DEVELOPMENT OF FIXED-SITE PHOTOGRAMMETRIC APPLICATIONS AND OPTIMIZATION FOR SLOPE HAZARD MONITORING

by

Brian Z. Gray
A thesis submitted to the Faculty and the Board of Trustees of the Colorado School of Mines in partial fulfillment of the requirements for the degree of Master of Science (Geological Engineering).

Golden, Colorado

Date ____________________________

Signed: ____________________________

Brian Z. Gray

Thesis Advisor

Golden, Colorado

Date ____________________________

Signed: ____________________________

Dr. Gabriel Walton
Professor and Department Head
Department of Geology and Geological Engineering
ABSTRACT

Geologic hazards present a growing concern for the safety of humans and the development of infrastructure. There are a variety of remote monitoring methods utilized to monitor these hazards for risk analysis and mitigation purposes. Of them, fixed-site photogrammetry is a relatively new and, therefore, underutilized remote monitoring method in geologic contexts that offers time efficient, low-cost, high temporal resolution data collection with fit-to-purpose accuracy. The development of applications and practices surrounding fixed-site photogrammetry is thus valuable for the advancement of hazard monitoring more generally.

The full capabilities of the high temporal resolution of fixed-site photogrammetric monitoring are currently unexplored in geologic contexts. Other industries have made many advances in utilizing 3D data and photogrammetry, coupling the data with other advances in machine learning, numerical modelling, and statistical shape modelling. Slope hazard management can greatly be assisted via the adoption of these emerging applications in a geologic engineering context, and potential avenues for adoption are evaluated in this thesis. In particular, a proof-of-concept methodology for the prediction of rockfall event volumes was developed, with demonstrated potential to predict volumes given limited surficial information, such as that available prior to failure.

Research into best practices in the design of fixed-site photogrammetric sites remains limited. Utilizing a combination of theoretical fundamentals and empirical data collected from Red Rocks Park, Colorado, US., this work has developed a framework to enable performance predictions of fixed-site photogrammetry, which can be useful both in the design of a fixed-site system and in comparative analyses between remote monitoring methods. Empirical trends correlating ground pixel pitch and model accuracy were identified. Comparisons to an active, fixed-site photogrammetric system were made to evaluate the performance of the framework. Overall, the approach performs adequately for initial performance prediction and for use in ‘go/no-go’ analysis.
TABLE OF CONTENTS

ABSTRACT .......................................................................................................................... iii

LIST OF FIGURES ................................................................. vi

LIST OF TABLES ............................................................................ ix

LIST OF SYMBOLS ................................................................................. x

ACKNOWLEDGEMENTS ................................................................................. xi

CHAPTER 1 INTRODUCTION ............................................................................ 1

1.1 Motivation .................................................................................................................... 1
  1.1.1 Fixed-Site Photogrammetric Systems and High Temporal Resolution Monitoring ...... 2

1.2 Photogrammetric Fundamentals ................................................................................. 4
  1.2.1 Object Delineation – Image Segmentation .............................................................. 5
    1.2.1.1 Gray level thresholding .................................................................................. 5
    1.2.1.2 Iterative Pixel Classification ........................................................................... 6
    1.2.1.3 Surface-Based Segmentation ......................................................................... 6
    1.2.1.4 General Comments on Segmentation ............................................................... 7
  1.2.2 Object Delineation – Edge Detection ..................................................................... 7
  1.2.3 Object Delineation – Fuzzy Set Theory .................................................................. 8
  1.2.4 Object Delineation – Scale Invariant Feature Transform (SIFT) ......................... 9
  1.2.5 Bundle Adjustment .............................................................................................. 11
  1.2.6 Registration and Georeferencing .......................................................................... 12

1.3 Example Utilities of Photogrammetric Data ............................................................... 13
  1.3.1 Slope Failure Monitoring ..................................................................................... 14
  1.3.2 Structure Mapping and Geologic Feature Classification ....................................... 15

1.4 Objectives .................................................................................................................... 16

1.5 Thesis Outline ............................................................................................................. 16

1.6 References .................................................................................................................. 17

CHAPTER 2 EMERGING APPLICATIONS OF FIXED-SITE PHOTOGRAMMETRY ....... 20

2.1 Photogrammetrically-Informed Numerical Modelling .............................................. 20
  2.1.1 Evaluation of Fixed-Site Photogrammetry in a Geologic Numerical Modeling Context. ................................................................. 21

2.2 Machine Learning and Fixed-Site Photogrammetry ................................................. 22
  2.2.1 Camera Calibration via Machine Learning .......................................................... 23
  2.2.2 Data Analysis via Machine Learning .................................................................. 24

2.3 Statistical Shape Modelling ....................................................................................... 25
LIST OF FIGURES

Figure 1.1: Sample workflow of a typical photogrammetric investigation (Westoby, et al., 2012). SIFT stands for Scale-Invariant Feature Transform and is discussed in section 1.2.4. Clustering Views for Multi-View Stereo (CMVS) is a software package for the densification of photogrammetric point clouds via contextualization of clustered images. ................................................................. 5

Figure 1.2: Example of SIFT Feature recognition across images (top) for the construction of a photogrammetric model (bottom). The number of features identified between images should typically be within the thousands. ................................................................. 10

Figure 1.3: The Sparse Cloud of a typical photogrammetry rock slope project. Camera positions (estimated algorithmically) are presented with imaged data in the foreground. This sparse cloud was constructed utilizing Agisoft Metashape from images collected at Red Rocks Park, Colorado. ................................................................. 11

Figure 1.4: Dense Cloud of the Rock Slope Sparse Cloud presented in Figure 1.3, constructed in Agisoft Metashape. Note the correlation of visual texture to the density of points in the sparse cloud. ................................................................. 12

Figure 1.5: Comparison results over a long period of time between photogrammetric models. The change detection has filtered out changes due to vegetation, leaving only rockfall events denoted in blue. The color intensity is proportional to the amount of displacement in the slope, which can be used to determine volume of rockfall event. Events are determined by a minimum threshold of change determined by the statistical detection limits of the M3C2 change detection (Kromer, et al., 2019). ................................................................. 15

Figure 2.1: Methodology for the shape and orientation prediction of a partially exposed rock block. ........................................................................................................................................................................ 28

Figure 2.2: Selected Rocks for model construction (above) and resulting models (below); Rock Block 1 (left) and Rock Block 2 (right). ........................................................................................................................................... 30

Figure 2.3: Partitions of Rock Block 1 for the simulation of missing information. Slices were added from left to right, ascending in simulated exposed volume. The partitions A, B, C, and D correspond to volumetric exposures of 28.3%, 49.7%, 74.2%, and 90.6% respectively. ........................................................................................................... 31

Figure 2.4: Statistical Model of Rock Block 2 (Left) fitted to an alternative Rock Block 1 (Right, Colored). The fit is aligned to the photogrammetrically produced rock block model. The fitted statistical model estimated the volume at 89% of the actual, calculated via AlphaShape. Volume estimations improved when missing information was simulated, likely due to an overcorrection regarding corners and smoothing .................................................................................................................................. 32

Figure 2.5: Predicted volume, relative to the total volume of Rock Block 1, compared to percentage of simulated volume exposed .......................................................................................................................... 32

Figure 2.6: M3C2 comparison of the fitted statistical model and the Rock 1 point cloud (focused center). Presented in a bottom left is the same comparison cloud, but
visualizing the projected statistical model in red. Change presented by the scale bar is in arbitrary units, as the models are not scaled. ........................................ 33

Figure 3.1: Camera projections and resulting error ellipsoids. The left camera configuration displays a convergent system (Nocerino, et al., 2014), where both cameras are angled towards the feature of interest, and thus the ellipsoid approaches a spherical geometry (Piermattei, 2016) ........................................................................................................ 46

Figure 3.2: A graphical representation demonstrating which input variables fundamentally impact which objective functions. ................................................................. 51

Figure 3.3: Empirical correlation between camera body cost and camera resolution (left). Empirical correlation between prime lens cost and focal length (right). .......... 55

Figure 3.4: Pixel Pitch vs Camera Resolution for a full frame, 36mmx24mm camera sensor, such as those found in DSLR cameras. ........................................................ 58

Figure 3.5: Optimization results given a fixed cost of $34,000. The tool suggests two end-member solutions within the constrained parameter space, one maximizing the area, another minimizing the error ellipsoid radii. The input parameters corresponding to the end members are presented in Table 3.3. ....................................................... 61

Figure 3.6: Optimization results given a fixed area of 1,250m2. The tool suggests two end-members within the constrained parameter space of optimal solutions, one minimizing error ellipsoid radii and one minimizing cost. The input parameters corresponding to the end members are presented in Table 3.4 ........................................... 62

Figure 3.7: Optimization results given a fixed error ellipsoid radii of 1.7cm. The tool suggests two end-members minimizing cost or maximizing areal coverage. The parameters resulting in the end members are presented in Table 3.5 ........................................ 63

Figure 3.8: Camera positions and outcrop of case study .......................................................... 66

Figure 3.9: Model Accuracy vs Distance, at varied focal lengths. The range of results for the Idaho Springs, Colorado monitoring site are in black. ........................................ 67

Figure 3.10: Model Accuracy vs Ground Pixel Pitch of Red Rocks Park, Colorado outcrop models. The resulting formula in the bottom right-hand corner of the figure was utilized as the new objective function for accuracy estimation in the empirical optimization framework, where ‘x’ is the formula for ground pixel pitch (Equation 10). The black point is the typical results for the Idaho Springs, Colorado rockfall monitoring Site, with vertical bars representing the usual range of site performance. ........................................................................................................ 68

Figure 3.11: Theoretical Error Ellipsoid Radii vs. Distance, fixing other parameters to those exemplified by the Idaho Springs Site. ........................................................................ 68

Figure 3.12: M3C2 generated model generated utilizing a 200mm focal length at 110m distance from the outcrop. Note regional inaccuracies toward the extents of the model, implying a high influence of bowling or poor overlap ........................................................................... 69

Figure 3.13: M3C2 generated model generated utilizing a 135mm focal length at 320m distance from the outcrop. The estimated accuracy was 2.85cm. Note intermediary mudstone sediment package layers are regions of high inaccuracy .......... 70
Figure 3.14: Optimization results utilizing the empirical model accuracy given a fixed cost of $34,000 for the photogrammetric network are presented in blue. The black marker indicates the Idaho Springs, Colorado photogrammetric rockfall monitoring site. 71

Figure 3.15: Optimization results utilizing the empirical model accuracy given a fixed area of 1,250m². The tool suggests a plurality of optimal solutions. The black marker indicates the Idaho Springs, Colorado photogrammetric rockfall monitoring site. Notably, the curve shifts left with decreasing areal coverage, indicating a portion of the disparity to the Idaho Springs site is related to the overlap constraint............ 72

Figure 3.16: Optimization results utilizing the empirical model accuracy given a fixed model accuracy of 1.7cm. The tool suggests nine groups of solutions exist within the parameter boundaries, varied by cost and area of coverage. steps in the Pareto Front result from increasing numbers of cameras, while the continuous portions per step result from variation of camera parameters. The black marker indicates the Idaho Springs, Colorado photogrammetric rockfall monitoring site. ............................ 73

Figure A.1: Organization release for paper in Section 2.3 ................................. 85
Figure A.2: Co-Author release for paper in Section 2.3 ................................. 86
LIST OF TABLES

Table 2.1: Volume predictions by partition ................................................................. 33

Table 3.1: Practical Constraints to the Optimization Parameters ............................... 53

Table 3.2: Comparison of optimization-estimated site performance to Idaho Springs with fixed specifications from the monitoring site utilized to solve the objective functions........ 60

Table 3.3: Optimization results compared to Idaho Springs case with fixed optimization cost at $34,000 ....................................................................................................................... 60

Table 3.4: Optimization to Idaho Springs Case Comparison Fixing Area Coverage at 1250m^2 .. 61

Table 3.5: Optimization to Idaho Springs Case Comparison Fixing Error Ellipsoid Radii at 1.7cm ........................................................................................................................................................................... 62

Table 3.6: Empirically-Derived Optimization to Idaho Springs Case Comparison ............... 73
LIST OF SYMBOLS

Focal Length (mm) ........................................................................................................... θ

Camera Resolution (MP) ..................................................................................................... ε

Cost of Housing (USD) ........................................................................................................ b

\[ n = \text{Number of Cameras} \]

Distance from Outcrop (m) .............................................................................................. δ

Pixel Pitch (mm) ................................................................................................................ γ

Distance Between Stations (m) .......................................................................................... ω
ACKNOWLEDGEMENTS

First and foremost, I would like to express sincere gratitude to my family, my father, and my loved ones for the critical support throughout the journey that is this thesis. To my steadfast advisor, Dr. Gabriel Walton, I extend the deepest respect and sincerest appreciation for the tireless efforts to help me achieve all that I could. This degree would not have been possible without his guidance. My thanks extends to Dr. Ryan Kromer for a plethora of reasons: for making the original research project that garnered my interest in photogrammetry, for guiding me in initially learning the fundamentals for this work, and for pushing me to create newer and better ideas. I would like to thank Luke Weidner, Heather Schovanec, and Adam Malsam for the many, many conversations forging and improving ideas, and for the assistance in the maintenance of the Idaho Springs, Colorado photogrammetry site. Finally, my appreciation to the Colorado Department of Transportation, whose original research project developing fixed-site photogrammetric systems became the initial platform for my exploration into the subject matter of this thesis. Finally, I would like to recognize Denver Mountain Parks for permitting off-trail access to Red Rocks Park, integral to developing the empirical trends in Chapter 3.
CHAPTER 1
INTRODUCTION

1.1 Motivation

Hazard management of rock slopes is essential to ensure the safety of people and infrastructure that could be affected by slope failure events, such as rockfall. The quantity of hazardous slopes necessitating monitoring is increasing as transportation routes through rugged terrain are expanded, and new developments are increasingly situated in areas of higher risk due to increasingly constrained spatial availability. 3D modelling and geometric point clouds are emerging as effective tools for analyzing rockfall hazards. Photogrammetric methods offer a relatively cost-effective option for high frequency data collection in isolated areas. However, the design of remote sensing site investigations remains heuristic in industry practice, with optimized investigations rarely achieved due to site specific conditions and complex variable system design. Additionally, impending rockfall events are difficult to model in 3D prior to failure, given the incomplete geometric information caused by lack of block exposure. In the context of rockfall hazard prediction, this incomplete geometric exposure can lead to inaccurate predictions of block volumes, leading to overly conservative or underdeveloped hazard mitigation measures.

Photogrammetry is a process of mathematically estimating the 3D geometry of objects by identifying distinctive imaged features from scale-invariant contextually unique points matched across images (keypoints) (Lowe, 2004). The methodology has a long history, from stereoscopic methods in the late 1800s to digital photogrammetry of the modern day (Luhmann, et al., 2011). As the number of sites requiring monitoring continues to increase due to growing populations and expanding development, the need for cost-effective, data-efficient remote sensing tools is also increasing. The full potential of the modernization of photogrammetry to meet these needs in the geologic context has not developed as quickly as in other fields, such as robot vision and corollary machine automation (Chen & Li, 2004; Mortensen, et al., 2016), or graphic design (Statham, 2018). The possible applications of photogrammetry in a geologic engineering context remain largely unrealized, and professional standards of practice are continuing to be developed (Mason, 1995; Lianheng, et al., 2020).
Fixed-site terrestrial remote sensing is a developing method of monitoring capable of more efficient and frequent data collection than many other methods of remote sensing (Kromer, et al., 2019). The capabilities of high temporal resolution monitoring also remain largely unexplored. This thesis addresses two topics relevant for the practical application of fixed-site photogrammetric in geological engineering. First, this work presents potential emerging analysis approaches and application cases for rock slope monitoring using fixed-site photogrammetry, contextualized with the most recent photogrammetric advances in both geologic and non-geologic contexts. The current applications of fixed-site photogrammetry are expanded by this work via the development of a statistical shape estimation methodology for pre-failure prediction of rockfall volume. Additionally, this thesis addresses the limitation that fixed-site photogrammetry currently lacks established methods for estimating the performance of a monitoring site without trial by simulation. Specifically, a non-site-specific decision aid framework utilizing multi-objective optimization to enhance pre-installation estimations of photogrammetry performance is developed. Data collected from Red Rocks Park, Colorado, are used to produce empirical relationships to be utilized in the development of this framework. This tool can assist project engineers in budgeting and planning of optimized photogrammetry site design, helping to replace heuristic approaches.

**Fixed-Site Photogrammetric Systems and High Temporal Resolution Monitoring**

Fixed-site photogrammetric systems are camera networks fixed in place for the purpose of high temporal resolution remote monitoring (Kromer, et al., 2019). Fixed-site photogrammetry is largely novel in the geologic context; research in geologic engineering has been more focused on Unmanned-Aerial Vehicle (UAV) photogrammetry (Tannant, 2015). The first automated fixed-site photogrammetry system created for long term rockfall monitoring was developed by researchers at the Colorado School of Mines with support from the Colorado Department of Transportation (Kromer, et al., 2019). This automated method additionally does not rely upon ground control points, a typically costly addition to remote monitoring. Previously, fixed-site photogrammetry in geologic engineering had most routinely been utilized as supplemental data to other remote monitoring systems in landslide contexts (Roncella & Forlani, 2015), or for extremely high temporal resolution monitoring of continuous geomorphic processes (Eltner, et
Fixed-site photogrammetric systems offer the utility of many other remote sensing methods, but with data collected automatically and at much higher temporal resolution. Terrestrial photogrammetry data collection for monitoring purposes can be performed relatively quickly: as quickly as required to walk between each designated camera position and capture an image with a camera, while fixed-site photogrammetry can effectively monitor changes in near-real time (Zhan, et al., 2020). The ability to efficiently collect monitoring data for slopes via photogrammetry is a consequential asset of the technology. Photogrammetric monitoring can be conducted with virtually any optical sensor device, such as a 16-megapixel cellular phone camera (Micheletti, et al., 2014), or those of consumer grade. Cameras are a device that can be left in the field with comparatively less housing and power considerations than other remote sensing devices and are more feasibly repairable or replaceable than higher cost remote sensing systems. As most organizations interested in monitoring slope failures have limited budgets in comparison to the quantity of hazards that could merit monitoring, photogrammetry offers a lower risk for low budget projects with the additional benefit of collecting data at a high temporal resolution: weekly, daily, hourly, or even near-real-time videogrammetry; the temporal resolution of data collection is solely dependent upon power. Low-grade solar panels have advanced to the point that a fixed-site monitoring system for photogrammetry has become commercially feasible (Kromer, et al., 2019). As data can be uploaded wirelessly given network connectivity, the site does not require human access at all, a major limitation to the temporal resolution of data collection of other monitoring schemes. When network connectivity is not available, routine manual download from the camera memory can occur infrequently relative to the quantity of data collection. Other remote monitoring systems are undesirable to leave in the field for prolonged periods of time. For example, a typical lidar device should not be left in the field without significant security, and usually requires more power than commercial solar panels (Kromer, et al., 2017). In addition, lidar devices are more sensitive to thermal cycles and field wear than cameras, which may deteriorate data quality over time or require frequent recalibration (Bergelt, et al., 2017). Manual lidar data collection for monitoring requires frequent human access, potentially with long travel times to remote sites, which typically means daily data collection is not feasible. In a rockfall monitoring context, this can lead to less accurate
volume estimates (Kromer, et al., 2017). Lidar has benefits regarding accuracy and being an active means of data collection; however, regarding cost and site autonomy, data collection via fixed-site photogrammetry has significant advantages. The camera networks are typically lower cost, can attain fit-to-purpose accuracy, and collect data more often than many other remote monitoring methods (Kromer, et al., 2019).

1.2 Photogrammetric Fundamentals

There are two critical processes that occur during the construction of a photogrammetric model: (1) identification of unique features in an image and (2) the matching of these features between images and determining the geometric relations between these photographed features. The former is known as object delineation, while the determination of geometric relations is referred to as bundle adjustment. Any photogrammetric investigation is critically dependent upon the methods with which these processes. The methods of feature identification are inherent limitations on the capabilities of photogrammetry, and should be accounted for when designing an investigation. The following is an in-depth summary of these key processes. Figure 1.1 provides a sample workflow of a typical photogrammetric monitoring operation.
1.2.1 Object Delineation – Image Segmentation

Older methods, primarily based on pixel or sub-pixel analysis, relied on algorithms that could be crudely divided into four sections: point-based, edge-based, region-based, and a combination thereof (Pal & Pal, 1993; Schiewe, 2002). A digital image is viewed as a two-dimensional matrix whose row and column indices identify a point, or pixel with corresponding indices identifying the intensity level of the pixel.

1.2.1.1 Gray level thresholding

By partitioning an image into regions and gray scaling by the intensity, gray level thresholding plots a histogram of gray scale values across an image. Objects are assumed to have a similar level of intensity and reflectance across their component pixels, resulting in a similar gray scale, and thus are identified as peaks separated by valleys along the histogram. The histogram is then
applied probabilistically to the image regions to delineate objects. This relies heavily on the aforementioned image partition being to a fine enough scale that distinctions between pixel objects are significant, allowing the establishment of valid thresholds via the valleys in the histogram (Pal & Pal, 1993). This method fails to handle poor image quality, fails to account for spatial patterns by relying solely on the histogram, and fails to capitalize on the information availably stored in the red-green-blue (RGB) color data of modern images (Pal & Pal, 1993). Alternatively, by defining regions through discretization of co-occurring pixels, one can systemically apply an algorithm to determine a threshold of delineation by pixel similarity (Pal & Pal, 1993). The advantage of this approach is its utilization of spatially distributed pixels, but it relies on the assumption that an imaged object has similar pixel characteristics to neighboring pixels; this is not always a valid assumption, depending upon lighting conditions and the material being captured (Pal & Pal, 1993).

1.2.1.2 Iterative Pixel Classification

Iterative pixel classification, a point-based method, uses various approaches (e.g., neural networking, Markov Random Field or Gibbs Random Field, relaxation to group pixels) in parallel such that each iteration of decisions to classify pixels is informed by the previous iteration. Algorithmically, these processes typically perform at a higher speed than gray level thresholding, allowing for real time photogrammetry; however, the robustness of the methods with regards to noisy data is diminished (Pal & Pal, 1993). Additionally, the resolution of output results is limited by the resolution of the pixels, potentially yielding poor representations of the actual data.

1.2.1.3 Surface-Based Segmentation

Surface-based segmentation assumes that the imaged objects have surficial coherence such that the data can be interpreted as noisy samples from a piece-wise smooth surface function. The segmentation and delineation then occurs at the interfaces of the piece-wise functions where continuity is not preserved. A surface is first identified from depth data in an image and is the seed of further growth if planar continuity is found to be preserved after statistical processing for random Gaussian noise. Depth data in this context is typically the grey scale intensity of the object. If planar continuity cannot be assured, a higher order piece-wise function is applied,
representing a higher order surface, such as valleys or ridges. Initial surface clustering is achieved via square error clustering, plotting depth values of the relevant quantity of the data and fitting an initial function of the form \( f(x,y) \). A surface normal is projected from this fit function, and collective unit normal vectors are grouped in a second phase of the method to classify the surface as planar, convex, or concave. Interfaces of surface patches are lastly classified as creased or non-creased to evaluate compatible patches for reasonable faces of the object (Pal & Pal, 1993).

\[ \text{I.2.1.4 General Comments on Segmentation} \]

Segmentation, in general, relies heavily on distinct intensities of light, making the methods highly susceptible to noise. In the context of photogrammetry for geologic evaluations, this noise could be caused by poor lighting, such as conducting data collection on a shadowed slope. Additionally, complex geologic masses may have ambiguous grey-scale boundaries between surfaces, which limits the ability of segmentation methods such as the iterative pixel classification and surface-based methods for determining where one object or surface should be bound from another. Most methods of segmentation utilize solely the intensity values stored in each pixel, as RGB data is difficult to compare objectively because similar colors of items proximal to each other are difficult to delineate (Pal & Pal, 1993). However, these methods are a starting point for understanding the basic schematics of determining features from images.

\[ \text{I.2.2 Object Delineation – Edge Detection} \]

By locating features of high change in gray level intensity values, edges between regions can be defined such that objects can be delineated algorithmically. Two forms of edge detection exist: sequential and parallel. In sequential methods, the classification of a pixel as an edge boundary (or not) is dependent upon the results from some previously examined pixels. Parallel techniques utilize neighboring pixels to inform the decision of whether a pixel is an edge or not, allowing for simultaneous operations on all pixels. Sequential techniques rely heavily on the starting base case pixels selected, as all future decisions are informed by these initial analyses. Both methods require mathematically robust methods of filtering noise and outlier points corresponding to sub-local variations in intensity; such algorithms utilize Sobel’s or Prewitt’s gradient operators (Pal & Pal, 1993). Laplacian operators are often utilized for the effective detection of corners by
location of discontinuities in the gradient of the gray scale intensity values. A well-tuned Laplacian operator has the flexibility to decrease the effects of blurry shadowed edges at the large scale and to detect subpixel detail at a finer scale. A Laplacian of Gaussian operator performs particularly well; the Gaussian operator smears the image such that any noise inside the standard deviation of the Gaussian operator is not detected, which is preferred for the property of being smooth and localized in both the spatial and frequency domains. A good edge detector should also have a low probability of false negative and false positive classifications, edge points should be as close to center as possible of edges with good localization, and multiple responses to a localized edge point should be disallowed (Canny, 1986). Detection via the method proposed by Canny (1986) can be accomplished via maximizing the signal to noise ratio, while achieving localization via utilizing the reciprocal of an estimate of the root mean square distance of the marked edge from the center of the true edge. The maximization of the product of the signal to noise ratio and the displacement of edge points, subject to a constraint eliminating multiple identifications of edge points, reduces the impact of noise and forms a good basis for edge detection (Canny, 1986). Of note, because the edges detected by these algorithms are typically imperceptible to the human eye, further statistical thresholding is required to summarize the objects delineated for human visual use at times (Pal & Pal, 1993).

1.2.3 Object Delineation – Fuzzy Set Theory

The fundamental concept of Fuzzy Set Theory is that imprecise knowledge can be used to define an event. The application of this theory was highly relevant to photogrammetry as the definitions of boundaries in raw images are, by nature, imprecise. The discretization of light information into pixels naturally incorporates inaccuracies: sensor pixels of cameras exist in a grid separated by very small gaps between sensors; light that hits these edges is not observed in cameras, and thus cannot be used to define boundaries; the value on a pixel is also a smearing of the light intensities and wavelengths alighting on that sensor during data capture. As regions in an image cannot be crisply defined, the utilization of classifiers poorly characterizes most images. Fuzzy set theory applies a secondary system of classifications to boundaries delineated via the previous methods, where those boundaries are represented as primitive geometric entities, such as arcs, and assigned an index representing the degree to which the boundary belongs in multiple classifications. A higher index represents a higher degree of imprecision in the boundary, or fuzziness in the image. Thresholding these indices via histogram frequency analyses by
minimizing global entropy of the image and geometrical ambiguity or the natural fuzziness of small images allows for the elimination of incongruent points (Pal & Pal, 1993). By applying the fuzzy theory via thresholds, soft decisions on the classification of points and boundaries can be made, allowing for a final analysis of all decisions made for compatibility.

1.2.4 Object Delineation – Scale Invariant Feature Transform (SIFT)

The above has focused on describing the process of distinguishing different features in singular images. The inherent next requirement to generate a photogrammetric model is to combine the separate images and separate segmented objects in said images together to form a 3D data set. As there is a non-uniqueness regarding scalability of objects, the 2D data is projected in some arbitrary 3D space such that the relative dimensions between features is scale invariant. Thus, in order to perform 3D projections of valid features, further constraints on the selection of features are applied. The cost of extracting unique features from 2D images is minimized by utilizing the more expensive operations only at locations that pass initial tests. The major steps of this computation are described by Lowe (2004):

1. **Scale-space extrema detection**: The first stage of computation searches over all scales and image locations. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and orientation.

2. **Keypoint localization**: At each candidate location, a detailed model is fit to determine location and scale. Keypoints are selected based on measures of their stability.

3. **Orientation assignment**: One or more orientations are assigned to each keypoint location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.

4. **Keypoint descriptor**: The local image gradients are measured at the selected scale in the region around each keypoint. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination.

More simply stated, the process searches for feature points that are unique regardless of any scaling that may be occurring in the images, such as extreme corners.

The SIFT method assumes that it is much less likely for key features to maintain the same orientation between other images than the chance of random error replicating the relationships.
In other words, if a certain set of features forms a triangle in every image, SIFT assumes a high probability that these features are the same across all images. This is a relatively safe assumption due to localization requirements of SIFT involving the rejection of low contrast features, and the alignment of orientations across images, which involves a system of either 32 or 128 variables, dependent upon the detail of the process (Lowe, 2004). The chance of all these variables randomly matching between two different sets of distinct features is negligible for most images.

Once features of SIFT have been parsed, comparison of SIFT features across images can be conducted to determine matching features across images. The distortion of the relative positions and angles of these SIFT features between images becomes the basis of the projection into a 3D coordinate space via a system of linear equations and trigonometric relations involving the calculated camera position, angle of view, camera calibration parameters, and various algorithms to reduce the impacts of image distortions, such as shadows. This image matching is presented in Figure 1.2.

Figure 1.2: Example of SIFT Feature recognition across images (top) for the construction of a photogrammetric model (bottom). The number of features identified between images should typically be within the thousands.
1.2.5 Bundle Adjustment

Once feature matching across photos has been completed, solving for camera intrinsic and extrinsic orientation parameters can be conducted algorithmically; typically, a greedy algorithm is applied initially with further refinement (Guidi, et al., 2014). At this point, a collection of points in 3D space has been created, dubbed a sparse cloud. An example sparse cloud is shown in Figure 1.3.

The number of points in a sparse cloud becomes crucial for the construction of the further dense cloud, as the construction of a dense cloud relies heavily on interpolation from the sparse cloud key points. Exact, smooth, and height-field methods, based on pair-wise depth map computation, are example algorithmic approaches to the construction of this point cloud. The most often used algorithms for this densification are Clustering View for Multi-view Stereo (CMVS) or Patch-based Multi-View Stereo (PMVS2) (Furukawa & Ponce, 2007). Further textures can also be applied to the dense cloud via parameterizing the now 3D accumulation of points in smaller localities and blending source photos to form a texture analysis. The corresponding dense cloud created from the sparse cloud presented in Figure 1.3 is available in Figure 1.4.

Figure 1.3: The Sparse Cloud of a typical photogrammetry rock slope project. Camera positions (estimated algorithmically) are presented with imaged data in the foreground. This sparse cloud was constructed utilizing Agisoft Metashape from images collected at Red Rocks Park, Colorado.
1.2.6 Registration and Georeferencing

Thus far, the method outlined produces a non-referenced, non-scaled collection of points, referred to as a point cloud, in an arbitrary 3D space, with any two points being an accurate relative distance apart at some arbitrary scale. Registration is thus required to format the point cloud into a more usable realm, real space. Various methods of registration exist, outlined as follows:

1. The installation of surveyed ground control points on the slope can provide a direct method of calibrating the locational information of the point cloud in Agisoft Metashape, or other photogrammetric software platforms.
2. Algorithmic alignment to a different, georeferenced data set, such as a lidar point cloud, can be performed on a point-to-point comparison basis.
3. Ground truth surveying of the camera locations can be performed.

These methods have vastly different impacts on the accuracy of the data dependent upon application. For long term monitoring with fixed installation, for example, alignment via surveying camera locations may not be appropriate, as the location of the cameras may change slightly over long periods of time, depending on wind or soil motion under the fixed installation.
The use of ground control points may be better, as the location of targets can be relatively more fixed than the camera, and small variations in camera position propagate to very large errors if camera locations are pre-defined for registration purposes.

Between Methods 1 and 2, a significant difference of cost exists. In the context of slope evaluation, installation of slope targets and ground truth surveying of such targets is expensive, occasionally involving a climbing team, drill rig, helicopter crew, etc., as determined by the accessibility of the slope. Not all slopes of great concern are easily accessible, but with remote sensing techniques such as those described here, detailed analysis of hard-to-access slopes is possible and effective. A non-invasive, truly remote fixed photogrammetric system thus must utilize Method 2. In summary, this method relies on the comparatively greater degree of accuracy produced by other remote sensing platforms, such as lidar (Adams & Chandler, 2003) to accurately transform the photogrammetric point cloud. Method 1 has a typical benefit of accuracy at a higher cost with all the associated difficulties of target installations on slopes. Method 2 has a potential loss of accuracy but can be strictly remote with no invasiveness to the slope. Method 3 makes a critical assumption that the location of cameras is completely fixed; variations in the camera locations, even induced via wind, can cause significant distortions in model quality (Khalil, 2011).

1.3 Example Uses of Photogrammetric Data

The process outlined in Section 1.2 produces a georeferenced data set of points in 3D space. Without any further processing, this data is useful for geospatial visualization, and companies have already utilized such data in conjunction with emerging ocular technologies, such as the Microsoft HoloLens via BGC Engineering (Kinakin, 2018). The visualization of this geospatial information has successfully helped BGC inform policy makers in California regarding highway route alignment and interactions with landslides, and is a validated method of good communication to those not directly educated in the geosciences. As a communication tool, photogrammetry thus allows the communication of highly technical information via a method that is more intuitive to a general populace than reports, charts, or figures.

The power of visual representation of data in communicable formats cannot be understated, especially in an industry attempting to communicate objectively about geologic hazards and
risks. However, photogrammetry would not be such a powerful tool if solely limited to these purposes. The benefits of photogrammetry in contrast to other remote methods of construction of 3D point clouds should also be considered. The following subsections present various utilities of photogrammetry in the context of slope monitoring and structure mapping for geologic hazards.

1.3.1 Slope Failure Monitoring
Remote sensing in the context of monitoring is typically conducted in the evaluation of failure patterns for a slope (Adams & Chandler, 2003). Such evaluations are important for the design of risk mitigation systems and maintenance. Typically, a slope is monitored through time, with multiple events of data collection, and multiple photogrammetric models constructed and compared to monitor deformation of the slope over time (Adams & Chandler, 2003; Javernick, et al., 2014; Kromer, et al., 2019). This comparison between models can be done via utilization of the iterative closest point (ICP) algorithm for cloud-to-cloud alignment and the Multiscale Model to Model Cloud Comparison (M3C2) algorithm (Lague, et al., 2013) for calculation of the degree of change between the points in 3D space.

As the process of constructing photogrammetric models naturally creates elements of noise along the slope, and the final alignment and comparisons of points may have a Gaussian error relative to the location of points constructed from the sparse clouds, the quality of photogrammetric model must be evaluated. As the point clouds being compared are georeferenced at this point to an actual metric scale, rates of deformation and amounts of deformation can be quantified in these comparisons. Presented in Figure 1.5 is one such example of a long term slope monitoring scheme for the purpose of rockfall frequency and volume analysis. Photogrammetry is thus a verifiably useful method of monitoring slopes with minor and major deformation events (Lucieer, et al., 2013; Kromer, et al., 2019).
1.3.2 Structure Mapping and Geologic Feature Classification

Both terrestrial and UAV-based Photogrammetry are most routinely used professionally in geologic engineering for the identification and mapping of geologic structures (Vasuki, et al., 2013). Semi-automated methods of structure and geologic feature classification have been developed, utilizing 2D image and 3D surface analysis to map faults (Johnson, et al., 2014), measure sedimentary features (Chesley, et al., 2017), and monitor braided stream evolution (Javernick, et al., 2014). Scales of investigations have included trench and outcrop level observations to terrain and topography, macro investigations. Such automation increases the efficiency by which project engineers can investigate areas of concern for hazard purposes, such as for open pit mines and landslides (Sturzenegger, et al., 2009).
1.4 Objectives

The objectives of this thesis focus on the development of tools to enable effective utilization of fixed-site photogrammetric systems. These objectives are:

1. Develop a methodology for the volumetric estimation of pre-failure rockfall that can capitalize on high temporal resolution monitoring via a fixed-site photogrammetric system.
2. Create an optimization framework to assist in the informed creation of fixed-site photogrammetric monitoring sites.
3. Develop a preliminary empirical relation between terrestrial photogrammetry model accuracy and ground pixel pitch.

1.5 Thesis Outline

This thesis has been organized into four chapters, outlined below:

Chapter 1: Introduction – This chapter outlines the motivation of the work of this thesis, and summarizes the fundamentals of photogrammetry as well as current common applications of terrestrial photogrammetry.

Chapter 2: Emerging Applications of Fixed-Site Photogrammetry Data – This chapter presents an overview of recent advances in photogrammetric methods that could improve the state of utility of fixed-site photogrammetric remote monitoring. The chapter concludes with a proof-of-concept demonstration of a novel method developed to predict the volume of rockfall blocks prior to failure and outlines the potential use of such a method in the context of fixed-site monitoring.

Chapter 3: An Optimization Framework for Fixed Terrestrial Photogrammetric Network Design for Rock Slope Monitoring – This chapter of this thesis documents the development of a novel optimization framework for the purposes of aiding in the design of fixed-site photogrammetry systems and estimating their performance. The proposed multi-objective optimization approach solves for a plurality of optimized solutions, optimizing for cost, accuracy, and areal coverage of the monitoring site. Both theoretical and empirical methods for quantification of model quality
were developed; this chapter additionally documents the case study conducted for evaluation of the empirical trends relating overall photogrammetric model accuracy to ground pixel pitch.

*Chapter 4: Conclusions* – This chapter offers closing remarks, a perspective on the current nature of fixed-site photogrammetry, and suggestions for future research.

### 1.6 References


CHAPTER 2
EMERGING APPLICATIONS OF FIXED-SITE PHOTOGRAMMETRY

Much of Section 2.3 of this chapter was published in the 54th US Rock Mechanics/Geomechanics Symposium Proceedings and reproduced here with permission from the American Rock Mechanics Association.

The following sections discuss emerging applications of fixed-site photogrammetry data. Sections 2.1 and 2.2 provide reviews of emerging practical applications of photogrammetry data in the context of slope hazard modeling and machine-learning-based analysis, respectively. Section 2.3 details a proof-of-concept for a novel methodology developed as part of this thesis that estimates the volume of rockfall events prior to failure and has the potential to approximate the geometry of a rockfall event as well.

2.1 Photogrammetrically-Informed Numerical Modelling

Numerical modelling in a geologic context is the discretization of a rockmass or landform into a finite or infinite number of well-defined components that mathematically interact with one another for the purpose of estimating deformation, rockmass characteristics, or failure hazards and risks (Jing, 2003). The process of constructing a numerical model involves proper estimation of the geometric and geologic characteristics of the investigation site and the calibration of geologic and model parameters. Most back-analyses in geotechnical engineering utilize displacement monitoring data for the estimation of rockmass characteristics integral to model accuracy (Cai, et al., 2007).

Photogrammetry has been routinely utilized for accurate geometric measurement at many scales of project size, from architectural objects to cultural heritage buildings (Shults, 2017). However, converting this geometric data for utilization in the context of finite element modelling becomes a nontrivial task, as the density of photogrammetrically derived point clouds is variable, while finite element modelling assumes similarly sized elements regionally. While Unmanned Aerial Vehicle (UAV) photogrammetry has been routinely utilized for the purposes of creating and verifying numerical models, fixed-site photogrammetry has yet to become a regular tool for this task. UAV photogrammetry has successfully provided the basis data and displacement measurements to calibrate numerical models for coastal cliff slope failure (Mancini, et al., 2017),
slope stability appraisal for open pit mining (Bar, et al., 2020), lava dome structural weakening (Darmawan, et al., 2018), and loess landslide evolution (Dalei, et al., 2017), while terrestrial photogrammetry has been utilized to evaluate stress evolution during tunnel excavation (Yang, et al., 2018).

### 2.1.1 Evaluation of Fixed-Site Photogrammetry in a Geologic Numerical Modeling Context

Fixed-site photogrammetry offers many desirable characteristics for support of numerical modelling activities, primarily for monitoring large, continuous failures. Fixed-site photogrammetry also offers the additional advantage of high temporal resolution monitoring. In many geologic contexts, the rockmass parameters most integral to numerical model accuracy may change over time, during failure, post-failure, or with engineered alterations. This has been studied for landslides (Popescu, 2002; McColl, 2015) and underground mining (Kalamaras & Bieniawski, 1995). In many landslide studies, this change in strength over time is noted by the authors to be ignored for modeling purposes (Poisel, et al., 2009). Poisel, et al. (2009) note this leads to inaccuracies in the estimations of failure occurrence intervals. Numerical modelling coupled with high frequency data collection could thus improve estimations of occurrence intervals by providing means to recalibrate models more frequently, and examine in finer detail the evolution of rockmass characteristics at a variety of temporal scales. This can extend to regional characteristics or even localized parameters, such as the friction angle of specific failing lobes in a landslide complex. With near-real time photogrammetric monitoring becoming increasingly plausible (Zhan, et al., 2020) and sufficient computational resources, the analysis of rockmass characteristic evolution during failure could additionally be observed at a variety of spatial scales. Beyond the research implications, the practical benefits of more accurately determining when crucial rockmass strength parameters degrade in monitoring contexts better informs engineers when critical failures may occur, which can be highly relevant for mining contexts (Hilbert, et al., 2014). As discussed in Chapter 1, other remote sensing methods can be performed at high temporal frequencies. Fixed-site photogrammetry, however, can attain workable accuracies at lower cost and with typically less required field work than many other remote sensing methods with similar performance (Kromer, et al., 2019).
Following is a proposed paradigm for the development of fixed-sites suitable for supporting numerical modelling. The primary obstacle to utilization of fixed-site photogrammetry in the contexts of numerical modelling is viewpoint obstructions that can significantly impact regional geometric data availability. UAV photogrammetry has a notable advantage regarding this specific limitation of fixed-site photogrammetry. Design of a fixed-site system for monitoring and to support numerical modelling would most ideally be coupled with an initial UAV or other method of remote sensing to attain a complete geometric model of the region of interest while utilizing the fixed-site for deformation monitoring of critical areas. Numerical models calibrated and recalibrated to this deformation data would then include specific analyses to determine if rockmass strength parameters are changing locally within the region of interest. Utilizing existing fundamentals such as the inverse-velocity method of failure forecasting (Rose & Hungr, 2007) and projections of the measured strength alteration trends, the accuracy of failure forecast and magnitude modelling could be improved.

2.2 Machine Learning and Fixed-Site Photogrammetry

A burgeoning problem in the engineering geology is the time required to analyze the “Big Data” being produced as methods for data acquisition improve and the quantity of sites requiring monitoring and the frequency of data collection increases (Chen, et al., 2020). Photogrammetric methods and workflows are increasingly being automated in a variety of contexts, typically themed around automatic identification or classification of 3D data features (Eastwood, et al., 2019; Braun & Borrmann, 2019; Borin & Cavazzini, 2019; Kromer, et al., 2019). Machine learning is an emerging system of data analysis that allows for higher automation and efficiency of data analysis. Such methods excel at the recognition of patterns, often beyond the capability of humans to interpret (Carbonell, et al., 1983). In geologic and photogrammetric contexts, many such patterns exist. Spatial, textural, and deformation patterns in slopes monitored in geologic contexts can also be analyzed via machine learning methods for a variety of purposes. Recent developments have demonstrated machine learning methodologies with UAV-photogrammetry can be used for automated landslide susceptibility assessment (Karakas, et al., 2021) (He, et al., 2021). In photogrammetry, image distortion is a major limiting factor to accuracy of generated models (Jiadong, et al., 2009). For a typical camera, these distortions can be mathematically corrected by camera parameter calibration, as discussed in Chapters 1 and 2. For handling
generalized 3D data, machine learning methods have been developed for trained slope material classification (Weidner, et al., 2019), rockmass characterization (Gaich, et al., 2007), and soil property profile analysis amongst many others. The emergence of more recent machine learning methods indicate two very plausible improvements for fixed-site photogrammetric terrestrial monitoring:

Methods for improving the accuracy of photogrammetric precalibration parameters, thus bypassing the need for ground control points or targets (Section 2.2.1).

Pattern recognition to enhance the capability of data analysis and failure warning (Section 2.2.2).

2.2.1 Camera Calibration via Machine Learning

Chapter 1 identified various factors that impact the accuracy of photogrammetric models. Many important parameters that will affect model accuracy are internal characteristics of the camera system. The standing research consensus is that precalibration of cameras improves overall model quality when ground referencing is not available in both fixed-site (Kromer et al., 2019) and UAV contexts (Harwin, et al., 2015). While these parameters can be estimated deterministically, such methods require ground control points or some form of ground truth that can be mapped within the images. The accuracy of models is highly sensitive to the accuracy of these ground control points. In the context of a fixed-site, methodologies have been developed that do not require ground control points. Kromer et al. (2019) utilized an initial lidar scan of a site to accomplish model referencing, while Forlani et al. (2014) utilized GPS antennae connected to the cameras to measure the location of cameras, simplifying the optimization of keypoint reprojections. Both methods represent viable alternatives for project sites at which installation of ground control or targets would be either hazardous or costly; however, the requirement of additional equipment utilized by these methods increases the costs of photogrammetric investigations. The cheapest method of camera precalibration, utilizing a chessboard pattern to determine image distortions, has been demonstrated to be flawed with regards to lack of roll angle variation, making the calibration process useless for scene independent parameterization (Remondino & Clive, 2006). Even with these methods, the accuracy of the precalibration parameters may still change over time, which may not be captured easily by examination of typical day-to-day or week-to-week model results (Li & Lavest, 1996).
The development of camera self-calibration methods via machine learning has begun in other industries, specifically for extraterrestrial photogrammetry (Li & Liu, 2018), where a micro-transceiver was utilized to generate a virtual calibration grid and to receive sub-beams carrying optical distortion and internal parameter variation information. Deep learning was then applied to this data to optimize parameters. While the methodology is not directly implementable in a close-range geologic context, a variant of this methodology could be developed for a geologic setting. The capability to achieve accurate camera calibration without site-specific constraints in a geologic context would reduce costs, improve efficiency, and improve accuracy of photogrammetric monitoring, especially since for a fixed-site, these methods could be more easily utilized to track camera parameter changes through time.

2.2.2 Data Analysis via Machine Learning

As discussed, the abundance of data that can be generated via a fixed-site photogrammetric site requires an intensive amount of data analysis. For remote sensing in general, the time interval over which data analysis occurs will significantly impact the detectable changes upon an imaged slope (Kromer, et al., 2017). Though a fixed-site may be collecting data daily, the time interval over which data analysis occurs can greatly impact the detected change, as deformation typically accumulates more over longer periods of time (Kromer, et al., 2017). However, processing and particularly analyzing this data at a variety of time intervals by an engineer can limit the effective temporal resolution, as the time taken to analyze the data can take longer than the frequency of data capture. Thus, data processing and analysis automation are highly desirable to increase the efficiency of fixed-site photogrammetric monitoring. Typical methods of automated failure prediction models in these contexts monitor displacement changes of specific areas in the monitoring systems, but typically ignore spatial correlations among deformation (Ma, et al., 2021). Spatial correlations between displacements that could alert engineers to occurring large failures can go unnoticed to the human eye as well, but to a properly robust machine learning algorithm, patterns can be recognized beyond the typically discernible. The application of machine learning to a large time series of data could detect accumulated spatially contextual changes that may otherwise go unnoticed, improving the ability to mitigate the hazards of large slope deformation events. At a minimum, implementation of machine learning could allow for the first layer of analysis that filters data sets into data requiring further analysis and not, such as a time interval with no significant changes. Full development of machine learning in conjunction
with fixed-site photogrammetry could see the real-time processing of data, allowing plausible utilization of videogrammetry (photogrammetry conducted on the image frames of videos).

2.3 Statistical Shape Modelling

A fundamental assumption of rockfall hazard analysis is that the size distribution of rockfall failures per site can be estimated by analysis of previous rockfall events at the same site (Stock, et al., 2011). Rock slope failure prediction for large rockfall events has been previously accomplished via high frequency remote monitoring and utilizing inverse-velocity methods to predict a time of failure (Fukuzono, 1985; Crosta & Agliardi, 2003; Royán, et al., 2013). However, methods for modelling the shape of these rockfall events prior to failure remain difficult to apply due to limited surficial exposure. Methods exist that estimate the in-situ block size distribution of a slope via fracture geometry (Elmouttie & Poropat, 2012; Umili, et al., 2020), but are most accurate when applied to large slopes as a whole; these do not assist in modelling individual rock blocks (Umili, et al., 2020). A recently proposed method for runout modelling utilizes the orientation and magnitude of the principal axes of a rock block (Wegner, et al., 2020). Others have utilized pre- and post-failure remote sensing data to calibrate numerical models of rock slope failure events (Agliardi & Crosta, 2003), but do not account for rock shape in their analysis. These methods are limited by the inability to generate accurate representations of rockfall geometries to be utilized in modelling. Rockfall shape and associated path trajectory characteristics have been demonstrated to greatly impact the overall runout of a rockfall event (Glover, 2015). Other industries have developed software tools for the statistical analysis of shapes given high resolution geometric information, such as point clouds or 3D meshes, including Statismo (Luthi, et al., 2012) (Luthi, et al., 2017) and Deformetrica (Durrleman, et al., 2014) (Bône, et al., 2018). Both of these open-source software packages have primarily been utilized for the statistical analysis of anatomical structures, including both soft tissue and bones. Statismo is a tool for Gaussian Process Morphable Modelling (GPMM) of 3D data (Luthi, et al., 2017), which is a principal component analysis (PCA) based method of developing a statistical model for the average shape of a population of objects from individual corresponding shape models. PCA modelling requires the utilization of corresponding meshes; the points on one mesh can be directly transformed into the points of alternative meshes. This is a severe limitation for utilization in a geological engineering context, as any ability to correspond the meshes of unique
rocks would most usually be coincidental. This limitation restricted the following analysis to consideration of volume estimation based on a statistical shape model developed from a single rock block, as correspondence could not be achieved to develop a model based on a database of multiple rock blocks. This work can therefore be considered an initial proof-of-concept for a *Statismo*-based method that was successfully utilized to predict the volume of a rockfall under controlled conditions. In future, shape modeling based on a database of multiple rock block shapes could be attempted utilizing approaches that do not require full mesh correspondence; current methods developing towards this still assume that at least a portion of the meshes correspond (Pokrass, et al., 2015).

The ability to conduct site-specific run-out modelling, improved by the consideration of rock geometry, can better inform mountainous highway corridor hazard mitigation efforts regarding run-out trajectories. This information is most beneficial to inform rockfall fence requirements, placement, and design. In addition, this work functions well with existing methods that model rockfall events utilizing 3D geometric data, as opposed to simply volume (Glover, 2015). Further applications when utilized in the context of data obtained from a fixed-site photogrammetric monitoring site are discussed in Section 2.1.1.

2.3.1 Proposed Method for Volume Prediction of Rockfall Events
BGC Engineering has been monitoring an active rock slope along a state highway near Manitou Springs, Colorado since February 2020 daily using a fixed-site photogrammetric camera system (Kromer et al., 2019). This work developed a method for rockfall volume estimation based on two rock blocks collected from the slope. Figure 2.1 presents the proposed workflow for rockfall volume and shape estimation.

*Step 1*: 3D point clouds of the selected rock blocks were generated. Photogrammetry was used for point cloud generation. Images of each rock block were captured with a Canon EOS 5DSR camera with an 85 mm prime lens. Half of each rock block was imaged, before flipping the rock and imaging the 2nd half. Alternatively, a turn table could have been used. Images were processed using Agisoft Metashape to create sparse point clouds. Multi-view stereo methods were then used to process the sparse point cloud into a dense cloud. To create full object models, the two halves of each rock were constructed separately, and aligned. The Poisson Surface
Reconstruction (Kazhdan et al., 2006) plug-in in CloudCompare was applied to create triangulated, closed meshes of each rock model.

**Step 2:** Many of the blocks found in the ditch by the aforementioned slope demonstrated a trapezoidal prism shape. Blocks qualitatively assessed to fall in this shape category were selected for testing the viability of this method, as this rock shape is most adverse to the projected fitting executed via *Statismo* because of distinct edges, with the objective being to demonstrate this method works given adverse circumstances.

**Step 3:** *Statismo*, a software framework for PCA-based statistical modelling (Luthi, Blanc et al. 2012), was used to build a statistical model from a trapezoidal prism rock block point cloud. Models were made using a gaussian kernel with a standard deviation of 50 (units arbitrary as mesh models were not scaled to reality) and a scale of 50 as a covariance function; the model was represented by 200 Karhunen-Loeve basis functions. These values were selected based on the examples presented by *Statismo* developers.

**Step 4:** In practice, this step would entail the utilization of pre-deformation data to identify rock blocks worthy of further analysis by this method, potentially greatly assisted by the high temporal resolution of fixed-site photogrammetric monitoring. Methods to identify high risk rockfalls have been developed (Rosser, et al., 2007; Kromer, et al., 2017). Though these methods utilized terrestrial laser scanning rather than photogrammetry, the fundamental analysis of 3D data for these purposes is consistent for different remote sensing methods.

**Step 5:** In practice, this step would entail the careful partitioning of available geometric data of the identified rock block in step 4 from the larger geometric data of the slope being monitored. For the purposes of testing the performance of the mathematical modelling, steps 4 and 5 were skipped as rockfall was collected from a catchment ditch, rather than being identified upon the slope. Pre-failure deformation was not currently noted at the monitored slope from which the rock samples were collected. For this analysis, two of the rockfall samples were selected. The influence of variable amounts of missing data on modelling results was investigated by partitioning one of the sample models along the characteristic dimension (long axis).
Step 6: Reparameterization of the statistical model was conducted via Statismo, utilizing the available point cloud to generate a posterior model. Extrapolation of the model volume was enforced (henceforth enforced extrapolation) via multiplication of the ratio of the characteristic dimensions of the posterior model and the original Gaussian model, henceforth enforced extrapolation.

Step 7: The reparametrized sample from the statistical model (Step 6) was aligned to the available geometric information of the simulated pre-failure rock from Steps 4 and 5. Alignment
was achieved by applying the Iterative Closest Point (ICP) algorithm to the volume partitions generated to satisfy Step 4 in this study. As the scale of the statistical model is defined by the input data, scaling to real spatial coordinates was irrelevant to this study. The volume of the statistical model was compared to the volume of the original, unpartitioned rock model utilizing the *alphashape* function in Matlab.

In the context of fixed-site photogrammetry, the exposed proportion of rock volume of a pre-failure rockfall event is a critical defining factor to the success of this method, as volume exposure directly determines the amount of 3D-data available with which to fit the statistical model. To study the impact of surficial exposure on quality of volume prediction, one of the rock models was segmented along the principal axis, and partitions were added to simulate increased surficial exposure. A statistical model was then fit to the partitioned volumes to observe performance of the volume prediction.

### 2.3.2 Proof-of-Concept Results

For proper functionality, *Statismo* assumes a rigid mesh correspondence, meaning points can be directly mapped between meshes via simple transformations. Figure 2.2 displays examples of two rock blocks considered as the corresponding 3D triangulated meshes generated from point cloud data. The models of Rock Block 1 and Rock Block 2 were generated using 112 and 332 images, respectively. Rock Block 2 is approximately twice as large as Rock Block 1 by volume and required further imaging for full photogrammetric coverage. The higher point density of the Rock Block 2 point cloud due to greater photo coverage was negligible after smoothing via the Poisson Surface Reconstruction step.
Figure 2.3 displays the partitions of the Rock Block 1 model that were used to simulate missing information, as might be the case where the rock block has yet to detach from the slope. Partitions were divided along the characteristic dimension of the rock block. The selected orientation of partitions along the principal axis of the block exacerbates the required extrapolation for the methodology to achieve accurate estimations. This best simulates adverse circumstances due to less available surface area when less volume is exposed, which is most similar to surficial information of a rock pre-failure on a slope.
Figure 2.4 displays the correspondence of the projection of the Rock Block 2 statistical model onto Rock Block 1. Practically speaking, this represents estimating the volume of a rockfall event via analysis of previous failures and available geometric data from the exposed portions of the pre-failure rock block. The generated statistical model volume Rock Block 1 was approximately 138% of that associated with the Rock Block 1 mesh, before reprojection onto the target mesh.

Figure 2.5 presents the predicted volumes for Rock Block 2 generated using the various partitions of Rock Block 1 as a proportion of the known volume. Relevant statistics associated with these results are presented in Table 2.1. A perfect volume estimation would attain 100% of the predicted volume.

Figure 2.6 presents a Multiscale Model to Model Cloud Comparison (M3C2) (Lague et al., 2013) between the statistical model of Rock Block 2 fitted to Rock Block 1, and the meshed point cloud of Rock Block 1. The large gaps in point coverage in the comparison cloud are where the projected fit poorly characterized the rock block. The areas of largest difference are near these gaps, indicating the statistical fitting smooths the corners, supported by the rounded edges visible in the projection. Large planar faces demonstrate a better fitting overall than the corners. Notable
smoothing is the primary cause for the observed decrease in accuracy when 100% of the volume is known.

Figure 2.4: Statistical Model of Rock Block 2 (Left) fitted to an alternative Rock Block 1 (Right, Colored). The fit is aligned to the photogrammetrically produced rock block model. The fitted statistical model estimated the volume at 89% of the actual, calculated via AlphaShape. Volume estimations improved when missing information was simulated, likely due to an overcorrection regarding corners and smoothing.

Figure 2.5: Predicted volume, relative to the total volume of Rock Block 1, compared to percentage of simulated volume exposed.
Table 2.1: Volume predictions by partition

<table>
<thead>
<tr>
<th>Partition</th>
<th>Known Volume (arb. unit 1)</th>
<th>Projected Volume (arb. unit 1)</th>
<th>Percentage of Volume Known</th>
<th>Volume Predicted without Enforced Extrapolation</th>
<th>Posterior Characteristic Dimension (arb. unit 2)</th>
<th>Model Characteristic Dimension (arb. unit 2)</th>
<th>Volume Predicted With Enforced Extrapolation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2.75</td>
<td>2.84</td>
<td>28.3%</td>
<td>29.2%</td>
<td>1.24</td>
<td>3.53</td>
<td>83.01%</td>
</tr>
<tr>
<td>B</td>
<td>4.84</td>
<td>4.72</td>
<td>49.7%</td>
<td>48.5%</td>
<td>1.73</td>
<td>3.53</td>
<td>98.99%</td>
</tr>
<tr>
<td>C</td>
<td>7.23</td>
<td>6.79</td>
<td>74.2%</td>
<td>69.7%</td>
<td>2.51</td>
<td>3.53</td>
<td>98.02%</td>
</tr>
<tr>
<td>D</td>
<td>8.82</td>
<td>7.87</td>
<td>90.6%</td>
<td>80.8%</td>
<td>3.01</td>
<td>3.53</td>
<td>94.78%</td>
</tr>
<tr>
<td>Full</td>
<td>9.74</td>
<td>8.70</td>
<td>100.0%</td>
<td>89.4%</td>
<td>3.53</td>
<td>3.53</td>
<td>89.39%</td>
</tr>
</tbody>
</table>

Figure 2.6: M3C2 comparison of the fitted statistical model and the Rock 1 point cloud (focused center). Presented in a bottom left is the same comparison cloud, but visualizing the projected statistical model in red. Change presented by the scale bar is in arbitrary units, as the models are not scaled.
2.3.3 Discussion of Developed Method

The results presented in Table 2.1 indicate that without some enforced extrapolation (see Step 6 of Section 2.3.1), this process as-is will tend to underestimate the volume of a rockfall event. However, with enforced extrapolation, the estimated volume tends to be on the order of 90% of the actual volume. This extrapolation assumes the rockfalls classified into characteristic block shapes that are congruent enough to justify assumed similarity in the characteristic dimension. The selection of the trapezoidal prism characteristic block enhances the viability of this assumption. The methodology requires further investigation considering alternative rock shapes before it can be used in such circumstances.

Statismo was originally developed for the statistical modelling of populations with more marginal variance, such as biomechanical modelling of bone structures (Luthi, Blanc et al. 2012). Variance in rockfall shape characteristics is much higher than the variance observed in the target populations the software was designed for, suggesting the need for further investigation of the mathematical parameterization of the statistical models in rockfall applications. These parameters control the allowable variance of the model and can therefore be adjusted to allow for more appropriate fitting of the statistical model to available rock faces. Methods of partial shape matching that do not require complete point-wise mesh correspondence are emerging, but still usually require regions of the meshes to match well (Pokrass, et al., 2015). The benefits of this would be a higher fidelity to the shape of the rock faces, and better guided projection of the statistical model into the missing regions. It must thus be noted that the results shown in this work are limited to a singular rock shape from a singular slope. We anticipate that, when tested under these broader conditions, the method will work best for simplistic geometries, and will perform poorly as geometric complexity increases.

The statistical shape modelling captures the finer lateral details that a coarse geometric projection would fail to emulate, as Step 6 (“model fitting prior to extrapolation”), can represent the cross-sectional face of the exposed rock well. However, the ability to fit to edges and corners is limited via smoothing utilized to clean the mesh models. The use of further example blocks in generation of the Gaussian model would impose more variability, allowing for a better fit to be developed and mitigate these limitations; however, efforts to generalize the procedure to populations rather than individual samples proved unfruitful given poor (or impossible) point
correspondence between individual rocks. The model fitting alone fails to extrapolate properly, thus Step 6 relied on the assumed similarity of the characteristic dimensions of the blocks. The ability of the statistical method to extrapolate without this assumption would be enhanced by the inclusion of further modelled samples to form a statistical shape database. However, in the interim, methods of predicting the characteristic dimension of a block exist requiring little further field work than that required in the proposed method (Medley, 2001). The methodology as written should be altered if the characteristic dimension is not the unknown axis. The extrapolation relying on the ratio of dimensions should utilize the respective unknown dimensions to characterize the direction requiring extrapolation.

Higher accuracy results could be obtained via the utility of a lidar scanner for creation of rock models. Photogrammetry was used for this study instead due to the wider availability of cameras than lidar systems in industry. Functionally, the process would be similar regardless of the point cloud acquisition method. The alignment phase of the photogrammetric modelling is a time-consuming task for cases with large numbers of images, as image masking (removal of non-important regions of photographs such as the background) and quality control effort scales with number of images taken; utilization of lidar would decrease the time required for rock model generation. However, the value of being able to execute this methodology with cameras associated with the typical modern cellular device should be noted.

Object modelling as conducted using photogrammetry can be accomplished either from turn table modelling or convergent imaging (i.e. fixing the object and taking pictures circumnavigating the object). The latter was the method employed for this work. Masking was deemed to be necessary due to early failures to generate accurate point clouds from the raw images. This step could be made semi-automatic via use of a turn table and application of Metashape’s automatic masking feature, thus reducing a significant amount of manual effort.

From a practical perspective, a proof-of-concept has been demonstrated regarding the use of a statistical model to estimate unknown rock block geometry information, but further research is required to attain higher accuracy estimations that are more broadly applicable. Proper estimation of the shape and orientation of the rock expands the available options for rockfall investigation. More accurate runout modelling informed by rock geometry (Glover, 2015) would
allow for the predictive analysis of rockfall paths, which could guide slope design regarding rockfall fence placement and design.

2.3.4 Applications in a Fixed-Site Photogrammetric Context

There are two significant improvements to fixed-site photogrammetric applications that could ultimately be achieved based on this work. As a pre-failure hazard estimation tool, the ability to accurately predict the size of a block is important and can be used to more accurately predict the path of a given rockfall. When coupled with high frequency data collection and advanced run out modelling, this method can be utilized to determine rockfalls that pose risk to infrastructure or not prior to failure. With current daily monitoring methods (Kromer et al., 2019), or even near real-time photogrammetric monitoring becoming plausible (Zhan, et al., 2020), this could decrease risk by flagging rockfalls posing risk and alerting relevant parties. This will only improve as the capabilities of cameras to capture finer details at longer distances improves, as the smallest size of detectable pre-failure deformation will correspondingly decrease. Furthermore, when coupled with potential applications in conjunction with numerical modelling as discussed in Section 2.2, the enhanced shape estimation can improve the calibration of rockfall simulation.

A major simplification of this work would be to utilize the geometry of the models generated in place of the geometric estimations of rockfall pre-failure. Instead of predicting geometry of specific rock blocks, simulation of rockfall events could utilize the photogrammetric models of rockfalls generated in Step 1 of the methodology. Though this is plausible, more accurate estimations of rock geometries would yield more accurate estimations of rockfall predictions. In the context of general hazard mitigation and warning management, it is important to reduce the quantity of false positives and negatives when involving decision makers and the public (Major & Atwood, 2014). Before adopting this simplification, work should be conducted verifying accuracy and viability and comparing it to the limitations imposed by poor surficial exposures.

2.3.5 Statistical Shape Modelling Conclusions

A proof-of-concept methodology was developed for the estimation of rockfall volume prior to failure utilizing previous rockfall events. Collected rockfall samples are grouped into characteristic rock shapes for the slope, and pre-failure blocks are estimated to belong to one of these groups. A statistical model is generated from the collected samples, and fit to any available
geometric data of the exposed rock block face, where extrapolation from the fitted model is achieved via a ratio of the most unknown principal axes. The method requires further development to ensure utility, validity, and accuracy, but shows promise at this early stage of development, estimating the volume of a prismatic rock block with 89-99% accuracy depending on the amount of the rock block of interest that is initially exposed.

2.4 References


Stock, G. et al., 2011. Quantitative rock-fall hazard and risk assessment for Yosemite Valley, California. s.l., s.n.


CHAPTER 3
AN OPTIMIZATION FRAMEWORK FOR FIXED TERRESTRIAL PHOTOGRAMMETRIC NETWORK DESIGN FOR ROCK SLOPE MONITORING

3.1 Introduction

Photogrammetry is a process of mathematically estimating 3D geometric data of objects by identifying distinctive imaged features from scale-invariant contextually unique points matched across images (keypoints) (Lowe, 2004). The utilization of photogrammetry as a geologic hazard site monitoring tool is increasingly prevalent. As the number of sites requiring monitoring continues to increase due to growing populations and expanding development, the need for cost effective, data efficient remote sensing tools is also increasing. The full potential of the modernization of photogrammetry to meet these needs in the geologic context has not developed as quickly as in other fields, such as computer vision and corollary machine automation (Chen & Li, 2004; Mortensen, et al., 2016), or even graphical design (Statham, 2018), for example.

Structure-from-Motion (SfM) and Multiview Stereo (MvS) Photogrammetry are increasingly prevalent remote sensing tools due to their budget efficiency, fit-to-purpose design, and the ability to collect geometric data on a fine temporal scale (Westoby, et al., 2012; Cucchiaro, et al., 2018; Kromer, et al., 2019). When SfM and MvS are used in combination, automatic generation of dense 3D-point clouds characterizing objects and surfaces is possible. Previous uses of 3D point clouds in geologic engineering include rock slope monitoring (Abellán, et al., 2014; Riquelme, et al., 2016; Bouali, et al., 2017; Kromer, et al., 2019), landslide monitoring (Bitelli, et al., 2004; Jaboyedoff, et al., 2012; Bozzano, et al., 2010), structure mapping (Vasuki, et al., 2014), erosion monitoring (James & Robson, 2012; Gómez-Gutiérrez, et al., 2014), and topographic change detection (Westoby, et al., 2012; Micheletti, et al., 2014; Smith & Vericat, 2015; James, et al., 2017), among many others (Eltner, et al., 2016). The process entails capturing images from multiple viewpoints, detecting features shared between the images, and projecting those features into a 3D coordinate space, ultimately generating a point cloud.

A fixed-site photogrammetric network is a collection of cameras mounted at fixed locations to image an area of interest, typically to allow for relatively long-term monitoring with high
temporal resolution. Much of the complexity of fixed-site photogrammetric design derives from the selection of a myriad of camera and site parameters (Mason, 1995), each of which fundamentally are driven by available budget, site details, and project requirements such as the required accuracy or area of coverage. Often, many alternate configurations exist that can achieve similar results, but not all solutions are equally cost-efficient or accurate. An initial estimation of many of these parameters and the achieved performance enhances the potential to compare photogrammetric remote sensing to alternative forms of monitoring, such as for a ‘go/no go’ analysis. With the overarching goal of enhancing the accessibility of photogrammetry for geologic engineering purposes, an optimization framework intended to aid in the design of a fixed-site terrestrial photogrammetric system with theoretical performance and cost predictions is presented in this paper. Then, a case study is used to investigate the relationships between distance, camera lenses, and the attainable accuracy of coverage such that these empirical relationships can be used to better define the optimization constraints. This approach thus gives a pre-site investigation estimation of photogrammetric feasibility, which can be compared to other remote sensing methods. Additionally, the approach provides suggestions to allow for more optimal monitoring system designs to be achieved than might otherwise be possible.

Though the framework developed in this study is broadly applicable, this study focuses on the use of photogrammetry in the context of a fixed-site terrestrial system for rock slope monitoring, such as a time lapse system. Additionally, the framework applies some logical parameter constraints determined by considering relative feasibility in comparison to other remote sensing methodologies.

We begin by presenting fundamental photogrammetric principles required to properly define the system to be optimized. Next, the proposed optimization framework is presented and tested in the context of an existing system designed without the aid of the optimization framework. Finally, a case study is used to develop empirical relationships to better constrain the model quality estimates that can be used in the optimization framework. Although the specific objective function parameters used in this study may not be generally applicable to all scenarios, the proposed framework can be used with adapted parameters in the context of other fixed photogrammetry scenarios.
3.2 Photogrammetry Principles

3.2.1 The Photogrammetric Process
The key process of converting 2D images into 3D geometric data occurs through object delineation and bundle adjustment. Prior to the development of high-resolution imaging, pixel resolution was coarse such that analysis was focused on pixel or subpixel analysis (Blashke, 2010). As resolution of images has improved, the capability to capture object details across multiple pixels has become feasible (Blashke, 2010). Object delineation is a methodology to parse surfaces from imagery while simultaneously combining image processing and geographic information system functionality to integrate spectral and contextual information for analysis (Blashke, 2010). Object-based image assessment (OBIA) utilizes older segmentation, edge-detection, feature extraction and classification concepts that have been utilized in remote sensing for decades (Kettig & Landgrebe, 1976; Baltasavias, 2004). Image segmentation can crudely be categorized into four principle thematic methods: point-based, edge-based, region-based, and a combination thereof. Sivakumar & Meenakshi (2016) present a review of methods, including the relative benefits and limitations.

Modern day structure from motion (SfM) photogrammetry was advanced via the Scale Invariant Feature Transform (SIFT) algorithm, which transforms images into collections of local feature vectors; these vectors are invariant regarding transformations and partially invariant to changes in illumination and affine or 3D projections (Lowe, 1999). Speeded Up Robust Features (SURF) is another promising feature recognition algorithm, more popular in machine vision for the speed of computation and purportedly higher repeatability (Bay, et al., 2008). The distinct points identified by feature recognition algorithms are called keypoints. Image keypoints are then matched in a process known as bundle adjustment, such as those derived from the Lucas-Kanade algorithm (Lucas & Kanade, 1981), allowing the refinement of 3D coordinate geometries, the motion between images, and the camera parameters via some optimality criterion (Granshaw, 1980). Bundler (Snavely, et al., 2006) is an exemplary algorithm for bundle adjustment. Keypoints across images may be incorrectly matched, which is mitigated by the application of algorithms similar to the random sample consensus algorithm (RANSAC) (Fischler & Bolles, 1981). As RANSAC and other similar algorithms are randomly seeded, however, there are limitations on the reproducibility of photogrammetric models that leverage these algorithms. In
summary, bundle adjustment algorithms applied to images identify keypoints that are distinct per image and match these points across multiple images, forming tie points. The algorithms then mathematically optimize the extrinsic and intrinsic parameters of the cameras (relative camera location and orientation, focal length, optical affinity and skew, and radial or tangential distortion corrections) to produce the geometric relations between the tie points, and re-project tie points into a 3D coordinate space to construct a sparse point cloud. Further projections following a multi-view stereo method can be made to interpolate between the tie points to produce a dense and texturized cloud by blending source photos. Scaling the coordinate-projected space to world space can be accomplished via ground control points demarcated in the images, georeferenced camera positions, or alignment with previously scaled data clouds, such as data from lidar scans (James, et al., 2017; Kromer, et al., 2019).

3.2.2 Photogrammetric Accuracy

The resolvability of feature boundaries within images is the limiting factor regarding the smallest features able to be delineated by photogrammetry (Nocerino, et al., 2014; Barazzetti, 2017). In practice, these boundaries are affected and may be distorted by a multitude of factors that will be addressed in this section. The achievable accuracy of an overall model is limited by regional variability in coverage quality and by the attainable accuracy relative to the true position of reprojected keypoints. The accuracy of a keypoint can be resolved into two components: planar and depth. Together, these form an error ellipsoid, which is a region within which a projected key feature could exist in real space (Chen, et al., 2016). This ellipsoid, shown in Figure 3.1, has been utilized as a conceptual model for error in photogrammetry for decades (Mason, 1995; Nocerino, et al., 2014; Mosbrucker, et al., 2016; Barazzetti, 2017). Such error ellipsoids exist for other remote measurement methodologies of 3D geometries, such as terrestrial lidar systems (Chen, et al., 2016), but may vary in size even when congruent parameters between methodologies are held constant.

Planar accuracy of key points is contingent upon the scale of the image and the image quality. Photons of light captured by a sensor pixel are averaged with all other photons incident upon the sensor, meaning that a feature detected on a pixel could reside anywhere within the conical projection of the pixel to the ground surface. Smaller pixels correlate to less photons averaged
across the surface and smaller conical projections into 3D-space as well; thus, higher resolution enhances photogrammetric reprojection accuracy. The scale of the image, which is defined by the distance from the subject of focus and lens focal length, determines the radius of the conical projection at the ground surface. The projection of the 2D image to the distance from the ground surface is the region within which an imaged point could exist.

Key point depth accuracy is contingent upon the geometric relationships between the ground surface and the camera locations used to capture the images. A point captured and identified in two images could exist in the intersection of the conical projections from each camera. If the point is imaged by more cameras, the bounded region is further constrained, increasing point accuracy (Barazzetti, 2017). The intersection of these two conical projections is dependent upon the conical radius, the distance, and the angle between the cameras from which the cones are projected. Any additional site or condition factors that impact the quality of reprojection of keypoints directly impacts the quality of an overall photogrammetric model. These factors can be characterized as either systematic or environmental in nature (i.e., the specific qualities of the camera and sensor and the specific conditions of the site being monitored, respectively).
Systematic factors that affect the single point accuracy include the number of cameras, camera lens, camera resolution, aperture, camera focus, and ground pixel pitch. Collectively, camera resolution (or pixel pitch), distance from the subject, and focal length control the ground pixel pitch for terrestrial photogrammetry. In general, random and systematic errors increase with increasing ground pixel pitch (Debella-Gilo & Kääb, 2010).

Major environmental factors that impact both point and model accuracy include surface reflectance, texture, opacity, lighting conditions, and occluding obstacles. One major site-specific factor is the number of identifiably distinct points that can be matched between the images, and the spatial spread of these points throughout the model (Barazzetti, 2017). Hence, distinctly textured surfaces with high contrast are most optimal for photogrammetric monitoring. Intuitively, this behavior also means that if identifiable features are uniformly distributed throughout the model, overall model accuracy will generally improve (Barazzetti, 2017).

Smith and Vericat (2015) compiled studies of aerial structure from motion photogrammetry results at various distances to the target being imaged and indicated precision and accuracy decrease with increases in aerial range. Barazzetti, (2017) demonstrated that within singular short baseline network models, the accuracy of coverage is regionally variable, trending to lower accuracy at the lateral limits of models, while increasing the number of images produces a stabilization of accuracy. Nocerino, (2014) discussed proper camera orientations regarding free or convergent networks. Kromer et al. (2019) demonstrated fixed-site photogrammetric system performance can fluctuate from day to day. Still, a well-designed network is able to attain accuracies of approximately 1.2-1.7cm (one standard deviation) at a 70m distance under average environmental conditions. Blanch et al. (2020) developed a methodology to utilize multiple temporally sequential sets of data to increase the precision and density of photogrammetric point clouds. While these previous studies have established the applicability and utility of fixed-site photogrammetry, best practices for the design of fixed-site photogrammetry remain heuristic or based on trial-by-simulation.
Utilized throughout this work are discussions of accuracy and precision. In a photogrammetric investigation, accuracy can be treated as the metric reality of either an individual point or an entire model, while precision better represents the consistency with which a given point or model will reproject into 3D space. Regional distortions in photogrammetric investigation can occur due to false minima in the optimization of camera coordinates and reprojected tie point coordinates. These would cause spatially variable accuracy, but when comparing photogrammetric to photogrammetric models, assuming the distortions are consistent between models (i.e. camera parameters are fixed), the precision will remain high despite accuracy being decreased (distortions can reasonably be assumed consistent with good geometry and fixed camera parameters). Non-fixed parameters are likely to cause temporally variant distortions (James, et al., 2017). The error ellipsoid for remote sensing has been discussed in the paradigms of both precision and accuracy; this paper adopts the paradigm that the size of the error ellipsoid is analogous to the attainable accuracy of singular points. Largely disregarded in the theoretical development of this work, but not in the later discussed empirical methodology detailed in Section 3.5, is the impact of spatially variable accuracy.

In the analysis of uncertainty, model quality is commonly analyzed using statistical differences between repeat models or by comparing a photogrammetric model to ground control or an independent 3D data source. Model accuracy is empirical estimated in this study by comparing a photogrammetric point cloud to a terrestrial lidar point cloud, making the valid assumption that the lidar data set is more accurate than the photogrammetric model.

This measurement method of model accuracy ignores the specific regional spatial variability of distortions by inclusion into the statistics utilized to determine the standard deviation. Regional distortions are a consequential aspect of photogrammetric investigation (James, et al., 2017). Regional distortions can impact model accuracy when not removed from a model (James & Robson, 2012): in general, models utilized for comparisons and development of the results throughout this work did not remove regional distortions because visual inspection of the results indicated the nature of these distortions to be variably related to photo scale, and thus relevant to the quantification of photogrammetric model quality.
3.2.3 Photogrammetric Network Design

Although photogrammetry has seen increasing use as a remote sensing tool for engineering applications in recent years, it has not yet fully achieved its potential for adoption by geological engineering practitioners. Previous efforts of establishing rules for photogrammetric network design accessible to non-specialists have been attempted (Mason, 1995), albeit in a general context, and prior to the development of the Scale Invariant Feature Transform algorithm (Lowe, 1999), which is integral to most modern automated software solutions. Graferand (1974) established the photogrammetric network design process via definition of a third order design problem outlined below; this framework of network design for photogrammetry was well adopted (Fraser, 1984; Mason, 1995; Olague & Dunn, 2007):

- Zero-Order Design (ZOD): The datum problem
- First-Order Design (FOD): The configuration problem
- Second-Order Design (SOD): The weight problem
- Third-Order Design (TOD): The densification problem

Explicitly, the ZOD is the methodology by which the photogrammetric coordinate space of a model will be scaled into world space. The FOD is the solution of the network geometry, which includes the solution of camera locations and parameters, bundle adjustment and any constraints on those processes, such as explicit control points in the model. The SOD is the solution of the covariance matrix of parameters, the error weights due to variance in the image space point coordinates. Finally, the TOD is the method of enhancing network precision through the addition of extra object points and observations. For close-range photogrammetry, the TOD is largely redundant (Mason, 1995).

The modern close range photogrammetry design process largely is focused on FOD and ZOD problems, as modern software has allowed for the handling of the SOD problem via self-calibration (Nocerino, et al., 2014). The consensus regarding the best method of solving ZOD and FOD problems at this point is by network simulation. Network simulations iteratively improve parameters until a desired threshold of accuracy is reached (Olague & Dunn, 2007) (i.e., iteratively improving an initial guess at the optimum network design). Such a process typically requires an expert photogrammetrist, and is time consuming (Fraser, 1984; Mason, 1995; Olague
& Dunn, 2007). Mason (1995) argued the complexity of the FOD, which is an NP-Complete problem with more degrees of freedom regarding station placement, camera configuration, sensor selection, etc. than constraints, indicates that regular network simulation requires heuristic methods to fully solve. In other words, trial-and-error approaches simply cannot guarantee the best results (Mason, 1995).

Photogrammetrists focused in computer vision have addressed the difficulty of network design via evolutionary optimizations (Chen & Li, 2004; Olague & Dunn, 2007). Computer vision applies photogrammetric methods for the purpose of machine interactions with environmental stimuli. Other methodologies for network design have applied ‘expert system’ processes, a branch of artificial intelligence, such as the CONSENS software (Mason, 1995). Such methods utilized in computer vision or CONSENS perform well for constrained environments and problems, such as for factory line automation, but are designed for extremely close range to the subject of modelling and are ill-suited for the ranges more useful for terrestrial remote sensing in the geological engineering context. In this paper, we present the development of an evolutionary optimization framework for the feasibility assessment and design of a fixed-site terrestrial photogrammetric system network in a geological engineering context. The framework is applicable in other contexts, although it would require modification oriented to reprioritizing key factors, such as time of flight for aerial surveys. As Mason (1995) argued, mathematical processes are too simple to fully derive a network design due to the individual uniqueness of every site. As such, the optimization framework proposed in this study was designed using fundamental principles, and without consideration of site-specific parameters as a necessary simplification. This limitation and the ultimate utility of the framework are discussed in detail in Section 3.6.

3.3 Optimization Framework Development

In establishing a fixed photogrammetric monitoring site, the performance of a given design can typically be quantified in terms of three attributes: the cost of monitoring, the extent of coverage, and the model quality achieved (Chen & Li, 2004; Olague & Dunn, 2007). This framework improves the ability to estimate proper station placement with regards to the aforementioned attributes, which is a site-specific process dependent upon far more than the easily measurable parameters described in Section 3.2.2, such as site geometrics and camera parameters. In
practice, other considerations such as right-of-way, vegetation, viewpoints, social concerns, and equipment safety must all be considered. All of these parameters can limit the choice of network positioning and geometries. However, such site-specific information may not be readily available in the early stages of project planning when different remote sensing methods are first being evaluated. In this section, we present an optimization framework to assist in the predictive evaluation of photogrammetric investigations, simplifying the complex issue of station placement and equipment specifications to the five, non-site-specific parameters displayed in Figure 3.2. Inherent limitations associated with these simplifications are discussed in Section 3.6. Site-specific effects and spatial variability were not considered during the development of the theoretical optimization tool. Point accuracy, predicted utilizing the error ellipsoid, is initially assumed to be an analogue to predict overall model quality, though the aforementioned spatial variability is in practice consequential to general model coverage. Spatially variable distortions are specific to site characteristics and network design at the site, and are thus cannot be represented in a non-site-specific tool.

![Variables and Objectives Diagram](image)

Figure 3.2: A graphical representation demonstrating which input variables fundamentally impact which objective functions.
In totality, this problem can be mathematically described as a mixed integer, multi-objective constrained nonlinear optimization problem, severely limiting available optimization options. As computer vision has already successfully applied evolutionary computing to network design, albeit not in geologic contexts (Chen & Li, 2004; Olague & Dunn, 2007), a similar optimization methodology was selected. The Matlab Optimization Toolbox was selected, utilizing the Matlab variant of NSGA-II (Deb, 2001) as implemented in the “Gamultiobj” function. Gamultiobj is a controlled, elitist genetic multi-objective optimization algorithm, meaning the algorithm ranks individual results per generation by dominance regarding the objective functions, and selects parents for the next generation. The optimization parameters are varied by genotypic evolution, the parent and children generation are reranked together, crowding distance computed, and the process is iterated until the spread of values is below a specified tolerance. The specifics of this algorithm and a broader summary of multi-objective optimization principles are discussed in further detail in Deb (Deb, 2001). Simply put, this optimization algorithm determines a plurality of optimum solutions balancing the objective functions by testing many combinations of parameters.

Many practical constraints were applied to the five input variables (see Table 3.1), as other remote sensing options become markedly more viable than a fixed photogrammetry system at certain parameter thresholds. For example, certain focal lengths of lenses are not currently commercially available, it is not appropriate to evaluate photogrammetric options requiring such. The minimum boundaries for the parameters were derived from either the minimum requirements to conduct a photogrammetric study (Luhmann, et al., 2011) or the minimum commercially available equipment specification (Best Buy, 2019). In addition to these constraints, the maximum boundaries also considered the limits of budgeting before other remote sensing methodologies, such as lidar, become more appropriate for most geological engineering monitoring tasks. These boundaries are easily adjustable or removable as appropriate for a specific project.

The framework was developed such that a user fixes any one of the three objective functions to a set value, treating the function as an inequality constraint, and optimization is then performed considering the remaining two objective functions. For example, a user could input a minimum area, maximum cost, or maximum allowable model accuracy. The additional implication of this
is that a user could then over-constrain the system by constraining two objective functions to solve for the remaining parameter, which is potentially useful for evaluating if site performance could be improved relative to an initial design.

Gamultiobj is by default seeded randomly based on a uniform distribution over the parameter space, which ensures initial population diversity and therefore increases the likelihood of discovering unique solutions. For the following optimization results, 66% of the initial population was seeded this way, while the other 34% of the initial population was selected to represent high-performing combinations of parameters identified through a preliminary parametric sensitivity analysis. The initial population was kept consistent for all of the presented analyses.

Table 3.1: Practical Constraints to the Optimization Parameters

<table>
<thead>
<tr>
<th>Practical Constraints</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal Length</td>
<td>15</td>
<td>135</td>
<td>mm</td>
</tr>
<tr>
<td>Distance From Outcrop</td>
<td>10</td>
<td>350</td>
<td>m</td>
</tr>
<tr>
<td>Distance Between Cameras</td>
<td>1</td>
<td>50</td>
<td>m</td>
</tr>
<tr>
<td>Number of Stations</td>
<td>3</td>
<td>10</td>
<td>Quantity</td>
</tr>
<tr>
<td>Camera Resolution</td>
<td>10</td>
<td>60</td>
<td>MegaPixel</td>
</tr>
</tbody>
</table>

From one constrained objective function, the optimization tool generates a Pareto Front, which is a set of objective function values such that any alteration to an objective function results in lesser optimality of the value of other objective functions. This Pareto Front is the collection of evolutionarily dominant solutions to the multi-objective problem and is robust when executed with large population generations and restrictive tolerance (5,000 and 1x10^-9, respectively, in this work). Also presented are the quantified input parameters producing the results corresponding to the Pareto Front. Dependent upon the further restrictions a user inputs, the Pareto Front may be a cluster of dominant points with only minor variations in optimization parameters, or a plurality of solutions across a broad range of objective function values.

The derivations of the three objective functions considered for optimization are presented in Sections 3.3.1-3.3.3.
3.3.1 Cost Derivation

The total cost of a photogrammetry station includes the costs of the camera body and prime lens, as well as the housing station. Empirical data from a commercial electronics distributor (Best Buy, 2019) were collected, allowing for resolution to be correlated to camera body price, and focal length to be correlated to camera lens price. Given costs are products of complex economic supply and demand curves, we allowed a relatively high tolerance for relatively poor correlation. The $R^2$ value for an exponential model describing the relationship between the camera body cost and camera resolution was 0.85 ($p$-value = 0.0065) based on 17 different DSLR or Mirrorless camera bodies of varying manufacturers being considered. Much more poorly correlated were the camera lens costs and focal lengths ($R^2 = 0.41$, $p$-value < 0.0001) based on 54 prime lenses considered; of the various trends tested, however, the linear trend had the highest $R^2$ value and is the most mathematically simple. The relatively poor correlation between camera lens cost and focal length reflects higher variability in lens type, manufacturer, and material treatments to improve quality or durability. These additional factors, such as optical lens treatment, or extra optical filters, have not been evaluated in terms of their impact on photogrammetric performance, and therefore cannot be factored into the optimization framework. To evaluate the potential impact of the poor correlation, the optimization framework results were recalculated utilizing linear trends one standard deviation of the residuals above and below the current trend for focal lengths. Results had concomitantly increased or decreased costs, but the overall trends of the results remained similar. Thus, any potential alterations to the lens cost formula would not be anticipated to significantly alter the overall trends present in the optimization results. A housing cost was applied as a set constant per camera station, included weather protective unit and electronics to maintain daily data acquisition, and was attained from the system design of Kromer et al. (2019). Although the specific best fit trends will likely change over time as equipment becomes cheaper, the general framework and the functional forms considered are expected to remain valid. The charts displaying the trend equations are presented in Figure 3.3.
Figure 3.3: Empirical correlation between camera body cost and camera resolution (left). Empirical correlation between prime lens cost and focal length (right).

\[ f(\varepsilon) = \text{Camera Body Cost} = c_1 e^{c_2 \varepsilon}, \quad R^2 = .85 \]  
\[ g(\theta) = \text{Lens Cost} = c_3 \theta + c_4, \quad R^2 = .41 \]  
\[ h(\theta, \varepsilon) = \text{Cost per Camera Station} = f(\varepsilon) + g(\theta) + b \]

**Objective Function 1, Cost (USD):**

\[ h(\theta, \varepsilon) \ast n \]

\( \theta = \text{Focal Length (mm)}, \varepsilon = \text{Camera Resolution (MP)}, \)  
\( b = \text{Cost of Housing (USD, Constant)}, \)  
\( n = \text{Number of Cameras} \)

### 3.3.2 Area Approximation

Traditional optical ray projections were utilized to determine the boundaries of areal coverage. Developing a convergent photogrammetric system enhances the accuracy of a photogrammetric model (Nocerino, et al., 2014); therefore, the equations for area developed assumed the outermost cameras would be angled inward to the extreme boundaries of the proximal cameras, to increase the effective image overlap. The area is estimated by finding the boundaries of coverage and assuming a perfectly rectangular coverage area, as if all cameras were focused at
the same elevation. The following function assumes a full frame camera sensor is being utilized, such as a DSLR or Mirrorless camera. In practice, image overlap can vary from 53% to 80% for successful model creation (Li, et al., 2018), but in this study, it was constrained to 80% to best approximate the conditions used for the empirical model quality evaluation described in Section 3.5. Additionally, if allowed to vary freely, the optimization framework would functionally always minimize image overlap to maximize areal coverage. Image overlap does not yet have a clear mathematically solved correlation with area in a terrestrial context, only that between 53% and 80% overlap is required for successful model creation, and higher overlap increases accuracy and decreases regional distortions (Li, et al., 2018). As such, 80% overlap was deemed appropriate to utilize for the optimization framework as the areal evaluation becomes a worst-case estimation of area.

\[
\text{Lateral Projection from Center of Camera} = j(\delta, \varepsilon, \theta) = c_5 \delta \left( \frac{\sqrt{3}}{2} \frac{\varepsilon}{\varepsilon^2 \theta} \right) \tag{3.5}
\]

\[
\text{Left Boundary} = x_1 = \omega - j(\delta, \varepsilon, \theta) \tag{3.6}
\]

\[
\text{Right Boundary} = x_2 = (\kappa - c_4)\omega + j(\delta, \varepsilon, \theta) \tag{3.7}
\]

\[
\text{Vertical Extent of Camera Coverage} = v = k(\delta, \varepsilon, \theta) = c_5 \delta \left( \frac{\sqrt{3}}{1} \frac{\varepsilon}{\varepsilon^2 \theta} \right) \tag{3.8}
\]

**Objective Function 2, Coverage Area:**

\[
\text{Maximized Area} = -1 \ast (x_2 - x_1) \ast v \tag{3.9}
\]

\(\delta = \text{Distance From Outcrop (m)}\)

As the optimization algorithm only minimizes objective functions, equation (9) includes a negative one multiplier to allow for maximization of areal coverage.

### 3.3.3 Error Ellipsoid Derivation

For initial implementation of the optimization framework, the principal axes of the error ellipsoid were resolved from traditional optical equations as outlined by Piermattei (2016). These axes denote the region a point is likely to exist within a certain statistical threshold, similar in concept to a standard deviation. A spherical approximation of the ellipsoid is reported for consistency
with other studies (James, et al., 2017; Kromer, et al., 2019). A purely optically-derived accuracy is considered to represent the best possibly attainable value, under completely ideal (and unlikely) circumstances, as image quality can only degrade from the purely theoretical optically-derived case. Additionally, such accuracy estimates only apply to individual points and neglect errors and broader-scale model distortions that can arise as a function of environmental conditions, camera calibration parameter errors, and georeferencing and registration errors.

\[ s(\delta, \gamma, \theta) = \text{Ground Pixel Size} = \frac{\delta \cdot \gamma}{\theta} \]  

(3.10)

\[ \text{Planar Accuracy} = \frac{s(\delta, \gamma, \theta)}{2} \]  

(3.11)

\[ t(\delta, \gamma, \theta, \omega) = \text{Depth Accuracy} = \frac{\delta \cdot s(\delta, \gamma, \theta)}{2 \cdot \omega} \]  

(3.12)

\[ \text{Error Ellipsoid Volume} = \phi(\delta, \gamma, \theta, \omega) = \frac{4 \cdot \pi \cdot s(\delta, \gamma, \theta)^2 \cdot t(\delta, \gamma, \theta, \omega)}{3} \]  

(3.13)

**Objective Function 3, Error Ellipsoid Volume:**

\[ \left( \phi(\delta, \gamma, \theta, \omega) \cdot \frac{3}{4 \cdot \pi} \right)^{\frac{1}{3}} \]  

(3.14)

\[ \gamma = \text{Pixel Size (mm)}, \ \omega = \text{Distance Between Stations (m)} \]

Assuming a full frame, 36mm x 24mm (3:2 aspect ratio) camera sensor, such as those found in DSLR cameras, the pixel pitch becomes a function of camera resolution, as demonstrated in Equation 3.15 and Figure 3.4. This relation between pixel pitch and camera resolution utilized is not appropriate for alternative sensor formats.

\[ \text{Camera resolution to pixel size} = \gamma(\epsilon) = c_5 \epsilon^{-\frac{1}{2}} \]  

(3.15)
3.4 Optimization Application Example

Previous work in conjunction with the Colorado Department of Transportation maintained a fixed-site terrestrial time-lapse system just west of Idaho Springs, Colorado for over two years (Kromer, et al., 2019). The analysis of information from this site provides an ideal opportunity to compare a well-calibrated system designed using expert judgement and considering site constraints to the theoretical optimization results. Following are tabulated results obtained using the proposed optimization approach, as well as example Pareto Fronts generated with project constraints similar to the actual monitoring system. The Idaho Springs site is a 5-camera station setup for rockfall monitoring with cameras located approximately 72m away from the slope of interest on average; the distance between cameras is approximately 7m on average. 85mm prime lenses were used on Canon EOS 5DSR 50.4-megapixel cameras. Coverage area is approximately 1,250m², with an accuracy estimate varying from 1.2 cm to 1.7 cm, determined as one standard deviation of the differences obtained from comparisons between photogrammetric models and terrestrial lidar scanning data (Kromer, et al., 2019). The total system cost was approximately $34,000 (after adjustment to 2019 market costs to ensure comparability with the cost data shown in Figure 3.3).
Table 3.2 presents a comparison of the actual performance metrics for the Idaho Springs site against estimated performance metrics for the site as output by the objective functions used in the optimization framework. Each of the objective functions were solved utilizing input parameters equivalent to the specifications of the Idaho Springs rockfall monitoring camera system. Note that these are not optimization results, but rather the solutions of the objective functions for a specific set of input variable values. If the objective functions were perfectly demonstrative of site performance, Table 3.2 would present approximate equivalencies between the site performance and the parameters-fixed estimation. However, there is a critical difference between how the theoretical optimization framework quantifies model accuracy versus the method utilized at the site: while the optimization framework utilizes theoretical optics to approximate the volume of the error ellipsoid for a single point, the Idaho Springs system overall model accuracy is empirical quantified as the 1st standard deviation of differences calculated between a lidar data set and photogrammetry model. Point accuracy and model accuracy should not be expected to be directly comparable for several reasons. Perhaps most significantly, model accuracy in the context of photogrammetry is anticipated to be worse than point accuracy because of regional distortions (James, et al., 2017). The cameras at the Idaho Springs site are non-orthogonal to the imaged slope, which limits accuracy and can increase non-uniform distortions regionally in the images. These regional distortions are reflected in the lidar-photogrammetry comparisons as characterized by the presented accuracy values. In practice, this discrepancy in model quality metrics means that the optimization results consistently provide more favorable model quality predictions than were documented for the Idaho Springs system. Further, the actual coverage area for the Idaho Springs site is greater than that estimated using the optimization framework objective functions; this is because the optimization framework assumes 80% image overlap, while the overlap at the Idaho Springs site is lower, meaning a larger coverage area was achieved in practice.
Table 3.2: Comparison of optimization-estimated site performance to Idaho Springs with fixed specifications from the monitoring site utilized to solve the objective functions

<table>
<thead>
<tr>
<th>Comparison to Idaho Springs:</th>
<th>Estimated Performance</th>
<th>Idaho Springs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (USD)</td>
<td>34,000</td>
<td>34,000</td>
</tr>
<tr>
<td>Model Quality Metric (cm)</td>
<td>0.68</td>
<td>1.2-1.7</td>
</tr>
<tr>
<td>Area (m²)</td>
<td>1,040</td>
<td>1,250</td>
</tr>
</tbody>
</table>

Table 3.3 and Figure 3.5 present summaries of a comparison generated by constraining the cost variable to the budget of the Idaho Springs project. The optimization framework converged to a front of solutions varying from error ellipsoid radii of 0.18 cm up to 2.2 cm, and areal coverage values from 330m² to 83,280m². Note that the discontinuity at approximately 2 cm ellipsoid radii is a gap in the parameter space where the optimization favors a higher quantity of cameras with lower quality camera bodies.

Table 3.4 and Figure 3.6 present a similar comparison with the coverage area fixed. Two end-member solutions on the front bounded a variety of solutions in the parameter space resulting in error ellipsoid radii ranging from 0.30 cm to 0.70 cm and costs ranging from $28,130 to $79,290.

Table 3.3: Optimization results compared to Idaho Springs case with fixed optimization cost at $34,000

<table>
<thead>
<tr>
<th>Comparison to Idaho Springs:</th>
<th>Minimized Error Ellipsoid Volume</th>
<th>Maximized Area</th>
<th>Idaho Springs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (Fixed, USD)</td>
<td>34,000</td>
<td>34,000</td>
<td>34,000</td>
</tr>
<tr>
<td>Model Quality Metric (cm)</td>
<td>0.18</td>
<td>2.2</td>
<td>1.7</td>
</tr>
<tr>
<td>Coverage Area (m²)</td>
<td>330</td>
<td>83,280</td>
<td>1,250</td>
</tr>
<tr>
<td>Focal Length (mm)</td>
<td>35</td>
<td>15</td>
<td>85</td>
</tr>
<tr>
<td>Distance from Outcrop (m)</td>
<td>17.0</td>
<td>104.1</td>
<td>72</td>
</tr>
<tr>
<td>Distance Between Cameras (m)</td>
<td>3.5</td>
<td>50.0</td>
<td>7</td>
</tr>
<tr>
<td>Number of Stations (Qt)</td>
<td>6</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>Camera Resolution (MegaPixel)</td>
<td>46.0</td>
<td>34.8</td>
<td>50.4</td>
</tr>
</tbody>
</table>
Figure 3.5: Optimization results given a fixed cost of $34,000. The tool suggests two end-member solutions within the constrained parameter space, one maximizing the area, another minimizing the error ellipsoid radii. The input parameters corresponding to the end members are presented in Table 3.3.

Table 3.4: Optimization to Idaho Springs Case Comparison Fixing Area Coverage at 1250m²

<table>
<thead>
<tr>
<th>Comparison to Idaho Springs:</th>
<th>Minimized Cost</th>
<th>Minimized Error Ellipsoid Volume</th>
<th>Idaho Springs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (USD)</td>
<td>28,130</td>
<td>79,290</td>
<td>34,000</td>
</tr>
<tr>
<td>Model Quality Metric (cm)</td>
<td>0.70</td>
<td>0.30</td>
<td>1.7</td>
</tr>
<tr>
<td>Area (Fixed, m²)</td>
<td>1,250</td>
<td>1,250</td>
<td>1,250</td>
</tr>
<tr>
<td>Focal Length (mm)</td>
<td>40</td>
<td>48</td>
<td>85</td>
</tr>
<tr>
<td>Distance from Outcrop (m)</td>
<td>33.8</td>
<td>40.0</td>
<td>72</td>
</tr>
<tr>
<td>Distance Between Cameras (m)</td>
<td>6.0</td>
<td>6.0</td>
<td>7</td>
</tr>
<tr>
<td>Number of Station (Qt)</td>
<td>8</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>Camera Resolution (MegaPixel)</td>
<td>10.0</td>
<td>60.0</td>
<td>50.4</td>
</tr>
</tbody>
</table>
Figure 3.6: Optimization results given a fixed area of 1,250m$^2$. The tool suggests two end-members within the constrained parameter space of optimal solutions, one minimizing error ellipsoid radii and one minimizing cost. The input parameters corresponding to the end members are presented in Table 3.4.

Table 3.5 and Figure 3.7 present the optimization results given a fixed error ellipsoid radius. Again, two end-members were identified with cost values ranging from $11,145 to $97,170 and coverage areas ranging from 8,840m$^2$ to 101,730m$^2$.

Table 3.5: Optimization to Idaho Springs Case Comparison Fixing Error Ellipsoid Radii at 1.7cm

<table>
<thead>
<tr>
<th>Comparison to Idaho Springs:</th>
<th>Minimized Cost</th>
<th>Maximized Area</th>
<th>Idaho Springs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (USD)</td>
<td>11,145</td>
<td>97,170</td>
<td>34,000</td>
</tr>
<tr>
<td>Model Quality Metric (Fixed, cm)</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
</tr>
<tr>
<td>Area (m$^2$)</td>
<td>8,840</td>
<td>101,730</td>
<td>1,250</td>
</tr>
<tr>
<td>Focal Length (mm)</td>
<td>35</td>
<td>15</td>
<td>85</td>
</tr>
<tr>
<td>Distance from Outcrop (m)</td>
<td>112.0</td>
<td>105.4</td>
<td>72</td>
</tr>
<tr>
<td>Distance Between Cameras (m)</td>
<td>23.1</td>
<td>50.0</td>
<td>7</td>
</tr>
<tr>
<td>Number of Station (Qt)</td>
<td>3</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Camera Resolution (MegaPixel)</td>
<td>21.6</td>
<td>60.0</td>
<td>50.4</td>
</tr>
</tbody>
</table>
Figure 3.7: Optimization results given a fixed error ellipsoid radii of 1.7cm. The tool suggests two end-members minimizing cost or maximizing areal coverage. The parameters resulting in the end members are presented in Table 3.5.

As noted above, the differences in the model quality metrics used for Idaho Springs (overall model accuracy) and the optimization framework (individual point error ellipsoid radius) mean that the Pareto Fronts obtained correspond to estimated model qualities that are consistently more favorable than the Idaho Springs site while performing better in cost and/or area. Comparisons presented in Tables 3.3-3.5 provide insight on the prioritized parameters as determined via the optimization framework, but do not present directly comparable results with regards to model quality.

3.5 Development of an Empirical Method for Model Accuracy Estimation

In the opinion of the authors, the largest limitation of the optimization framework as proposed in Section 3.3 and demonstrated in Section 3.4 is the resolvability-based theoretical estimation of the error ellipsoid radii. The above results indicate that, at close range, practical limitations of model accuracy such as spatial distortions, software capabilities, lighting, site geometry, internal camera parameters, photogrammetric model parameters, and object characteristics affect model quality more than resolvability. Accordingly, there is a need to develop an empirical method to better define an objective function that reflects the practical model quality. To this end, previous
works have investigated the relationship of accuracy and distance at a range of 2m to 20m in a controlled laboratory setting (An, 2017). Other works have investigated the relationship between flying altitude and accuracy in an Unmanned Aerial Vehicle context (Agüera-Vega, et al., 2016). However, existing research examining the impact of ground pixel pitch on terrestrial photogrammetry at distances farther than 20m, and under non-idealized conditions, remains limited. The following case study was designed to study the impacts of focal length and distance (effectively, photo scale) on model accuracy for purposes of improving the optimization framework.

3.5.1 Site Selection and Geology
An ideal site for this study was deemed to be an outcrop, greater than 50 m across and 20 m high, that is large enough to be imaged from a 350 m distance without obstructing vegetation or obstacles. Outcrops in Red Rocks Park, Colorado, USA were considered ideal due to proximity to large, open areas devoid of significant visual obstructions at close to moderate range (Figure 3.8). The selected outcrop is comprised of coarse-grained arkosic sandstone conglomerate units with sparse mudstone interbedding within the Fountain Formation (Cross, 1894). The selected outcrop face has a dip greater than 70°, and strikes south. Images were collected in the afternoon, with the sun directly illuminating the outcrop, causing minimal obstructive shadows.

3.5.2 Equipment Selection and Methods
Previous correlations between high photo resolution and high 3D model accuracy (Dai, 2012) led to the selection of the Canon EOS 5DSR, 50.4MP camera for use in this study. In addition to its high resolution, the EOS 5DSR has an extra optical filter that decreases potential inaccuracies occurring from the lens’s low-pass filter. Four lenses were selected for investigation: 35 mm, 85 mm, 135 mm, and 200 mm. A lidar scan was collected of the outcrop of interest for registration, scaling, and alignment purposes, and for estimation of photogrammetric model accuracy. Three transverse lines away from the outcrop were selected and images were taken approximately every 5 m, estimated by stride length. Camera positions are demarcated by points relative to the outcrop in Figure 3.8. Images were taken focused on a central visually distinct point on the outcrop; camera angles were thus convergent with high overlap (80% or higher).
3.5.3 Calibration Parameters

Ground control points were not available to perform site-specific camera calibration at the Red Rocks site. Our previous work supported the standing research consensus that camera pre calibration improves the accuracy of photogrammetric coverage when ground control points are not available (Kromer, et al., 2019). Calibration parameters were back calculated per camera lens via constructing models per lens at a nearby site with available ground control points and applying those calibration parameters to the Red Rocks data. Calibration parameters were then fixed for the generation of all Red Rocks models. This means that the empirical relations for model accuracy estimation developed herein only apply to cases with fixed camera precalibration.

3.5.4 Model Generation and Model Accuracy Assessment

The automated method for photogrammetric model generation and estimation of model accuracy outlined by Kromer et al. (2019) was applied to the generation of models at varying distances from the outcrop and focal lengths. Additionally, models were regenerated four times from each photo set to investigate the impact of the randomly seeded algorithms utilized by Agisoft Photoscan on the results. Images were collected utilizing the aforementioned Canon EOS 5DSR 50.4MP camera. Sparse cloud models were created utilizing Agisoft Photoscan’s highest accuracy alignment setting, with generic preselection for pre-process image matching. The keypoints were filtered and camera parameters optimized until the registration error of the sparse cloud was below 0.2. Specific models failed to maintain enough keypoints after this rigorous filtering, and thus were filtered down until 70,000 keypoints were remaining. This threshold was selected based on the estimated number of keypoints to sufficiently capture the coverage area. A dense cloud was constructed from the sparse cloud utilizing aggressive depth filtering, specified to Agisoft’s medium-density. The dense clouds were then scaled to the lidar scan of the outcrop. The accuracy was assessed on the basis of comparison to the lidar data set, utilizing the modified M3C2 algorithm developed by Kromer et al. (2019).
Figure 3.8: Camera positions and outcrop of case study

### 3.5.5 Empirical Model Accuracy Results

Figure 3.9 presents the model accuracy measured (one standard deviation difference) based on comparison to a lidar data set over the entirety of each model. Each point presented in Figure 3.9 represents the average accuracy estimation of four models, each generated from the same set of original photos. Figure 3.10 presents the same results, but utilizing the distances and focal lengths to calculate a ground pixel pitch to correlate to the model accuracy values.
For comparison, Figure 3.11 presents the theoretical optimization functions evaluated over the same distance and at same focal lengths. Notably, the empirical trend is approximately logarithmic, whilst the optically-derived theoretical performance estimations scale exponentially with distance.

![Graph showing model accuracy vs distance at varied focal lengths.](image)

Figure 3.9: Model Accuracy vs Distance, at varied focal lengths. The range of results for the Idaho Springs, Colorado monitoring site are in black.
Figure 3.10: Model Accuracy vs Ground Pixel Pitch of Red Rocks Park, Colorado outcrop models. The resulting formula in the bottom right-hand corner of the figure was utilized as the new objective function for accuracy estimation in the empirical optimization framework, where ‘x’ is the formula for ground pixel pitch (Equation 10). The black point is the typical results for the Idaho Springs, Colorado rockfall monitoring Site, with vertical bars representing the usual range of site performance.

Figure 3.11: Theoretical Error Ellipsoid Radii vs. Distance, fixing other parameters to those exemplified by the Idaho Springs Site.
Figures 3.12 and 3.13 show representative M3C2 (Lague, et al., 2013) photogrammetry model to lidar comparison results utilized to estimate the accuracies presented in Figure 3.9. These models were selected as examples of two data trends seen across multiple models: bowling distortions and localized regional inaccuracies correlated with mudstone sediment packages. The skew observable in Figure 3.12 indicates that bowling dominantly impacts the models of smaller coverage areas. These distortions likely increased the variance observed in the data presented in Figures 3.9 and 3.10.

Figure 3.12: M3C2 generated model generated utilizing a 200mm focal length at 110m distance from the outcrop. Note regional inaccuracies toward the extents of the model, implying a high influence of bowling or poor overlap.
Figure 3.13: M3C2 generated model generated utilizing a 135mm focal length at 320m distance from the outcrop. The estimated accuracy was 2.85 cm. Note intermediary mudstone sediment package layers are regions of high inaccuracy.

3.5.6 Implementation into the Optimization Framework

The observed empirical model accuracy trend shown in Figure 3.10 was implemented as an objective function into the multi-objective framework. This simplifies the equation for model quality to be derived solely from ground pixel pitch, which is mathematically derived from camera resolution and photo scale. In practice, bundle adjustment of tie points can converge to false local minima during reprojection optimization, causing regional distortions such as bowling. This is not accounted for when utilizing the theoretical error ellipsoid equations, and would likely vary when utilizing the empirical model accuracy trend depending upon individual camera and lens calibration parameters.

Figures 3.14-3.16 are the results of the optimization framework when utilizing the empirical accuracy trend shown in Figure 3.10 as the model quality objective function (with constraints applied based on values from the Idaho Springs system). Table 3.6 presents selected optimization results from the generated Pareto fronts that are proximal to the performance of the Idaho Springs site.
The empirical optimization results when cost is constrained (Figure 3.14) demonstrate a sharper, exponential increase than the theoretical results. This is associated with the logarithmic trend of the accuracy at the distances considered; camera properties like resolution and especially focal length can be increased to compensate for accuracy loss at an increased distance, while coverage area remains highly sensitive to distance increases. The comparison to the Idaho Springs sites indicates an under-evaluation of attainable coverage area at reasonable model accuracies. As noted in Section 3.3.2, this is partially explained by the 80% overlap constraint utilized during the optimization. Additionally, accuracy at the Idaho Springs site has been improved by site-specific camera calibration with ground control points, resulting in improved, lower value accuracies relative to the results obtained from the Red Rocks Park models. Site-specific precalibration for the Red Rocks data set would likely cause a translation of the produced Pareto fronts towards improved (lower) model accuracy values. These empirical results thus better reflect projects in which ground control points are not available for camera calibration purposes.

Figure 3.14: Optimization results utilizing the empirical model accuracy given a fixed cost of $34,000 for the photogrammetric network are presented in blue. The black marker indicates the Idaho Springs, Colorado photogrammetric rockfall monitoring site.
Figure 3.15: Optimization results utilizing the empirical model accuracy given a fixed area of 1,250m$^2$. The tool suggests a plurality of optimal solutions. The black marker indicates the Idaho Springs, Colorado photogrammetric rockfall monitoring site. Notably, the curve shifts left with decreasing areal coverage, indicating a portion of the disparity to the Idaho Springs site is related to the overlap constraint.

Of the three comparisons performed, the model accuracy and cost optimization (Figure 3.15) demonstrated the least agreement with the Idaho Springs site, suggesting the observed accuracy was not attainable for $34,000. As noted above, this is primarily due to non-site-specific precalibration utilized at Red Rocks Park versus site-specific camera calibration utilized at the Idaho Springs site, and the aforementioned 80% overlap constraint upon area.

The overall trends of the optimization using an empirically constrained model quality metric (Figure 3.16) are similar to those shown in the corresponding optimization using the theoretical error ellipsoid radii function (Figure 3.7). Namely, both cases exhibit the same pattern of 7 discontinuities resulting from increasing numbers of cameras, each with a clustered tail associated with varying camera parameters.

Table 3.6 presents selected optimization solutions most proximal to the Idaho Springs site performance from each of the previously presented result sets in Figures 3.14-3.16. These results were selected first visually and then from the plethora of points within a cluster, solutions were found with the most proximal parameters to the Idaho Springs site for that cluster.
Figure 3.16: Optimization results utilizing the empirical model accuracy given a fixed model accuracy of 1.7 cm. The tool suggests nine groups of solutions exist within the parameter boundaries, varied by cost and area of coverage. Steps in the Pareto Front result from increasing numbers of cameras, while the continuous portions per step result from variation of camera parameters. The black marker indicates the Idaho Springs, Colorado photogrammetric rockfall monitoring site.

Table 3.6: Empirically-Derived Optimization to Idaho Springs Case Comparison

<table>
<thead>
<tr>
<th>Performance Metric</th>
<th>Cost Constrained</th>
<th>Area Constrained</th>
<th>Accuracy Constrained</th>
<th>Idaho Springs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area (m²)</td>
<td>480</td>
<td>1,250</td>
<td>540</td>
<td>1,250</td>
</tr>
<tr>
<td>Cost (USD)</td>
<td>34,000</td>
<td>35,600</td>
<td>35,280</td>
<td>34,000</td>
</tr>
<tr>
<td>Model Accuracy (cm)</td>
<td>1.7</td>
<td>2.0</td>
<td>1.7</td>
<td>1.2-1.7</td>
</tr>
<tr>
<td>Focal Length (mm)</td>
<td>94</td>
<td>55</td>
<td>70</td>
<td>85</td>
</tr>
<tr>
<td>Distance from Outcrop (m)</td>
<td>64.6</td>
<td>45.8</td>
<td>43.7</td>
<td>72</td>
</tr>
<tr>
<td>Camera Spacing (m)</td>
<td>4.9</td>
<td>6.0</td>
<td>4.5</td>
<td>7</td>
</tr>
<tr>
<td>Number of Cameras</td>
<td>4</td>
<td>8</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>Camera Resolution</td>
<td>56.0</td>
<td>37.0</td>
<td>46.0</td>
<td>50.4</td>
</tr>
</tbody>
</table>

As noted above, the optimization framework consistency predicts marginally less favorable coverage area and model accuracies than are achievable in reality. The monitoring site was limited by right-of-way with regards to camera position selection; with these practical constraints in mind, the results obtained suggest that the expert-designed system at Idaho Spring is likely near-optimal in practice. Noteworthy, with the considerations to the impact of the overlap...
constraint and precalibration limitations on area and accuracy, all of these selected optimization solutions are congruent with the Idaho Springs site with regards to the objective functions.

3.6 Discussion on Optimization Framework and Results

One strength of the proposed optimization framework is its modular nature, such that individual parts of the framework can be adapted as newer and better approximations of the objective functions are developed. For example, adaptations of already existing empirical relations between distance and accuracy (James & Robson, 2012; Micheletti, et al., 2014; Mosbrucker, et al., 2016) could be developed into new objective function equations, or adjustments to cost equations could be made as economic conditions evolve. The methodology of the network design optimization was developed from the perspective that the specific equations should be fair approximations, but the methodology should be flexible regarding the utilization of alternative objective functions.

The NP-Complete complexity of the FOD problem for photogrammetric network design (Mason, 1995) requires simplifications for the development of a generalizable, non-site-specific tool. However, simplifications inevitably require divergence from the complexity of real geological contexts. This is a very significant limitation of the proposed network design optimization framework. The theoretical optimization methodology outlined ignores site-specific parameters, meaning the predictive guesses at optimality purported by the tool do not account for the many conditions that degrade the quality of photogrammetric investigation. However, as the framework generates a Pareto Front of optimal points, further selection via the engineer can incorporate these site-specific constraints. If such extreme conditions as outlined in Section 3.2.2 exist commonly within the region being considered for photogrammetric investigation, consideration and evaluation of alternative remote sensing schemes should be considered. As noted by Smith and Vericat (2015), broader work remains to be completed regarding comprehensive analysis of the impacts of the various photogrammetric parameters on terrestrial geologic remote sensing investigations. Conversely, the plurality of solutions derived from the framework allows for consideration of the flexibility allowed by a given site. When multiple optimal solutions are identified, realistic constraints reported at a site can better be accounted for via elimination of some of these solutions and focus can be placed on portions of the pareto front satisfying the imposed constraint(s).
The accuracy presented for the Idaho Springs site and utilized throughout this work is an empirical accuracy measure derived from comparisons between daily generated photogrammetry models relative to a terrestrial lidar scan, using an initial registration and scaling based on a lidar data set. The theoretical optimization framework as applied above relies on optical limitations imposed by the camera sensor and site geometries interacting, a maximum attainable accuracy for a single point as defined systematically and disregarding site and model specific conditions. Site-specific conditions, such as lighting, could severely deteriorate the attainable accuracy of a model, the optimization framework should be regarded as a best-case scenario regarding accuracy because these factors can only decrease the quality of coverage from the optimum. This assumed best case scenario is the strongest contributor to the difference between the error ellipsoid radii predicted by the tool in comparison to the actual Idaho Springs system model accuracy when utilizing the theoretical model quality metric for the optimization. Because of this systematic limitation to the framework, utilization of the developed empirical method instead is advised in practice. Notably, site generalizability of these empirical trends remains yet to be verified, and likely these results are best when utilizing the same workflow and similar site conditions; we expect the overall trends to hold in a non-site-specific context, though the specifics are likely to vary.

The higher variability observed at lower distances in Figure 3.9 indicates an algorithmic limitation imposed by the software utilized to construct the photogrammetric models, with the accuracy varying by proportions as high as 100% at extremely low ranges. The software is likely highly variable at a low range due to a limitation of contextual information, increasing the likelihood of optimizing to a false minima in the reprojection of key points. A continued limitation of utilizing Agisoft Metashape is the proprietary nature of the algorithms used. Though the impacts of regional distortion could have been muted by parsing regions of high distortion, it was noted that the nature of the distortions varied with the photo scale. At close distances, distortions were typically best characterized by poor keypoint reprojection and significant bowling, while at longer distances the characteristics of the studied outcrop limited photogrammetric capabilities to generate accurate 3D points in certain regions, such as the recessed mudstone layers. As this trend was impacted by the primary variables of the study, the regional distortions were not parsed out for analysis purposes; in other words, these distortions
were deemed relevant to the performance of photogrammetric methods and valuable to reflect in the empirical accuracy prediction model.

The empirical trends for model accuracy improved the predictive capabilities of the optimization framework to address some of the accuracy limitations that exist in reality. These results are closer to the expert-design photogrammetric site maintained at Idaho Springs, with predicted model accuracy values higher (worse) than the best performances of the site but close to the range of model accuracies observed from day to day.

3.6.1 Red Rocks Case Study Discussion
The previously observed disparity between the theoretical ellipsoid-based methodology and practical application of photogrammetry indicates the effective overall accuracy of a given photogrammetry model depends on the distance from which the constituent photos were taken in a complex manner; the theoretical curves predict exponential decay of accuracy as a function of distance from the object being imaged, whereas the empirical case study results indicate a logarithmic trend. The results imply that digital photogrammetric methods over the considered range of distances are less affected by optical resolvability, and more by practical constraints, including georeferencing and camera calibration, as well as site conditions, such as lighting and surface coloring or textures. Figure 3.12 demonstrates characteristic photogrammetric bowling, while Figure 3.13 demonstrates geometrically and spectrally imposed constraints on accuracy. From a photogrammetric perspective, the mudstone sediment packages are poorly textured, and recessed into the outcrop; the photogrammetric projection failed to properly capture the depth of this concavity. Each of the generated models demonstrates some impact from one or both of these factors. This likely skews the empirical accuracy results obtained at the Red Rocks Park site to be somewhat higher than what can be attained in practice. Thus, when utilizing the empirical trends from this study in the optimization framework, it is reasonable to expect higher model accuracy predictions than the truly attainable optimum. Specifically, model quality could generally be improved by site-specific camera precalibration or through the use of ground control points. The data collected did not utilize ground control points to correct for model distortions; the addition of these points would decrease model distortions and thus improve model accuracy. This impacts the empirical accuracy trend utilized by the optimization framework, but not the framework methodology. The authors also expect utilization of these
trends will be most accurate when used to estimate highly convergent camera systems, as that was the methodology utilized for data collection at Red Rocks Park. The observed trend of the impact of ground pixel pitch on accuracy for strictly parallel cameras remains yet to be verified in a terrestrial setting. We anticipate similar overall trends, but likely the curve relating accuracy and ground pixel pitch will translate towards a poorer accuracy for parallel camera networks due to higher regional accuracy discrepancies (Barazzetti, 2017). Additionally, the photos collected in the case study were highly orthogonal to the outcrop in general, with minimal alteration in elevation. Systems that require a more oblique angle between the object of study and the camera systems are likely to suffer from a higher degree of regional distortion towards image peripherals, and poorer accuracy than the empirical results utilized in this study.

Regarding the comparisons with the Idaho Springs system, the selected outcrop in Red Rocks, Colorado was distinct from the outcrop in Idaho Springs, Colorado, in terms of geology and color. At the photo scales of investigation, the former is comprised of red and dark red sedimentary units whilst the latter is a grey biotite schist with white pegmatites. The outcrops additionally strike perpendicular to each other, which is important for relative lighting conditions. The previous are indications the empirical trends are somewhat robust to varying site conditions, however more outcrops should be investigated to verify this trend. Additionally, repetition of the presented case study at alternative sites is required to verify the accuracy of the empirical trends in a broader geological context. Relative position to the source of light is likely the most influential factor on the specific relationship between photo scale and attainable accuracy; however, the authors anticipate the trends will remain logarithmic as a function of ground pixel pitch in general. The camera model, and consequentially camera resolution, was held constant throughout the empirical comparison; varying camera models may have unique empirical trends regarding photo scale and accuracy (James, et al., 2017).

3.7 Conclusions

Photogrammetry is a useful tool for making geological engineering measurements and models, but the myriad of components to be considered in the development of a photogrammetric investigation contributes to the difficulty of planning a fixed-system photogrammetric installation. In this study, an optimization framework was developed utilizing genetic optimization for the purpose of assisting early project design of terrestrial fixed-site
photogrammetry investigations, to assist in feasibility assessment for comparison to other monitoring technologies, and to decrease the necessity of trial by simulation during photogrammetry site design. Optimizations utilizing both theoretical and empirical metrics for model quality were constructed. Comparisons with a long-term fixed-site photogrammetry site indicate the optimization framework produces reasonable estimations of site performance, cost, and areal coverage. The tool enhances the efficacy of a ‘go/no go’ analysis.

An additional contribution of this work is documentation of the impact of ground pixel pitch on overall terrestrial photogrammetric model accuracy and identification of an associated empirical trend. Results indicate that for close range photogrammetry, image resolvability is less of a limitation than site-specific and software algorithm limitations. The empirical trends observed in this study have thus deemed an improvement over the theoretical optics equations for a close-range terrestrial system. Further research remains to be performed considering altered site geometries and monitoring requirements to evaluate the validity of the obtained empirical accuracy trend for broader application.

3.8 References


Cross, W., 1894. Pikes Peak folio, Colorado. *Geological Survey (United States).*


CHAPTER 4
CONCLUSIONS

4.1 Research Summary and Conclusions

Fundamentally, the work of this thesis focuses on applications of fixed-site photogrammetry and the development of methods to more optimally conduct fixed-site photogrammetric monitoring. The novel contributions of this thesis are:

1. Development of a methodology for the volumetric estimation of pre-failure rockfall that can capitalize on high temporal resolution monitoring via a fixed-site photogrammetric system.
2. Creation of an optimization framework to assist in the informed creation of fixed-site photogrammetric monitoring systems.
3. Development of a preliminary empirical relation between terrestrial photogrammetry model accuracy and ground pixel pitch.

In order to develop the method for volumetric estimation, rockfall samples from a catchment ditch were collected from a site with ongoing monitoring via fixed-site photogrammetry. 3D mesh models were then created of the rock blocks. A software for statistically modelling shapes was utilized to estimate the volume of one block from another given simulated missing degrees of information. Overall volume predictions were promising, although the models generated demonstrated significant smoothing along edges, limiting the current use as a tool for predicting rock block geometry. With advances in partial shape matching, the method could be expanded to predict rock geometric characteristics prior to failure as well. In the context of fixed-site photogrammetry, this type of method would be most useful when pre-failure deformation is identifiable, which is more likely when temporal resolution is high relative to the length of the period of precursor deformation prior to failure. In the context of broader research, more accurate pre-failure rockfall geometry predictions improve geometry informed runout modelling, and thus can improve the efficiency of hazard mitigation designs.

This work also developed a method to improve the design process for fixed-site photogrammetric systems. A novel optimization method for the evaluation of fixed-site photogrammetric performance prior to necessary site investigation was developed. The tool
increases the ease of executing ‘go/no-go’ analyses, estimating system performance relative to other remote monitoring methods, and provides optimal recommendations for fixed-site photogrammetric network design. As part of this method, an empirical relation for the prediction of terrestrial photogrammetry model accuracy was developed. 283 images were collected of an outcrop at Red Rocks Park, Colorado at varying photo scales. Photogrammetric models were created at a myriad of distances and focal lengths to develop empirical trends relating photogrammetric model accuracy and ground pixel pitch, which was previously unexplored in a terrestrial setting. This work therefore establishes a point for comparison in the research literature for the performance of all future fixed-site terrestrial photogrammetric monitoring systems. While theoretical trends for point accuracy indicate an exponential deterioration of point accuracy with ground pixel pitch, the empirical trends suggest a logarithmic increase over the range of ground pixel pitches at which data was collected.

Fixed-site photogrammetry remains an under-utilized tool in the context of modern geologic engineering. However, there is a great potential for improvement of the approach both for academic and industry contexts. The advances in this work increase the utility of fixed-site photogrammetry, and improve the capabilities of engineers to remotely monitor slopes at lower costs, higher accuracies, and with higher time efficiency than previously. With advances in shape modelling, numerical modelling, machine learning, and general photogrammetric methods, the utilization of 3D-data in geologic contexts will improve concomitantly with regards to generation, accuracy, and both budget and human resource efficiency.

4.2 Recommendations for Future Research

The currently sparse analysis of terrestrial photogrammetry regarding mathematical correlations of the myriad of photogrammetric parameters to accuracy means many future studies similar to the analysis presented in Section 2.3 could be conducted. The empirical trends measured in Chapter 3 relating ground pixel pitch and model accuracy should be validated via similar study methodologies at alternative rock outcrops with varying color, texture, and lighting conditions. The quantity of cameras could also be adjusted for purposes of study. Additionally, these empirical trends should be analyzed for fundamentally different network geometries: the Red Rocks Park, Colorado case study simulated a convergent network system, while many sites may utilize parallel camera systems. Though less optimal from an accuracy perspective, parallel
camera systems offer more areal coverage, meaning budget-limited monitoring schemes may be more appropriate for large hazard areas. Further, a plethora of factors (e.g. image overlap, lens “quality”, etc.) and their impacts upon photogrammetric accuracy remain to be explored in a terrestrial context, particularly with regards to model distortions or the variability in model quality.

The methodology developed in Section 2.4 presents a pre-failure method of estimating rockfall volume. This method could be expanded to accurately estimate the geometry of rockfall pre-failure as well, but requires advances in partial shape modelling to advance further. A wider variety and quantity of rock block shapes should also be investigated, and practical applications tested as well to fully develop the utility of this method.

More broadly, many of the additional applications outlined in Chapter 2 provide opportunities for future work as well. Emerging technologies in machine learning and better coupling of fixed-site photogrammetry and numerical modelling can greatly benefit the geo-sciences and hazard monitoring. With continued advancement and development, the wide-spread utilization of fixed-site photogrammetry could become routine for geologic hazard monitoring.
APPENDIX A

PERMISSIONS FOR REUSE OF COPYRIGHTED MATERIAL

Figure A.1: Organization release for paper in Section 2.3
Figure A.2: Co-Author release for paper in Section 2.3