module (Innovmetric 2016). First, a coarse alignment was performed by manual point picking of stable areas of the slope with sharp identifiable geometry, such as stable bedrock and infrastructure. The coarse alignment was followed by a fine alignment process using Polyworks’ iterative surface matching based on the iterative closest point (ICP) algorithm (Besl and McKay 1992). Areas of significant known change were manually removed from the fine alignment process to improve the quality of alignment (Lato et al. 2015). The Riegl VZ-400i scans were processed in a similar fashion solely using the RiScan Pro software package (Riegl Laser Measurement Systems 2019b). Coarse and ICP fine alignment was conducted to align the scans to the September 2017 baseline. The registration error for all the datasets varied between 1 and 2 cm. The point spacing typically ranged between 3 cm and 10 cm across the site for all datasets, and is predominantly a function of the scanner range and the specified horizontal and vertical angular increments, in addition to the aforementioned factors influencing the return intensity of the laser pulses.

2.2.1.2 High-Resolution Panoramic Photography

High-resolution panoramic photos were generated from a series of photos captured during each field campaign to aid in the interpretation of TLS data. High-resolution photographs were taken from the scan position (Figure 2-2 and Figure 2-6) using a 36 megapixel Nikon D800 full frame (November 2013 to September 2017) and a Nikon 24 megapixel D7200 cropped (September 2017 to December 2018) DSLR camera, both equipped with a Nikkor 135 mm f/2.0 prime lens. The camera was mounted onto a Gigapan Epic Pro motorized panoramic head (Lato et al. 2012). The photos were stitched together using the GigaPan Stitch software, resulting in a seamless high-resolution panoramic photo of the rock slope.

2.2.1.3 Oblique Helicopter Photogrammetry

An oblique aerial photogrammetry survey from helicopter (OAP-H) was conducted in December 2014 after two 200 m$^3$ rockfall events and a 3300 m$^3$ event (Kromer et al. 2017b). Photos were captured using a Nikon D800 full-frame DSLR camera equipped with a Nikkor 50 mm prime lens. Structure-from-motion multi-view-stereo (SfM-MVS) photogrammetry was used to build a model from 162 photos using
the Agisoft PhotoScan Professional V.1.3.2 software package (Agisoft 2017). The point cloud was built using a typical SfM-MVS workflow (Westoby et al. 2012, Smith et al. 2016). The point cloud was aligned and scaled to the September 2017 Riegl TLS baseline using point picking coarse alignment and ICP fine alignment within CloudCompare (Girardeau-Montaut 2019), resulting in a root mean square error of approximately 3.3 cm. To improve the results, areas of significant known change were excluded from the alignment procedure.

2.2.2 Rockfall Extraction and Database Aggregation

The rockfall extraction process is depicted in Figure 2-7 on the following page. Change detection was conducted to outline active areas of change due to rockfall. Change forward in time (A to B) highlights the back surfaces of areas of loss. Change backwards in time (B to A) highlights the fronts of changing features. A limit of detection threshold was used to extract the fronts and backs of loss features. The extracted features were merged to create an unorganized point cloud of loss objects. Clutter and change detection artifacts were manually removed from the point cloud. Clutter was generated as a result of random noise within the TLS datasets and change detection. Artifacts were generated as a result of systematic errors within the M3C2 change detection algorithm, mainly edge effects near occlusions and noise caused by the search cylinder passing through multiple separate surfaces (Williams et al. 2018). Objects attributed to talus, soil, and vegetation movements were also manually removed, resulting in an unorganized point cloud of solely rockfall objects. Density-based clustering was used to give a unique ID to each of the rockfall objects, and to remove any remaining noise left over. For each object, 3D volume and shape were computed, and the lithology was classified by comparing the rockfall centroids to a mapped 3D geological model of the site. Lastly, false positive rockfalls were filtered out using: (1) a ratio threshold of positive to negative points and (2) a lowest volume threshold (van Veen et al. 2017). These steps were conducted for each sequential TLS dataset, resulting in 25 clustered rockfall datasets, each containing the extracted rockfall events with the numerous computed attributes. Further details of the rockfall extraction workflow are explained in the following subsections.
2.2.2.1 M3C2 Batch Change Detection

M3C2 change detection was conducted for all 26 sequential TLS datasets using a Python batching script to access the command line API of CloudCompare. An intermediate affine transformation was applied to the TLS datasets prior to the M3C2 distance computation to align the point clouds with a
Cartesian axis, which ensures the correct orientation of normal vectors. Core points were defined at a subsampled point spacing of 10 cm, representing the maximum point spacing across the datasets. Subsampling normalized the point spacing across the study site and was important for the use of a density-based clustering algorithm in a later step of the workflow. The full resolution of the clouds was used for the normal vector estimation and distance computations, even though the data was subsampled. The projection diameter was varied at the following six different multiples of the point spacing: 20, 30, 40, 50, 75, and 100 cm. The projection length was fixed at 15 m for all computations. In order to ensure that the normal vector orientation is not affected by roughness, it has been recommended that the normal search diameter, D, is at least 20–25 times larger than the roughness computed at the equivalent scale (Lague et al. 2013). The normal search diameter was fixed at 1 m, which was approximately 30 times the average surface roughness. See Appendix B for all the change detection datasets, utilizing the 20 cm projection diameter.

2.2.2.2 Extraction of 3D Loss Objects

M3C2 calculations were conducted for all sequential datasets, forward in time. Negative change areas corresponded to rockfall back scarps and areas of talus or soil depletion. Significant negative change was extracted using a consistent 5 cm limit of detection at 95% confidence (LoD\textsubscript{95}), representing two times the maximum root mean square error determined during the point cloud alignment procedure. Then, M3C2 calculations were conducted for all sequential datasets, backward in time. Similarly, positive change extracted using the LoD\textsubscript{95} delineated the fronts of rockfalls, talus, or soil movements. For each pair of sequential datasets, the extracted negative and positive change were merged together, resulting in a point cloud of 3D loss objects yet to be clustered. Clutter and artifact points could remain in the loss object cloud, as a result of their M3C2 distances being larger than the LoD\textsubscript{95}.

2.2.2.3 Classification of Rockfall and Removal of Clutter and Artifacts

Objects that were not the result of rockfalls had to be removed, such as remaining low-lying vegetation, talus, and soil. The classification of points corresponding to rockfall can be automated by comparing extracted objects to a 3D classified mask, as demonstrated by Bonneau et al. (2019b). Work has
been undertaken to start automatically classifying point clouds into areas of vegetation, soil, talus, and bedrock (Weidner et al. 2020), although in complex terrain such as at Mile 109.4, automated classification methods may not be sufficiently robust to have complete confidence in the resulting mapping. Additionally, the study site has undergone significant natural and engineered slope changes throughout the period of the monitoring program (Figure 2-5). A singular bedrock classification mask would likely not suffice for accurate automated rockfall classification. Therefore, this step was done manually to maximize the accuracy of classification, and to prevent the omission of events or inclusion of false positives as a result of potential systematic error within an automated workflow.

Points not attributed to rockfall were removed in CloudCompare using the snipping tool. Gigapixel panoramic photos taken with each data acquisition were used to identify loss features that were located in areas of talus, soil, and vegetation. Additional tools within CloudCompare were used to aid in classifying the change signatures. These tools included the visualization of normal vectors and slope angle in an underlying terrain model, and the visualization of accumulation areas in previous change detection time intervals. For a singular change detection time interval, the point clouds corresponding to all six projection diameters were processed simultaneously to ensure the equal treatment of each dataset.

Remaining clutter and artifacts were removed in parallel with the rockfall classification. This included edge effects near the borders of occluded data (areas not in the line of sight of the scanner), noise as a result of high scanner incidence angles and positional uncertainty, and noise generated by the M3C2 projection cylinder contacting multiple surfaces (Williams et al. 2018). This process was a much simpler task as compared with rockfall classification, as these points were apparent with strong linear features or noisy sporadic magnitudes of change, with little to no defined geometry.

2.2.2.4 Clustering Individual Rockfalls

As discussed by Tonini and Abellán (2014), an adaptation of the density-based spatial clustering of applications with noise (DBSCAN) algorithm (Ester et al. 1996) was used to cluster individual rockfall events from the unorganized input point cloud. The DBSCAN algorithm is depicted in Figure 2-8. The
clustering algorithm uses a search radius and a minimum number of points to define a cluster. These two parameters were tested in a trial and error process using datasets of varying difficulty, and the results were visualized in CloudCompare. Similar to the findings by van Veen et al (2017), it was determined that the DBSCAN algorithm performed optimally when using a minimum of 12 points and a 30 cm search radius. The DBSCAN algorithm was implemented in C++. The clustering process resulted in a point cloud of grouped rockfall objects, each with a unique ID.

![Illustration of the DBSCAN algorithm and two generated clusters.](image)

**Figure 2-8: Illustration of the DBSCAN algorithm and two generated clusters.** Illustration of the DBSCAN algorithm and two generated clusters. There are three types of points as follows: key points (red) are points that satisfy the cluster criteria (termed core points by Ester et al. (1996); border points (blue) do not satisfy the cluster criteria but are within a key point’s reach; noise points (grey) are neither of the two aforementioned types. The DBSCAN algorithm uses the two following rules: (1) points within the search radius of a key point are part of its cluster and (2) key points which share common border points are part of the same cluster, shown for p1 and p2 in Cluster 1. Adapted from Tonini and Abellán (2014).

### 2.2.2.5 Volume Calculations

Surface reconstruction was used to compute the volume of each rockfall 3D object extracted. This study used the alpha-shape algorithm developed by Edelsbrunner and Mücke (1994). An alpha shape is a generalization of the convex hull of a point set. An alpha shape is defined as the union of all simplices
covered by its alpha complex, where the alpha complex comprises all Delaunay tetrahedra (and encompassing faces, edges, points) which have empty circumspheres, with radii less than the defined alpha radius. Therefore, for a set of points, there exists a family of alpha shapes, with each member corresponding to a different value of alpha radius, ranging from zero to infinity. An infinite alpha radius produces the convex hull of the set of points, and thus simplifies the geometry. An alpha radius of zero results in solely the set of points, with no edges or faces defined, thus, having no geometry. Therefore, an optimal alpha radius is required to best approximate the geometry of the object. Readers are referred to Edelsbrunner and Mücke (1994) for further details and discussions of alpha shapes.

As mentioned earlier, the triangulated mesh resulting from surface reconstruction needs to be manifold and fully watertight in order to ensure the accuracy and reliability of volume calculations. The alpha-shape approach does not guarantee either of these characteristics. Therefore, the iterative alpha-shape approach, by Bonneau et al. (2019a), was implemented to guarantee that all resulting alpha shapes were fully watertight and manifold. This was performed by iterating through each member of the alpha shape family and finding the lowest alpha radius which satisfied the aforementioned criteria. A lower alpha radius also results in a better approximation of the surface geometry of the rockfall object, as well as a better estimation of volume. The iterative alpha shape surface reconstruction was implemented in MATLAB (Mathworks 2019).

2.2.2.6 Shape Calculation

The shape of a rockfall can provide insight into the structure of the sourcing rock and the failure mechanics. With a new generation of 3D rockfall modeling software, the shape of a rockfall and the quality of the rock can also give insight into its chaotic interaction with terrain and the potential runout of the fragment(s) (Caviezel et al. 2019, Harrap et al. 2019, Sala et al. 2019). Blott and Pye (2008) described shape using four important characteristics; form, roundness, irregularity, and sphericity. The quantification of form involved the measurement of the length, breadth, and thickness of a particle, typically with all measurements being mutually orthogonal (Blott and Pye 2008). In 1958, Sneed and Folk proposed a ternary
diagram to classify the form of pebbles into 10 categories, as relations among the longest (A), intermediate (B), and shortest (C) axes. This study, in addition to several other studies (Williams 2017, van Veen et al. 2017, Benjamin 2018), used the Sneed and Folk classifications to classify the shape of 3D rockfalls extracted from TLS. The Sneed and Folk ternary diagram and classifications are shown in Figure 2-9.

Figure 2-9: The Sneed and Folk ternary diagram, adapted from Blott and Pye (2008). The Sneed and Folk ternary diagram, adapted from Blott and Pye (Blott and Pye 2008). (a) A visual representation of the different shapes on the depicted on the diagram. The relations between the shape axes A, B, and C are shown along each ternary axis; (b) The 10 classifications of shape, given by Sneed and Folk (1958).

The rockfall shape was computed using the adjusted bounding box algorithm from Bonneau et al. (2019b). The rockfall point cloud is rotated to align the direction of maximum variance with the x-axis in Cartesian space, and its axes are computed using a bounding box. In contrast to a regular bounding box approach, this method guarantees that the A-axis is the longest dimension of the object (Bonneau et al. 2019b).

2.2.2.7 Lithology Classification

The extracted rockfalls were also classified into different lithologies by comparing the source area to a surficial geological model. Due to logistical and safety constraints, field mapping of the study slope was not possible. Therefore, a 3D geological model was created by visually mapping the OAP-H point
cloud in Agisoft PhotoScan into the five lithology classes defined previously (Figure 2-3). Various visual 
aids, in addition to the colored 3D point cloud, were used to improve the geological interpretation. These 
included the use of gigapixel panoramic photos where lithological features were prominent, and reference 
to the geological interpretation and field mapping conducted as part of the study by Sturzenegger et al. 
(2015). Each rockfall object centroid was computed and compared to the surficial geological model 
(Bonneau et al. 2019b). A vote was conducted using nine nearest neighboring points to give each rockfall 
a hard classification of lithology.

2.2.2.8 Filtering

The last step in the rockfall extraction process was filtering and removal of false positive rockfall 
events. First, the rockfalls were filtered based on the ratio of positive to negative points (M3C2 distance), 
to ensure all rockfall clusters were 3D objects with fronts and backs. A minimum ratio of 1:3 was selected 
(van Veen et al. 2017). Secondly, volume filtering was conducted to remove rockfalls which were, 
theoretically, too small to be extracted given the workflow and data density. A minimum volume of 0.001 
m$^3$ was defined, suggesting a 12-point rectangular prism with dimensions 30 by 10 by 5 cm, corresponding 
to the 10 cm point spacing, 5 cm limit of detection, and 12-point minimum cluster size used in the DBSCAN 
algorithm.

2.3 Results

A total of six rockfall inventories were created for the 20, 30, 40, 50, 75, and 100 cm M3C2 
projection diameters. All inventories contained 25 scan intervals, although in two intervals no rockfall 
activity was identified. The centroids of each rockfall in the 20 cm projection diameter inventory are plotted 
in Figure 2-10: CN Ashcroft Mile 109.4 5-year rockfall database., with their date range of occurrence and 
volume discretized.
Figure 2-10: CN Ashcroft Mile 109.4 5-year rockfall database. (a) The photogrammetry model; (b) The centroids of each extracted rockfall event from the 20 cm projection diameter inventory. This inventory contains the most extracted events. Centroids are colorized and sized based on their date range of occurrence and their volume, respectively. Volume size references are shown in the legend. Rockfalls that appear on the rock shed and talus cone occurred in the early intervals of monitoring prior to the construction of the structure and eventual talus buildup. Areas that appear less active could have been monitored for shorter durations (Figure 6).
Table 2-1: The number of rockfalls extracted and filtered for each inventory with differing M3C2 projection diameters.

<table>
<thead>
<tr>
<th>Number of Rockfalls</th>
<th>20 cm</th>
<th>30 cm</th>
<th>40 cm</th>
<th>50 cm</th>
<th>75 cm</th>
<th>100 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conglomerate</td>
<td>12</td>
<td>11</td>
<td>11</td>
<td>10</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>Sandstone</td>
<td>923</td>
<td>866</td>
<td>804</td>
<td>689</td>
<td>487</td>
<td>308</td>
</tr>
<tr>
<td>Shale</td>
<td>897</td>
<td>820</td>
<td>750</td>
<td>639</td>
<td>455</td>
<td>290</td>
</tr>
<tr>
<td>Sandy siltstone</td>
<td>1547</td>
<td>1436</td>
<td>1287</td>
<td>1124</td>
<td>815</td>
<td>531</td>
</tr>
<tr>
<td>Argillite</td>
<td>262</td>
<td>247</td>
<td>230</td>
<td>200</td>
<td>147</td>
<td>95</td>
</tr>
<tr>
<td>Total filtered</td>
<td>14</td>
<td>16</td>
<td>10</td>
<td>11</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td>Grand total</td>
<td>3641</td>
<td>3380</td>
<td>3082</td>
<td>2662</td>
<td>1912</td>
<td>1229</td>
</tr>
</tbody>
</table>

Table 2-1 summarizes the number of rockfall events extracted in each inventory and Table 2 summarizes the rockfall volume properties for each inventory. The study site has been fairly active over the five years of monitoring, likely due to the major slope changes that occurred prior to the beginning of the monitoring campaign. There is a significant variation in the number of rockfalls in each of the inventories. As the projection diameter increases, the total number of extracted rockfall events decreases. This decrease is attributed to a higher degree of spatial averaging occurring with larger projection diameters, which makes smaller changing features less prominent, and therefore less likely to be clustered into individual rockfall events.

Table 2-2: Rockfall volume properties of each inventory with differing M3C2 projection diameters.

<table>
<thead>
<tr>
<th>Rockfall Volume [$m^3$]</th>
<th>20 cm</th>
<th>30 cm</th>
<th>40 cm</th>
<th>50 cm</th>
<th>75 cm</th>
<th>100 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>$1.01 \times 10^{-3}$</td>
<td>$1.02 \times 10^{-3}$</td>
<td>$1.03 \times 10^{-3}$</td>
<td>$1.25 \times 10^{-3}$</td>
<td>$1.11 \times 10^{-3}$</td>
<td>$1.43 \times 10^{-3}$</td>
</tr>
<tr>
<td>Maximum</td>
<td>3850</td>
<td>3852</td>
<td>3856</td>
<td>3859</td>
<td>3913</td>
<td>3862</td>
</tr>
<tr>
<td>Median</td>
<td>$1.19 \times 10^{-2}$</td>
<td>$1.27 \times 10^{-2}$</td>
<td>$1.50 \times 10^{-2}$</td>
<td>$1.92 \times 10^{-2}$</td>
<td>$3.64 \times 10^{-2}$</td>
<td>$7.39 \times 10^{-2}$</td>
</tr>
<tr>
<td>Average</td>
<td>1.63</td>
<td>1.76</td>
<td>1.96</td>
<td>2.28</td>
<td>3.30</td>
<td>5.19</td>
</tr>
<tr>
<td>Total</td>
<td>5944</td>
<td>6002</td>
<td>6113</td>
<td>6186</td>
<td>6443</td>
<td>6582</td>
</tr>
</tbody>
</table>

Table 2-2 demonstrates the calculated volume of the rockfall events, depending upon the projection diameter. Increased projection diameters cause the minimum, median, and average rockfall volumes to increase. The cumulative rockfall volume also increases as the projection diameter increases, and therefore
is controlled by the uncertainties on larger rockfall events, rather than the omittance of many low magnitude rockfall events. The increase in uncertainty is likely due to spatial averaging resulting in the extraction of points which are not part of the rockfall area. Extraction of additional points expands the convex hull of the object, and therefore expands the domain of the alpha shape, and its volume. Interpolation error following the iterative alpha-shape surface reconstruction can result in a higher volume captured (Bonneau et al. 2019a), shown by the volume of the largest event increasing as the projection diameter increases (Table 2-2). Interestingly, the maximum rockfall magnitude begins to decrease between the 75 and 100 cm inventories, suggesting that each rockfall has a projection diameter which maximizes its boundary and volume estimate. Beyond the volume-maximizing projection diameter, the degree of spatial averaging begins to reduce the object’s convex hull, therefore, reducing the boundary of its alpha shape and subsequent volume.

Another consideration is the production of larger magnitude rockfalls by the coalescence of multiple smaller rockfalls, as a result of spatial averaging in M3C2. This would be possible through the intermediate points separating multiple rockfalls in close proximity, if their calculated M3C2 distances exceed the LoD$95$ due to spatial averaging. The intermediate points would be extracted and allow for the multiple density-based clusters to be connected across them. The trends interpreted and discussed from Table 2-1 and Table 2-2 are further illustrated in Figure 2-1, where the volumetric distributions of rockfall for each inventory are shown.

An increase in the projection diameter significantly reduces the number of lower magnitude rockfalls that are extracted, specifically in the range of $10^{-3}$ to $4 \times 10^{-1}$ m$^3$, shown by the downward shift in the early portion of the cumulative frequency-magnitude relationships in Figure 2-12. The linear portions of all the cumulative frequency-magnitude relationships are similar for the tested projection diameters. The relative deviations in volume are higher at the magnitudes of 5 to 400 m$^3$, causing the cumulative frequency-magnitude curves to diverge. The curves converge again at the largest magnitude event recorded, where there is less relative deviation in volume.
Figure 2-11: Visual representation of the distribution of rockfall events with respect to their volume and lithology, for each of the six rockfall inventories. (a) The oblique helicopter photogrammetry point cloud; (b) The photogrammetry point cloud classified by lithology; (c)–(g) Histograms for each of the six rockfall inventories using different M3C2 projection diameters. Rockfalls are binned according to their volume. The colors in the histograms correspond to the lithologies mapped in (b).
Figure 2-12: Cumulative frequency-magnitude curves for all six inventories. The larger projection diameters cause a downward shift in the beginning of the curve. The linear portion of each curve remains similar but diverge at magnitudes greater than 5 m$^3$.

Figure 2-13 and Figure 2-14 show the reduction of lower magnitude rockfall events, spatially, at select areas of the study site. As the M3C2 projection diameter increases, the smaller rockfalls are not captured in the inventories. Remaining rockfalls begin to lose their defined shape as the change detection signature can appear "blurred" as a result of the spatial averaging. In special cases of multiple discrete rockfall events in close proximity to one another, the blurring of the change detection signature causes events to be coalesced into one clustered rockfall.
Figure 2-13: A depiction of the effect of spatial averaging on the rockfall inventories as a result of increasing the M3C2 projection diameter: Examples A and B. Individual rockfall point clouds are colorized by binning their volume as shown in the color scale. Cooler colors indicate smaller volumes and warmer colors indicate larger volumes. Each cluster of a distinct color represents a single rockfall event. All change detection timesteps are plotted at once.
Figure 2-14: A depiction of the effect of spatial averaging on the rockfall inventories as a result of increasing the M3C2 projection diameter: Examples C and D. Individual rockfall point clouds are colorized by binning their volume as shown in the color scale. Cooler colors indicate smaller volumes and warmer colors indicate larger volumes. Each cluster of a distinct color represents a single rockfall event. All change detection timesteps are plotted at once.
The shift in the change detection signatures resulting from increasing the spatial averaging is further reflected in the shape of the extracted rockfall events. The shape of each rockfall was computed using the adjusted bounding box approach discussed in the Methods section. Two distinctly different lithologies, the shale and the sandy siltstone, were analyzed to see how the M3C2 projection diameter influences the shapes of the rockfall events. The average shape for (a) the sandy siltstone rockfalls and (b) the black shale rockfalls is plotted in Figure 2-15. The average rockfall shape for both the sandy siltstone and the shale tended to be bladed, with the shale being slightly more bladed. It is noted that the average shape of rockfall, ranging from $10^{-3}$ to 1 m$^3$, generally becomes more platy as the projection diameter is increased. The extraction of more points bordering the rockfall events is a result of the spatial averaging. These additional points increase the A and B axes of the shape (Figure 2-13 and Figure 2-14), while the C axis (which is typically the thickness for bladed rockfalls) exhibits little change. The end result is the shapes becoming more platy.

![Figure 2-15: Sneed and Folk ternary plots plotting the average shape of the extracted rockfalls for each projection diameter.](image)

Sneed and Folk ternary plots plotting the average shape of the extracted rockfalls for each projection diameter. Average shapes are plotted with color corresponding to the projection diameter. (a) The average sandy siltstone rockfall shape; (b) The average shale rockfall shape. The rockfalls were sorted into bins of differing orders of magnitude, considering that interaction of different joint sets is responsible for differing rockfall magnitudes and shapes.
The last comparison among the databases discusses the spatial relationship between rockfall events and the potential implications of M3C2 projection diameter on our ability to understand progressive failure of the rock mass. Precursor rockfalls bounding the zone of an eventual failure have been detected (Kromer et al. 2015b). A 16.7 m$^3$ rockfall was captured between 12 October 2016 and 8 April 2017; over the preceding several years, precursor rockfalls bounded the area of the eventual failure. The rockfall event is outlined in Figure 2-16.

Figure 2-16: A 16.7 m$^3$ rockfall which occurred at interbeds between the argillite and sandy siltstone layers, displayed in gigapixel photographs and in TLS data. (a) Rockfall data with the area of interest circled; (b) Pre-failure photograph and surface model overlaid with the outline of the post failure rockfall boundary; (c) Post-failure identification of the rockfall back scarp.
The precursor rockfall activity is illustrated in Figure 2-17. As with the previous results, the lower magnitude rockfall events are no longer extracted by the inventories using larger M3C2 projection diameters; this is noticeable at the projection diameter of 75 cm (or 7.5 times the average point spacing). Too much spatial averaging therefore reduces some precursor rockfall indicators.

Figure 2-17: Precursor rockfall activity seen prior to the 16.7 m$^3$ event, which can be seen outlined by the white dashed line. All six inventories are shown, and events are colored according to their time range of occurrence. Events within the perimeter of the eventual failure correspond to fragments which failed off the face of the eventual 16.7 m$^3$ event.

2.4 Discussion

This study shows that rockfalls can be extracted in 3D from sequential TLS datasets utilizing a semi-automated workflow, developed with the consideration and inclusion of methods from several of the aforementioned studies. The workflow removes the aforementioned censoring issues that are present in visual inspection-based rockfall inventories, however, there is a limitation of the spatial coverage with a terrestrial laser scanning platform. A similar rockfall extraction workflow could be utilized on large mobile laser scanning datasets to increase the spatial coverage of the 3D rockfall inventories, assuming that the
mobile scanner is positioned to be able to capture oblique views of near-vertical rock slopes (Benjamin 2018).

There are many processes within the 3D rockfall extraction workflow, all of which can certainly have an impact on the resulting rockfall inventory (Figure 2-7). Here, we show that the M3C2 projection diameter is a key consideration for 3D rockfall extraction and analysis. Six rockfall inventories were created using M3C2 projection diameters ranging from two times the point spacing to ten times the point spacing. The key findings are summarized as follows:

- Smaller projection diameters result in more detailed change objects delineated. More rockfalls can be captured and extracted, at the cost of accepting more random noise in the computed distances.
- A projection diameter which is large in comparison to the footprint of a rockfall reduces the likelihood that the rockfall can be extracted. Spatial averaging causes the changing feature’s outer boundary M3C2 distances to fall beneath the LoD95. This ultimately reduces the likelihood that the rockfall’s extracted points meet the density-based cluster criteria.
- Missed lower magnitude events inhibit our ability to identify and document precursor rockfall activity observed prior to the occurrence of larger magnitude rockfalls.
- An increased projection diameter results in the average shape of rockfalls in sedimentary sequences to become more platy.
- Spatial averaging causing an expansion of a rockfall feature footprint can challenge clustering algorithms in cases where multiple discrete events have occurred in close proximity.

To extract the optimal rockfall data from sequential TLS datasets, the best projection diameter is, therefore, the smallest possible diameter which guarantees that at least one point is captured by the projected cylinder. This diameter would be one to two times the point spacing, depending on the expected variability in point spacing. For example, Williams et al. (2018) found that a projection diameter of 0.15 m (approximately the point spacing) was found to be optimal to capture the shape of rockfalls, however, they found that a 0.25 m search diameter was able to approximate the shape of the rockfalls while ensuring at least one point was consistently captured within the search cylinders.
Although a diameter that is one to two times the point spacing extracts the most rockfalls from the TLS datasets, it may not be the most optimal value to be incorporated in a semi-automated workflow. There is a benefit with spatial averaging, which is, that it reduces the amount of random noise left over in the M3C2 distances. The amount of noise generated from M3C2 increases with a smaller projection diameter and an increasingly irregular rough surface (Benjamin 2018). Ample noise which satisfies cluster criteria results in the inclusion of false positive rockfalls. Moreover, noise that is included in a clustered rockfall object can increase its boundary, its alpha shape, and ultimately, its volume. Therefore, the presence of noise is potentially a setback which would make users opt for a larger diameter. In this study, the majority of clutter (artifacts and noise) was very diligently removed by an experienced 3D program user. This is certainly inefficient and infeasible in circumstances where there are larger numbers of TLS datasets. The development of robust noise removal algorithms for the preservation of detailed change detection signatures, would effectively reduce the amount of spatial averaging necessary for the raw distance computations, thus greatly improving the degree of automation in the rockfall extraction workflow.

Summarizing, the optimal selection of the M3C2 projection diameter for rockfall extraction depends on numerous factors as follows:

1. Point spacing
2. Complexity and roughness of the terrain (generates more noise)
3. Quality of data (precision, accuracy, atmospheric conditions, human processing error)
4. Importance of preserving rockfall geometry
5. Effectiveness of noise removal by the combined effort of filtering and clustering algorithms
6. The minimum rockfall volume that is of interest for the particular rockfall inventory/study

As noted, the purpose of the inventory can influence the projection diameter selection. For example, CN Rail utilizes a rockfall hazard and risk assessment system (CNRHRA) where rockfall fragments with largest dimensions of 0.3 to 1 m are a concern for potential derailment; this fragment range is capable of wedging underneath locomotives (Abbott et al. 1998). A projection diameter able to effectively capture the
equivalent minimum volume would be acceptable in the scope of the CNRHRA analysis. In contrast, if highly focused active monitoring were to be conducted, on a pit wall for example, a smaller projection diameter able to pick up small precursor activity would be more suitable for the application. To this date, however, no studies have utilized automated precursor rockfall extraction, in addition to deformation, to forecast rockfall.

The selection of the projection diameter utilized within an automated framework is case dependent and, to some degree, subjective. Future users of this methodology should be aware of the information that they are able to extract and the impact that parameter selection in their workflow can have on resulting inventories. These impacts include low magnitude rockfall censoring, coalescing events, volume overestimation, and skewed rockfall shape estimates. Semi-automated rockfall inventories derived from TLS datasets should be presented with reference to their limitations and with a complete disclosure on the methods and parameters used. It is likely that practitioners will find a use for remotely sensed rockfall inventories, particularly for frequency-magnitude studies and regional hazard assessments in areas where there are few records of rockfall activity. Inaccurate or undisclosed methods can result in an incomplete assessment of rockfall hazard, which jeopardizes the effectiveness of a risk management framework.

As discussed earlier, M3C2 is a preferred change detection methodology for rock slopes with challenging geometries, because it computes distances along locally oriented normal vectors, instead of arbitrary vectors determined by the nearest points (C2C), mesh facets (C2M), or by a predetermined raster grid orientation (DoD). M3C2 normal vectors are computed using a plane fitted to the core point’s equidistant local neighborhood (Figure 2-1). The geometry of blocky rock masses, with discrete boundaries, thus, are not well represented with these equidistant normal vector computations. Points proximal to discrete changes in surface orientation have normal vectors influenced by multiple differing surfaces. Whether the M3C2 surface normal vectors are accurate and suitable, is therefore a site-specific question. The development of methods for automatic mapping of geological structures and segmenting planes in point clouds has been an active area of research (Lato et al. 2009, Riquelme et al. 2014). The incorporation
of structural information into M3C2 operations would make the change detection more suitable for rock masses with well-defined structures at variable scales.

Another consideration for automated rockfall extraction is to have adequate temporal frequency. Williams et al. (2019) noted the effect of coalescing rockfalls on the cumulative frequency-magnitude power law relation, which had a significant shift downwards (reduction in the frequency of large magnitude events) once acquisition intervals were reduced below 12 h. van Veen et al. (2017) also noted this trend, but to a lesser extent, as their data acquisition frequencies ranged from 38 to 461 days. Because reducing the data acquisition frequency is not feasible for most monitoring programs, methods should be investigated to increase the accuracy of remotely sensed rockfall inventories which have infrequent data collection. Such methods should include different clustering algorithms that are capable of separating coalescing change detection features. All of the studies to date have utilized variations of the DBSCAN algorithm (Ester et al. 1996), however, other approaches exist that are more robust at separating clusters in close proximity or touching one another. Utilization of these other approaches requires information regarding how the rockfall occurred. In other words, was it a discrete event or a series of smaller events? Unless there is a high enough temporal frequency of data acquisition to determine this question, practitioners are forced to select either a method which lumps all the events together or which potentially induces artificial breaks that may not exist. This phenomenon is one of the central issues associated with the presented approaches to date; the workflow at present cannot distinguish between these two potential types of false positive rockfall events. Future work is suggested to investigate the implications of using alternative clustering algorithms and the implications on database development. However, as demonstrated with the present study, all of this work is predicated on having confidence in the parameters used in the change detection process to minimize noise and capture true slope activity.
2.5 Conclusions

Rockfall inventories are essential for capturing rockfall activity and understanding hazard. TLS platforms have resulted in detailed monitoring and documentation of rockfall activity at a new level of accuracy and detail. Automation of workflows to automatically extract rockfall as 3D objects and conduct analysis on their shape and volume have improved the accuracy and efficiency of remotely sensed rockfall inventories. The initial step of the rockfall extraction workflow relies on the extraction of moving features using change detection and limit of detection thresholding. M3C2 has become the preferred change detection method with two key input parameters: (1) the normal search diameter and (2) the cylindrical projection diameter. The projection diameter and its influence on semi-automated rockfall extraction was analyzed in the presented study. Six rockfall inventories were produced by varying the M3C2 projection diameters from two times the point spacing to ten times the point spacing. It was determined that the projection diameter has a substantial impact on the automated rockfall inventories. The largest number of rockfalls are captured with the smallest possible projection diameter that is able to consistently capture at least one point within the searching cylinder; roughly one to two times the normalized point spacing. Increasing the projection diameter beyond this optimal size results in substantial censoring of lower magnitude rockfall events. Complex terrain and rough surfaces can generate a considerate amount of noise within the M3C2 distances which cannot be filtered through a limit of detection threshold of 95% confidence. Therefore, increasing the diameter beyond the optimal level could be preferred in certain circumstances, as long as users understand the features that are not extracted. With advancements in technology allowing for higher spatial and temporal resolutions of TLS datasets (Telling et al. 2017), we can decide to observe earth surface processes at higher levels of detail, or to leverage the resolution for a higher confidence in the changing features we detect. For automated rockfall extraction, improvements can be made which include the determination and incorporation of normal vectors indicative of rock structure to be used in M3C2 change detection, incorporation of clutter and smart artifact removal, further automation of change detection feature classification, and use of clustering algorithms capable of separating coalescing
rockfall events. Future methods to reduce the effect of coalescing rockfalls captured with infrequent data acquisition should be investigated.

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Chapter 3

Computational Geometry-based Surface Reconstruction for Volume Estimation: A Case Study on Magnitude-Frequency Relations for a LiDAR-Derived Rockfall Inventory

Abstract

Key to the quantification of rockfall hazard is an understanding of its magnitude-frequency behaviour. Remote sensing has allowed for the accurate observation of rockfall activity, with methods being developed for digitally assembling the monitored occurrences into a rockfall database. A prevalent challenge is the quantification of rockfall volume, whilst fully considering the 3D information stored in the point clouds. Surface reconstruction is utilized to construct a 3D digital surface representation, allowing for an estimation of the rockfall volume. Given various point cloud imperfections, it is difficult for methods to generate digital surface representations of rockfall with detailed geometry and correct topology. In this study, we tested four different computational geometry-based surface reconstruction methods on a database comprised of 3,668 rockfalls. The database was derived from a 5-year LiDAR monitoring campaign of an active rock slope in interior British Columbia, Canada. Each method resulted in a different magnitude-frequency distribution of rockfall. The implications of 3D volume estimation were demonstrated utilizing surface mesh visualization, cumulative magnitude-frequency plots, power-law fitting, and projected annual frequencies of rockfall occurrence. The 3D volume estimation methods caused a notable shift in the magnitude-frequency relations, while the power-law scaling parameters remained relatively similar. We determined that the optimal 3D volume calculation approach is a hybrid methodology comprised of the Power Crust and the Alpha Solid reconstructions. The Alpha Solid approach is to be used on small-scale point clouds, characterized with high curvatures relative to their sampling density, which challenged the Power Crust sampling assumptions.
3.1 Introduction

3.1.1 Rockfall Hazard

Landslides are defined as mass movements of geological materials downslope (Varnes 1978), and are further classified by their failure mechanisms, geotechnical material, and propagation dynamics (Hungr et al. 2014). Rugged mountainous terrain around the world is often the source of substantial landslide hazards, particularly related to rock slope instability, where rockfall represents the lower magnitude of rock slope failures. Rockfall is characterized as discrete fragment(s) of rock which detach from a cliff face and, subsequently, fall, bounce, and roll as the fragment(s) propagate downslope as individual rigid bodies (Hungr et al. 2014). Rockfall is a challenge to manage in mountainous regions, because occurrences can exert large amounts of kinetic energy on impact and may be frequently distributed throughout the area (Volkwein et al. 2011). Quantitative hazard and risk assessment frameworks are utilized to understand and manage rockfall hazard, where an understanding of the magnitude-frequency behaviour of rockfall is required (Hungr et al. 1999, Guzzetti et al. 2004, Corominas et al. 2005, Corominas and Moya 2008). As part of these assessments, the development of rockfall magnitude-frequency relations has therefore become a common procedure, in which an inventory of known events across a sufficiently long time interval is used to derive the relation across a corresponding spatial domain (Corominas et al. 2018).

Over decades of research, it has been noted that rockfalls exhibit a magnitude-frequency behaviour which can be described by a power law across a range of magnitudes (Corominas et al. 2018). The power law probability distribution is given by the following probability density function (PDF):

$$ P(x) = Cx^{-b} $$

Eq. 3-1

Where $b$ is the scaling parameter, $x$ is the observed value (i.e. rockfall magnitude), and $C$ is the normalization constant. At lower magnitudes, a rollover effect in the magnitude-frequency relation of landslides has been noted, where the power-law relation no longer describes the relation (Malamud et al. 2004, Guthrie and Evans 2004b). The rollover effect can be viewed as an inflection point occurring in the low-magnitude region of the relation, corresponding to a lower-than-expected frequency observed in the
data. The power-law PDF diverges as $x \to 0$ and thus requires a lower bound $x_{\text{min}} > 0$. It is therefore said that the ‘tail’ of a distribution follows a power law (Clauset et al. 2009). For normalization to hold true, the distributions must have $b > 1$, thus the PDF is given by:

$$P(x) = \frac{b - 1}{x_{\text{min}}} \left(\frac{x}{x_{\text{min}}}\right)^{-b} \quad \text{Eq. 3-2}$$

Research surrounding landslides have considered that the rollover effect may be a result of the physical and mechanical characteristics of landslides, in addition to data censoring (Pelletier et al. 1997, Hovius et al. 2000, Martin et al. 2002, Brardinoni and Church 2004, Guthrie and Evans 2004b). As such, numerous power-law based distribution models which consider the rollover effect have been utilized to represent the magnitude-frequency relation of landslides (Stark and Hovius 2001, Guthrie and Evans 2004a, 2004b, Malamud et al. 2004).

For rockfall hazards, the magnitude-frequency rollover is thought to be caused solely by censoring (Malamud et al. 2004). This censoring is attributed to the underreporting of rockfall events, the obscuring of physical rockfall evidence, and the lack of a sufficiently long time interval or high frequency of observation needed to capture a true measurement of rockfall activity (Hungr et al. 1999). Rockfall magnitude-frequency is therefore commonly represented by a power law relation which utilizes a minimum magnitude cutoff where the rollover occurs (Hungr et al. 1999, Williams et al. 2019). Corominas et al. (2018) suggest that there should also be an upper bound truncation on the magnitude-frequency relation with regards to a maximum credible event, where the magnitude should be defined considering the geostructural and geomechanical setting.

### 3.1.2 Rockfall Magnitude-Frequency Relations in the Digital Age

To derive magnitude-frequency relationships, landslide inventories are traditionally created by actively documenting recent occurrences, gathering relevant historical data, and by conducting field mapping. In appropriate environments, dendrogeomorphological investigations may be feasible as well to investigate historical occurrences (Stoffel et al. 2005). Over the past few decades, the development of
remote sensing platforms for capturing highly detailed spatial data of the surface environment, in addition to the parallel evolution of modern computer hardware and software, has provided a means for landslide inventories to be built digitally, by monitoring changes in the terrain through a comparison of spatial data acquired over a time interval (Nichol and Wong 2005, Rosser et al. 2007, Lu et al. 2011, Kromer et al. 2015, Warrick et al. 2017, Williams et al. 2019).

To detect rockfall, light detection and ranging (LiDAR) or photogrammetry surveys are deployed in terrestrial and oblique configurations in order to collect information of the steep source areas (Lato et al. 2015). Recently, a helicopter mounted mobile LiDAR system has been used to increase the extents of rockfall monitoring to a 20km length of coastal cliffs in England (Benjamin et al. 2020), and the development of several automated acquisition and processing workflows have supported the increased frequency of rockfall monitoring (Kromer et al. 2017a, 2019, Eltner et al. 2017, Williams et al. 2019). LiDAR and photogrammetry are used in many fields outside of landslide hazards as well. Telling et al. (2017) provide a review of applications of terrestrial laser scanning (TLS) applications in the geosciences and the application of TLS for monitoring rock slope instabilities is reviewed by to Abellán et al. (2014). Readers are referred to Smith et al. (2016) and Anderson et al. (2019) for reviews on the use of structure from motion multi-view stereo photogrammetry in the geosciences.

The detailed spatial information captured by LiDAR and photogrammetry is stored within a point cloud, a collection of points in 3-dimensional (3D) space. Each point cloud provides a permanent digital record of the terrain visible by the survey at a particular instance in time, while their spatial coverage is limited by the survey view. Changes in the terrain over time can be identified by computing distances between co-registered point clouds, in a process called change detection. Conducting change detection on the sequential clouds twice – treating both clouds as the reference, allows for the identification of the backs and fronts of the changing features captured within the point cloud (Tonini and Abellán 2014). The changing features can be extracted from the change detection results by extracting significant changes with respect to a limit of detection, and merging the backs and fronts into a singular cloud. The limit of detection
typically determined as a function of the global registration error, and can be spatially varied considering local point cloud roughness (Lague et al. 2013). Extracting rockfall from the significant change requires classifying the detected areas of loss corresponding to rockfall, removing noise and artifacts in the change detection signature, and clustering the filtered changes into individual point cloud subsets corresponding to discrete 3D rockfall events. All portions of the semi-automated processing workflow can have a substantial impact on the efficiency, accuracy, and robustness of the resulting digital rockfall database.

Measurement of failed rockfall volume is critical in the development of a magnitude-frequency relation. To determine rockfall volume in 3D, a representative digital surface must be reconstructed from the extracted point cloud. This task is addressed by the field of surface reconstruction, in which the goal is to recover an accurate digital representation of a physical object that has been scanned from the real world (Hoppe et al. 1992). There is an inherent difficulty in doing so for our application, considering the desired reconstruction accuracy, versus the existence of various point cloud imperfections, as we note in Section 1.3. Table 1 summarizes several recent examples of semi-automated rockfall extraction from TLS, and highlights the volume computation methods utilized.

To simplify the issue of computing rockfall volumes in 3D, numerous workflows have projected the rockfall point clouds into 2.5D raster datasets, known as height maps. Height maps are rasterized planar grided datasets, augmented with elevation or depth values. Rasterized (i.e. 2.5D) rockfall extraction workflows therefore compute the volumes as a summation of the grid cells multiplied by their change value (Table 1). However, Benjamin et al. (2016) showed that raster-based volume calculations result in high volumetric errors. These computations are sensitive to the projection method and orientation as well as the cell size. Geometrically challenging terrains, with large variations of surface orientations and overhanging features, are not captured well by 2.5D rasters. Therefore, there are merits in assembling digital rockfall inventories with fully 3D methods.
Table 3-1: Summary of several recent rockfall extraction methodologies, ordered by the most recent publications. Some methods additionally conduct post-database filtering by the point cloud volumes, number of points, or the change detection signature. Site dimensions preceded with a tilde indicate approximate measurements made when the dimensions were not explicitly stated in the text. Data acquisition frequencies were taken as median, or as fact from the texts.

<table>
<thead>
<tr>
<th>Study</th>
<th>Timespan [years]</th>
<th>Median Frequency</th>
<th>Site Dimensions</th>
<th>Change Detection Method</th>
<th>Clutter Removal</th>
<th>Clustering</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Guerin et al. (2020a)</td>
<td>11</td>
<td>365 days</td>
<td>~160 × 600 m</td>
<td>C2M ¹</td>
<td>Neighbour averaging</td>
<td>DBSCAN</td>
<td>SfR ²: Manually w/ 3D software</td>
</tr>
<tr>
<td>Hartmeyer et al. (2020)</td>
<td>6</td>
<td>yearly</td>
<td>5-rockwalls: 234 700 m²</td>
<td>M3C2 ³</td>
<td>-</td>
<td>Region growing</td>
<td>Sum of raster cells</td>
</tr>
<tr>
<td>DiFrancesco et al. (2020)</td>
<td>5.0</td>
<td>69 days</td>
<td>240 × 120 m</td>
<td>M3C2</td>
<td>Manual</td>
<td>DBSCAN ⁴</td>
<td>SfR: Alpha Solid</td>
</tr>
<tr>
<td>Benjamin et al. (2020)</td>
<td>2.6</td>
<td>309 days</td>
<td>20.5 km × (30 – 150 m)</td>
<td>M3C2</td>
<td>Manual</td>
<td>DBSCAN</td>
<td>SfR: Power Crust</td>
</tr>
<tr>
<td>Guerin et al. (2020b)</td>
<td>40</td>
<td>34 years – 1 month</td>
<td>~0.8 × 0.6 km; ~1.5 × 0.8 km; ~1.8 × 0.8 km;</td>
<td>C2M</td>
<td>Neighbour averaging</td>
<td>DBSCAN</td>
<td>SfR: Manually w/ 3D software</td>
</tr>
<tr>
<td>Williams et al. (2018; 2019)</td>
<td>0.8</td>
<td>1 hour - 30 days</td>
<td>210 × 60 m</td>
<td>M3C2 (variable search lengths)</td>
<td>Waveform + edge filter; Noise mask</td>
<td>Region growing</td>
<td>Sum of raster cells</td>
</tr>
<tr>
<td>van Veen et al. (2017)</td>
<td>1.3</td>
<td>76 days</td>
<td>1.1 km × 500 m</td>
<td>M3C2 (nearest neighbors)</td>
<td>-</td>
<td>DBSCAN</td>
<td>SfR: Alpha Shapes*</td>
</tr>
<tr>
<td>Olsen et al. (2015)</td>
<td>1.8</td>
<td>11 months</td>
<td>340 × 170 m; 110 × 11 m; 90 × 8 m</td>
<td>DoD ⁵</td>
<td>Raster averaging</td>
<td>Region growing</td>
<td>Sum of triangulated raster cells</td>
</tr>
<tr>
<td>Carrea et al. (2015)</td>
<td>3.0</td>
<td>6 months</td>
<td>~80 × 40 m</td>
<td>C2M</td>
<td>-</td>
<td>DBSCAN</td>
<td>SfR: Alpha Shapes*</td>
</tr>
</tbody>
</table>

¹ Cloud-to-model comparison (Cignoni et al. 1998). Computes the distance from each point to a neighbouring triangular mesh facet, along the facet normal.

² Surface reconstruction for three-dimensional volume estimation.

³ Multiscale model-to-model cloud comparison (Lague et al. 2013). Computes locally averaged change between two-point clouds along a locally oriented surface normal.

⁴ Density-based spatial clustering of applications with noise (Ester et al. 1996). Clusters data considering a minimum number of points within a minimum search radius.

⁵ Difference of digital elevation models (DEMs). Computes change between rasters, orthogonal to the raster image orientation.

*Surface reconstruction mesh hole filling method not specified and/or provided.
3.1.3 Surface Reconstruction Challenges and Requirements

As introduced earlier, to compute the volume of a point cloud in 3D, a representative surface must be reconstructed, from which the volume can be estimated. Berger et al. (2014) review the state-of-the-art methods in surface reconstruction. The authors note that the overarching challenge within the field of surface reconstruction is to recover an accurate digital surface representation of an object, given a point cloud input with imperfections summarized in Figure 3-1. Evidently, not all resulting point clouds from a semi-automated rockfall extraction will be perfect candidates for surface reconstruction applications; this is a result of the site geometry relative to the survey setup, instrumental error, human error during the data processing pipeline, environmental factors such as lighting for photogrammetry, or atmospheric and surface moisture for LiDAR, as well as potential systematic errors within the semi-automated rockfall extraction.

![Figure 3-1: Point cloud imperfections known to challenge surface reconstruction algorithms. Adapted from Berger et al. (2014).](image)

Our utilization of surface reconstruction therefore requires methods to be robust in dealing with these various point cloud imperfections. Further, the methods must produce surfaces with correct topology and global geometry, leading to a correct estimation of volume. It should be noted that local errors in the surface representation can accumulate to cause an incorrect rockfall volume. Therefore, a good surface reconstruction method should be able to reconstruct the correct topology considering the presence of point cloud imperfections, while also capturing the local surface details.
Given that we are concerned with reconstructing the surface of real world scanned rockfalls, there are a few topological requirements for our reconstructed surface: (1) the surface must be fully enclosed (i.e. watertight), and (2) the surface must be topologically equivalent to 3D objects in the real world. These requirements are encapsulated by the definition of a 2-dimensional manifold, or 2-manifold (Figure 3-2).

A manifold is a topological space, where locally, subsets are homeomorphic to the Euclidean space of the equivalent topological dimension (Edelsbrunner and Harer 2010). For a 2-manifold, this concept of homeomorphism means that local portions of the surface can be continuously deformed onto a 2D Euclidean disk without requiring cutting, gluing, or self intersection. An example of a 2-manifold is a sphere. A sphere is homeomorphic to an open disk when we evaluate it at local sections, however globally, it is not.

![Figure 3-2: Visual definitions of a 2-Manifold, modified after Bonneau et al. (2019).](image)

There are two further requirements for surfaces to be topologically equivalent to the solid rockfall objects. Firstly, the 2-manifold must be orientable, meaning it has consistent orientation; traversing along the surface should not allow one to mirror onto the other side of the surface. Secondly, the 2-manifold
should be free of self-intersections when realized in 3D Euclidean space. In topology, the “Klein bottle” is a well-known exemplification of a 2-manifold which does not fulfill these two criteria.

3.1.4 Digital Surface Representation and Reconstruction Methods Background

Surface reconstruction methods produce either implicit or explicit digital surface representations (Zhao et al. 2001). Implicit surface representations define a surface as a particular isocontour of a scalar function (Zhao et al. 2001), such as the zero-value of the signed distance function (Hoppe et al. 1992), or an iso-value of the indicator function which approximates the surface boundary (Kazhdan 2005). Triangulated meshes can then be extracted from the implicit functions utilizing volumetric methods, such as the Marching Cubes algorithm (Lorensen and Cline 1987). Implicit surface reconstruction methods typically require an estimate of the oriented point cloud normals, however, determining consistent orientation across the point cloud is a difficult task with the presence of point cloud imperfections (Berger et al. 2014). Some methods may treat randomly distributed incorrect orientations as noise, although most methods struggle when encountering clusters of incorrect normal orientations (Berger et al. 2014). Some surface reconstruction methods have utilized additional point cloud information such as scanner or camera positions to achieve correct point normal orientations. Another difficulty with the implicit surface reconstruction methods is that point cloud imperfections make it difficult to determine an appropriate scale, or neighbourhood, used to estimate the point normal vectors (Hoppe et al. 1992, Lague et al. 2013).

Explicit surface representations precisely define a surface as (1) a single parametric function, or (2) a set of surface patches allowed to show curvature, such as Non-Uniform Rational Basis-Splines (NURBS), or (3) a discrete surface tiled by flat surface patches, such as a discrete polyhedron. The much higher complexity of geometric operations on continuous curved surfaces resulted in a preference towards the discrete representation of explicit surfaces utilizing discrete polyhedrons, such as triangulated meshes. Discrete polyhedrons allow for the fast robust implementation of geometric operations, which are well suited for rapid processing on a graphics processing unit (GPU). Explicit surface reconstruction methods
therefore have focussed on the topological connection of the point cloud as a subset of its Delaunay Triangulation (Boissonnat 1984, Edelsbrunner and Mücke 1994, Amenta et al. 1998, 2001a).

The computational geometry based explicit surface reconstruction methods have therefore been adopted for several of the examples of semi-automated rockfall extraction and volume computation workflows as shown in Table 1. Further, the discrete computational geometry-based surface reconstruction methods directly honour the input data points, while continuous surface representations might not. Additionally, the requirement for accurate normal vectors with correct orientations adds a degree of complexity into the implicit surface reconstruction methods, which makes them less desirable to incorporate within more automated systems. In this study, we therefore exclusively focus on the discrete polyhedral surface representations determined via computational geometry.

3.1.5 Study Objectives

In a short case study utilizing a synthetic test object and three real rockfall events, Bonneau et al. (2019) determined that computational geometry-based surface reconstruction methods include explicit biases which can cause substantial error on the volumes of the reconstructed 3D rockfall objects. The presented article aims to further the study of Bonneau et al., by investigating the influence of volumetric error across an entire magnitude-frequency relation. This endeavour requires a much larger scale of analysis, with a high number of rockfall events across varying orders of magnitude. We therefore investigate four surface reconstruction techniques on a high quality digital rockfall database derived from 5-years of terrestrial laser scanning monitoring at an active rock slope in southwestern British Columbia (BC), Canada, using the digital rockfall database from DiFrancesco et al. (2020). This database contains 3,668 rockfall point clouds ranging from 12-points to nearly 100,000-points.

In this study, we summarize four computational geometry surface reconstruction methods and cover the fundamental tools used in their process. We present a technique to automate the Power Crust surface reconstruction method developed by Amenta et al. (2001a), and devise a method to deal with erroneous outputs. We evaluate the results of applying each surface reconstruction technique to the 5-year
long digital rockfall database. We discuss the results using rank-frequency cumulative distribution plots, maximum likelihood estimation of power law parameters, and projected annual frequencies computed with the power-law models. We discuss the trends and provide visual examples of reconstructed 3D meshes to support the observations. To conclude, we make recommendations for the future usage of these methods for determining the volume of digital objects described by point clouds, in the domain of quantitative rockfall hazard assessment.

3.2 Materials and Methods

3.2.1 LiDAR-derived 3D Rockfall Database

This study utilized the 5-year long rockfall inventory presented by DiFrancesco et al. (2020), derived from 27 sets of TLS data acquisitions captured at weekly to seasonal frequencies from Nov. 2013 to Dec. 2018. Figure 3-3 shows the 5-year rockfall monitoring conducted at the study site, across three selected time intervals for enhanced visualization. Each individual rockfall extracted is colourized differently and projected onto a photogrammetry model for visualization. The study site is an active engineered rock slope located adjacent to the Canadian National rail line, which runs along the Fraser River in Interior British Columbia, Canada. The bedrock consists of a succession of Cretaceous deltaic sedimentary rocks (MacLaurin et al. 2011). Local scale faulting has been identified as a key factor for contributing to the relatively high activity of rock slope failures seen early in the 2010’s, which sparked interest in monitoring the site (Sturzenegger et al. 2015a, Lato et al. 2015, Kromer et al. 2017b).

The TLS data was captured with an Optech Ilris 3D time-of-flight system (20 datasets; Nov. 2013 – Sep. 2017), and a Riegl VZ-400i time-of-flight system (7 datasets; Sep. 2017 – Dec. 2018). The Optech system has a manufacturer-specified accuracy of 7mm in range and 8mm in vertical and horizontal directions from a distance of 100 m (Teledyne Optech 2014). The Optech system has a maximum range of approximately 800 m at 20% target reflectivity (Pesci et al. 2011).
Figure 3-3: Rockfall data of the CN Ashcroft Mile 109.4 study site, across a 5-year span from Nov. 2013 to Dec. 2018. Individual rockfall point clouds are randomly colourized. Presented in 3 different intervals to reduce overprinting data in the visualization; (a) 347 days, from 2013-11-28 to 2014-11-10; (b) 104 days, from 2014-11-10 to 2015-02-17, occurrence of an approximate 3000m³ rockfall and several other events in the hundreds of cubic meters; (c) 1381 days, from 2015-02-17 to 2018-12-04.
The Riegl system has a manufacturer-specified accuracy of 5 mm and precision of 3 mm from a distance of 100 m, and a maximum range of approximately 400 m at 20% reflectivity with a 100 Hz pulse rate (Riegl Laser Measurement Systems 2019). Scans were taken from a vantage point approximately 400 to 500 m away from the slope. Vertical extents ranged from 130 to 170 m and horizontal extents ranged from 200 to 300 m. The typical registration error ranged between 1 – 2 cm, and a conservative limit of detection of 5 cm was utilized in extracting rockfall. The extracted change corresponding to rockfall was subsampled to a point spacing of 10 cm.

The rockfall database used in the present study was one of six created, as part of a parametric analysis evaluating semi-automated rockfall extraction. DiFrancesco et al. (2020) considered the impact of the spatial averaging component of a widely used point cloud-based change detection algorithm (multiscale model-to-model cloud comparison, or M3C2). The database used in the current study is the most detailed database generated from the study, and contains 3,668 rockfalls. The numerous stages in the semi-automated rockfall extraction workflow briefly discussed in Section 1.2 greatly influence the resulting rockfall database (DiFrancesco et al. 2020). For brevity, the volume computation component is the sole focus of this study. In the presented study, the authors therefore work with a collection of discrete rockfall point clouds which have already been detected and manually verified. Chapter 2 contains the detailed overview of the study site, survey, data processing, and the rockfall extraction workflow used. Other adaptations of rockfall extraction workflows can be found in Table 1.

3.2.2 Computational Geometry Tools

Computational geometry methodologies are more than often presented in mathematical notation, as lemmas and algorithms, rather than in a qualitative and graphical manner suitable for wider audiences. There are several computational geometry concepts that form the basis for understanding the more complex surface reconstruction algorithms – which are the main focus of this article. This section provides general descriptions of several fundamental structures of computational geometry. These structures are the Voronoi Diagram and its dual graph, the Delaunay Triangulation. The 3D explanations of these concepts transfer
appropriately into 2D, and are visualized in Figure 3-4 to aid our definitions. Note that all proximity and
distance metrics utilized in the definitions refer to Euclidean distance.

Figure 3-4: Key computational geometry tools presented in 2D. (a) The Voronoi diagram of the point set. Voronoi cells contain all space nearest to its sample; (b) a Power diagram, with weights denoted by the radius of the circle surrounding each point. Power cells contain all space in which the distance subtracted by its cell weight (i.e the Power distance), is less than competing cells. The cell edges of competing samples are drawn at the distance where the outer circle boundaries intersect. If all weights are equal it would result in the same diagram as in (a); (c) The Delaunay triangulation (blue), which is the dual graph of the Voronoi diagram (black). An example of an empty circumcircle (red), centered at a Voronoi vertex (red), showing that its triangulation is Delaunay; (d) A restricted Voronoi diagram (black), with a uniform weight determining the maximum extent of the cells. The resulting Delaunay triangulation (blue) is made for the trios of adjoining cells. A lack of cell adjacencies results in several points becoming excluded from the triangulation. Visualization adapted from Devert (2018) and Royer (2018) with the Scipy Spatial (Virtanen et al. 2020) and Matplotlib (Hunter 2007) libraries for Python.
The first concept is the Voronoi Diagram. A 3D Voronoi cell is a 3D space which contains all space most proximal to its sample point. A 3D Voronoi cell is bounded by a series of planes. A Voronoi diagram is the collection of these Voronoi cells (see Figure 3-4a). The second concept is a variant of the Voronoi Diagram, called a Power Diagram. A 3D Power cell incorporates weights for each of the sample points. The 3D Power cell contains all 3D space, in which the Power distance (the distance subtracted by its weight) is less than the Power distance of competing cells (see Figure 3-4b). The last variant of the Voronoi diagram does not have a formal name. We refer to it as the “restricted Voronoi diagram”. Similarly, each restricted Voronoi cell contains its most proximal space. However, a uniform weight (i.e. distance) is used to limit the maximum span of all cells (see Figure 3-4d).

The Delaunay Triangulation is closely related to the Voronoi diagram. A 3D Delaunay Triangulation is built with tetrahedra, which encompass corresponding triangles, edges, and points. A Delaunay tetrahedron is defined from an empty circumsphere, which intersects 4 of sample points along its boundary without containing any sample points inside of it (see an empty circumcircle plotted in red in Figure 3-4c). A Delaunay tetrahedron can be drawn by connecting the samples corresponding to 4-adjoining Voronoi cells. Similarly in 2D, triangles are connected by 3-adjoining 2D Voronoi cells. This is the dual-graph relationship between the Voronoi Diagram and its Delaunay Triangulation, and is illustrated in Figure 3-4c and Figure 3-4d. Note that the restricted Voronoi diagram in Figure 3-4d changes the cell adjacencies, and therefore results in a different triangulation; this is also called an Alpha Complex (Edelsbrunner and Harer 2010), which we discuss further in the next subsection.

Readers are referred to Edelsbrunner (1987) for a thorough definition of the Voronoi Diagram and its dual Delaunay Triangulation in 2D, as they relate to the fundamental concepts and algorithms of computational geometry.
3.2.3 Computational Geometry Surface Reconstruction for Volume Estimation

With knowledge of some of the fundamental computational geometry concepts, we now set to describe each of the 3D surface reconstruction methods with the aid of 2D graphical descriptions. We hope that readers will understand the underlying assumptions that each method makes, and how they relate to the errors that are realized in estimating the volumes of the LiDAR-derived rockfall database.

3.2.3.1 Convex Hull

The Convex Hull is a fundamental concept of topology and computational geometry, and is used throughout numerous fields. The Convex Hull of a set of points, \( S \), is the smallest convex set that contains it, which is the set of all convex combinations containing \( S \) (Edelsbrunner and Harer 2010). The Convex Hull of a 3D point set thus results in the smallest convex polyhedron encompassing all points (see bottom right subfigure of Figure 3-5). The Convex Hull reconstruction was implemented using the tetrahedron-based Alpha Shape implementation in Matlab (Mathworks 2019), utilizing an infinite Alpha Radius (see next subsection). Computing the volume of the tetrahedron-based shape representations simply requires the summing of the tetrahedron volumes, which was also carried out in Matlab.

3.2.3.2 Three Dimensional Alpha Shapes

Edelsbrunner and Mücke (1994) formally defined the three-dimensional Alpha Shape of a point set as the union of simplices covered by all Delaunay tetrahedra having empty circumspheres, with radii less than the defined radius – referred to as the Alpha Radius. Simplices are thus the building blocks of the Alpha Shape, with a \( k \)-dimensional simplex being the convex hull of \( k + 1 \) affinely independent points (Edelsbrunner and Harer 2010). A point, edge, triangle, and tetrahedron are respectively described by the 0, 1, 2, and 3-simplex.

The value of Alpha Radius prescribes a limiting distance for the extents of all Voronoi cells, and thus determines the connectivity of the Delaunay triangulation. Figure 3-5 shows the progression of an increase in the Alpha Radius, leading to a change in the resulting Alpha Shape. For a set of points, there therefore exists a family of Alpha Shapes, with each member corresponding to a different value of Alpha
Radius. The value of Alpha Radius determines the tetrahedra and encompassing $k$-dimensional simplices generated by the Delaunay triangulation. The Alpha Radius can range from zero to infinity, where an infinite value results in the convex hull, thus simplifying the surface of the shape (bottom right subfigure of Figure 3-5), and a zero-Alpha Radius results in an empty shape, comprised of only 0-simplices (top left subfigure of Figure 3-5). Therefore, an optimal value of Alpha is required to best approximate the geometry of the object while producing a 2-manifold watertight reconstruction. Lower values of Alpha can capture local shape details while larger values of Alpha can capture the global shape (Figure 3-5). Readers are referred to Edelsbrunner and Mücke (1994) for further details and discussions of Alpha Shapes. Two variations of the Alpha Shape algorithm are utilized in this study, both of which were implemented in Matlab. The Alpha Shape volumes were computed by summing the volume of the tetrahedra in Matlab.

The first method is the Default Alpha Shape, which has an Alpha Radius such that all points are utilized in the Delaunay Triangulation – referred to as the Default Alpha Radius. The exterior boundary of the Default Alpha Shape, defined by triangular facets, is therefore not guaranteed to be 2-manifold and watertight.

The second variation is the Alpha Solid method, which iterates through the family of Alpha Shapes of the input point cloud and determines the smallest Alpha that produces a mesh whose boundary facets are 2-manifold and watertight. This is achieved by ensuring that for each edge $p_1p_2$ there exists the edge $p_2p_1$ corresponding to the shared edge with an adjacent face, which we refer to as the “half edge criteria”. The family of unique Alpha Shapes is given by the Alpha Spectrum, which is the set of all unique values of Alpha, corresponding to all possible $k$-simplices with empty circumspheres for $1 \leq k \leq 3$. We follow the method of Bernardini et al. (1997) to reduce the computation time, by bisecting the Alpha Spectrum list to find the lowest value of Alpha. In this process, we only consider Alpha Radii which include all input points (i.e. radii larger than the Default Alpha Radius). A previous implementation of this method without bisection was presented by Bonneau et al. (2019) as the “iterative Alpha-shape” approach.
Figure 3-5: Restricted Voronoi diagrams and their resulting Delaunay Triangulations producing the triangulated Alpha Shape, adapted from Royer (2018). The Alpha Radius increases from left to right, and top to bottom, respectively, ranging from the empty point set (upper left), to the Convex Hull (bottom right). Visualization aided by the Scipy Spatial (Virtanen et al. 2020) and Matplotlib (Hunter 2007) libraries for Python.

In our tests implemented in MATLAB, there was no critical level of Alpha, above which all resulting Alpha Shapes fit the half edge criteria. We found that alternating chunks of the Alpha Spectrum had instances of an edge repeated 4 times, thus not satisfying the half edge criteria. To overcome this issue, we bisect the Alpha Spectrum to find the lowest Alpha Radius with only one instance of 4 repeated edges. Then, we ascend the Alpha Spectrum list from this position to find the lowest Alpha Radius which satisfies the half edge criteria. We compared the results to those achieved by ascending the Alpha Spectrum list
without bisecting, and confirm that the results agree with each other. This results in a fast, robust implementation that guarantees a 2-manifold and watertight Alpha Shape.

3.2.3.3 Power Crust

The last surface reconstruction method we investigate also computes the surface as a subset of the Delaunay Triangulation, and utilizes interesting properties of the object’s shape related to the Voronoi Diagram of its point set. The Power Crust algorithm created by Amenta et al. (2001a), takes the sample of points and constructs a piecewise-linear approximation of the object’s surface, as a polygonal surface mesh, which is guaranteed to be watertight. Several concepts must be defined, with knowledge of the computational geometry concepts introduced earlier in Section 2.2. These additional tools are illustrated in Figure 3-6 and defined below:

- **Poles**: A subset of the Voronoi vertices, located on the interior and exterior of the object, but not along the object’s surface;

- **Polar balls**: The balls centered at the poles, each with radii such that they are touching the nearest input point sample;

- **Medial axis**: The skeleton of a closed shape, along which, points are equidistant to two or more locations along the shape’s boundary.

Filling a shape with maximal balls (i.e. spheres) centered at its medial axis produces a watertight shape which approximates the shape’s geometry. The algorithm builds from this idea in order to construct the Power Crust. Conceptually, the algorithm approximates the medial axis, and then fills the interior and exterior of the object with maximal balls. The Power Crust is the piecewise-linear surface constructed at the point where the interior and exterior maximal balls intersect (Figure 3-6). The Power Diagram is a key tool utilized in determining the Power Crust. The Power Diagram is constructed using the location and weights of the polar balls (i.e Voronoi vertices), rather than the sample points themselves (i.e. the example in Figure 3-4b). The Power Crust can then be determined from the Power Diagram of the polar balls, at the polygonal boundaries between the interior and exterior Power cells.
The key requirement for the Power Crust algorithm to be successful, is an input point cloud which is sufficiently sampled. The sampling density of points should be inversely proportional to the nearest distance to the medial axis. A closer distance from the surface to the medial axis corresponds to a higher curvature (i.e. Figure 3-6a), which thus requires a larger sampling density (Amenta et al. 2001a). An important note follows this – smaller scale rockfalls will have surfaces closer to their medial axis, however, our point spacing is uniform at 10 cm (excluding occlusions). Therefore, small-scale rockfall point clouds will challenge the Power Crust algorithm. Many of the smaller rockfalls cause the algorithm to break down, which we address at the end of the subsection and further analyze throughout the Results and Discussion sections.

The Voronoi diagram of a sufficiently sampled point cloud will be composed of Voronoi cells that are long, skinny, and perpendicular to the surface (Figure 3-6c). This is due to the proximity of samples along the surface, the lack of samples in the interior of the shape, and the distance from the surface to the medial axis (Figure 3-6a and Figure 3-6c). The medial axis can then be approximated by the Voronoi vertices found at the intersection of the long and skinny Voronoi cells found in the interior of the shape. The Voronoi vertices approximating the medial axis correspond to interior poles. The interior poles converge to the medial axis as the sampling density goes to infinity (Amenta et al. 1998, 2001b).

The main challenge for the Power Crust algorithm occurs when the input point clouds are not well sampled: it is difficult to determine which poles correspond to Voronoi vertices along the medial axis within the interior of the shape, and which poles correspond to the Voronoi vertices on the exterior of the object. This has problematic effects on volume estimation if not properly handled. To deal with this potential ambiguity, the Power Crust algorithm computes the unlabelled poles at Voronoi vertices belonging to the long and skinny Voronoi cells. The algorithm then determines the weights of the polar balls, constructs the Power Diagram, labels the poles as interior or exterior, and then extracts the Power Crust as the boundary separating the interior Power cells from the exterior.
Figure 3-6: A 2D illustration of the Power Crust algorithm, adapted from Amenta et al. (2001a). (a) the object with its medial axis; (b) the sampled point cloud, \( S \), with an inset image showing the 5-times bounding box points added to the samples; (c) the Voronoi diagram of \( S \), with Voronoi vertices, \( V \), plotted in blue; (d) maximal balls centered at the Voronoi vertices. The straight lines are a result of far outer polar balls with large radii such that they simplify to half-spaces intersecting the convex hull of \( S \), (e) Power diagram of \( V \), constructed with the weights of the maximal balls in (d). Polar balls within the envelope of another do not have their own Power cell, as they are overpowered; (f) the labelled Power diagram with the medial axis approximation. The boundary between the interior and exterior Power diagram cells is the Power Crust. Visualization adapted from Devert (2018) and aided by the Scipy Spatial (Virtanen et al. 2020) and Matplotlib (Hunter 2007) libraries for Python.

With an overview on how the Power Crust algorithm functions and its main challenge, we now explain in detail the process of the algorithm. Figure 3-6 outlines the Power Crust in two-dimensions. First, eight points are added to the input point cloud, via a bounding box which is 5-times larger than the minimum bounding box of the sample points – in our 2D example four points are added (Figure 3-6b). Next, the Voronoi diagram of the point set is constructed. The bounding box vertices create Voronoi vertices sufficiently far away from the sample points, such that they fit the Voronoi cell shape criteria, and will be confidently considered as known outer poles in the future pole labelling process.
Next, two poles are determined for each sample point, with exclusive consideration of Voronoi vertices belonging to the Voronoi cell of the sample point. The first pole is selected such that it is the furthest connected Voronoi vertex found. The second pole is selected such that it is the furthest Voronoi vertex in the opposite direction from the first. With proper sample point clouds, these poles should be on either side of the surface, with one located in the interior of the object near its medial axis.

Next, the Power diagram is constructed for all poles, with the weight of each cell corresponding to the radius of its polar ball. The Power Diagram splits the 3D space into polyhedral cells, with a cell corresponding to each pole. The polygonal faces belonging to the Power Crust are those which separate the interior Power Diagram cells from the exterior cells, hence the importance of the labelling step.

To label the poles and their corresponding Power Diagram cells as interior or exterior, a graph data structure is constructed. Two poles are connected in the graph, if they correspond to the pair of poles for a particular sample point (i.e. one inner and one outer). Additionally, two poles are connected if their corresponding Power Diagram cells are adjacent, and share a polygonal face. The labeling algorithm then begins, first by labeling the poles which are closest to the bounding box vertices, as there is a high confidence that they are outer poles. The algorithm knows if two adjacent Power diagram cells both belong to outer poles if their polar balls intersect deeply. This is because an outer polar ball is almost entirely contained on the exterior, while an inner polar ball is almost entirely contained in the interior. The intersection of two outer or two inner polar balls is thus deep, while the intersection of an outer and inner polar ball is thus shallow. Considering the assumptions that (1) each sample point has an inner and outer pole and (2) deep intersections result in the adjacent pole having the same label, the labelling algorithm therefore simply traverses the graph and labels the poles. Note that these assumptions do not hold true if the point set is not sufficiently sampled, and therefore some poles may be incorrectly labelled.

We utilize the Power Crust software provided by Amenta et al. (2001a) which has been ported to Microsoft Windows by Alhashim (2012). The implementation of Power Crust was built from Ken Clarkson’s Hull (1995) with modifications to construct the Power Diagram. Hull utilizes pseudorandom
sampling to increase the expected time of incrementally constructing the Voronoi Diagram as the dual to its Delaunay Triangulation (Clarkson and Shor 1989). The usage of random sampling can therefore change the order of the graph utilized to label the interior and exterior poles. For point sets which do not meet the sampling assumptions, this potentially changes the labels of ambiguous poles.

We confirm in our experience that the Power Crust algorithm struggles when the sampling assumptions are not met. Small scale rockfall point clouds, which also have 10 cm point spacing, produce Voronoi diagrams square-like cells. Large relative gaps can also result in a square-shape of Voronoi cell. These cells can cause some of the labelling assumptions to not hold true, causing incorrect pole labels. Considering the graph-propagation method used by the labelling algorithm, and incorrect labels can amplify. The volume of the Power Crust can be significantly overestimated if an outer pole is mislabeled as inner.

To combat the issue with mislabeled outer poles, we conduct a bounding box analysis between the resulting mesh versus the input point set. If the ratio of the bounding box dimensions exceeds a value of 1.2, we reject the result and attempt the reconstruction again. Here we utilize the random sampling of Hull to our advantage; while one Power Crust execution could incorrectly label the poles, the following execution might not. We set the maximum number of attempts to a very conservative number of 50. We flag the IDs of the point clouds which cannot be reconstructed by Power Crust, and discuss the inputs that failed in the Results Section.

The Power Crust software also prescribes parameters corresponding to the sampling assumptions, and the criteria for rejecting poles. The sampling density constant, R, was set to 1, which is more suitable for sparse point cloud inputs with limited noise and no sharp corners (Amenta et al. 2001a), often providing a more robust fit (Benjamin et al. 2020). The remainder of parameters were left as default. For a key overview of Power Crust, readers are referred to Amenta et al. (2001a). For further details on the sampling assumptions and subsequent proofs, readers are referred to Amenta et al. (2001b).
3.2.3.4 Power Crust Mesh Volume Computation

To prep the Power Crust mesh for automated volume computation, the polygonal mesh must be triangulated. To do so, we utilized the triangulation algorithm from Liepa (2003) implemented within the Polygon Mesh Processing C++ library (Sieger and Botsch 2020). The volume of the triangulated Power Crust mesh can then be determined using the divergence theorem, in which the volume enclosed by the surface can be given by a surface integral of its vector field:

\[
\iiint_{R} (\nabla \cdot F) \, dV = \iint_{S} (F \cdot \hat{n}) \, dS
\]  

Eq. 3-3

Where the \( R \) is a solid region (subset of \( \mathbb{R}^3 \)), \( S \) is its surface boundary with local normal vectors \( \hat{n} \), and \( F \) is a continuously differentiable vector field defined on a neighbourhood of \( R \). The divergence theorem states that the total divergence of \( F \) across the region, is equal to the flux of \( F \) across its surface.

![Figure 3-7: A mesh facet expanded into a signed tetrahedron with its apex at the origin. Adapted from Lien and Kajiya (1984).](image)

For a closed triangulated surface mesh, the divergence theorem expands one sixth of the sum of all triple products, given by each triangulated facet. Geometrically, this is equivalent to the sum of signed
tetrahedra (Lien and Kajiya 1984), with the apex of each mesh facet placed at the origin (illustrated in Figure 3-7).

\[
V = \frac{1}{6} \sum_{i}^{n} \frac{(a_i - d_i) \cdot ((b_i - d_i) \times (c_i - d_i))}{6}
\]

\[
V = \frac{1}{6} \sum_{i}^{n} a_i \cdot (b_i \times c_i)
\]

Eq. 3-4

where \(d_i = (0,0,0)\)

Incorrect mesh facet orientations can produce sign errors, and thus inaccuracies in the volume computation. Following the right-hand rule, all mesh facet normals should point to the interior of the object, or all normals should point to the exterior of the object. It is possible for the resulting summation of tetrahedrons to be negative, therefore we take the absolute value of the volume. Holes in the mesh cause there to be some volume unaccounted for – since volumes are signed, holes can either result in an overestimation or underestimation of volume. This, however, is not an issue for the Power Crust because it is guaranteed to be 2-manifold and watertight.

It should be noted that achieving consistent orientation for a 2-manifold watertight mesh is trivial.

For all edges \(p_1p_2\), there should be a compliment edge \(p_2p_1\) which is part of an adjacent facet. We compute the volume utilizing the mesh data structures provided by the Polygon Mesh Processing C++ library (Sieger and Botsch 2020).

3.3 Results

Rockfall volume was calculated using each of the four surface reconstruction methods, for the database of events detected during the 5-year monitoring period. The surface reconstruction results for the largest rockfall point cloud extracted are highlighted in Figure 3-8. Figure 3-8a shows the extracted point cloud, comprised of 98,903 points, which is shaded corresponding to its change detection signature. The Convex Hull (Figure 3-8b) drastically overestimated the shape across concave geometries as expected and thus overestimated the volume with an estimate of 5,331 m³.
Figure 3-8: Surface reconstruction results for the largest rockfall point cloud, with a side view (top) and a front view (bottom), rendered in Blender (Blender Foundation and Community 2020). The point cloud is visualized by its change detection signature. Missing surface information in the point cloud is observed where the back (cold-coloured) points are visible through the gaps in the front (warm-coloured). Missing information occurs between the boundaries of the back and front data, and across surfaces with high incidence angles relative to the scanner.

The Default Alpha Shape (Figure 3-8c) captured the detailed surface information of the point cloud, although, it underestimated the volume by an order of magnitude, with an estimate of 341 m$^3$ in comparison to the estimates of 3,851 m$^3$ from the Alpha Solid and 3,133 m$^3$ from the Power Crust. The issue causing this underestimation of volume has to do with the definition of the Default Alpha Radius, and the definition of a Delaunay tetrahedron. As noted in the methods section, the Default Alpha Radius is prescribed to be sufficiently high in order to connect all point within the Alpha Shape. A Delaunay tetrahedron is defined by the connection of 4-points, if they can be bounded by an empty circumsphere with a radius less than the value of Alpha (i.e Figure 3-4). Restricted Voronoi Cells (i.e Figure 3-4d & Figure 3-5) do not intersect in the interior of the Default Alpha Shape when the Default Alpha Radius is not larger than roughly $\frac{1}{2}$ of the “thickness” of the rockfall point cloud – where the point cloud object “thickness” is the maximum distance which a Delaunay tetrahedron must span in order to bridge occupy the interior of the point cloud. The Default Alpha Radius is a function of the point cloud spacing, and thus has no correspondence with the thickness of the point cloud. Therefore, a point cloud with a thickness greater than roughly two-times the
point spacing, will have Delaunay tetrahedra missing from its interior, where the majority of the shape’s volume is contained. The volumetric estimates of the Default Alpha Shape are therefore very poor in the instance of rockfall point clouds which have large thicknesses relative to their point spacing – even though the Default Alpha Shape seems to capture the detailed topological connections along the surface of the shape (Figure 3-8c). Further, the Default Alpha Shape tetrahedra are unable to bridge across large sections of missing surface information. This is revealed by the presence of holes in the Default Alpha Shape (Figure 3-8c). Sections of missing information in the point cloud therefore also result in underestimated Default Alpha Shape volumes.

The Alpha Solid (Figure 3-8d) was capable of assuring that the resulting shape was 2-manifold and watertight, thus well approximating the global shape. With rockfall point clouds that have large thicknesses relative to their point spacing, the value of Alpha Radius must be fairly high in order to connect Delaunay tetrahedra across the point cloud. In the instance of these relatively thick point clouds, the Alpha Solid is therefore likely to over-interpolate across concave geometries. The surface detail of the Alpha Solid relative to the Default Alpha Shape and the Power Crust is shown in Figure 3-8.

The Power Crust was much more suitable for reconstructing the surface of thick point clouds with prominent concave geometric features on its surface. This is the advantage of the Power Diagram; unique weights allow for localized increases in mesh resolution where information is abundant. The Power Crust is able to create connectivity across the missing (occluded) information, while making use of the detailed surface information when it is available.

The four resulting databases were compared on a rank-frequency plot, shown in Figure 3-9. Differences in the surface reconstruction volume estimation are illustrated by the x-axis shift between the relations. The slope of each relation, corresponding to the power-law scaling parameter, remained relatively similar.
Figure 3-9: The rank-frequency (cumulative) distributions generated by each of the surface reconstruction methods, with cumulative frequencies normalized by the 5-year monitoring period. The Power Crust dataset does not include the rockfalls for which the reconstruction failed, hence its more significant rollover and unique cumulative frequency. The majority of failed reconstructions were for small-scale point clouds and thus for small volumes.

The Convex Hull continuously overestimated the rockfall volume as expected and the Default Alpha Shape continuously underestimated the rockfall volume. On average, the Default Alpha Shape volume was 50% less than its corresponding Alpha Solid volume. The Default Alpha Shape became more noticeably erroneous with the larger point clouds. The Power Crust algorithm failed to successfully reconstruct 1,237 rockfall point clouds, shown by its lower maximum cumulative frequency (Figure 3-9). The Power Crust failed reconstructions were for small scale point clouds with smaller volumes. A total of 95% of Power Crust failures occurred for point clouds with (1) less than 40 points or with (2) corresponding Alpha Solid volume estimates less than $2.6 \times 10^{-2}$ m$^3$. 
Power-law model scaling parameters were determined with the maximum likelihood estimation (MLE) method using a minimized Kolmogorov-Smirnov statistic for the optimal value of $x_{\text{min}}$ (see Appendix A for methodology). The truncated datasets along with their power-law models are presented in Figure 3-10a, where it is seen that the power-law model does not well-reflect the tail-end of the empirical distribution. Therefore, a second set of power-law models were created, aimed at improving the power-law fit to the higher magnitude data points, using a lower-bound cutoff of $1\text{m}^3$ (Figure 3-10b).

**Figure 3-10: Power-law magnitude-frequency distribution models.** (a) the maximum likelihood estimation of power-law models, with the datasets truncated at their estimated values of $x_{\text{min}}$ found by minimizing the Kolmogorov-Smirnov statistic; (b) the maximum likelihood estimation of the power-law models, truncated at $1\text{m}^3$ in order to better fit the tail-end of the distribution.

The parameters determined for each set of power-law models are presented in Tables 2 and 3, where a higher scaling parameter indicates an increased proportion of smaller rockfall events in the distribution. A power-law model with a minimized Kolmogorov-Smirnov statistic was also fitted to the Power Crust dataset substituted with the Alpha Solid volume data in the case of a reconstruction failure (Table 2). The Alpha Solid data was used as a substitute because it is a reliable method for determining the volume of the small-scale point clouds that challenged the Power Crust method. A smaller value of Alpha is required for the 2-manifold watertight reconstruction of small-scale point clouds. Therefore, the Alpha Solid is unlikely to interpolate across concave features in the small-scale point clouds. Also, the smaller scale point clouds
have less potential for complex geometry. No Power Crust failures occurred above 1m$^3$ and therefore an Alpha Solid volume substitution dataset was not created for the second set of power-law models.

The power-law models were used to determine the annual frequency of rockfall occurrence across a range of magnitudes, which is a common practice in rockfall hazard and risk analyses (Hungr et al. 1999, Guzzetti et al. 2004). We applied the models in the domain over which they represent the datasets well, in order to better reflect the differences at the tail end of the datasets. As such, we utilized the minimized Kolmogorov-Smirnov models (Table 2) to estimate the lower magnitude ranges, and the 1m$^3$ cutoff models (Table 3) to estimate the larger magnitude ranges. It is, however, up for discussion as to which model would be better in practice for determining the return period of the larger magnitude events, considering the history of the study site, as we note in the Discussion Section.

**Table 3-2: Upper: power-law PDF fits for each of the datasets utilizing the Kolmogorov-Smirnov statistic for estimating $x_{min}$ and the MLE of the scaling parameter; Lower: sample annual rockfall frequency calculations.**

<table>
<thead>
<tr>
<th>Convex Hull</th>
<th>Default Alpha Shape</th>
<th>Alpha Solid</th>
<th>Power Crust</th>
<th>Power Crust Substituted $^1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_{min}$ [m$^3$]</td>
<td>0.0501</td>
<td>0.0272</td>
<td>0.0339</td>
<td>0.0279</td>
</tr>
<tr>
<td>$b$</td>
<td>1.6315</td>
<td>1.7193</td>
<td>1.6808</td>
<td>1.7012</td>
</tr>
</tbody>
</table>

$f(V_1 < V < V_2) \text{ [#Rockfalls per Year]}$

| $0.01m^3 < V < 0.1m^3$ | 494 | 327 | 374 | 366 | 382 |
| $0.1m^3 < V < 1m^3$ | 115 | 62.4 | 77.9 | 72.8 | 74.8 |
| $1m^3 < V < 10m^3$ | 26.9 | 11.9 | 16.2 | 14.5 | 14.6 |

$^1$ Failed Power Crust reconstructions substituted with the Alpha Solid volumes.

The variation in the annual frequencies of rockfall shows that the different surface reconstruction techniques can have a fundamental impact on the assessment of rockfall events and hazards, and thus on rockfall risk analysis as well. The surface reconstruction techniques could also have an impact on infrastructure design when the design criteria is derived from a rockfall magnitude with a given return period (i.e designing for the 50-year rockfall event).
Table 3-3: Upper: Power-law PDF fits for each of the datasets utilizing MLE with a defined $x_{\text{min}}$ of 1m$^3$; Lower: sample annual rockfall frequency calculations.

<table>
<thead>
<tr>
<th>$x_{\text{min}}$ [m$^3$]</th>
<th>Convex Hull</th>
<th>Default Alpha Shape</th>
<th>Alpha Solid</th>
<th>Power Crust $^1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$</td>
<td>1</td>
<td>1.6001</td>
<td>1.5743</td>
<td>1.5757</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$f(V_1 &lt; V &lt; V_2)$ [ nº Rockfalls per Year]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1m^3 &lt; V &lt; 10m^3$</td>
</tr>
<tr>
<td>$10m^3 &lt; V &lt; 100m^3$</td>
</tr>
<tr>
<td>$100m^3 &lt; V &lt; 1000m^3$</td>
</tr>
<tr>
<td>$1000m^3 &lt; V &lt; 10,000m^3$</td>
</tr>
</tbody>
</table>

$^1$ No Power Crust failed reconstructions occurred above the 1m$^3$ value of $x_{\text{min}}$.

3.4 Discussion

There is a significant variation in the properties of a rockfall database and its fitted power-law model, corresponding to the surface reconstruction volume estimation method utilized. We have shown that these variations have a direct impact on the estimation of the temporal frequency component of rockfall hazard determined with a magnitude-frequency analysis.

The Alpha Solid method guarantees a 2-manifold watertight reconstruction of the point clouds. However, due to the rigid usage of a maximum Voronoi cell extent by the Alpha Shape algorithm, the Delaunay Triangulation tends to over-interpolate across prominent concave geometry features in instances when the Alpha Radius must be relatively high in comparison to the point spacing. Because smaller point clouds have a limited opportunity for complex concave geometry, the Alpha Solid method was very suitable for the small point clouds for which the Power Crust algorithm was unsuccessful. The potential for the Alpha Solid to have significant over-interpolations is attributed to the presence of concave features, in addition to the thickness of the point cloud object. If the thickness of the rockfall point cloud is roughly the same as the point density, then no significant over-interpolations are possible.

The Convex Hull method overestimates the rockfall volume across all scales due to significant interpolation across concave features. In the absence of concave features, and with a point cloud thickness roughly equal to the point spacing, the Convex Hull would be equivalent to the Alpha Solid.
The Default Alpha Shape method performs worse with larger rockfall point clouds that typically have more challenging geometries and higher thicknesses relative to their point spacing. With these point clouds objects, the Delaunay tetrahedra of the Default Alpha Shape are unable to bridge the thickness, thus producing internal voids that cause for an underestimation the volume (Figure 3-8).

We determined that the Power Crust algorithm is the best performing algorithm for the reconstruction of large-scale rockfall point clouds with significant concave geometric features. The use of a Power Diagram permits mesh connections to be detailed where there is abundant spatial information. A total of 95% of Power Crust failures occurred for point clouds with less than 40 points, and 95% of the failures occurred for point clouds with a corresponding Alpha Solid volume less than $2.6 \times 10^{-2}$ m$^3$. Because smaller scale rockfalls have surfaces closer to their medial axis, whilst the point spacing is relatively uniform (i.e. subsampled to 10 cm), our survey resulted in the smaller rockfall point clouds not having sufficient sampling for the Power Crust algorithm. This is also partially due to the reality that data resolution is not a typical constraint within the field of surface reconstruction; the Power Crust algorithm was not designed to reconstruct extremely small point clouds with relatively low data resolution. Keep in mind – the typical point spacing for the TLS surveys was subsampled to 10 cm and the limit of detection was 5 cm. Different point clouds causing failed Power Crust reconstructions are to be expected with different data resolutions and limits of detection.

It is possible to provide quantitative evaluations of the surface reconstruction accuracy, for individual point clouds. This was demonstrated in the previous study conducted by Bonneau et al. (2019). To do so, the volume must be known, and therefore digital surface representation of the object must be known. The degree to which conclusions can be made, however, is case specific and sensitive, considering the synthetic object tested. The degree of error found in the methods is closely tied to the geometry of the synthetic object, the point cloud sampling density, and the presence of point cloud imperfections, as we discuss in this article. For this reason, the authors believe that the application of surface reconstruction across a wide spectrum of real rockfall point clouds allows for a better representation of the potential errors.
In volume estimation, in comparison to the detailed quantitative analysis possible with hand-picked synthetic objects.

In the previous study conducted by Bonneau et al. (2019), the importance of surface reconstruction for volume estimation was demonstrated using three real rockfall objects ranging from approximately 1 to 120 m$^3$. In this work, we found similar results, however, the larger scale of analysis (i.e. 3,668 rockfalls ranging from approximately 0.001 to 3000 m$^3$) allows us to make much broader conclusions concerning the development of magnitude-frequency relations. We observed significant overestimates in the Alpha Solid volume, due to larger-scale point clouds with significant concave features. For the largest rockfall tested, Bonneau et al. (2019) saw a 5% larger estimate in volume by of the Alpha Solid in comparison to the Power Crust. The largest event presented in the current study had an Alpha Solid reconstruction with a 23% larger estimate (Figure 3-8). This study therefore demonstrates that the Power Crust is the better method to use on large-scale point clouds.

While Bonneau et al. did not run into any issues utilizing the Power Crust algorithm and considered it to be the best method, we determined that small-scale point clouds can result in failed reconstructions, requiring for a hybrid methodology which utilizes the Alpha Solid reconstruction on small-scale point clouds. The potential for complex topological connections in small point clouds is small. Therefore, it makes sense that the simpler Alpha Solid method should be suitable for reconstructing the smaller point clouds. It is imperative that bounding box checks are completed on the outputted Power Crust meshes, to ensure that the algorithm did not mislabel the poles, as it can drastically alter the volume estimate.

Surface reconstruction for volumetric estimates will remain a challenge in natural environments due to all the factors that can contribute to erroneous reconstruction. There are many algorithms that have been presented in the computational geometry and computer vision fields (Berger et al. 2014) that have yet to be tested for automated volumetric estimation for rockfall events. To date, rockfall related work in this area has focused on the use of explicit polyhedron representations determined using computational geometry. Menegoni et al. (2020) present the use of Poisson’s reconstruction (Kazhdan and Hoppe 2013)...
to back analyze a rockfall event that occurred in the Western Italian Alps. This case demonstrates that implicit surface representations can also be used for rockfall volumetric estimation. Although, for Poisson’s reconstruction, point-normal estimates with correct orientation must be provided as input, and a voxel size used for the Marching Cubes algorithm (Lorensen and Cline 1987) variant must be specified. This adds a further level of complexity to an automated 3D rockfall volume calculation system, as the determination of optimal scales for the geometric point cloud operators remains a consistent challenge. Further work is required to investigate the viability of implicit and explicit surface reconstruction by comparing their precision, accuracy, and ability to automate. Nevertheless, a sound understanding of the processes and algorithms being used to facilitate the surface reconstruction and subsequent volume estimates is needed in order to have confidence in digital rockfall databases and their resulting magnitude-frequency relations.

All things considered, given a rockfall database with volume estimates, there remains the crucial step in building a magnitude-frequency model. We utilized the maximum likelihood estimation technique (Appendix A), which is robust in determining the scaling and resulting normalization parameter (Goldstein et al. 2004, Clauset et al. 2009). Determining an appropriate lower bound truncation on the dataset is important, as there is a rollover point in the magnitude-frequency behaviour of rockfall inventories. The Kolmogorov-Smirnov test (Appendix A) determined an optimal minimum truncation. In practice, goodness of fit tests are necessary to determine whether an empirical dataset is in fact best modeled using a power-law distribution (Clauset et al. 2009). Validation for this study was simply completed in a qualitative manner considering the wide acceptance of power-law models for rockfall in the literature, and given our goal to compare volume estimation methods.

For this dataset it was noted that the empirical data does not agree with the power-law towards the tail-end of the distribution, and we have considered whether this is due to natural behavior, statistical bias, or error in the methods. Firstly, this rock slope has had a recent history of significant large-scale failures, including a 50,000 m$^3$ rockslide in November of 2012, and a 3,000 m$^3$ rockfall in December of 2014 (i.e. Figure 3-8). The large failures would have destabilized a significant section of the rock mass. The
increased proportion of large rockfall events may have been further amplified by the fact that this rock slope was monitored throughout a highly active time period (Nov. 2013 – Dec. 2018). The 50,000m$^3$ rockslide was not included in the magnitude-frequency relations because it is a different classification of landslide with fundamentally different mechanisms (Hungr et al. 2014).

In regards to errors in the methods, longer intervals between data collection for this site may permit several proximal smaller volume rockfalls to be clustered together as a singular event (van Veen et al. 2017, Williams et al. 2019), thus increasing the proportion of large rockfall events in the distribution. Lastly, natural geological factors could also be at play for increasing the proportion of large magnitude events, considering the elevated activity of the site. The moderate spacing of wedge forming joints, and presence of local faults (Sturzenegger et al. 2015b) could form blocks which fail at relatively higher frequencies than those predicted by the power-law. The further investigation of these hypotheses requires the continued monitoring of the site as it adapts following the recent activities in rockfall. Increasing monitoring frequency will give a truer reflection of the rockfall activity without the artifacts of coalescing rockfalls. Further understanding the geostructural and geomechanical characteristics contributing to rock mass failure will also aid in further understanding the magnitude-frequency distribution of rockfall at the site.

3.5 Conclusion

With the development of cheaper remote sensing platforms capable of capturing detailed spatial information of near vertical rock cliffs, comes the opportunity to rigorously monitor and understand rock slope hazards across larger areas of mountainous terrain. The coevolution of modern computing hardware and 3D software has provided the capability to rapidly, and intuitively, process the data acquisitions. Over the past decade, more custom tools have been created to extract important information from the processed datasets, in order to further our understanding of rock slope hazards. One of these tools has been the extraction of rockfall from these datasets in 3D, in which the occurrences can be assembled into a rockfall database providing critical information pertaining to rockfall hazard. This work was started by Tonini and Abellán (2014), and has since been improved by many complementary studies (Olsen et al. 2015, Williams
et al. 2018, 2019, Bonneau et al. 2019, Guerin et al. 2020a, DiFrancesco et al. 2020). In further developing these tools, there is a need to reduce the amount of error present in the systems which document rockfall occurrence, as they can have a direct implication on our measure of rockfall hazard. Thus, errors can further impact risk mitigation decisions, and infrastructure design criteria. With evolving methods, there has been a push to increase the portion of tools to be fully 3D, rather than rasterized (2.5D). We show that the determination of volume for rockfall point clouds may be a difficult task, considering the presence of point cloud imperfections generated as a result of the instruments, survey design, processing, and rockfall extraction algorithms. We summarize four different computational geometry surface reconstruction techniques, used to create a digital representation of the rockfalls and determine their respective volumes.

We determined that the Alpha Solid technique is simple enough to provide an accurate estimation of rockfall volumes of small-scale point clouds beneath 40 points. The Alpha Solid method will begin to overestimate the volume of larger point clouds with prominent convex geometry features due to over-interpolation. We determined that the Power Crust algorithm is a much better approach for large-scale point clouds with prominent convex geometry. The Power Crust algorithm is more likely to fail the reconstruction on small-scale point clouds, which do not have sufficiently dense sampling relative to their curvature (i.e. a small distance from the surface to their medial axis). As such, we provide a robust workflow to ensure that the incorrect reconstructions are rejected from the database. The optimal computational geometry-based surface reconstruction method for determining rockfall volume in 3D was determined to be the Power Crust method, substituted with the Alpha Solid method for the small-scale point clouds with insufficient sampling density and less complex geometry.

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References


Chapter 4

Discussion and Conclusions

4.1 Discussion

This thesis shows that, with the ability to observe rockfalls from point clouds, comes the necessity to understand and remove the errors present in the rockfall extraction and analysis methodologies. Doing so will result in a more confident quantification of rockfall hazard, better rockfall forecasting models, and a better understanding of earth surface processes related to rockfall. Note that because the thesis is manuscript based, additional reviews of the literature relevant to this discussion have been included for completeness.

As presented throughout the thesis, there are many operations throughout the workflow which can have a significant influence on the results of the rockfall database. Figure 4-1, on the following page, presents a workflow for creating a digital rockfall database from sequential point clouds. Generally, the workflow relies on: (1) the alignment of sequential point clouds, (2) the computation of distances between the datasets, (3) the extraction of significant changes, (4) the removal of noise in the change detection signature, (5) the classification of changing features, (6) the clustering of individual changing features, and (7) the computation of metrics on individual clusters (e.g. volume and shape). The considerations for the reduction of errors in the digital rockfall database workflow are briefly discussed below:

- **Point cloud registration**: poor alignment will result in non-uniform registration error across the point cloud, causing some surfaces to show erroneous change.

- **Changing feature segmentation**: Appropriate direction in the distance computations, and querying of sufficient points to reduce noise.

- **Rockfall Extraction**: inclusion of talus or soil movements, and the over-segmentation, or under-segmentation of rockfall occurrences, can considerably alter the database.

- **Surface reconstruction volume estimation**: over or under-estimation of rockfall volume.
Figure 4-1: Digital rockfall database generation workflow, with the areas improved in this thesis highlighted.
4.1.1 Best Practices for Digital Rockfall Databases

Figure 4-1 also highlights the best practice recommendations that have been created as part of the thesis, which are further discussed in the following section. Chapters 2 and 3 cover the additions that myself and co-authors have made towards creating best practices for developing digital rockfall databases. In Chapter 2, we demonstrate that the reduction in degree of spatial averaging, utilized in the change detection process, preserves the signature of smaller rockfalls that can be extracted from the dataset. We displayed the differences in the change detection signatures recorded with six different spatial averaging parameters. We recommended that the M3C2 projection diameter should remain in the range of 1-2 times the point cloud spacing, taking some consideration of how variable the point spacing is. The reduction in spatial averaging increases the presence of noise in the change detection signature – methods alternative to spatial averaging will need to be developed in order to optimize the finite details that can be extracted from the raw change detection signature without adding false positives into the database. We also discussed the application of digital rockfall extraction. Active monitoring applications focused on forecasting hazardous areas are more concerned with detecting as many rockfalls as possible from the change detection, because the spatial proximity of failing blocks can give some precursory indication of the destabilization of blocks within the rock mass (Rosser et al. 2007, Kromer et al. 2015, DiFrancesco et al. 2020). Passive monitoring applications, more heavily focused on documenting rockfall occurrence, may not be as concerned with low magnitude rockfalls, assuming that the omitted rockfalls do not hold a significant portion of risk to the public.

In Chapter 3, we determined that the Alpha Solid surface reconstruction algorithm is suitable for computing the volume of thin point clouds, without prominent convex geometric features. Here, we described “thin” point clouds as those whose thickness was less than or equal to its point spacing. The Alpha Solid algorithm is prone to the overestimation of rockfall volume when applied to thick point clouds with prominent convex geometric features. This is a result of the rigid Alpha Radius required to construct
Delaunay tetrahedra across the thickness of the point cloud. An Alpha Radius which is sufficiently large for doing this, will also produce tetrahedra that will interpolate across the surface, if there are significant convex geometric variations contained in the input point cloud. The Power Crust method performs much better in producing a watertight mesh which also captures the surface details contained within the input point cloud. This is an advantage of the Power Crust algorithm, which conceptually fills the interior and exterior of the surface with maximal (i.e. maximum sized) balls, and builds a piecewise linear surface representation at their intersection. The piecewise surface interpolate across missing to some degree, while making use of the high resolutions of spatial information when they are available. It was confirmed that the Power Crust algorithm has difficulty in reconstructing the surface of small-scale point clouds. This is because the algorithm requires the sampling density to be inversely proportional to the distance from the surface to its medial axis. With uniform point spacing, and smaller point clouds, the Power Crust reconstruction becomes inherently more difficult. We concluded that the more challenging small-scale point clouds (in our study, beneath 40 points), could be confidently reconstructed using the Alpha Solid method. The larger scale rockfall point clouds with complex geometry should be determined using the Power Crust algorithm. Other additions to the best practices for digital rockfall databases are outlined in the Recommendations for Future Work section.

4.1.2 The Potential for Error in Digital Rockfall Databases

The extraction of changing features from point clouds requires a workflow involving a series of spatial algorithms. Errors present in the early stages of the workflow can amplify throughout the rockfall extraction workflow, having significant and possibly problematic effects on the final results. This is shown in the M3C2 change detection study in Chapter 2, where differences in the initial change detection signature drastically alter the shape of the rockfall events that are extracted from the data. This was further shown for the volume estimation of rockfall in Chapter 3; even with a very good extraction technique, an erroneous 3D volume calculation could result in a misrepresentation of the data when compiling a magnitude-
frequency relation. Further, a fault in the clustering of rockfall objects could also have negative implications. Very conservative clustering strategies could result in multiple singular rockfall events becoming lumped together, therefore being considered as one discrete event. In contrast, very optimistic clustering strategies could result in a singular rockfall event being extracted as multiple parts. Undoubtedly, these effects of clustering would completely change the measure of magnitude-frequency for that particular database. These are the types of concerns that show a need for the establishment of best practices in generating digital rockfall inventories.

The comparison of two different studies, monitoring cliffs along the Eastern English coast, provides some examples of concerns surrounding the accuracy of information provided from digital rockfall databases. In the first study, Benjamin et al. (2020) monitored 20.5 km of North Yorkshire (England) coastal cliff ranging from 30 m to 150 m in height, across a monitoring period of 2.6 years, with an acquisition frequency ranging from 293 to 355 days. Benjamin et al. extracted over 58,000 rockfalls, with limit of detection of 10 cm and a minimum volume of $1 \times 10^{-4} \text{ m}^3$. In another recent study, Westoby et al. (2020) monitored a 600 m length of 25 m high coastal cliffs in Marsden Bay, approximately 60-80 km north of the North Yorkshire coast studied in Benjamin et al. Over two years with monthly TLS surveys, Westoby et al. identified over 30,000 rockfalls, using a limit of detection of 10 cm and a minimum volume $1 \times 10^{-3} \text{ m}^3$. Westoby et al. observed a higher frequency of rockfall occurrences in comparison to Benjamin et al. If the two studies had covered a similar area, Westoby et al.’s study would be expected to identify more rockfall events, due to the higher frequency of data collection campaigns, which reduces the coalescence of rockfalls as a result of proximity and overprinting. However, Benjamin et al.’s study considered a larger area and longer period of time. The extra half-year monitored by Benjamin et al. also corresponded to another winter season; where the coastal rockfall activity in the region is known to be higher through the winter, as a result of winter storm events (Lim 2014). On balance, particularly given the substantial difference in cliff area covered, it would be expected that the number of rockfall events identified by Benjamin et al should be much greater than the number identified by Westoby et al.
The difference in rockfall activity between the two studies could be attributed to the lithological, geomechanical and geostructural setting, as well as the foreshore geometry and coastal bathymetry influencing the degree of wave action on the coastal cliffs. The site monitored by Westoby et al. was characterized by very weak successions of middle to late Permian magnesium limestone, a dedolomitized limestone, and a brecciated limestone. Weathering of the limestone rock mass was apparent from dissolution and resulting karstic collapse. The retreat rates observed by Westoby et al. ranged from $0.01 \text{ m a}^{-1}$ to $0.079 \text{ m a}^{-1}$, where the dedolomitized limestone saw the highest retreat rates. Considering the geological setting of Westoby et al., the weak structural characteristics of the rock mass may have contributed to the elevated occurrences of rockfall – for example, the very weak brecciated unit saw the smallest retreat rate, but the highest occurrence of individual rockfall events. The sites monitored by Benjamin et al., on the other hand, were comprised of much more competent sedimentary sequences; younger interbedded mudstones, shales, siltstones, limestones, and sandstones from the Jurassic and Cretaceous periods. Benjamin et al. measured retreat rates ranging from $1 \times 10^{-5}$ to $1.6 \text{ m a}^{-1}$.

All geomorphological factors considered, some differences in rockfall activity measured by Westoby et al. (2020) and Benjamin et al. (2020) could be a result of the rockfall extraction methodologies utilized by each of the studies. Westoby et al. utilize a 2.5D rasterized approach for extracting rockfall, where an individual cell of significant change (i.e change $> 10 \text{ cm}$) is considered as a rockfall. Thus, any errors in the change detection signature greater than the 10cm limit of detection, would be extracted and considered as a rockfall. Further, a conservative limit of detection paired with a fine raster grid could result in the over-segmentation of larger features, leading to a higher proportion of small rockfall events. Benjamin et al. (2020) utilized a fully 3D approach, in which the stringent clustering criteria required for density-based clustering (i.e DBSCAN) ensures the extraction of features, which is not limited by simplified gridded change detection signatures.

In another study, Williams et al. (2019) monitored a 210 by 60 m area of Eastern English coastal cliffs comprised of interbedded Jurassic shales, sandstones, and mudstones, near the town of Whitby.
Williams et al. found that the interval of monitoring substantially influences the proportion of small rockfall events that are extracted from their highly automated workflow. By testing rockfall databases developed with acquisition frequencies ranging from hourly to monthly intervals, for the same site, Williams et al. determined that there was a non-linear increase of the magnitude-frequency probability distribution of rockfalls once the interval of data capture was less than 12 hours. From 12-hour to 30-day frequencies, the probability distributions were found to be similar. The number of rockfalls determined from the hourly monitoring was an order-of-magnitude higher than that determined from the 30-day monitoring. Williams et al. (2019) suggest that this increase is the result of discrete rockfall events coalescing together to appear as one event, across the less frequent change detection intervals. Several examples of the progressive failure of rock mass leading to a superimposition of rockfall occurrence has been shown in the literature (Kromer et al. 2015, van Veen et al. 2017, Williams et al. 2019, DiFrancesco et al. 2020). In the study by Williams et al. (2019), the 1-hour frequency dataset resulted in the processing of more than 5,000 TLS change detection intervals, while the 12-hour, 7-day, and 30-day processed approximately 227, 32, and 7 change detection datasets, respectively. Therefore, there is the question of whether there were indeed a significant number of proximal rockfall events leading to coalescence, or if it was due to the much higher amount of data processed – was the extraction of more small-magnitude rockfalls, in the high-frequency inventories, facilitated by the amplification of undetected systematic errors in the workflow?

Considering the two examples discussed, the development of a best practice guide for developing digital rockfall inventories will help to alleviate the potential concerns that practitioners have, when utilizing digital geohazard inventories to do their work. Two key challenges given the methodologies used are (1) recognizing the minimum size of features that can be confidently extracted from the data and (2) developing methods which work at scale (e.g. the detection of small rockfall and large rockfall are both correct under the same umbrella of tools).

Another process that can have a considerable impact on the amount of rockfall extracted from change detection is the classification of changing features considering their geomorphological processes.
The accumulation and movement of talus is related to rockfall; however, it represents an entirely separate hazard which should be considered separately from rockfall hazard. For the CN Ashcroft Mile 109.4 study site discussed in Chapter 2, there are small channels, benches, talus cones, and other accumulation zones, which the rock fragments and soil traverse as they propagate downslope. Given these challenging conditions, classification was undertaken manually in a rather time-consuming process. Inaccurate classification of the geomorphological processes and their material could result in false additions to a digital rockfall inventory. A rock fragment could be recorded moving numerous times within a channel. Without proper classification of the different erosion mechanisms, all of those movements could be mistakenly considered as rockfall. The importance of rockfall classification is site dependent, and may not hold as much importance for sites which do not have debris accumulating terrain features. Whereas a process such as a rockfall clustering, has a high importance regardless of the site. As rock slope point cloud classifiers are further developed and verified, we could have more confidence in automating the classification stage at challenging sites such as Mile 109.4.

The thesis also showed that errors within the computation of rockfall volume should be considered. With geometrically challenging change detection signatures, rasterized volume computation is prone to error as a result of the raster-projection and cell size (Benjamin et al. 2016). Chapter 3 demonstrates the use of computational geometry for surface reconstruction of rockfall point clouds, producing 3D surface meshes and corresponding estimates of volume. It is shown that the surface reconstruction algorithms must produce surface representations which are topologically equivalent to rockfall, and which sufficiently use the detailed surface information contained in the input point cloud, in order to accurately estimate rockfall volume in 3D. The assumptions of the algorithms used to compute the volume can have significant influences on the magnitude-frequency power-law relation determined using the digital rockfall inventory. Therefore, the estimated annual frequency for a rockfall within a particular range of magnitudes, \( f_m \), can be completely altered by the presence of error in the volume computation algorithm. Design criteria derived from the magnitude-frequency relation, such as projections of 50-year return period magnitudes, would also
be negatively impacted by faulty magnitude-frequency relations – greatly so for the very infrequent events, considering that the largest variation in the surface reconstruction results was seen for the largest of rockfall point clouds.

4.1.3 Applicability of Digital Rockfall Inventories in Hazard and Risk Analysis Frameworks

One of the applications of digital rockfall inventories is for quantitative rockfall hazard and risk analyses along transportation corridors. This application has remained a key consideration throughout this thesis, as the majority of RGHRP sites are adjacent to the CN rail line, the CP rail line, or the Trans-Canada Highway (BC-1). In understanding the potential application of digital rockfall databases, we look to two studies conducted in Western Canada which were some of the first to use rockfall databases in quantitative risk analysis.

Hungr et al. (1999) compiled a rockfall database comprised of the BC Ministry of Transportation and Highways (MOTH), CN and CP Rail, supplemented with additional documentation of large magnitude rock slope failures in the region. They developed magnitude-frequency relations via linear regression of rank-frequency distribution plots. They applied the relations for determining the annual frequency of rockfall occurrence within a range of magnitudes. The risk of traversing vehicles being impacted by rockfall was then quantified for each range of rockfall magnitudes and summed together.

Bunce et al. (1997) assessed the rockfall risk at a smaller scale, alongside an argillite roadcut in between Horseshoe Bay and Squamish on the BC-99 Highway, where a fatal rockfall accident occurred in 1982. They compiled a database of events from asphalt impact mapping, supplemented with MOTH records, and estimated the frequency of all rockfalls greater than the clearance of an average car, assuming spherical rockfalls. This annual frequency was applied within a binomial theorem-based risk calculation to determine different scenarios of cars being impacted by rockfall along the argillite roadcut.

Considering these two studies, there is a fundamental difference between traditional rockfall databases compiled from documented occurrences and digital rockfall databases extracted from remote
sensing data. Rockfall databases compiled from documentation also include some of the spatial probabilities involved with the rockfall propagation, because they are greatly impacted by data censoring, as noted by Hungr et al. (1999) and Guzzetti et al. (2004). Occurrences of rockfall are more likely to be documented when significant evidence is present, such as large rockfall fragments collecting in ditches, impacting a highway, or impacting a rail line. Traditional databases are therefore prone to censor rockfall events, such as rockfalls with fragments that are not large enough to be noticed, rockfalls that did not propagate near enough to an element at risk, or rockfalls that propagated far beyond the element at risk unbeknownst to the infrastructure managers. The censoring that occurs in some traditional inventories, therefore, results in the derived magnitude-frequency relation underestimating the true level of rockfall activity. This lower level of measurement, however, also contains some of the spatial components of the risk chain; the factors that increase the likelihood of a rockfall occurrence being recorded, are also related to the more threatening occurrences of rockfall.

The true level of rockfall activity is better estimated with the use of digital rockfall database methods. These methods are limited by the vantage of survey positions and the limit of detection (stemming from registration error and local point cloud roughness), but otherwise, alleviate most of the censoring issues that traditional rockfall databases face. In order to use digital rockfall inventories in quantifying the risk due to rockfall, much more effort therefore needs to be focused on understanding the rockfall dynamics, given the detailed knowledge of rockfall source zones and the spatial distribution.

Guzzetti et al. (2004) give an example of this type of analysis in their field mapping and GIS-based hazard assessment for a 32 km-long highway corridor, which traverses through the Nera River valley, in Central Italy. They compiled a detailed rockfall database from a field mapping campaign after a sequence of earthquakes in 1997. They mapped source areas with aerial photographs, mapped terrain types, and determined their physical parameters from field mapping. GIS-based rockfall modelling was conducted to quantify rockfall hazard, considering the frequency distribution of different lithologies. Results from the
rockfall modeling produced hazard mapping, from which hazard zones were defined, and a further risk analysis was conducted.

In order to apply digital rockfall databases into rockfall hazard and risk assessments, there is a need to understand the dynamic interaction of rockfall with the terrain, and its potential for runout. As mentioned earlier, digital rockfall inventories contain key information which can serve as input into the models, which we summarize on the following page. The digital rockfall inventories make rockfall risk assessments more complex in comparison to the methodologies of Bunce et al. and Hungr et al., but are likely to improve our ability to confidently quantify risk.

These types of works are increasingly possible with the new developments in rockfall modeling tools, which are capable of simulating the chaotic interaction of rockfall with terrain models. Rockyfor3D (Dorren 2016) simulates the 3D interaction of primitive rockfall shapes with rasterized terrain models. The Rapid Mass Movements Simulation (RAMMS) offers the ability to simulate the 3D interaction of custom rockfall objects with rasterized terrain models (Bartelt et al. 2016, Caviezel et al. 2019). Other approaches have made use of optimized physics engines and universal spatial data formats to simulate the completely 3D interaction of rockfall with 3D terrain models (Ondercin 2016). Newer developments in modelling of rockfall with physics engines have modelled fragmental rockfalls in 3D, with interacting fragments (Harrap et al. 2019, Sala et al. 2019). Sophisticated physics engines have promising possibilities allowing for the addition of more complex physics systems corresponding to appropriate geological environments, such as fragmental rockfall, or interaction of rockfall fragments with talus. The information contained within digital rockfall databases contains key information relative to rockfall modeling:

- Magnitude-frequency behavior of the rock slope, relative to its lithological units.
- Spatial distribution of rockfalls allowing for the variation of simulations depending on the source zone.
- Rockfall shape (Bonneau et al. 2019).
• Rockfall accumulation areas for calibration (Sala et al. 2019), although, infrequent monitoring on
managed rock slopes makes it difficult to find good use cases for rockfall calibration.

4.2 Recommendations for Future Work

Beginning with the note of the discussions from the previous subsection, some of the future work
involving digital rock inventories is to utilize them to inform cutting edge rockfall modeling. Application
of digital rockfall inventories into rockfall modeling will demonstrate what the future of rockfall hazard
and risk analysis may look like.

Further developments in rockfall modeling will help inform the rockfall extraction methods, on
what other rockfall metrics are useful to store digitally, for future usage in rockfall modeling. One of these
concerns could be which surface mesh is best used in rockfall modelling. Power Crust is able to construct
objects with such great detail, that it may be overwhelming to the physics engines; perhaps meshes with
less facets, such as the Alpha Solid meshes, are better to use? Or is a simplified object, that generally
describes the shape according to the Snee and Folk (1958) classifications, sufficient for the modeling?

Next, there are various aspects of the semi-automated rockfall extraction workflow which can be
improved upon, and additional modules which can improve the degree of automation to an optimal amount.
Firstly, better understanding of how limit of detection relates to the local geometry of the point cloud and
to the registration of the datasets is required. Lague et al. (2013) developed a method for determining the
spatially variable limit of detection in the M3C2 algorithm based on parametric Gaussian statistics, which
was applied by Kromer et al. (2018) to observe the pre-failure deformation of rockfall:

\[
LOD_{95\%}(d) = \pm 1.96 \left( \sqrt{\frac{\sigma_1(d)^2}{n_1} + \frac{\sigma_2(d)^2}{n_2} + reg} \right) \quad \text{Eq. 4-1}
\]

Where \( reg \) is the registration error, and is assumed to be isotropic and spatially uniform. \( \sigma_1(d) \) and \( \sigma_2(d) \)
are the local surface roughness for clouds 1 and 2, determined as the average distance from the best fitting
plane of the point neighbourhood defined at a radius of D, and \( n_1 \) and \( n_2 \) are the number of points in each local sub-cloud (radius \( d \)). Lague et al. note that this spatial limit of detection performs well when \( n_1 \) and \( n_2 \) are greater than 4 (i.e. more than 4 points are used in the spatial averaging step of M3C2). As we determined in Chapter 2, spatial averaging reduces the fine details of rockfall extraction, and can alter the geometry of the change detection signatures. Another issue with the spatially variable limit of detection is the assumption related to registration error, which does not always hold true. Errors such as temperature drift are not normally distributed or spatially uniform. Further, poor alignments across oriented surfaces causes the registration error to be locally anisotropic. There is therefore future work to identify optimal methods for determining a spatially variable limit of detection, which considers local roughness, local registration error, and global registration error.

Next, noise removal algorithms should be further investigated, as they relate to the change detection algorithm. As we discussed in Chapter 2, the M3C2 algorithm can create systematic artifacts with the presence of challenging terrain geometry. Prior to change detection, Williams et al. (2018) filtered points near areas of occlusion, to increase measurement certainty. Williams et al. also conducted full waveform analysis to reduce erroneous points. Afterwards they identified areas prone to systematic errors, and generated a mask in order to ignore erroneous changes. Additional geometric-feature based noise removal algorithms should be investigated.

Developments in novel change detection methods can reduce some of the noise created in the change detection signature, and can improve the spatial information captured of the changing features. Williams et al. (2018) made improvements to the M3C2 change detection algorithm, by altering the searching cylinder projection length to ensure that multiple different surfaces are not considered in the distance computation. Further Williams et al. (2021) proposed a new methodology which computes the change along a dominant movement direction (DMD), instead of the normal vector utilized by M3C2. They found differences between the DMD and normal vectors, and found that utilizing the DMD vector preserves more spatial information of the changing features. In Chapter 2, we also recommend that a change detection
method capable of considering rock mass structure may be a better approach for extracting changing features pertaining to rock mass failure.

Developments in novel approaches for clustering are also recommended for future work. Every 3D digital rockfall extraction methodology to date has used DBSCAN, while rasterized approaches have utilized region growing methods. There may be alterative clustering approaches which are smart enough to segment coalescing rockfalls from the change detection signature, which could improve the data extracted from more infrequent monitoring, as we note in Chapter 2.

Lastly, improvements in computer vision methods capable of semantic classification of change detection features will significantly improve the degree of automation with the digital rockfall extraction workflow. In this work, manual separation of rockfall events from debris movements was required, in order to have confident results. The use of multi-scale geometric point cloud operators paired with machine learning can be a great tool for classifying point clouds (Brodu and Lague 2012, Bonneau and Hutchinson 2019, Weidner et al. 2020). More recently, Farmakis et al. (2020) have developed a supervoxel based classification for rock slope point clouds with promising results, using the Fractal Net Evolution Approach (FNEA) in a purely geometric fashion. They are able to build a hierarchical network of objects, which are merged to minimize the object’s heterogeneity, with base object size determined as the initial voxel size. Rule-based classification of the object segmentation can be tailored for different sites. More confident automated point cloud classifiers for rock slopes will further automate digital rockfall extraction, and will allow the methodology to be deployed in more challenging geomorphological environments.

4.3 Summary and Conclusions

Mountainous terrain throughout the world is often accompanied with the presence of hazards related to rock slope instability, such as rockfall. Key to the improvement of safety practices to reduce the threat of rockfall is an understanding of its spatial and magnitude-frequency distribution. Remote sensing platforms capable of capturing detailed point cloud representations of the earth’s surface, have provided a
means to accurately document and characterize rockfall occurrence. The development of workflows for extracting changing features from sequential point clouds have allowed for the semi-automated construction of rockfall databases. Improvements in computing tools and algorithms have provided the opportunity to completely leverage the detail of 3D datasets, allowing us to detect and measure rockfall in completely 3D. This thesis demonstrates that individual steps within the workflows can significantly alter the information extracted; errors throughout a rockfall extraction methodology can amplify and misrepresent the activity of rockfall. This thesis has demonstrated that preserving the features in a 3D change detection signature is predicated on the degree of spatial averaging used in point cloud distance calculations. There should be a cost-benefit decision made considering the details lost with spatial averaging, versus the cleaner (e.g. less noisy) change detection signature produced. The thesis further shows that explicit assumptions in volume estimation algorithms can misrepresent the magnitude-frequency relationship determined from digitally extracted rockfall databases. The hybrid surface reconstruction solution for low level-of-detail (Alpha Solid) and high level-of-detail (Power Crust) point cloud objects, should be utilized to have confidence in 3D rockfall volume estimates at all scales.

Additional improvement to semi-automated rockfall extraction methodologies should be pursued, particularly related to optimal and reliable quantification of a limit of detection, the robust classification of changing features, and the confident segmentation of individual occurrences. Further advancements in these best practices for digital rockfall databases will allow for more confident estimates of rockfall hazard and risk. Robust implementation of automated rockfall extraction methods will allow for its application onto more frequent datasets with higher spatial coverages, and onto datasets with more challenging characteristics (e.g. challenging terrain geometry and erosion mechanisms). The full application of digital rockfall databases remain to be demonstrated within the realm of rockfall hazard and risk analysis. Detailed rockfall metrics concerning size, shape, source zone, and failure mechanics, will critically change how we think about conducting probabilistic modeling of rockfall. However, before this can be done, the utmost confidence is required in digital rockfall database generation.
References


Appendix A

Magnitude-Frequency Visualization and Power-Law Fitting

Rockfall magnitude-frequency is commonly represented by power-law relations which utilize a lower bound magnitude cutoff where the rollover occurs. This study evaluated the magnitude-frequency relations in a qualitative and quantitative manner in order to discuss the volume computation error imposed by the different surface reconstruction methods.

For qualitative evaluation of the relations, we followed Hungr et al. (1999) and visualized the rockfall magnitude-frequency as a cumulative distribution by a magnitude rank ordering of the data (also called a rank-frequency plot). The ranked frequencies were normalized by the 5-year monitoring interval. For quantitative evaluation of the relations, we fitted a power-law distribution to each dataset. Clauset et al. (2009) addressed the challenges in fitting a power-law distribution to empirical data. The maximum-likelihood estimation is most robust and reliable method for determining the scaling parameter of the power-law distribution. The commonly used least-squares linear regression techniques are subject to bias, and do not produce normalized distributions, with the total probability summing to one (Goldstein et al. 2004, Clauset et al. 2009).

Given the power-law PDF introduced in Equations 1 and 2, the probability of rockfall occurrence in the magnitude range between \( x_1 \) and \( x_2 \) is given by the integral:

\[
Pr (x_1 < X < x_2) = \int_{x_1}^{x_2} \frac{b-1}{x_{\text{min}}} \left( \frac{x}{x_{\text{min}}} \right)^{-b} dx \quad \text{Eq. A-1}
\]

The power-law cumulative distribution function (CDF) is simplified to the following:

\[
Pr (X \geq x) = \int_{x}^{\infty} \frac{b-1}{x_{\text{min}}} \left( \frac{x}{x_{\text{min}}} \right)^{-b} dx = \left( \frac{x}{x_{\text{min}}} \right)^{-b+1} \quad \text{Eq. A-2}
\]
Often the CDF scaling parameter is simplified into a singular constant and also presented as $b$, which can cause some confusion. Benjamin (2018, pp. 187-188) provides a summary of rockfall magnitude-frequency studies, with the power-law scaling parameters presented for both PDF and CDF functions. The maximum-likelihood estimation for the scaling parameter is given by the following equation, for $x_i \geq x_{min}$:

$$\hat{b} = 1 + n \left[ \sum_{i=1}^{n} \ln \frac{x_i}{x_{min}} \right]^{-1}$$

Eq. A-3

There is difficulty in determining the lower bound $x_{min}$. An underestimation results in bias due to an attempt to fit a power-law relation to data which is not power-law distributed, while an over-estimation removes too much data resulting in more statistical error in the scaling parameter maximum-likelihood estimator (Clauset et al. 2009). We utilized two different approaches for determining the value of $x_{min}$. The first approach followed Clauset et al. (2009) and computed the optimal value of $x_{min}$ for each of the distributions by minimizing a weighted Kolmogorov-Smirnov statistic (Clauset et al. 2009). With this method, we find the $x_{min}$ which reduces the maximum distance between the CDF of the truncated data, $S(x)$, and the CDF of the power-law model, $P(x)$:

$$D = \max_{x \geq x_{min}} |S(x) - P(x)|$$

Eq. A-4

The second approach utilized a constant value of $x_{min}$ for all of the distributions, in an effort to produce a power-law model which agreed with the sparse data points of the large magnitude rockfall events. As mentioned in the discussion, the better of the two power-law models to use for estimating the return period of large magnitude rockfall events is up for debate.

To compare the resulting power-law models with our datasets, we converted them into a frequency distribution. This is a common practice, as rockfall hazard is typically expressed as an annual frequency within a given area Hungr et al. (1999). The conversion is given by Equation 9, where $n_{tail}$ is the number of rockfalls in the truncated inventory, and $t$ is the monitoring time interval.
\[ f(X > x) = \frac{n_{\text{tail}}}{t} \cdot \left( \frac{x}{x_{\min}} \right)^{b+1} \]

Eq. A-5
Appendix B

CN Ashcroft Mile 109.4 Change Detection Data

This appendix contains all 25 change detection intervals for the CN Ashcroft Mile 109.4 rock slope. The change detection was conducted with the multiscale model-to-model cloud comparison (M3C2) plugin implemented in CloudCompare (Lague et al. 2013, Girardeau-Montaut 2019). A normal scale of 1 m and a projection diameter of 20 cm were used for the change calculations (DiFrancesco et al. 2020). The scarps of rockfall, talus, and soil, are shown in cooler colours. The fronts of accumulated material are shown in warmer colours. Each of the change detection intervals were rendered in CloudCompare, with normals and a light source to visualize the terrain. Change signatures which appear black are instances where the normal vector is pointing away from the light source. These points are mostly a result of sporadic normals computed with low lying vegetation points, which were not completely removed from the point clouds.

Figure B-1: Change detection from 2013-11-28 to 2014-06-04.
Figure B-2: Change detection from 2014-06-04 to 2014-09-03.

Figure B-3: Change detection from 2014-09-03 to 2014-09-13.
Figure B-4: Change detection from 2014-09-13 to 2014-11-04.

Figure B-5: Change detection from 2014-11-04 to 2014-11-10.
Figure B-6: Change detection from 2014-11-10 to 2015-02-17.

Figure B-7: Change detection from 2015-02-17 to 2015-02-22.
Figure B-8: Change detection from 2015-02-22 to 2015-03-28.

Figure B-9: Change detection from 2015-03-28 to 2015-04-03.
Figure B-10: Change detection from 2015-04-03 to 2015-06-11.

Figure B-11: Change detection from 2015-06-11 to 2015-08-23.
Figure B-12: Change detection from 2015-08-23 to 2015-10-22.

Figure B-13: Change detection from 2015-10-22 to 2016-02-16.
Figure B-14: Change detection from 2016-02-16 to 2016-05-07.

Figure B-15: Change detection from 2016-05-07 to 2016-07-25.
Figure B-16: Change detection from 2016-07-25 to 2016-10-12.

Figure B-17: Change detection from 2016-10-12 to 2017-04-08.
Figure B-18: Change detection from 2017-04-08 to 2017-05-23.

Figure B-19: Change detection from 2017-05-23 to 2017-08-31.
Figure B-20: Change detection from 2017-09-04 to 2018-04-21.

Figure B-21: Change detection from 2018-04-21 to 2018-05-31.
Figure B-22: Change detection from 2018-05-31 to 2018-06-27.

Figure B-23: Change detection from 2018-06-27 to 2018-08-02.
Figure B-24: Change detection from 2018-08-02 to 2018-09-24.

Figure B-25: Change detection from 2018-09-24 to 2018-12-04.