Advances in Pit Wall Mapping and Slope Assessment using Unmanned Aerial Vehicle Technology

by

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Abstract

As mining in open pits progresses deeper, keeping slopes stable becomes more complex. Multi-bench scale instabilities can result in significant economic loss. To address this concern, systematic documentation and evaluation of the performance of benches in open pit mines is essential for pit slope assessment. This includes collecting structural and geomechanical data for rock mass characterization as well as information on the geometry and configuration of the benches.

Advances in technology have made the use of unmanned aerial vehicles (UAV) for photogrammetry data collection more feasible. This thesis presents methodologies to integrate the UAV technology in open pit mine operations for collecting high quality data. The collected data was processed and useful information was extracted for design compliance audits, blast optimization studies, and slope stability analysis. This research aims to demonstrate the advantages and limitations of using this technology to collect and process field data.
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Chapter 1
Introduction

1 Introduction

Depletion of the reserves has pushed companies to mine lower margin deposits, making them particularly sensitive to fluctuations in commodity prices. This economic pressure has led to a focus on optimizing current processes in the hopes of improving profits at mining operations. As the mining industry moves forward with these goals, increased importance is placed on collecting high quality data and advanced modelling techniques for resolving technical challenges, as well as utilizing data analytics to optimize extraction, and improve workers’ safety.

A good understanding of rock mass properties and structural complexity has a significant impact on ore delineation, blasting, and slope stability. Existing field data collection methods are manual, time-consuming, and can expose technical human resources to hazardous conditions. Using commercially available UAVs and aerial photogrammetry techniques can improve geotechnical data collection in open pit mines. This aerial approach is fast, on demand and can improve the spatial and temporal resolution of the collected data. With this approach, significantly more data is collected which can be used to assess design compliance. Moreover, the collected data can be used as input for advanced modelling of rock mass structural complexity which is consequently used for optimizing blasting and evaluating the kinematic stability of pit slopes.

1.1 Motivation

Geotechnical information of a rock mass is limited to what can be seen on outcrop exposures, excavated faces, and in boreholes. In general, geotechnical investigations and analyses are data limited problems (Starfield and Cundall, 1988). This is related to the fact that the current practice of collecting geotechnical data is highly manual and provides data with low temporal and spatial resolution. Gathering high quality geological and geotechnical data can address mine design issues early in a mining project life cycle, at minimal cost (Pitman, 2016). Moreover, such information provides suitable input data for more targeted and sophisticated geotechnical design later in the project’s life. Lack of consistent and high-quality data can result in major reassessment of mine design down the road at a significant extra cost. One way of addressing this challenge is increasing the quantity and quality of geotechnical data as shown in Figure 1-1.
Knowledge of rock mass structural characteristics is necessary for most geotechnical engineering analyses. The information required includes the geometrical description of discontinuities present in the rock mass such as their orientation, persistence, size, intensity, roughness, and general condition. Kinematic analysis of pit slopes and in-situ block size analysis are examples of such analyses that rely on detailed rock mass structural characteristics. Geotechnical engineers have different tools at their disposal for doing these types of analyses. This includes using discrete fracture networks (DFNs) modelling, limit equilibrium programs, and empirical relationships. The selection of the appropriate tool depends on the type and quality of data available, and the desired output; for example, DFNs can be used to conduct slope stability assessments. However, the reliability of these techniques depends on the accuracy of the input data. Moreover, the outputs need to be verified and calibrated, which also requires the collection of accurate follow-up data.

Conventional techniques for field data collection can be disruptive to mining operations and can expose technical staff to hazardous conditions. These restrictions often lead to low spatial and temporal resolution of data, as access to exposures is limited and infrequent. Recent developments in technology, specifically, using UAV technology can provide a means for on-demand, fast, real-time, high-quality, automated data acquisition and feedback for mining operations. Despite the application of the UAV and photogrammetry techniques in quarries with simple geologies (Francioni et al., 2015; Salvini et al., 2017) and to identify mine structures larger than 6 m in size (Bemis et al., 2014; Menegoni et al., 2018; Sayab et al., 2018), the extent of its application for pit slope monitoring in open pit mines has not yet been fully appreciated. This work provides a
framework for integrating UAV technology for geotechnical data acquisition in operating mines. The results are used to extract geotechnical information that can be used as input for blast optimization, and to conduct geotechnical stability analysis. It also explores utilizing aerial photogrammetry techniques for faster and more efficient monitoring of the mining process.

1.2 Research Objectives

The main goal of this thesis is to investigate the application of UAV technology and photogrammetry technique for geotechnical data collection and pit design compliance. This principal objective is divided into the following secondary objectives:

1. Developing a UAV based methodology to collect high quality data from pit walls for highwall analysis, including equipment selection, flight plan creation, and point cloud generation;

2. Conducting aerial photogrammetry for detailed high wall mapping;

3. Analyzing the performance of benches (e.g. bench face angle (BFA), bench width characterization, pre-split hole deviation) using aerial photogrammetry techniques; and

4. Developing DFN models based on aerial photogrammetry techniques, to estimate in-situ block size distribution and to conduct kinematic slope stability analysis.

1.3 Methodology

The methodology used in the thesis is broadly summarized in the following procedures. First, a background discussion of the challenges related to current techniques for geotechnical data collection is provided. The modelling techniques that are used for geotechnical data analysis and their purposes are reviewed. Subsequently, the data collection sites, UAV systems used, and procedures followed to collect geotechnical data using UAV systems are presented. The collected image data is processed using photogrammetry techniques to generate point clouds and digital surface models. The point clouds are used for virtual mapping of pit walls in CloudCompare. The information obtained from the developed point clouds includes: geometry of discontinuities such as their dip and dip direction, trace length and coordinates of the trace centroids, and orientation of pre-split half cast blastholes. Digital elevation models (DEMs) are developed to assess design
compliance. Discontinuity data are used as input to develop DFN models of rock mass which are subsequently used to optimize blast induced rock fragmentation and to analyze pit slope stability. The results of these models are discussed in detail, including their implications for design work.

1.4 Thesis Outline

The thesis is comprised of six chapters structured as follows:

- **Chapter 1**: introduces the motivation behind the research, as well as the objectives, methodology and structure of the thesis.

- **Chapter 2**: states the importance of geotechnical mapping and the standard approaches to collecting geotechnical data. The literature on advanced geotechnical mapping techniques is reviewed. Moreover, the application of DFN models for estimating in-situ block size distribution and for slope stability analysis are described.

- **Chapter 3**: describes each of the data collection sites and the UAV systems used for geotechnical data collection. The methods for collecting the aerial images are presented, including the theory behind photogrammetry reconstruction.

- **Chapter 4**: explains the methods used for virtual point cloud mapping, the results of which are then used to analyze the impact of the jointing intensity on the final slope angles and quality of pre-split blasting. In addition, DEM models are created for design compliance assessment.

- **Chapter 5**: illustrates the application of the UAV based geotechnical data for generation of DFNs, which are subsequently used for blast optimization and pit slope stability assessments.

- **Chapter 6**: provides a summary and the conclusions of the thesis and outlines recommendations for future work.
2 Introduction

A fundamental aspect of mine design is the characterization of rock masses encountered in the mine area by collecting and analyzing geotechnical data. This data is commonly used to design pit slopes in the preliminary stages of mine design and to re-evaluate the slope stability as mining progresses during the operations. The rock mass characterization data can be further leveraged and used for other analyses, such as blast optimization or kinematic analysis. Accordingly, it is critical to ensure the collected geotechnical data is accurate, well documented, and sufficient to develop a knowledge of the rock mass (Hadjigeorgiou, 2012).

This chapter provides an overview of the literature on geotechnical data such as intact rock properties and rock structural data, and its importance. The methods for collecting geotechnical data, with a focus on the structural data collection, are described. Subsequently, structural data analysis methods including the creation and applications of deterministic and stochastic models, such as DFNs, are discussed. Finally, the use of these models, developed using the collected geotechnical data, to assess the pit slope performance is reviewed.

2.1 Geotechnical Data and its Importance

Excavations in rock cause a disturbance in the rock, which needs to be estimated in order to ensure the excavation is designed properly and performs as desired. Geotechnical data needs to be collected and analyzed to determine the impact of excavations on the surround rock mass. Intact rock properties were the focus of research in the 1960s; however, in the 1970s it was recognized that structural data is another crucial aspect of understanding the rock response to excavations (Hudson and Harrison, 1997). To effectively design a slope both components and their interaction need to be considered; in stronger rock structure may be the controlling factor, while in weaker rock the intact rock strength may be more critical (Read and Stacey, 2011).
2.1.1 Intact Rock Properties

Intact rock refers to rock which has no structural defects within it that occurs between the joints bounding it, identified by the red outline in Figure 2-1. The geomechanical properties of intact rock include the uniaxial compressive strength (UCS), triaxial compressive strength, and tensile strength, and are usually determined through laboratory testing. Intact rock sample testing can result in an overestimation of the rock strength because intact rock has the highest peak shear strength and often the best samples are selected for testing (Barton, 2013; Read and Stacey, 2011).

Figure 2-1: Structural properties of a rock mass, after Wyllie and Mah (2005).
Obtaining the UCS involves laboratory testing a cylindrical core sample, with a specified height: diameter ratio of 2.5:3.0, by applying a load along its axis until the specimen fails and the failure planes are identified. The test should only be accepted if the failure occurs within the intact rock. Similarly, triaxial testing involves applying a load axially in addition to confining pressure, as seen in Figure 2-2. It is possible to conduct direct tension tests to determine the rock tensile strength; however, these tests are rarely performed because of their complicated setup and the fact direct tensile failure does not occur in situ (Hudson and Harrison, 1997). Instead, indirect tests, such as the Brazilian test or Beam test, can be used to estimate the tensile strength based developed correlations (Zhang, 2006).

![Triaxial testing apparatus](image)

**Figure 2-2:** Triaxial testing apparatus, after Brady and Brown (2004).

Additionally, index tests are an alternative to laboratory testing cases where the number of tests required to characterize a rock mass is prohibitive, or simply the facilities for conducting laboratory tests are unavailable. The index tests can qualitatively describe the rock or be easily applied in the field to measure some properties of the rock. However, the results of index tests should be differentiated from laboratory tests since index tests cannot directly measure mechanical properties. An example of this is point load testing on core samples, cut blocks, or irregular lumps, which can provide an estimate of the UCS by applying a load using a pair of spherically truncated, conical platens. The results of the point load test are related to the UCS through an empirical relationship (Brady and Brown, 2004).
2.1.2 Rock Structural Characteristics

A rock mass is a heterogeneous composition of different rock types, formation contacts, and joints of varying orientation, persistence, roughness, frequency, infill, and surface geometry (Grenon et al., 1998). These joint properties are both geometric (e.g. orientation, size, or roughness) and non-geometric such as stiffness and infilling (Slob et al., 2010). The structural components of the rock mass can be seen in Figure 2-1 and are elaborated in the following section.

The orientation of joints, which are assumed to be planar, is described by the dip and dip direction. The dip is the line of maximum declination, while the dip direction is the azimuth of this line. Figure 2-3a illustrates the orientation components of a joint described by its dip (β) and dip direction (α), and Figure 2-3b shows the stereographic projection of the joint on a stereonet. Stereonets are a projection system used to visualize the dip and dip direction information. When presenting orientation information, poles are typically used to represent the joints. The pole concentration can be calculated, which allows for the identification of groups of joints with similar orientations called joint sets.

Figure 2-3: a) Joint orientation properties where α is the dip direction, and β is the dip b) stereographic projection, after Hudson and Harrison (1997).

Spacing is the true perpendicular distance between the joints in the rock mass. It can be calculated from the apparent spacing in drill core or scan lines. This measure can give an estimate of the
intensity of jointing of an area or a given set and is an important measure for defining the size and shapes of intact blocks. Moreover, highly jointed rock can be an indication of a weaker rock mass as the fractures are more likely to coalesce, forming a zone of weakness (Wyllie and Mah, 2005).

The size or persistence of joints is typically considered the length of the visible trace on the rock face. The shape of discontinuities is assumed to be circular, rectangular or polygonal for ease of modelling as their shape is never fully known (Esmaieli, 2010). Similar to the joint spacing, the persistence has an impact on the size and shape of intact blocks. Furthermore, large joints are particularly important as they create a more likely plane along which failure can occur.

Another feature to note is the termination of joint sets. Joints can terminate against other joints or intact rock. Moreover, the joints can also cross other joints without terminating. Terminations can be used to determine the structural hierarchy of the rock mass; younger joint systems are more likely to end against older, more persistent joints (Tuckey, 2012).

Joints are assumed to be planar for orientation and persistence analysis, but the surface of joints may have a roughness. The roughness is a measure of the surface unevenness or waviness and can affect the frictional properties of the joints and the slope stability. The roughness can be defined through standard charts. Barton and Choubey (1977) present a method assessing the impact of joint roughness through a joint roughness coefficient (JRC), estimated by using the chart shown in Figure 2-4.
The aperture is the perpendicular separation between rock on either side of a joint. These apertures can be open or have infilling, such as calcite or gouge material. The infilling can have an effect on the joint behaviour and requires characterization to ensure the sliding potential is considered. Moreover, groundwater flow called seepage can occur through the joints, providing further information on the aperture.

As previously discussed, intact rock blocks are formed when discontinuities are sufficiently connected to bound a volume. These blocks vary in size and shape, and together they form a distribution of intact rock blocks within the rock mass, called the in-situ block size distribution (IBSD). Knowing the IBSD is useful for estimating the support requirements, blasting requirements, or the potential size of sliding block at mines.

Figure 2-4: Standard chart for determining JRC, after Barton and Choubey (1977).
Therefore, to gain knowledge of a rock mass requires geotechnical data of both the intact rock and the structural properties. All the geotechnical data collection requires some fieldwork, whether by obtaining laboratory intact rock samples or gathering data for identifying structural features. The methods for geotechnical data collection, with a focus on structural data, are outlined below.

2.1.3 Geotechnical Data Collection

It is known that collecting high-quality geotechnical data that matches the sophistication of the design methods used is one of the most challenging tasks in the field of geotechnical engineering (Bieniawski, 1989). Furthermore, this data is critical for any project as many subsequent analyses and designs depend on it; incorrect input parameters result in incorrect designs. The general methods for conducting data collection are outlined below.

There are several sources of geotechnical data: oriented boreholes can be drilled, logged, and samples from the drill core laboratory tested; rock exposures such as outcrops, bench faces, and development heading can be mapped. These sources need to be logged and mapped by properly qualified personnel to ensure valuable information is obtained from each process. The data must be measured in an objective and replicable manner to ensure the robustness of the input geotechnical data for future design work. The challenge with collecting geotechnical data is that access to this information is often limited, depending on the stage of the mining project. During preliminary mine development only boreholes or surface outcrops are available, compared to later stages of open pit mining where more bench surfaces are exposed for field data collection. However, as the mining continues to deeper levels, the upper benches become inaccessible for data collection.

2.1.3.1 Borehole Drilling

The use of boreholes to collect drill core is a common practice through all stages of a mining process both for delineating the mineralization and for geotechnical purposes. Furthermore, drilling boreholes allow information to be collected from inside the rock mass which would otherwise be unavailable. The objective of geotechnical boreholes is to obtain a sample of correctly oriented core that is as undisturbed as possible. The target recovery for this type of core is 100% because the gouge or weaker material should be recovered, since their presence may have a significant impact on the rock mass. However, the cost of drilling for geotechnical purposes is
often higher than for exploration and requires at least NX (54 mm) size core (Bieniawski, 1989). An example of core is shown in Figure 2-5. This core is first logged and then samples can be cut for laboratory testing.

![Figure 2-5: Examples of geotechnical drill core a) with better quality rock and b) highly joint rock (courtesy of Kinross Gold).](image)

Once the core is drilled, its logging can proceed, i.e. the manual recording of the geotechnical information. Since this is both a manual and critical step of the process, it requires sufficient care and the use of proper techniques to ensure the most value is extracted from the logging process (Brady and Brown, 2004). The core needs to be photographed and the logging needs to be well documented so that the data can be revisited as required. Samples are selected for laboratory testing, and typically the following data is recorded for all the core drilled:

- Logging of rock units and types;
- Alterations and weathering;
- Rock quality designation;
- Fracture orientations and spacing; and
- And large-scale structure logging.
Additionally, once the borehole is drilled the downhole imaging can be used to provide a continuous and complete view of the drill hole wall. This is done using acoustic (ATV) and optical (OTV) televiewers. ATV systems record the amplitude of the pulse-echo signal reflected back from the drill hole walls. OTV systems measure the colour spectrum intensity in red, green and blue from a light source that is reflected back from the rock wall (Read and Stacey, 2011). Both systems can identify lithology and structures.

Several issues exist with the use of boreholes for geotechnical data collection. First, it provides a relatively small physical sample from which information is extrapolated; the borehole diameter is on average 54 mm wide. This is a one-dimensional sampling method from which information for a much larger area is extracted. The presence of blind zones is another limitation. The blind zone refers to the structures and joints that run sub- or parallel to the drill hole which cannot be seen in the drill hole. This blind zone is a common form of orientation bias which can be addressed by drilling sufficient drill holes of differing orientations (Terzaghi, 1965).

2.1.3.2 Field Mapping

When outcrops or rock faces are available it is possible to conduct field mapping to collect the structural properties identified in Figure 2-1; however, the three-dimensional nature of joint geometry poses a challenge since mapping methods are two dimensional (Dershowitz and Einstein, 1988). The field mapping usually involves some form of measurement along the rock exposure, and can be divided into conventional and remote sensing methods. The conventional methods include scanline mapping, window mapping and circular mapping. All the conventional methods involve having a person conduct the mapping close to the rock face. Due to advances in technology, more sophisticated geotechnical mapping techniques have been developed using remote sensing techniques. The remote sensing approach is being slowly adopted by the mining industry, reflected in the significant increase in research in this field, with the number of published works increasing from fewer than 50 to at least 250 over a span of 10 years (Derron and Jaboyedoff, 2010). The field mapping methods, limitations, and comparisons are discussed in more detail in the subsequent section, 2.2 Conventional and Remote Sensing Methods for Structural Data Collection.
2.2 Conventional and Remote Sensing Methods for Structural Data Collection

Conventional and remote sensing data collection methods are described in this section. Within each category, there are a subset of methods e.g. photogrammetry and laser scanning are both remote sensing methods.

2.2.1 Conventional Mapping Techniques

Conventional mapping techniques such as line mapping or window mapping are well established for collecting data with defined guidelines for systematic collection of the data (Brady and Brown, 2004; Priest and Hudson, 1981; Read and Stacey, 2011). Line mapping involves drawing a horizontal or vertical line across a rock face and measuring the structural properties such as orientation, spacing, frequency and trace length or semi-trace length of joints crossing the lines. Similarly, with window mapping, a specified vertical and horizontal distance is used to define an area within which the structural properties of joints above a specified cut-off size are mapped. Circular mapping is similar to window mapping insofar as that an area is mapped; however, a circular area is defined to be mapped. The key advantage to circular mapping is that some of the length and censoring biases, discussed in 2.2.2 Limitations and Biases of Conventional Mapping Techniques, encountered in window and scan line mapping can be taken into account by adjusting for the number of one and two end censored traces (Sturzenegger et al., 2011). Figure 2-6 shows a schematic of the different conventional techniques. All of the aforementioned techniques require technical personnel at the rock face doing the measurements.
Figure 2-6: Schematic of conventional mapping methods, with censoring bias shown for a circular mapping window, after Zhang and Einstein (1998).

Also, a key consideration when mapping is a sampling problem; it is unknown what area needs to be mapped in order to sample enough structure data for satisfactory results. Different areas may also have dissimilar geotechnical properties further compounding this sampling problem. Obtaining an accurate representation of the structural properties is the primary objective when carrying out field investigations so this problem requires careful consideration, as the rock properties are critical for the subsequent analysis. Furthermore, the confidence in the collected data should be examined. However, limited guidelines in the literature exist for estimating the number of samples required (Fillion et al., 2019). Nonetheless, collecting more data can improve the accuracy and confidence in the results.

2.2.2 Limitations and Biases of Conventional Mapping Techniques

There are some well-documented disadvantages and biases associated with conventional techniques. Some of the biases and limitations are common to all mapping techniques; however, they are generally more prevalent with conventional mapping.
These techniques require mine technical services staff to be at the rock face to conduct the mapping limiting the data collection to areas that can be accessed. The height of mapping is restricted to approximately 2 m, regardless of the overall accessibility of the rock exposure, since a person is unlikely to be able to safely reach above 2 m. The workers are exposed to potential rock falls and equipment that is operating in the area. In some mining jurisdictions and companies, there are minimum distances that need to be maintained from the rock face, further reducing the quality of the data collected. Additionally, the collection process is manual and time-consuming. The exposure to hazards can lead technical staff to increase the speed of mapping to reduce the health and safety risk resulting in poor quality, inaccurate, or insufficient data being mapped. It also raises the question of the resolution of structural mapping; having a small joint cutoff this will increase field time, whereas larger cutoff sizes result in a lower resolution. Figure 2-7 shows an example of window mapping at the West Branch pit; the resolution is low since only the large joints are identified, few data points are collected, and the person is exposed to rock fall risk at the base of the bench.

![Figure 2-7: Window mapping at the West Branch pit with identified joints superimposed](courtesy of Kinross Gold)

As with most sampling methods, there are biases associated with conventional mapping. Five significant bias sources exist and are described below. Figure 2-8 shows a schematic of the biases present during structural data collection.

- Orientation bias is caused by the relative orientation of the sampling plane to the joint data, similar to borehole blind spots, when joints are sub- or parallel to the orientation of the sampling plane.
- Size bias refers to the bias caused by the scale of the joints; larger joints are more likely to be sampled than smaller ones.

- Truncation and censoring are similar biases since both refer to data that is not recorded; the truncation bias refers to joints that are not sampled because they are below the cutoff size.

- Censoring occurs when joints extend beyond the sampling area.

- F-bias occurs due to the fact that the traces seen on the face are chords created by the intersection of a joint with the exposure face, and therefore may not represent the true diameter of that joint (Priest, 2004).

![Figure 2-8: Types of bias occurring during mapping, modified after Tuckey (2012).](image)

2.2.3 Remote Sensing Methods for Structural Data Collection

Some remote sensing such as photographic and laser techniques have been developed in response to the limitations of conventional methods. Photographic techniques have been used as early as the 1960s for the mapping of the dip and strike of geological features using black and white images (Lo, 1971). The photogrammetry methods can be used for conducting rock mass characterizations, collecting structural data and for creating 3-dimensional models of the exposure (Ferrero et al.,
The models generated can be used for back analysis of failures that already occurred and to which access is restricted. Bonilla-Sierra et al. (2017) used digital photogrammetry to identify joint planes along which wedge failure occurred, and conducted a back analysis using numerical methods. Elmouttie and Karekal (2017) used photogrammetric models to develop a DFN to assess the stability around underground accesses in an open cast coal mine. The photogrammetry tools used allowed for the collection of significant data; however, occlusions were caused by the survey set-up at the base of the open cast. Some efforts have been made to automate the structural data collection process using photogrammetry; however, this still remains a challenge (Chen et al., 2017; Lato et al., 2010; Riquelme et al., 2018). As noted by Francioni et al. (2015), relatively few published works have addressed the use of UAVs and aerial photogrammetry for mining and geotechnical applications.

The use of terrestrial laser scanning (TLS) has also advanced significantly since its original development in the 1960s (Vanneschi et al., 2017). TLS has been used to monitor slopes, conduct back-analyses of failures, and characterize rock masses (Abellán et al., 2006; Ferrero et al., 2011; Jaboyedoff et al., 2012; Sturzenegger and Stead, 2009). TLS can have a range of up to 1km. However, the resolution of the TLS can be lower than that of photogrammetry and cannot capture colour unless the scanning unit has an integrated camera.

Remote sensing techniques offer many advantages over the conventional data collection method: increased areal coverage, access to previously unreachable areas, reduced cut-off and censoring bias, reduced field data collection time, and improved safety (Read and Stacey, 2011). However, there are several limitations associated with terrestrial remote sensing techniques. These include lighting conditions, vegetation or occlusions, multiple survey location requirements, and an incomplete field of view. Figure 2-9 shows a schematic of some of the limitations encountered by all of the terrestrial methods. Using UAVs can reduce the limitations of terrestrial-based remote sensing, most notably, it improves accessibility, eliminates the need for multiple survey locations, and further increases the speed of data collection.

Since remote sensing for mapping is relatively new in the field of geotechnical engineering, it requires a strong user knowledge for the data collection, processing, and analysis. This prerequisite makes it a relatively specialized field that has not experienced main-stream adoption that may have been expected with a tool that brings as many advantages as remote sensing does (Lato and Vöge,
This is the case with UAV-based photogrammetry as well. This work aims to provide readers with a practical methodology for integrating UAV-based data collection into geotechnical assessments and analyses.

2.2.4 Comparison of Conventional and Remote Sensing Methods

Photogrammetry and laser scanning techniques have eliminated some of the challenges related to conventional scan-line and window mapping, such as the difficulty of measuring large scale geological structures, limited rock face access, and exposure to hazardous conditions at the rock face. Moreover, using remote sensing methods allows for more detailed data sets to be collected, increasing the resolution of the 3D models generally created for the mapping area and consequently improving the robustness of modelling and analyses performed for the area of interest. An additional advantage is that these data sets are saved as permanent records of the rock conditions at the time. Collecting more data can be considered a necessary response to the fact that rock mechanics is a data limited problem (Starfield and Cundall, 1988).

Remote sensing has been effectively applied to areas that are difficult to assess using conventional mapping techniques or to span larger areas (Abellán et al., 2006). With better characterization of the rock mass, it is possible to develop more accurate models. For these reasons, remote sensing techniques are becoming more prevalent in the mining industry. However, there is room for improvement in the procedures used for conducting photogrammetry and mapping (Tuckey et al., 2012).
2016). This work develops this further by providing a framework for collecting photogrammetry data using UAVs.

2.3 Structural Data Analysis

Using the structural data collected, it is possible to assess the stability of slopes or in-situ block size for design purposes. Deterministic and stochastic analysis methods, such as DFNs, can be used to conduct these assessments. If the quality of the structural data is sufficient, it is possible to model the complexity of the rock mass using DFNs (Esmaieli, 2010). This section outlines the analysis types and their applications.

2.3.1 Deterministic Analysis

Deterministic analyses are based on the principle of using a single value for the geotechnical rock properties. The input values are applied to limit equilibrium equations for an assumed material behavior, such as Mohr-Coulomb, along a potential failure plane, or planes in the case of wedge failure. The results are presented as a factor of safety which is a ratio of the resisting forces to the driving forces. The desired factor of safety varies depending on the type, purpose, and risk tolerance for an excavation. Typically the minimum factor of safety for an excavation or rock slope is 1.2 (Read and Stacey, 2011).

Deterministic methods can both lead to an over-conservative design or under design, and are not suitable for capturing the inherent variability present in the rock mass (Amoushahi et al., 2018). Sensitivity analysis can be done on the input parameters to partly determine the impact of the data variability. The limitations of using single values as input parameters have led to an increase in the use of probabilistic analyses, where the inputs are modelled by a distribution. However, the perception is that having a factor of safety is still more meaningful as it is difficult to accept that there is a probability of failure; furthermore, there is the problem of defining what probability of failure is acceptable for a design (Hoek, 2006).

2.3.2 DFN Modelling

DFN modelling is a fracture system model of a rock mass. It is a stochastic model for joints within a rock mass that can capture the inherent rock mass structural variability. To develop a DFN model data about the rock mass needs to be collected; specifically, the trace lengths, orientations, sets
and terminations of the joints within it (Dershowitz and Einstein, 1988). Collecting data required for building a robust DFN model is critical, particularly one that incorporates the variability of the data (Elmo et al., 2015; Hadjigeorgiou, 2012). High quality input data is required to ensure a DFN model represents the field observations and reliable for further analyses.

Several DFN generators have been developed over the years. In this work, a commercially available code, FracMan (Golder Associates Ltd, 2018a), was used to generate the models. The input parameters, generation, and validation of the model are described below. These procedures are common to all fracture system generators.

2.3.2.1 Input Parameters

Elmo, Stead, and Rogers (2015) provide an extensive guideline of the required input parameters for generating a DFN model. The basic input data are those described in 2.1.2 Rock Structural Characteristics; specifically the fracture orientations, termination, and size. Since a DFN is a stochastic model it is possible to use a statistical distribution function to describe all of the structural characteristics. This feature makes it possible to overcome some of the limitations of deterministic models, as the inherent data variable can be taken into account.

The joint intensity is the final parameter required to generate the DFN model. This refers to the degree of jointing in a rock mass. The intensity parameter used is determined by the type of sampling done. Table 2-1 describes the intensity terminology used in DFN modelling. To generate a model, the volumetric intensity (P_{32}) is required since the model refers to a 3D rock mass. However, the P_{32} cannot be directly measured and needs to be inferred, as it is not possible to measure the area of fractures (Esmaieli, 2010).
### Table 2-1: DFN modelling intensity terminology, after Golder and Elmo (2006)

<table>
<thead>
<tr>
<th>Dimension of Feature</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>0</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
| **P00**              | Length⁰  
Number of fractures |   |   |   | Point Measure |
| **P10**              | Length¹  
Number of fractures  
per unit length of scanline  
(linear intensity) |   |   |   | Linear Measure  
e.g. Borehole |
| **P01**              | Length²  
Number of trace centres  
per unit area of sampling  
(areal density) |   |   |   | Areal Measure  
e.g. Window |
| **P02**              | Length³  
Number of fracture centres  
per unit volume of rock mass  
(volumetric density) |   |   |   | Volumetric Measure |
| **P11**              | Length⁰  
Length of fractures interferes  
per unit length of scanline |   |   |   |
| **P21**              | Length¹  
Length of fractures  
per unit area of sampling plane  
(areal intensity) |   |   |   |
| **P22**              | Length⁰  
Area of fractures  
per unit area of sampling plane |   |   |   |
| **P31**              | Length¹  
Area of fractures  
per unit volume of rock mass  
(volumetric intensity) |   |   |   |
| **P32**              | Length⁰  
Volume of fractures  
per unit volume of rock mass |   |   |   |
| **P33**              | Length⁰  
Volume of fractures  
per unit volume of rock mass |   |   |   |

The $P_{32}$ can be estimated based on 1D or 2D sampling techniques. 1D sampling methods can provide the $P_{10}$ (the number of fractures per unit length) values, which are obtained by mapping boreholes or scanlines. 2D sampling techniques, window counts and mapping, are used to calculate the $P_{20}$ (number of fractures per unit area) and $P_{21}$ (the length of fractures per unit area), respectively. These approaches all have limitations such as directional bias, truncation bias, and location bias. Values of $P_{21}$ or $P_{10}$ can be converted into $P_{32}$, either analytically or through simulation (Rogers et al., 2015). Equations 2-1 and 2-2 can be used to obtain the $P_{32}$; however, the conversion is heavily influenced by the orientation bias of the sampling method, and truncation bias in the case of 2D sampling methods (Elmo et al., 2015).

\[
P_{32} = C_{32} P_{21} \quad 2-1
\]

\[
P_{32} = C_{31} P_{10} \quad 2-2
\]
2.3.2.2 DFN Generation and Validation

Dershowitz and Einstein (1988) describe the various computational models for generating a DFN, such as the Baecher or Veneziano models. In this work, the Baecher model is used with the FracMan code. Miyoshi et al. (2018) and describe the general workflow that was followed in this work for integrating the collected data and developing a DFN (see Figure 2-10). This approach is similar to others presented in the literature (Grenon and Hadjigeorgiou, 2003). This is an iterative process that requires some trial and error to ensure accurate results. The end product is a calibrated DFN that can be one possible representation of the rock mass.

Figure 2-10: DFN model generation workflow, after Miyoshi et al. (2018)

Two methods exist for modelling the joint sets: an aggregate and disaggregate approach. In aggregate approaches, all the joints are modelled as a single set. An alternative method is modelling the data disaggregately, where all the joint sets are modelled individually. Using the
aggregate approach can result in inaccuracies related to overestimating or underestimating joint sizes, intensity and orientation.

A statistical analysis is conducted on each joint set, and a distribution is fit to the orientation and trace lengths. The distribution is used to provide a first estimate for the mean, the largest and smallest equivalent diameter used for generating a DFN model. An arbitrary $P_{32}$ is assigned to each joint set and generated in the model, with the joint locations defined stochastically by a Poisson process within the model (Esmaeili, 2010).

To validate the model, first, a trace plane representing the mapped wall or an as-built surface is introduced into the DFN models. Each generated joint set is intersected with the surface to produce a tracemap and compared to field measurements. A Kolmogorov – Smirnov goodness of fit test at a desired significance level is used to compare the distributions of field trace lengths and DFN trace length. If there is a fit, the joint set model is accepted; however, if it is not a fit, the model distribution parameters are modified. This process is done iteratively until a satisfactory fit is achieved. A similar approach can be used to estimate the $P_{32}$, or by using equations 2-1 and 2-2. Once the model replicates the field observations, it can be accepted and used for further analysis.

2.3.2.3 Impact of Input Data Quality

It is has been well established that the input of data quality has a significant impact on the results of a DFN model (Elmo et al., 2015; Hadjigeorgiou, 2012). The models can misrepresent reality if the sampling and data variability is not carefully considered. Nonetheless, even inappropriate or subjective (having significant epistemic uncertainty) DFNs could still provide some valuable, though limited, information that may not be available if a deterministic approach were used (Lorig, 2014).

Increasing the amount of data collected can improve modelling results; however, field work to collect data using conventional methods is time-consuming and, therefore, costly. The practical implication of this expense is that insufficient, or just sufficient, data is collected. Remote sensing has enabled faster collection of data, and thereby allows more data to be collected improving the reliability of models.
2.3.3 Application of DFN modelling

DFNs have become a common means of conducting rock mass analysis since 2010 (Onederra et al., 2014), in a variety of applications in both underground and surface mines. Applications in the underground environment have included optimizing stope design to reduce dilution costs (Urli and Esmaieli, 2016); assessing fragmentation potential for block caving mines (Brzovic et al., 2015; Rogers et al., 2015); and for ground stability (Esmaieli and Hadjigeorgiou, 2015). In surface mines, DFNs have been useful for conducting blasting optimization, assessing the viability of quarries for production (Latham et al., 2006b; Yarahmadi et al., 2018), and instability modelling (Rogers et al., 2016). Furthermore, they can be used as a tool to explore the impact of data variability on the results of an analysis (Grenon et al., 2017, 2014; Grenon and Hadjigeorgiou, 2008).

2.3.3.1 In-situ Block Size Distributions

As discussed previously, the interaction of joints within a rock mass can form rock blocks of different size, which is characterized as IBSD. Understanding the IBSD of a rock mass has many applications in mining and civil engineering. In mining, it can be used to determine mine cavability, structural stability of surface and underground excavations, and performance of blast-induced fragmentation. The applications IBSD are discussed below.

Block caving is an economical mining method for low grade and large tonnage deposits that cannot be mined by traditional open pit methods mainly due to their depth or other constraints. As such, it is becoming an increasingly popular mining method (Woo et al., 2013). Conceptually, caving is initiated by removing the support from under an ore body, which leads to the propagation of internal fractures that weaken the rock material, thereby freeing the rock blocks and allowing them to cave. The ability of an ore body to cave, given that the size of the undercut is sufficient, is described as its cavability. The $P_{32}$ has a direct influence on the cavability and volume of material extracted (Rafiee et al., 2018). The transition from massive rock to kinetically mobile rock mass is critical for caving, and the value of $P_{32}$ at which this occurs helps determine whether or not the rock mass is suitable for block caving (Rogers et al., 2015). If the average in-situ block size is too large, the primary fragmentation might not reduce the material to a suitable draw-point size, making block caving an inadequate mining method. For these reasons, knowing the IBSD is critical before selecting block caving as a mining method.
In blast-induced rock fragmentation, the objective is to reduce the IBSD to a target size distribution, i.e. the blasted block size distribution (BBSD). Typically, rock masses with smaller IBSD require less blast energy to achieve the target size BBSD (Scott, 1996). Several relationships have been used to predict the fragmentation results based on the IBSD curves, such as the Kuz-Ram, Bond-Ram, and EBT models (Latham et al., 2006a). More recent research has focused on updating the relationships with additional case studies to create more robust estimates of the blast energy required to reduce IBSD to BBSD (Kahriman et al., 2001).

### 2.3.3.2 In-situ Block Size Distribution Analysis

Elmouttie and Poropat (2012) provided a literature survey on the current techniques for estimating IBSD and presented an overview of the evolution of these techniques since their earlier implementations. The first techniques, developed in 1977, implemented a computer algorithm to determine the volume of in-situ blocks based on persistent joints (Da Gamma, 1977). More advanced applications started using DFNs containing information on the finite persistence of joints to simulate a rock mass and obtain the IBSD (Rogers et al., 2007). Increasingly sophisticated models have been developed but limitations exist; however, appropriately accounting for non-persistent joints and dangling joints is still a challenge in the determination of IBSD (Boon et al., 2015). DFN represent an improvement over previous IBSD estimation methods, undulating and round shapes joints still cannot be modelled.

When estimating the IBSD of the rock mass, the algorithm used is a critical factor since several methods exist. One method uses a grid search, where the volume of the DFN is sub-celled into smaller blocks and the joints are incorporated into the model. The cells not separated by joints are combined and their volume is calculated, producing a block size distribution. To ensure accurate results, the cell size has to be smaller than the minimum anticipated block size (Golder Associates Ltd, 2018b). In a sub-cell algorithm, the total volume of the region is equal to the total volume of the blocks. Despite the accuracy of this method, it is very computationally intensive. Figure 2-11 shows a conceptual example of the grid search algorithm for estimating the IBSD, the cells forming blocks are colour coded in the models.
Other less computationally intensive algorithms are based on randomly selected points within the DFN model. One method generates a series of lines in user-defined directions, passing at random points in the model, where the locations of the joint intersections with the lines are recorded. The spacing of discontinuities along the lines is then used to create a distribution of block volumes. An alternative algorithm also selects a random point within the DFN volume from which rays are sent out until they hit a joint. The volume is then calculated using the mean lengths of the ray at each point and a shape correction factor. A limitation of both random point methods is that the full volume of the DFN may not be analyzed, potentially reducing the accuracy of the IBSD estimate. Using additional points reduces this potential; however, using more points increases the processing requirements. With the cast ray method, a further limitation is a bias towards larger blocks, as the random points are more likely to occur within them (Golder Associates Ltd, 2018b). Figure 2-12 shows a schematic of these two computationally less intensive algorithms for estimating the IBSD.

Another consideration for generating the IBSD are the shapes of the blocks within the rock mass, which are harder to characterize. The block shape should be taken into account since it influences the properties of the rock mass, including stability and fragmentation results. By incorporating the elongation and shortening of the major and minor axes, respectively, the shape of the blocks could be better captured (Kalenchuk et al., 2006).
While the methods selected to estimate the IBSD and block shapes have an impact on the results of the analysis, the primary factors affecting the IBSD are the $P_{32}$ and the persistence of joints (Wang et al., 2003). The $P_{32}$ is derived based on the mapping results, and the persistence of joints is directly measured in the field. This demonstrates the importance of collecting high quality data to improve the modelling results.

### 2.3.3.3 Stability Analysis

DFNs can be used for kinematic stability analysis, in addition to stability assessments based on IBSD estimations in both underground and surface mining applications.

In surface applications, an attempt to improve awareness of failure mechanisms has increased as a result of the challenges faced in larger open pit mines. This effort includes a better understanding of the in-situ rock conditions, among which is the block size distribution (Stead and Wolter, 2015). Assessment of the kinematically unstable blocks and wedges is required to maintain safe operations. Anticipating potential pit wall instability comes from an understanding of the IBSD, the joint orientations, and pit wall advance. The use of DFN models allows for relatively quick evaluation of the structural stability of pit walls; however, it does not incorporate mechanisms...
involving progressive and stress-induced failures (Bonilla-Sierra, 2017). In underground applications, DFNs have been used to model ore passes (Esmaieli, 2010; Esmaieli and Hadjigeorgiou, 2015).

Similarly, the impact of leaving an ore skin in an open stope to reduce dilution has been modelled (Urli and Esmaieli, 2016). The IBSD was used to estimate the volume of dilution that would be mined as a result of structural failure in the stope and was compared to the economic benefit of leaving various ore-skin thicknesses. As previously discussed, the use of DFNs and estimating IBSD for underground excavations have similar limitations, since the induced stresses and more complex failure mechanisms are not considered. However, the use of hybrid models by incorporating DFN models within discrete element models enables accounting for different failure modes (Urli and Esmaieli 2016).

The data variability, which is often difficult to define, needs to be taken into account for stability analyses. An advantage of DFNs is that they can partially capture this variability, and have been used to explore the impact that input data variability has on slope stability. Grenon et al. (2017) considered the implications of joint variability by performing a wedge stability analysis in an underground tunnel based on the use of DFNs. The results showed that variation in the trace length and input parameters had the most significant influence on the size of unstable wedge formed. This conclusion is in line with that of Wang et al. (2003), further reinforcing the previous discussions regarding the need for improved data quality. Rogers et al. (2016) conducted a similar stability analysis in an open pit environment. Here, the focus was to investigate the use of DFNs to identify optimal mining sequence to minimize instabilities, while considering the data variability. To do this, Rogers et al. (2016) generated and combined multiple DFNs to create a probability plot showing the volume of unstable wedges for each mining option. The discussed examples made good use of DFNs to assess or mitigate the impact of data variability. A similar approach is taken in this work, where multiple generations of a stochastic DFN model are used to examine how the deterministic joints mapped interact with those stochastically generated and their combined impact on the slope stability.

2.4 Pit Slope Performance

It is important to develop a blast and slope monitoring program to ensure the design parameters are maintained. Having a structured approach that monitors geotechnical and blast performance
can improve the condition of the final walls (Catalan and Onederra, 2016). The catch bench widths and bench face angles are monitored as part of these programs. If back break occurs, this could result in more waste mined and reduced catch benches, increasing costs and reducing safety. Therefore, this is an economic and safety incentive to ensure the performance is as desired.

2.4.1 Conventional Assessment Methods

Conventional methods used for pit slope performance assessment are relatively manual and time consuming. They involve visual inspections and assessment of blast damage, which can be highly subjective. Moreover, there are multiple methods for assessing blast damage. Lupogo (2017) proposes a more systematic approach for determining blast damage by using blast damage quality designated index. Other methods include GPS surveying of the crests of benches; however, due to regulations on how close to the edge personnel can walk, these are often estimates of the crest location. Clinometers and Brunton compasses can be used to measure slope angles. Figure 2-13 shows an application of an inclinometer to measure the bench face angle.

![Figure 2-13: Inclinometer use, after Read and Stacey (2011).](image)

2.4.2 Remote Sensing Performance Assessment

Remote sensing techniques are increasingly being used for slope assessments, such as slope failure back analysis, calculating displaced rock volumes, and assessing landslide risk (Alexakis et al., 2014; Derron and Jaboyedoff, 2010; Ferrero et al., 2011; Oppikofer et al., 2009). Furthermore,
TLS surveys can be used to assess the slope performance as sub-centimetre accuracy can be achieved by scanning the slope from multiple survey points. These surveys can be used to create a precise DEM, which can be used for joint mapping, design compliance metrics, and modelling.

DEM and geographic information systems (GIS) are powerful tools available for geotechnical modelling. They provide a platform for simple and effective visualization of geospatial data, such as georeferenced images that can be overlaid with the processed data to provide a quick method for identification of features. DEMs are often in raster formats, which are matrices representing a rectangular grid of pixels or cells. The principal advantage is that rasters of DEMs are extremely flexible, and multiple data sets can be merged and used together. A pixel or cell within a raster can store elevation data, slope geometry information, joint information, and any other information required. The geometry information can provide useful information on the slope performance compared to the slope design, such as catch bench width, sloughed material coverage, and bench face angles.

Nelson et al. (2007) used GIS tools to integrate and analyze multiple rock mass structures types at the Chuquicamata pit to determine their impact on slope stability. A vast amount of data from different sources was relatively easily integrated using these tools, and modelling techniques ranked the relative importance of factors affecting the slope stability. Similarly, it is possible to transform a DEM into a slope and slope direction model. This slope information is stored in a raster, and supplemental structural information can be added into it. A kinematic or limit equilibrium analysis can be carried out based on the slope orientations and structural joint set data in each cell (Grenon and Hadjigeorgiou, 2010). Since a value is calculated for each cell, it can be used to identify more specific areas of concern and produce a more reliable slope design. Moreover, it can be used at different scales to assess the bench level stability and inter-ramp stability (Grenon and Laflamme, 2011). These results can then be effectively plotted and communicated on a map.

2.5 Summary

Geotechnical data form one of the key basis for open pit slope design; however, collecting high quality data with the current manual and terrestrial techniques is challenging. Some of the known limitations are described and presented in Figure 2-9. The use of UAVs for remote sensing may
resolve some of these limitations. UAVs can supplement traditionally collected field data and have the following advantages:

- A permanent visual record of the data is created;
- The field mapping time is reduced;
- High quality and resolution data can be collected;
- Fewer operations disruptions for data collection; and
- Significantly improved safety for personnel.

Using UAVs, mapping of large areas of varying scale is possible without the loss of accuracy or resolution. Large scale features, which were previously difficult to identify, such as tightly sealed faults, can be recognized (Read, 2018). Finally, more data of higher quality can be produced using UAVs, improving the data analyses and modelling results.

The overview of DFN modelling shows the advantages of using a stochastic model; the variability of the data can be better modelled, which can produce more reliable results. Furthermore, the models can be used for purposes beyond stability analyses, such as blast optimization. However, using input parameters that accurately represent the field data is critical for meaningful results. The use of UAVs can add to the amount of data collected: the high resolution models can reduce truncation bias, the large area covered reduces censoring bias, and finally more time can be dedicated to mapping, thereby improving the quality of data collected.

A discussion of DEMs and GIS tool capabilities to evaluate the actual performance of slopes, integrate data, and conduct stability analyses was provided, in particular, their effectiveness for communicating results. The GIS analysis can be further improved by DFNs to gain an understanding of the IBSD and the stability of a slope. The data variability can be better captured by using stochastic modelling. DFN models can then be utilized to assess fragmentation based on IBSD and BBSD relationships. Moreover, DFN models can be used for stability analysis of the slope.
3 Using UAV System for Geotechnical Data Collection-Case Studies

Different field experiments were conducted to investigate the application of UAV and aerial photogrammetry technique in structural data acquisition and analysis as well as the assessment of pit wall performance. This chapter provides an overview of the mines where the data was collected, the equipment used, the methods for collecting data, and the computer vision theory for creating the point clouds from images.

3.1 Data Collection Sites

The data used for this study were collected from four different mining complexes, in geologically and geographically diverse settings: the Lupita and Central pits in the El Gallo mine in Mexico, the Bowmanville quarry in Canada, the West Branch pit in the Tasiast mine in Mauritania, and the Top 2B pit in the Bald Mountain mine in the USA. The data collection was done over one and a half years, between December 2017 and April 2019. The mine operations and regional geology of each site are described in this section.

3.1.1 El Gallo Mine Complex

The El Gallo mine complex, owned by McEwen Mining, is located in the state of Sinaloa, Mexico, approximately 100 km northwest of Culiacan. Gold is the primary metal produced with some silver by-product. During two data collection campaigns (December 2017 and April 2018), the mine complex was fully operational; however, mining and crushing activities have concluded since the site visits (McEwen Mining Inc., 2019). The data was collected from the Lupita and Central pits, shown in Figure 3-1. The mine is set in the Lower Volcanic Series of the Sierra Madre Occidental, dominated by rocks of Andesitic composition. Within the local geological context, the two pits are located along a northeast striking structural trend and the mineralization is hosted within numerous sub-structures, consisting of quartz stockwork, breccia, and vein mineralization (Read and Willis, 2013). The pits are structurally complex, and this was reflected in the collected data.
3.1.2 Bowmanville Quarry

The Bowmanville quarry is situated in southern Ontario, Canada, approximately 70 km east of Toronto. The quarry, which mines limestone, has been in production since 1968 and is operated by St Marys Cement, a subsidiary of Votorantim Cimentos North America. The limestone is used for the production of cement, aggregate, and building stone. The mine is contained within Middle to Upper Ordovician Lindsay Formation. The mine has well developed vertical jointing as well as the bedding planes and horizontal jointing (Derry Michener Booth and Wahl and Ontario Geologic Survey, 1989). This well-developed jointing can be seen in Figure 3-2 along with the DJI Matrice 600 pro UAV system that was used for structural data collection. The data was collected over three days in September 2018.
Figure 3-2: Well developed vertical and horizontal jointing at the Bowmanville Quarry.

3.1.3 Tasiast Mine Site

The Tasiast project is found in Northwestern Africa in Mauritania (shown in Figure 3-3), approximately 300 km north of its capital, Nouakchott. It lies in a Precambrian greenstone belt, specifically, the Aouéouat belt which hosts the West Branch deposit and the pit where the experiments were conducted. The deposits are strongly folded and sheared, contributing to significant foliation dipping approximately 40° to 65° to the east (Sims, 2016). This can be clearly identified in the mapping conducted at the site and is one of the key structural features within the pit. The Tasiast project is active, and 3.7M tonnes of ore were mined in 2018 (Kinross Gold, 2019). At the time of the site visit, in November 2018, the West Branch pit was approximately 223 m deep. The UAV mapping data were collected over four days. The extended time required for data collection, was in part due to the heat restrictions and a limited number of UAV battery sets on site for the data collection.
3.1.4 Bald Mountain Mine Site

Bald Mountain mine complex is situated in the southeastern extension of the Carlin Trend, which is one of the most prolific gold producing areas in the USA. The mine is located approximately 113 km south of Elko. It is postulated that most of the mineralization at Bald Mountain is an intrusion-related hydrothermal system, unlike the Carlin-type deposits found in the area. The mineralization is typically located along high angle faults, dykes, certain strata, and in quartz stockworks, which has been caused by a Jurassic aged intrusion, creating several deposits in the area (Nutt and Hofstra, 2007). Bald Mountain is an active multi-pit operation, producing approximately 24.4M tonnes of ore (Kinross Gold, 2019). The mine operates as two distinct areas:
the North Operating Area (NOA, shown in Figure 3-4) and the South Operating Area (SOA), dispersed over a large area. This presents the operations with several challenges, among which is the effective and rapid collection of geotechnical data. The operations’ the technical staff and resources are spread among multiple pits. It is time consuming for the staff to travel between pits, and the instrumentation and equipment needs to be carefully managed in order to ensure the appropriate locations are being monitored. Mapping of the Top 2B northeastern pit wall (Figure 3-5), located in the NAO, was identified as a priority due to a major fault structure crossing the area and structural instability concerns. The data was collected in April 2019, over 11 days. The site visit was extended to 11 days because of extreme weather conditions and a restriction on the number of consecutive workdays allowed on the site.

Figure 3-4: Map showing the Bald Mountain North Operating Area (courtesy of Kinross Gold).
3.2 UAV Systems Used for Field Data Collection

The following section outlines the equipment used to collect the data. This includes: UAV systems, cameras, lenses, and data processing software.

3.2.1 Unmanned Aerial Vehicles (UAVs)

Three UAV systems were used for data acquisition in these case studies: DJI Matrice 600 Pro, DJI Inspire 2, and DJI Phantom 4 Pro (see Figure 3-6). The Matrice 600 Pro is a hexacopter drone with a high payload capacity of up to 6 kg. Due to this high payload capacity, it could be outfitted with a multiple gimbal configuration, making a LiDAR, high-speed camera, or dual camera set-up possible. For this research, only the single camera set-up was used. The maximum flight time is approximately 16 to 32 minutes, depending on the payload (DJI, 2018a). The DJI Matrice 600 Pro was also equipped with a Manifold onboard computer and a GitUp Git2 action FPV camera.

The Inspire 2 is quadcopter drone with a flight time of approximately 25 minutes (DJI, 2018b). The photogrammetry conducted at the Bald Mountain and Tasiast mines was done using the
Inspire 2. It is the preferred choice over the Matrice 600 Pro because of its simpler set-up before flights and the faster battery charge. It is also easier for handling and carrying. However, it is limited to a single camera set-up.

The DJI Phantom 4 is a small quadcopter with a fixed camera. It was typically used as a spare vehicle when other UAVs were unavailable. It was also used to conduct rapid aerial surveys of the topography for generating flight plans when mine survey data was unavailable. All three UAVs used GPS time synchronization to produce georeferenced images, allowing generation of georeferenced point clouds. Figure 3-6 shows the drones used for the data collection.

![Figure 3-6: UAVs used for site data collection. From left to right: Matrice 600 Pro, Inspire 2 and Phantom 4 Pro.](image)

### 3.2.2 Cameras

The DJI Zenmuse X5 was mounted on the Matrice 600 Pro drone. This is a 16 MP camera with a default 15 mm f/1.7 ASPH prime lens resulting in a 72° angle of view (AOV). The Inspire 2 was equipped with a Zenmuse X5S 20.8 MP camera and its default 15mm f/1.7 ASPH prime lens. An additional lens with a longer focal length, the Olympus M.Zuiko 45mm/1.8 (with balancing ring), was used for instances when higher resolution pictures were required.

The focal length describes the light-bending power of a lens: the distance light travels between the lens and the point of focus which is the camera sensor (Langford et al., 2010a). A longer focal length lens will provide more image detail due to enlargement; however, the field of view becomes narrower (Langford et al., 2010b). Figure 3-7 shows 15 mm focal length lens (Figure 3-7a)
photogrammetry results compared to those of a 35 mm focal length lens (Figure 3-7b). As seen, the longer focal length lens produces a significantly more detailed model of the pit wall, but due to the reduced AOV, more images are required to cover the same area and thus the UAV flight time is increased. Therefore, the camera and lens pairing needs to be carefully selected during field data collection to ensure appropriate results. This is discussed in further in the subsequent sections of the thesis. The Phantom 4 Pro UAV has a fixed 20 MP camera with an 8.8 mm/24 mm lens, which could not be modified or changed.

![Figure 3-7: Difference in image detail between a) a 15 mm lens and b) a 45 mm lens](image)

### 3.3 Image Collection for Photogrammetry

Generally, photogrammetry refers to any process by which a 3D model is created from 2D images (Kasser and Egels, 2002). In this work, the 2D images were collected by using the previously described UAV systems. The quality of the images significantly impacts the results of photogrammetry and depends on multiple parameters: overlap between photos, distance from the
target, flight height, lighting conditions, weather conditions, lens focal length, lens AOV, and camera resolution. Some of the parameters can be controlled by the operator, whereas others such as the weather and lighting conditions cannot be controlled. Figure 3-8 shows the effect of light condition on the quality of images, capturing the same feature, represented by the green cross. The images were all collected by DJI Inspire 2 using the Zenmuse X5S 20.8 MP with the Olympus M.Zuiko 45 mm lens. The quality of image DJI_0658_2 is much better than image DJI_0846_1, which is shadow covered, and DJI_0588_2, in which there is glare due to direct sunlight. This comparison demonstrates that the results of photogrammetry reconstruction can vary greatly depending on the weather and lighting conditions.

Unfortunately, limited guidelines exist for flight planning for UAV photogrammetry in mining operations, which may lead to poor results if the user is not experienced with developing flight plans (Salvini et al., 2017; Tziavou et al., 2018). Understanding the relationship between the flight and image quality parameters is crucial for obtaining the desired results. The image spacing can be effectively designed for, whereas lens and camera features are fixed once the UAV system is selected.

Figure 3-8: Lighting condition influence on the quality of image and feature identification.

In order to design a suitable flight plan (with the appropriate distance from a pit wall), the ground sampling distance (GSD) has to be determined. The GSD is the ground distance covered within a pixel and can be determined using equation 3-1. The image size is a camera sensor parameter, defined by its image width and height in pixels. The aspect ratio (the ratio of image height and
width) and the camera lens AOV, which is the angular extent of the scene captured, can be used to calculate the vertical and horizontal field of view with equations 3-2 and 3-3, respectively. The side and front spacing can be designed using equations 3-4 and 3-5, respectively. Equation 3-6 is used to define the distance from the target and equation 3-7 to plan the speed of the flight.

\[ GSD = \sqrt{\frac{sf}{i_wi_h}} \]  

\[ f_v = 2 \arctan \left( \frac{\tan \left( \frac{AOV}{2} \right)^2}{H^2 + 1} \right) \]  

\[ f_h = 2 \arctan \left( \frac{\tan \left( \frac{f_v}{2} \right) \times \frac{H}{V}}{1 - \text{overlap}_{\text{side}}} \right) \]  

\[ s = 2z \tan \left( \frac{f_h}{2} \right) \left( 1 - \text{overlap}_{\text{side}} \right) \]  

\[ f = 2z \tan \left( \frac{f_v}{2} \right) \left( 1 - \text{overlap}_{\text{front}} \right) \]  

\[ z = \sqrt{\frac{GSD^2 i_wi_h}{4 \tan \left( \frac{f_h}{2} \right) \tan \left( \frac{f_v}{2} \right)}} \]  

\[ v_f = \frac{s}{t_p} \]

Where \( s \) is the side spacing between pictures; \( f \) is the front spacing between pictures; \( i_w \) and \( i_h \) are the camera image width and height, respectively; \( H \) and \( V \) is the horizontal and vertical aspect ratio, respectively; \( z \) is the flight height or distance from the face; \( f_h \) and \( f_v \) are the lens horizontal and vertical angle of view, respectively; \( v_f \) is the flight velocity; and \( t_p \) is the time between pictures taken (shutter interval).

In pit wall mapping using UAVs, the smallest measurable joint trace length needs to be identified. This can be used to determine a GSD suitable for the structural mapping at the target scale.
Therefore, to design a flight plan, prior knowledge of the local geology and structural complexity of the rock wall exposure is required. For the field experiments conducted in this study, the target GSD varied from 0.9 cm/pixel to 2.5 cm/pixel, and the smallest measured joint size varied from 0.1 m to 0.4 m. These results suggest that the GSD should be at least an order of magnitude smaller than the smallest joint trace length measured.

The following is an example used to create the flight plans for the Bald Mountain Top 2B pit UAV experiment. The northeastern wall of the pit was selected for mapping because of the major faulting outcropped on the wall, and this wall is being pushed back for the Top pit expansion. The Zenmuse X5S camera with the Olympus M.Zuiko 45 mm/1.8 lens were used in this case. The given camera and lens parameters are described in Table 3-1. A minimum safe flight distance of 80 m from the wall was chosen to reduce risk of collision. The calculated parameters are also presented in Table 3-1 and used to create flight plans in the DJI GS Pro (DJI, 2019) application.

Table 3-1: Table showing the given and calculated parameters for flight planning.

<table>
<thead>
<tr>
<th>Given parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i_w$</td>
<td>5280</td>
</tr>
<tr>
<td>$i_h$</td>
<td>3956</td>
</tr>
<tr>
<td>H</td>
<td>4</td>
</tr>
<tr>
<td>V</td>
<td>3</td>
</tr>
<tr>
<td>AOV</td>
<td>27°</td>
</tr>
<tr>
<td>Overlap</td>
<td>80%</td>
</tr>
<tr>
<td>$z_{min}$</td>
<td>80 m</td>
</tr>
<tr>
<td>Target GSD</td>
<td>0.7 cm/pixel</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Calculated parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_v$ (eq. 2)</td>
<td>16.4°</td>
</tr>
<tr>
<td>$f_h$ (eq. 3)</td>
<td>21.7°</td>
</tr>
<tr>
<td>$z_{req}$ (eq. 6)</td>
<td>96.2 m</td>
</tr>
<tr>
<td>$s$ (eq. 4)</td>
<td>7.4 m (36.9 m without overlap)</td>
</tr>
<tr>
<td>$f$ (eq. 5)</td>
<td>5.5 m (27.7 m without overlap)</td>
</tr>
<tr>
<td>Achieved GSD (eq. 1)</td>
<td>0.69 cm/pixel</td>
</tr>
</tbody>
</table>

The flights for highwall mapping are best executed when the UAV flies in a horizontal line parallel to the wall of interest. This is because the flight elevation is only set once for the complete horizontal flight line, whereas with a vertical flight line the elevation needs to be set manually for each waypoint. Having vertical flight lines also increases the number of flight lines required,
making the process of creating a complete flight plan for an area significantly lengthier and more time-consuming. Furthermore, it is easier for the pilot to monitor the progress of a horizontal flight and identify any flight issues.

In this case, the front spacing is the distance between the horizontal flight lines (shown in Figure 3-9). The side spacing is a factor of the shutter interval and horizontal flight speed. Since the DJI GS Pro application only supports some shutter intervals such as 2, 3, 5 or 10 s, the interval is selected pre-flight and used to calculate the horizontal flight speed. The image quality is better at slower flight speeds due to less vehicle vibration and improved stabilization; however, longer flights require additional field time and cause more flight interruptions for battery changes. At Top 2B pit, a shutter interval of 3 s was used and the horizontal speed of the vehicle was set as 2.5 m/s.

Image overlap is extensively discussed in the literature, with ranges from 70% front and 30% side, to 85% in both directions (Bamford et al., 2017; Dash et al., 2017; Francioni et al., 2015; Palleske et al., 2014; Salvini et al., 2017; Tziavou et al., 2018). Figure 3-9 shows a schematic of the front and side overlap for a high wall flight. An 80% front and side overlap were used at Bowmanville quarry, Top 2B pit, and West Branch pit; while 90% front and 70% side overlap were used at the El Gallo mine. The overlap selected is within the recommended ranges for producing high quality orthophotos and point clouds.

![Figure 3-9: Flight line schematic showing image overlap](image)
The information calculated in Table 3-1 was then used to design the flight plans in QGIS (QGIS Project, 2019). Once the required spacing parameters were calculated, the area of interest was identified. Figure 3-10 shows the area of interest outlined in red for the Top 2B Pit. This area was converted into a DEM, and it was used to generate contour lines at specified intervals of 5.5 m (front spacing). These contour lines were offset 96.2 m from the wall and simplified, reducing the points along each line to ensure smoother UAV flights (shown in magenta in Figure 3-10). Finally, the lines were exported from QGIS in the WGS 84 coordinate reference system and imported into DJI GS Pro. While importing the flight parameters, it is important to note that the flight elevation constitutes the elevation from takeoff, not the WGS 84 elevation. Each flight line elevation needs to be manually set. To reduce flight time, the start point of a new flight line coincided with the end of the previous one. A total of 20 flight lines were generated to cover the Top 2B northeastern wall, with a total flight distance and time of 6,831.8 m and 63 min, respectively.

The weather conditions can determine whether it is best to conduct the flights top-down or bottom-up. If poor or rain conditions are expected, it can be beneficial to begin the flights using a top-down approach since the UAV would be moving towards the landing site in case an emergency landing is required. In good weather conditions the selection of flight direction does not need to be a consideration. However, once a flight direction selection is made, the plan should be executed in a systematic manner with the upward or downward direction maintained for the whole flight plan.
Figure 3-10: Top 2B flight planning, area of interest and DEM for mapping shown in the red outline with the generated flight lines in magenta.

3.4 Georeference Accuracy

The image georeference accuracy is critical for the point cloud reconstruction. If a cloud is incorrectly oriented or in the wrong location it is not possible to use this 3D point cloud for any analysis. The images captured using the UAV systems are georeferenced using the onboard GPS; however, it is difficult to obtain reliable positional data in the air. Conventionally, ground control points (GCPs) can be used during the data collection to address this issue. The GCPs are points of known locations that can be identified in the captured images. Using GCPs can improve the accuracy of the point clouds, and can be used to quantify the error.

To verify the point cloud accuracy without GCPs, known measurements such as bench height, orientation, and location need to be compared to those of the point cloud. If there is a match
between them, the point cloud is deemed suitable for mapping. It was not possible to place ground control points (GCPs) on the walls in Lupita, Central, Bowmanville, and West Branch pits.

Furthermore, it is particularly difficult to set up GCPs on a pit slope as there is usually no access to the target areas. Pit wall prisms along the benches which can be used as GCPs if they are clearly visible; however, they are a relatively small target to identify and often are not identified during the 3D point cloud reconstruction (see Figure 3-11). Another possible solution to this is the use of post-processing kinematic (PPK) technology which can eliminate the need for traditional GCPs. PPK systems use the UAV system geotagged coordinates for each image based on the onboard GPS, in addition to a base station that records significantly more exact positional information. The image timestamps are used to match the two data sets resulting in precisely georeferenced images. Also, using PPK can increase the speed of data collection as the use of GCPs can be reduced.

![Figure 3-11: Prism on bench at Top 2B pit, note its relatively small size.](image)

### 3.5 Photogrammetry Reconstruction

The images captured with the UAV are used to reconstruct a 3D model. The software used to generate the 3D color point clouds was OpenDroneMap (“OpenDroneMap,” 2018), an open source software, and Agisoft Metashape (Agisoft LLC, 2018), a commercially available software. The 3D point structure is estimated from 2D feature matches (triangulations) and the camera motion, structure from motion (SfM), to build 3D models (Szeliski, 2011). These are commonly employed algorithms for digital photogrammetry reconstruction in photogrammetry programs.
Before generating the point cloud, the images need to be aligned by feature identification. Two types of features exist; those used to align images and stitch them into a composite mosaic, and those used to build correspondences for constructing an in-between view. The first set of features are referred to as key-point or interest points, edges or points that can be matched in images. These define locations in the various images and are used to compute the camera pose (orientation and location). The second set of features is used to do stereo matching, the process of converting a 2D location into a 3D depth by measuring the disparity, the horizontal motion, between the same features in different images (Szeliski, 2011).

With the features identified, using SfM, simultaneous estimation of pose and triangulation occurs. The process can be sped up by using the approximate GPS location of the camera from the drone for pose and keypoint matching (Wu, 2013). To improve the pose and triangulation accuracy, a bundle adjustment is performed. Bundle adjustment is a process whereby the 3D feature locations and camera parameters are simultaneously optimized to reduce the re-projection error. This is typically a non-linear least squares minimization formulation (Triggs et al., 1999). The end product of this procedure is a sparse cloud and image alignment. Depth maps are based on image stereo pairs creating a united depth map, with excessive information being the basis for noise reduction (Agisoft LLC, 2019).

The dense cloud construction can begin once the images are aligned, the depth maps are produced, and the sparse cloud is generated (Agisoft LLC, 2019; Szeliski, 2011). The processing time depends on the desired quality of point cloud, which can be determined by the end-user. If a low resolution is required, it may be ineffective to generate a dense, high-resolution cloud. The higher resolution requires longer processing time, and more memory to open and manipulate in software. Time saving can be achieved by constructing a point cloud of appropriate resolution for the desired task.

The point clouds generated for this research varied from 0.2 GB, for low resolution clouds of small areas, to 21.2 GB, for high quality clouds. The size of the cloud impacts the speed of mapping and computer memory resources. More memory is required to open and visualize 400M points than 10M points. Furthermore, the number of decimal digits saved during export influences the size and quality of the point clouds. If the point cloud is exported without the required precision, banding often occurs, as shown in Figure 3-12. For these reasons, it is recommended that high
quality and large point clouds are segmented into smaller but more manageable clouds, such as 50 m by 50 m sections. This was done for the West Branch and Top 2B point clouds due to their large size. The data were processed on several computers; however, the fastest process times were achieved using a dedicated “workstation” computer with the following specifications:

- Intel Core i9 12-Core/24-Thread Processor, 2.90 GHz Base/4.3 GHz Max Turbo
- Nvidia RTX 2080 Ti 11 GB
- 64 GB DDR Ram.

Figure 3-12: An example of banding in a point cloud because of inadequate digit precision.

3.6 Summary

The four mine sites visited to conduct field experiments and their local geology were described in detail. All the sites had different geologies, providing a diverse dataset for testing the performance of UAV mapping techniques which are discussed in Chapter 4. All the sites also had different challenges for UAV flight, from regulatory compliance to extreme weather conditions. The largest image data set was collected for the West Branch pit in Tasiast mine as the whole pit was covered; however, in this work only smaller sections were used to present the potential of UAV data collection.
DJI UAVs were used as platforms to conduct the field experiments. While other suppliers are available, the DJI platforms were selected because they offer the most camera options and configurations and for their technical support and accessibility. The cameras used were a key component for data collection as they determined the potential resolution of the point clouds generated. Specifically, the camera and lens pairing, and their interaction are critical parameters to understand. The image quality and results of photogrammetry reconstruction are highly dependent on this interaction. Longer focal lengths covered a smaller area but produced more detailed images. Furthermore, the weather and lighting conditions affect the captured image quality, and understanding their impact can assist in determining the optimal times for flight.

The procedure for creating a flight plan was discussed in detail since the equipment variables were known. Equations 3-1 through 3-7 were provided for flight planning, and the flight for the Top 2B is used as a worked example. The calculated flight parameters are subsequently used for design in QGIS. A DEM was built and contoured at the appropriate interval spacing. The contours were offset and simplified to create the final flight plan. Finally, these plans were transferred to the UAV app, GS Pro, the elevations were set, and image collection was executed. Careful planning was required to ensure the georeferencing accuracy of the image data collected. The general workflows and algorithms for reconstructing these images into dense point clouds were also explained.

This chapter provided an overview of the mine sites, equipment and methods used to collect and generate the data that will be used in the following chapters for analysis. Moreover, the procedures for UAV data collection described in this chapter can be applied to any site where UAV data collection is necessary.
Chapter 4
Point Cloud Data Analysis

4 Structural data analysis and pit slope assessment using 3D point cloud models generated from UAV systems

Chapter 3 provided a description of pit wall mapping using UAV systems and illustrated how the drone captured images can be used to generate 3D point cloud models using photogrammetry techniques. This chapter outlines how the generated 3D point clouds models can be used to obtain valuable information for open pit operations. This includes structural mapping of pit walls, assessing the quality of pre-split drilling by mapping half-caste pre-split holes, as well as pit slope assessment. The methodologies are described, and their importance, advantages and limitations are discussed.

4.1 Structural Mapping using 3D Point Cloud

One of the key advantages of photogrammetry is that once a 3D point cloud model is generated, it is possible to conduct virtual structural mapping on the cloud. Furthermore, a permanent record of the rock conditions and mapping is created. As previously discussed, joints are defined by their orientation, persistence, frequency and surface geometry. The availability of a 3D point cloud for detailed mapping can ensure collecting accurate joint parameters, increasing the reliability of 3D structural models that could be developed using input joint parameters (Elmo et al., 2015). The permanence of this data is important because the mapper can spend the required time for data processing without being limited by field conditions or increasing their exposure to hazards. Having a larger area for mapping also reduces size and truncation biases, but wall orientation bias remains an issue with UAV photogrammetry, unless walls of different orientation could be mapped. The use of UAV for pit wall mapping does not entirely eliminate field work, as the point cloud mapping results need to be verified through ground spot check measurements.

In this study, 3D point cloud manipulation and mapping was conducted in CloudCompare (“CloudCompare,” 2018), an open-source software running under a General Public License, giving
users the freedom to use and modify the software. There is other software that can be used for generating and manipulating 3D point clouds, however in the Author’s view, CloudCompare is the most useful program for structural mapping and analysis. It has specific features and tools designed for structural and geological mapping which can be used to measure geometrical characteristics of discontinuities such as dip, dip direction, and trace length.

The point cloud data can be simply imported into CloudCompare for joint mapping. This mapping can be done using fully-automated, semi-automated, or manual methods.

- The automated joint identification algorithm, Facets (Dewez et al., 2016), detects planes by clustering cloud points with similar normal vectors. The size, grouping, and variability of the facets (planes) identified depend on the user input parameters: the minimum number of points required to identify a joint, the maximum change in normal angle, and the maximum distance from the points within the joint and its contour. This fully automated method performs well in areas where the joints are fully exposed and well defined (see Figure 4-1a)

- The Compass Tool (Thiele et al., 2017) was used for semi-automatic and manual mapping. The semi-automatic method performs well in high-quality clouds where the joints run into the rock face or can be identified by a colour difference (see Figure 4-1b). The semi-automatic tool functions based on a least-cost path function to follow a joint trace between the user specified start and end points (“Compass (plugin),” 2018). Then, to estimate the joint orientation, the principal components of the points along the trace are calculated and their planarity is evaluated. If the points pass a planarity test, planes are fit to the points using a RANSAC algorithm and the plane with the largest number of inliers (points below a threshold distance from the plane) is used to calculate the joint orientation using a least squares regression after removing the outliers (Thiele et al., 2015). Several least-cost path functions can be used, each being best suited for different scenarios.

- Manual mapping involves estimating a plane orientation and adjusting it until a visually satisfactory fit is achieved; subsequently, the length of the trace is measured. These fits are relatively subjective as they are based on visual inspection. Finally, dip, dip direction and trace length are transcribed, significantly adding to the time required for manual mapping.
Manual mapping is necessary in highly complex geology conditions or for low-resolution point clouds (see Figure 4-1c).

Figure 4-1: Examples of geological conditions favourable for a) fully-automated mapping, b) semi-automatic mapping, and c) manual mapping.

4.1.1 Structural Mapping of Pit Walls

The point cloud mapping results are summarized in Table 4-2 for each mine site. This includes the area mapped, the time required for mapping, the number of images used for the photogrammetry reconstruction, and the total number of joints identified. A total of 40,310 m² was mapped in 179 h, which does not include field time or the time spent on point cloud reconstruction. An average mapping rate of 226 m²/h was achieved over the whole project. The El Gallo, Bowmanville and West Branch data was mapped on the “desktop” computer while the Top 2B northeastern wall was
mapped on the “workstation” computer. Table 4-1 presents the comparison between the specs of the desktop and workstation computers:

Table 4-1: Comparison of computer specifications.

<table>
<thead>
<tr>
<th></th>
<th>Workstation</th>
<th>Desktop</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processor</td>
<td>Intel Core i9 12-Core/24-Thread Processor, 2.90 GHz Basel/4.3 GHz Max Turbo</td>
<td>Intel(R) Core(TM) i7-3770 CPU @ 3.40GHz, 3401 Mhz, 4 Core(s), 8 Logical Processor(s)</td>
</tr>
<tr>
<td>Graphics Card</td>
<td>Nvidia RTX 2080 Ti 11 GB</td>
<td>AMD Radeon 7000 Series 1 GB</td>
</tr>
<tr>
<td>GB of DDR Ram</td>
<td>64</td>
<td>16</td>
</tr>
</tbody>
</table>

A total of 2,020 images were used, with an average GSD of 1.4 cm/pixel. For each mine site, a statistically significant number (100+) of joint data points were collected. Figure 4-2 shows how the 3D point cloud was segmented for mapping at the Top 2B pit due to its large size. Figure 4-3 shows an area of the mapping done at Bowmanville, West Branch and Central pits which used fully-automatic, semi-automatic and manual mapping, respectively. The lower quality of the Central point can be seen in Figure 4-3c by the gaps and low relief. The largest area and most detailed mapping was done on the Top 2B northeastern wall; the dip angle, dip direction, trace length, and coordinates were measured for each joint that could be identified on the wall. Major structures were identified, including the main fault running along the wall at an orientation of 85°/052° (dip/dip direction) with a true thickness of approximately 3.8 m (gray outline in Figure 3-5).

Table 4-2: Summary of the mapping results for each site.

<table>
<thead>
<tr>
<th>Location</th>
<th>Area (m²)</th>
<th>Mapping Time (h)</th>
<th>Images (number)</th>
<th>Joints (number)</th>
<th>GSD (cm/pixel)</th>
</tr>
</thead>
<tbody>
<tr>
<td>El Gallo (Central)</td>
<td>3,170</td>
<td>79.5</td>
<td>111</td>
<td>311</td>
<td>2.2</td>
</tr>
<tr>
<td>Bowmanville</td>
<td>5,210</td>
<td>5</td>
<td>128</td>
<td>132</td>
<td>1.5</td>
</tr>
<tr>
<td>West Branch</td>
<td>3,510</td>
<td>36</td>
<td>163</td>
<td>402</td>
<td>0.9</td>
</tr>
<tr>
<td>Top 2B</td>
<td>28,420</td>
<td>58</td>
<td>1,618</td>
<td>1,146</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Figure 4-2: Example of point cloud segmenting and mapping done on the Top 2B northeastern wall.

Figure 4-3: Example of a) Full-automated mapping at Bowmanville pit, b) semi-automated mapping at the West Branch Pit, and c) manual mapping at Central Pit.
Mapping the Central pit required the most time because of the low quality point cloud generated and the highly irregular geological conditions. The UAV captured images needed to be referenced to ensure accuracy, increasing the total time for mapping. The Bowmanville quarry mapping was the fastest because the geology lent itself well for fully-automatic mapping. Using Facets resulted in a 78% reduction in mapping time: 5 h compared to 24.5 h for manual mapping with similar orientation results for both (see Table 4-3). It should be noted that a t-test statistical analysis (Kremelberg, 2011) with a 95% confidence interval conducted on the trace length mean concluded that the trace lengths were only similar for set 2, while sets 1 and 3 had a statistically different mean trace length in the two mapping methods. This difference was caused by Facets splitting slightly offset joints in close spatial proximity into smaller components, whereas in manual mapping those were mapped as a single joint, resulting in longer trace lengths. The overall areal joint intensity (P21) was similar for both manual and automated mapping, indicating that the total length of joints for each set was similar. However, the fully-automated mapping still required manual post-processing to identify the joint sets and calculate the average trace lengths. This method was unable to detect the horizontal bedding which was exposed as traces on the surface of the rock mass. Semi-automated mapping was used for the West Branch and Top 2B pits, which resulted in reduced mapping time compared to Central pit, but longer than Bowmanville. The increased speed at which Top 2B was mapped can be attributed to increased CloudCompare proficiency and the use of the “workstation” computer (see Table 4-1). The stereonet of the pit wall mapping and joint trace lengths for each mine are presented in Figure 4-5 and Figure 4-6.

Table 4-3: Bowmanville mapping results; fully-automated compared to manual.

<table>
<thead>
<tr>
<th>Set</th>
<th>Dip (°)</th>
<th>Dip Direction (°)</th>
<th>P21 (m⁻¹)</th>
<th>Dip (°)</th>
<th>Dip Direction (°)</th>
<th>P21 (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>71</td>
<td>160</td>
<td>0.13</td>
<td>69</td>
<td>160</td>
<td>0.15</td>
</tr>
<tr>
<td>2</td>
<td>78</td>
<td>81</td>
<td>0.05</td>
<td>78</td>
<td>87</td>
<td>0.06</td>
</tr>
<tr>
<td>3</td>
<td>80</td>
<td>273</td>
<td>0.03</td>
<td>83</td>
<td>265</td>
<td>0.03</td>
</tr>
</tbody>
</table>

The mapping results at Central pit show the joints are generally steep and there are three main sets without significant dispersion in the joint sets. The Bowmanville data is clustered together as would be expected from the well-developed jointing present at the mine; there are three sub-vertical sets, with two forming a conjugate set. The jointing at the West Branch pit is dominated
by the foliation of the rock mass. At Top 2B, the joint data is highly dispersed, which can be attributed to the relatively large area covered by the mapping. The total trace length data does not match the expected negative exponential distribution (Priest and Hudson, 1976). This may have been caused by truncation bias, as the joint data in the 0 to 1 m bin is harder to identify than joints larger than 1 m. With the Bowmanville quarry the high persistence of the limited jointing resulted in the histogram seen in Figure 4-5b.

The point cloud used for structural mapping can be used to conduct further geospatial analysis of the pit walls. The areal fracture intensity ($P_{21}$), a ratio of the total length of joints to the area mapped, can be easily obtained and mapped on the pit wall, to describe the quality of the rock mass along the pit wall. A high $P_{21}$ indicates higher fracture intensity, whereas a lower $P_{21}$ indicates that the rock is not heavily jointed and likely contains large rock blocks. If the mapping is completed in CloudCompare it is possible to estimate a heat map of the $P_{21}$ spatial variation. Figure 4-4b shows the $P_{21}$ heat map of a section of the Top 2B pit, as can be seen there is an increase in jointing around a smaller fault structure.

Figure 4-4: a) Section of Top 2B pit mapped and analyzed for b) $P_{21}$ intensity.
Figure 4-5: Stereonet and trace length histogram of a) Central and b) Bowmanville pits.
Figure 4-6: Stereonet and trace length histogram of a) West Branch and b) Top 2B.
4.1.2 Comparing Mapping Efficiency

The virtual mapping with 3D point cloud was compared to the conventional mapping done at the West Branch and Top 2B sites to assess its speed improvements. Figure 4-7 shows the difference between the virtual structural mapping created by the UAV photogrammetry and the conventional pit wall mapping conducted by the mine technical staff. A significant difference can also be seen in the level of detail identified between virtual and conventional mapping (see Figure 4-7). At West Branch, the data points are doubled in only two months, while at Top 2B a seven-fold increase is accomplished in 1.5 months. This demonstrates the time savings that are attainable by using UAV photogrammetry to generate point clouds. Moreover, the mapping can be done over an extended time for a single area, as practical considerations which can limit field time activity such as face advance, machinery operating in the vicinity, or inaccessibility, are eliminated.

<table>
<thead>
<tr>
<th></th>
<th>Manual</th>
<th>Virtual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time Period</td>
<td>Data Points</td>
</tr>
<tr>
<td>West Branch</td>
<td>2.5 years</td>
<td>172</td>
</tr>
<tr>
<td>Top 2B</td>
<td>NA</td>
<td>160</td>
</tr>
</tbody>
</table>

Figure 4-7: Difference in number of joints identified between a) virtual mapping and b) manual mapping at the West Branch Pit

At Bald Mountain, geologists or geotechnical engineers currently map approximately 20 cells, 6 ft high by 40 ft long in size, during an eight-hour shift. This time includes the field data collection, transfer of data to an electronic database, and analysis (Esmaieli, 2019). A total of 65 h were spent collecting 1,146 data points from 28,420 m² at Top 2B. Of these 65 h, approximately 4 h were used to create and transfer the flight plans to GS Pro, 3 h were field time, and 58 h were spent on
virtual mapping. A mapping rate of 44.6 m$^2$/h is achieved with the manual mapping methods at Bald Mountain compared to 437.2 m$^2$/h for the proposed virtual mapping using UAV collected data. The mapping is completed an order of magnitude faster: what would take 50 shifts to map could be achieved in 5 shifts. Therefore, using this approach could result in significantly more and higher quality data. Furthermore, the time savings could be applied to processing and analyzing the data.

4.2 Quality control of pre-split drill holes

In addition to mapping the joints on the pit walls, the 3D point cloud models of the pit walls can be used to assess the quality of pre-split holes drilled on the final pit walls. Pre-split holes are drilled to control blast-induced pit wall damage along the final planned pit wall. The holes are typically drilled on a tight spacing along the final walls and loaded with decoupled or light charges. The charge in all the holes is blasted simultaneously creating a tension crack between them, thereby reducing the potential damage caused by near-by production or trim blasting (Read and Stacey, 2011). The final product of the pre-split blasting is a half-cast that remains on the wall, as seen in Figure 4-8. The lengths, dip and azimuth of the half-casts can be mapped using 3D point cloud models. The results can be used to conduct quality control of the pre-split drilling and allows providing feedback to drillers.

Figure 4-8: Half casts remains from pre-split blasting.
With the pre-split mapping, it is possible to evaluate the half cast factor (HC10), which is defined as a ratio of the visible half casts on the wall to the total drilled pre-split hole length in the same area. An example of calculating the P21 (in cyan) and HC10 (in orange) on a pit wall can be seen in Figure 4-9. In addition to half cast factor, the deviation of the pre-split holes can be assessed by comparing the as drilled holes orientation (dip/azimuth) vs. as designed holes orientation.

Accuracy and proper alignment of the pre-split holes is critical for a mining operation as deviation can result in uneven, over-hanging, or stepped bench face conditions. Furthermore, the final bench face angle (BFA) can be affected, resulting in over-steepening or shallower than designed walls with significant economic repercussions. Measuring the accuracy of pre-split drilling orientation and the HC10 can be a method for assessing the performance of pre-split blasting; however, the HC10 can also be affected by the quality of the rock mass in the pit area (Paswan et al., 2017). The local geology and rock mass condition have an impact on the results of the pre-split blasting; in particular, the pre-split alignment with the dominant foliation. Birhane (2014) concludes that pre-split blasting oriented parallel to foliation produced the best results, due to the presence of a plane of weakness in the same direction as tension cracking developed by the blasting.

Figure 4-9: A 32 m section of a bench mapped for joint (cyan) and half-cast (orange) on a highly fractured wall in the West Branch pit.
The relationship between the quality of pre-split drilling and the local rock mass condition was further explored in this work by comparing the \( HC_{10} \) and the pre-split deviation to the \( P_{21} \) of the rock mass. This comparison was made in four different areas in the West Branch pit, highlighted in Figure 4-10, and in four benches of the Top 2B pit (Figure 3-5). This is a minimal data set for a robust statistical analysis; however, within these areas multiple pre-split hole dip deviation measurements were taken. The results of the \( HC_{10} \) against \( P_{21} \) are present in Figure 4-11. As expected, the results from the West Branch pit show decreasing \( HC_{10} \) with increasing \( P_{21} \) (or decreasing quality of the rock mass). The results in Top 2B pit show no relationship between the two parameters. The lack of relationship between the results from Top 2B could be attributed to the close proximity of the data collection areas to a major fault which can cause degradation of the rock mass that is not reflected by the jointing. Furthermore, the data is clustered in a single area, whereas the West Branch data was collected from distinct areas.

Figure 4-10: West Branch pit mapped areas outlined in red and image.
The results of pre-split deviation show that drilling done at West Branch is more accurate than that done at Top 2B despite the higher jointing present in the mapped area of West Branch pit. The histogram of pre-split holes dip deviation is presented in Figure 4-12. The pre-split deviation for each section of the two pits can be seen in Table 4-5. Statistical tests were done to compare the different areas mapped. While the benches in Top 2B pit were all from the same area, the pre-split deviation of the holes was statistically different (at a 95% confidence interval) for all the benches. Comparatively, the pre-split deviation was similar in two areas of the West Branch pit. These results indicate that site practices have a significant impact on the success of the control blasting as well as geology; however, the extent to which geology affects the final result also depends on the site. Figure 4-13 presents the dip of the half cast holes traced on the Top 2B walls, it shows that the holes follow a normal distribution around 70° with a minimum of 60°, a maximum of 79°, and a standard deviation of 2.2°. A significant portion of the holes, 31.8%, have a deviation greater than ±2.2°, this relatively high deviation can account for some of the as-built BFA deviation.
Figure 4-12: Histogram of pre-split dip deviation for the Top 2B site and the Tasiast Site (West Branch).

Figure 4-13: Distribution of pre-split dip angles from the Top 2B pit.

The results presented in Table 4-5 show that the West Branch pit has more structure than the Top 2B pit, as seen by the higher $P_{21}$. However, the $HC_{10}$ is higher at the West Branch indicating better blasting practices or that the structure may be of a favourable orientation for pre-split blasting,
resulting in more visible half-casts. The overall average pre-split deviation is similar between the two pits but the spread of deviation is higher in the West Branch pit, varying from 1.3° to 4.2° compared to 2.1° to 4.3°. In the West Branch section 1 the large pre-split deviation may be attributed to the high P$_{21}$.

Table 4-5: Results of pre-split mapping

<table>
<thead>
<tr>
<th>Wall</th>
<th>P$_{21}$ (m$^{-1}$)</th>
<th>HC$_{10}$</th>
<th>Pre-split Dip Deviation (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tasiast Section 1</td>
<td>0.74</td>
<td>0.24</td>
<td>4.2</td>
</tr>
<tr>
<td>Tasiast Section 2</td>
<td>0.28</td>
<td>0.41</td>
<td>1.3</td>
</tr>
<tr>
<td>Tasiast Section 3</td>
<td>0.39</td>
<td>0.4</td>
<td>1.7</td>
</tr>
<tr>
<td>Tasiast Section 4</td>
<td>0.32</td>
<td>0.64</td>
<td>3.1</td>
</tr>
<tr>
<td><strong>Tasiast Avg.</strong></td>
<td><strong>0.43</strong></td>
<td><strong>0.42</strong></td>
<td><strong>2.6</strong></td>
</tr>
<tr>
<td>Top 2B Bench 1</td>
<td>0.14</td>
<td>0.15</td>
<td>2.7</td>
</tr>
<tr>
<td>Top 2B Bench 2</td>
<td>0.13</td>
<td>0.09</td>
<td>2.1</td>
</tr>
<tr>
<td>Top 2B Bench 3</td>
<td>0.07</td>
<td>0.15</td>
<td>2.2</td>
</tr>
<tr>
<td>Top 2B Bench 4</td>
<td>0.11</td>
<td>0.07</td>
<td>4.3</td>
</tr>
<tr>
<td><strong>Top 2B Avg.</strong></td>
<td><strong>0.11</strong></td>
<td><strong>0.12</strong></td>
<td><strong>2.8</strong></td>
</tr>
</tbody>
</table>

4.3 Slope Assessment

A bench performance program should include the comparison of as-built geometry of the bench with as designed geometry, including orientation and break back angle of the bench face, bench height and bench width. In addition, the program should include monitoring the factors contributing the bench geometry, observations regarding specific failure mechanisms, observations of blast damage and the effectiveness of controlled blasting. 3D point cloud and DEM model of pit slopes generated from UAV images can be used to conduct slope assessment analyses as part of a design compliance program. Measuring the as-built slope angle is a method for evaluating blast and bench performance by comparing it to the design geometry (Read and Stacey, 2011).

4.3.1 Assessment of Bench Face Angle (BFA)

Ensuring that the design BFA is achieved is a critical component of an open pit operation because it gives feedback to technical staff whether the current practices are adequate. If the BFA is shallower than design this will result in more waste mining and potentially the loss of ore. These
two consequences can have a large negative economic impact on the operation. Having a BFA that is steeper than design can reduce the stability of the slope, thereby increasing the safety and economic risk profile of an operation. Therefore, a monitoring and assessment strategy is required.

Using the 3D point cloud data, it is possible to assess the bench face angles achieved for the pit walls. BFA measurement can be done directly in CloudCompare by calculating the point normals and comparing those to the design. High-resolution point clouds may give erratic results due to the presence of a large number of points in an area. Clustering points in close spatial proximity can yield better results for this analysis; however, doing so can smooth out the variation in slope because clustering averages the point normal dips. The results of this analysis on the West Branch section 1, with a $P_{21}$ of 0.74, can be seen in Figure 4-14a. The blue coloured squares signify a dip of less than 72°, white colour a dip of 75±3°, and red colour a dip greater than 78°. The designed bench face angle for this slope is 75°. Figure 4-14b is a histogram export of the point normals indicating that 75% of the points have a deviation from slope design of at least -5° and the average slope angle for this section of wall was 67°. The achieved BFA of this wall is significantly below the design target of 75°.

![Figure 4-14: a) Point normal dips of West Branch pit wall to assess BFA: blue represents angles below design (less than 72°); white represents areas where design was achieved (75°±3°); and red represents slopes steeper than design (>78°) b) Histogram of the point normals exported.](image)

The West Branch mapping analysis is summarized in Table 4-6. As can be seen, the benches with less jointing (lower $P_{21}$) performed better, and the target slope angle was achieved. The $P_{21}$ has an impact on the pre-split deviation, which affects the slope angle achieved. The table shows that more pre-split dip deviation results in more variation in the slope angle. The slope difference
between wall section 1 and 3 can be seen in Figure 4-15, which shows the point normals of a wall where the design was achieved and those it was not achieved. Section 3 follows a normal distribution centred around 74°, compared to section 1 where 95% of the data lies below the design face angle.

Generally, the two southwest walls (section 3 and 4) achieved the design BFA. This is likely due to the angle of the foliation relative to the walls, which is almost perpendicular. BFA of wall section 2 is only 2.3° degrees below design with minimal variation. These results show that the blasting practices at the West Branch pit are conducive to realizing the design BFA.

Table 4-6: Results of the mapping and BFA analysis from West Branch

<table>
<thead>
<tr>
<th>Wall Section</th>
<th>( P_{21}(m^{-1}) )</th>
<th>Pre-Split Deviation (°)</th>
<th>( HC_{10} )</th>
<th>Wall Angle (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dip</td>
<td>Strike</td>
<td>Achieved</td>
<td>Std</td>
</tr>
<tr>
<td>1</td>
<td>0.74</td>
<td>4.2</td>
<td>4.4</td>
<td>0.24</td>
</tr>
<tr>
<td>2</td>
<td>0.28</td>
<td>1.3</td>
<td>1.2</td>
<td>0.41</td>
</tr>
<tr>
<td>3</td>
<td>0.39</td>
<td>1.7</td>
<td>1.4</td>
<td>0.40</td>
</tr>
<tr>
<td>4</td>
<td>0.32</td>
<td>3.1</td>
<td>1.9</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Figure 4-15: Comparison of BFA from wall section 1 (orange) and 3 (green)
An alternative method to assess bench performance is by creating a digital elevation model (DEM) raster using the 3D georeferenced point cloud. This model can either be created from the captured images themselves, in *Metashape* or *OpenDroneMap*, or from the point cloud in *CloudCompare*. Once a DEM is created, it can be analyzed in GIS software such as *QGIS*. This raster is a 2D map in which each pixel represents an area at a specific elevation. The smallest GSD, in this case, should be maintained in the raster since identifiable features are typically an order of magnitude larger than the size of the GSD. The slope angles are calculated from the raster based on nearest-neighbour algorithms, which rely on small GSDs for accuracy. Once the slope is calculated the raster can be down-sampled to increase the size of the GSD, to give more meaningful results such as those presented in Figure 4-16. As with the point cloud, if the GSD is too small, the results are erratic and difficult to interpret correctly. Furthermore, the DEM can be used to create sections to estimate the average slope of each bench.

This method was used to analyze the BFAs of the northeastern Top 2B pit wall (Figure 4-16). The designed BFA for the Top 2B pit is 70°. Figure 4-16 shows the slope model of the five benches covered by the UAV survey, with colours used to visualize the slope angles. The blue, purple and pink colours identify areas where the slope is below 68°, green the regions where the target slope angle is achieved, and red the areas which are steeper than design. Green is the dominant colour on the lower benches and east side; however, areas around the fault red is the primary colour with sections of pink and blue. This suggests that the fault has a major impact on the BFA.

The design bench height at Top 2B is 40 ft (12.2 m) for single, and 80 ft (24.3 m) for double benches. In the sections (Figure 4-17), the bottom and top bench are single with the three benches between being double benches. Sections A-A’ and B-B’ (Figure 4-17) show that the target BFA slope is somewhat achieved with each of the benches; however, angles lower than the design target are likelier to occur than steeper ones.
Figure 4-16: A slope model with a 0.35 m GSD of the Top 2B northeast wall. The target slope is $70^\circ$.

Figure 4-17: Sections A-A’ and B-B’ of the DEM created and shown in Figure 4-16.
4.3.2 Assessment of Bench Width

Using the DEM models it is possible to conduct a bench width analysis which can be used as an evaluation criterion for blasting performance (Catalan and Onederra, 2016) as well as bench coverage. Catch benches are legislated safety design features in open pits. Their primary purpose is to prevent rock blocks from flowing down and thus damaging equipment or injuring personnel. These benches also increase wall stability by reducing the bench-scale block sizes and overall slope angle. Taking this into consideration, it is crucial to ensure the bench width satisfies the design specifications which requires a monitoring strategy. This work presents a possible methodology for monitoring using the slope model built. To measure the bench width in the DEM models, first, the toe and crest are identified in the model; manual delineation is required for this. Once the toe and crest of each bench have been traced, they are discretized into equally spaced points, and the perpendicular distance between them is calculated. The discretization impacts the results, so a sensitivity analysis is required to select the optimal value. At Top 2B pit, a 0.5 m spacing resulted in the correct matching of 91% of the points. This data was used as the basis of a statistical analysis of bench width. Using UAVs can help increase the scan frequency, and using the methodology above can improve width compliance. Furthermore, areas of concern can be easily identified, and their causes investigated.

A catch bench analysis was conducted at the Top 2B pit to showcase how this can be done to quickly gain useful insights into the current conditions of the benches at an operating mine. The catch bench design width at Top 2B is 32 ft (9.7 m). The slope model was used to determine the variation of the bench width starting with the lowest bench (1) to the top bench (5). Figure 4-19 presents the histogram of bench width analysis for Bench 1 which shows the distribution of distances from the toe to the crest measured in 0.5 m intervals. These results indicate that the design bench width is achieved on Bench 1.
In addition to the bench width analysis, the volume of sloughed material can also be calculated using the DEM by outlining the areas where the sloughed material are accumulated and calculating the volume for them (Figure 4-19). The results of the width and sloughed material analysis for Top2B pit wall are presented in Table 4-7. As can be seen from the results only bench 5 shows good agreement with the designed bench width; the width of benches 1, 2, and 3 are smaller than design; and bench 4 is larger than design. The smaller benches may have been caused by back break of the slope, specifically towards the crests of the benches. Some visible wedge failures along bench 2 and 4 can be identified. Significant sloughed material is accumulated on bench 2, with other benches ranging from 16% to 24% coverage. Bench 5 was clean, and no sloughed material was visible. These results show that generally the catch bench width is maintained; however, some care might be required in areas the ground conditions are poor. The areas along the main fault account for most of the back break. This analysis can be used to supplement visual observations of sloughage and for developing a criterion for recognizing when benches require clean up, e.g. if the more than 40% of the bench is covered or if the volume of an area exceeds the theoretical volume required to create a slope of 30° (where material can slide down).
Figure 4-19: Top 2B DEM showing the bench outlines and the sloughed material.

Table 4-7: Results of the bench width and coverage analysis

<table>
<thead>
<tr>
<th>Bench</th>
<th>Bench Area (m$^2$)</th>
<th>Bench Coverage (m$^2$)</th>
<th>% Coverage</th>
<th>Volume Coverage (m$^3$)</th>
<th>Avg. Width (m)</th>
<th>Median Width (m)</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1529.6</td>
<td>238.7</td>
<td>16%</td>
<td>421.1</td>
<td>8.6</td>
<td>9.1</td>
<td>1.4</td>
</tr>
<tr>
<td>2</td>
<td>1816.6</td>
<td>684.7</td>
<td>38%</td>
<td>1448.3</td>
<td>7.0</td>
<td>7.5</td>
<td>2.4</td>
</tr>
<tr>
<td>3</td>
<td>1775.1</td>
<td>349.6</td>
<td>20%</td>
<td>1331.9</td>
<td>7.8</td>
<td>7.8</td>
<td>1.0</td>
</tr>
<tr>
<td>4</td>
<td>2163.2</td>
<td>528.2</td>
<td>24%</td>
<td>1461.3</td>
<td>11.1</td>
<td>11.5</td>
<td>2.1</td>
</tr>
<tr>
<td>5</td>
<td>1869.2</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>9.9</td>
<td>10.4</td>
<td>2.1</td>
</tr>
</tbody>
</table>

4.4 Summary

This chapter outlined the current methods available to conduct virtual cloud mapping for structural data analysis in CloudCompare: manual, semi-automated, and fully-automated. The reliability of each method is highly dependent on the quality of the 3D point cloud and the local geology. The
fastest mapping is achieved using the fully automated method; however, the geology must be favourable for this. Most geologic conditions are suited for semi-automated mapping, as long as the point cloud is of reasonable quality (a GSD of 2 cm/pixel or lower). The computer specifications play an important role in the speed of mapping as well. Nonetheless, the time gains made by virtual point cloud mapping, even with slow computers such as a normal “desktop” are notable. The overall field time is reduced while increasing the quality and quantity of the mapping data.

With detailed mapping, the areal fracture intensity \( (P_{21}) \) on the pit wall can be easily obtained to be used for assessing the impact of jointing on the slope angle results or pre-split drilling in the local mine setting. No relationship was determined between the \( P_{21} \) and the \( HC_{10} \) for the Top 2B pit. This may be due to the proximity of the investigated areas to each other. The West Branch results seemed to follow the expected relationship: as the jointing intensity increases, the visible pre-split half casts decrease (Singh et al., 2014). Moreover, even if no relationship is established, measuring the \( HC_{10} \) could be useful as part of a drilling QA/QC or design compliance program.

Additional design compliance assessments based on UAV generated point clouds were discussed. Using UAV data is advantageous as it can quickly cover a large area. Furthermore, the data is of high temporal resolution, as flyovers of the same areas can be done even once access is lost. The presented methods for assessing the slope are rapid and relatively simple to integrate into a slope monitoring program. The point cloud availability makes it possible to revisit areas of interest and preserves a record of the rock conditions at the time, e.g. the catch bench loss can be monitored over time. The visible modes of failure can be easily identified and documented. The achieved bench face angles can be recorded to track performance against design, since monitoring the BFA is critical as a shallower face angle can reduce the inter-ramp and overall pit slope angles. This can increase the stripping required, lead to more waste rock generation and larger waste rock dumps, cause loss of ore and reserves, and have a significant negative impact on the economic value of a mine. Conversely, if the slope is steeper than design, the stability may be compromised causing an increased safety risk to equipment and personnel in the mine. Ultimately, all these tools can be integrated to create a blasting or slope performance matrix to ensure design compliance.
Chapter 5
Modelling Using UAV Collected Data

5 DFN Modelling Using UAV Collected Structural Data

This chapter presents the structural modelling completed using the joint information collected from the point cloud analyses discussed in the previous chapter. The UAV collected data is used as input to generate more reliable DFN models. These models are subsequently used for blast optimization and slope stability analysis.

5.1 DFN Modelling

In this study, DFN models are developed using input data from drone pit wall mapping conducted in two mine sites. The models are used to estimate the IBSD of the jointed rock masses in the surveyed mine sites and were subsequently utilized for optimization of blasting operations in the two mines.

Using drone mapping data from the Top 2B pit wall a deterministic-stochastic DFN model is developed. The model is conditioned to the joints identified and mapped on the pit wall, while a stochastic approach was used to generate joint sets behind the mapped pit wall. This innovative approach allows for the generation of a more realistic representation of rock structural complexity. The DFN model is subsequently used for stability analysis of the pit wall to determine areas of concern and size of potential failed blocks. The results are compared to the slope failures observed in the walls, and to determine the failure mode.

5.2 Blast Optimization using DFNs

Drilling and blasting is one of the critical processes in open pit mining which reduces the rock size from in-situ block size distribution (IBSD) to a target blasted block size distribution (BBSD) which can be handled by mine equipment. IBSD can influence the fragmented muck pile size distribution and the amount of drilling and explosive required for adequate fragmentation. Rock masses with a smaller IBSD and more naturally occurring fractures require less blast energy to obtain the BBSD (Scott, 1996). Figure 5-1 shows the aim of a typical blast process for rock fragmentation. In open
pit mines, drilling and blasting accounts for almost 15% of the mine operating cost. Therefore, optimizing the explosive and drilling required for the rock mass can result in an economic benefit to the operation. Measurement of the pre- and post-blast rock block size distributions can be used to calibrate and optimize the blasting process.

![Fragmentation process](image)

**Figure 5-1: Fragmentation process (Scott, 1996)**

To obtain an IBSD of a jointed rock mass, a DFN model can be used. In this study, the DFN models were created in *FracMan 7* (Golder Associates Ltd, 2018a). Once the models were generated, they were verified and calibrated against the field data. Subsequently, an algorithm is run to approximate the block size distribution within the DFN model. Several methods exist to estimate the ISBD, each with advantages and limitations, as discussed in Chapter 2 (section 2.3.3.2). To estimate the BBS.D of the blasted rock piles, UAV images of the blasted muck piles were collected, which were used to develop an orthophoto of the blasted muck pile and estimate the BBS.D using image analysis techniques. The calculated BBS.D, ISBD and the actual explosive amount used in the blast were compared to the theoretical powder factor (a measure of the mass of explosive used to break a unit volume of rock) required to achieve the same fragmentation result using empirical relationships.

### 5.2.1 Estimating the IBSD

In order to estimate the IBSD of jointed rock masses in the El Gallo mine site and the Bowmanville quarry, three DFN models were generated for the jointed rock mass in the Central, Lupita, and
Bowmanville pits. The point clouds of the pit walls, developed from UAV collected field data, were used to extract joint information for each of the sites. The joint information was used as input to develop DFN models. The general process of generating the DFN model, calibrating it, and using it to estimate the IBSD is described below.

During the initial site visit to the El Gallo mine, UAV and weather issues prevented the collection of high quality UAV data. Window mapping done by CNI in December 2016 was used to supplement the UAV data (Cylwik et al., 2016). The northeastern wall of the Lupita pit, where 29 windows were mapped, was identified as the target area. The locations of the mapping are shown in Figure 5-2 as red crosses, and the UAV flight area is labelled by the red box. At the time of the visit the mining had progressed, and some of the windows mapped in 2016 were no longer visible; however, windows 50-62 and 20-28 were present because of their location on main ramp walls. The UAV structural data collected was in the same geotechnical domain and could therefore be aggregated with the manual mapping data. The results of the UAV collected data confirmed those collected manually by CNI. Additionally, two major structures (fault zones) were identified using the UAV data. Medinac et al. (2018) provide information on the Lupita pit DFN generation and validation.

Figure 5-2: Location of window mapping (red crosses) and UAV flight area at Lupita pit.
The second visit to the El Gallo mine was more successful, as no weather or UAV issues were encountered. The data collected was of higher quality and reliable for mapping. The northwestern wall, where several wedge failures had occurred, was mapped at the Central pit. Similarly, the conditions during the Bowmanville quarry site visits were favourable for field work and the data collected was also of high quality. The 3D point clouds from which the structural data was collected covered an area of 3,170 m² and 5,210 m² from Central and Bowmanville, respectively. A statistically significant number of over 100 joints was collected from each site, improving the reliability of the input parameters for the DFN model. The identified joint sets used for the DFN generation are presented in Table 5-1 and Table 5-2 for the Central and Bowmanville pits, respectively.

Table 5-1: Central Pit mapping joint set orientation information.

<table>
<thead>
<tr>
<th>Joint Set #</th>
<th>Dip (°)</th>
<th>Dip Direction (°)</th>
<th>K Fisher Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>45</td>
<td>356</td>
<td>13.5</td>
</tr>
<tr>
<td>2</td>
<td>85</td>
<td>345</td>
<td>88.5</td>
</tr>
<tr>
<td>3</td>
<td>78</td>
<td>104</td>
<td>15.9</td>
</tr>
<tr>
<td>4</td>
<td>89</td>
<td>60</td>
<td>27.1</td>
</tr>
</tbody>
</table>

Table 5-2: Bowmanville Quarry mapping joint set orientation information.

<table>
<thead>
<tr>
<th>Joint Set #</th>
<th>Dip (°)</th>
<th>Dip Direction (°)</th>
<th>K Fisher Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>69</td>
<td>160</td>
<td>121</td>
</tr>
<tr>
<td>2</td>
<td>78</td>
<td>87</td>
<td>49.5</td>
</tr>
<tr>
<td>3</td>
<td>83</td>
<td>265</td>
<td>96.1</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

For generating the DFN models, a disaggregate approach was used, where each joint set was modelled individually. With this approach, first, a statistical analysis is conducted on each joint set, and a distribution is fit to the trace lengths. The distribution is used to provide a first estimate for the mean, the largest and smallest equivalent diameter. An arbitrary volumetric fracture intensity (P_{32}, m²/m³), which cannot be measured directly in the field but can be inferred through P_{21} (Esmaieli et al., 2010), is assigned to each joint set. The orientations of the joint sets are obtained from Dips (Rocscience, 2018a). The mean dip and dip direction are used. The joint set variability is described by the Fisher dispersion coefficient “K”, where a larger “K” indicated a
tighter cluster. Each joint set is generated separately in a large model of 100 m x 100 m x 100 m. The four joint sets and DFN models created for Bowmanville and Central pits are shown in Figure 5-3. A trace plane representing the mapped wall or an as-built surface is introduced into the DFN models. Each generated joint set was then intersected with the surface to produce a tracemap of the joints on the wall (see Figure 5-4). The tracemaps are used to compare the trace size distribution of the model to the field observations, and a Kolmogorov – Smirnov goodness of fit test is used to compare the distributions. If there is a fit, the joint set model is accepted; however, if it is not a fit, the model distribution parameters are modified. This is done iteratively until a satisfactory fit is achieved. Table 5-3 and Table 5-4 show the comparison between the mean trace length and fracture intensity ($P_{21}$) between the DFN model and field observations for the Bowmanville and Central pits.

Figure 5-3: DFN models of the a) Bowmanville pit and b) the Central pit.
Figure 5-4: Trace plane of mapped area with traces (in red) of jointing intercepting it of the a) Bowmanville and b) Central pits.

Table 5-3: Bowmanville pit DFN and field data comparison.

<table>
<thead>
<tr>
<th>Set #</th>
<th>Field Data</th>
<th>DFN Model Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Trace Length (m)</td>
<td>$P_{21}$ (m$^{-1}$)</td>
</tr>
<tr>
<td>1</td>
<td>5.5</td>
<td>0.13</td>
</tr>
<tr>
<td>2</td>
<td>3.0</td>
<td>0.04</td>
</tr>
<tr>
<td>3</td>
<td>2.0</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Table 5-4: Central pit DFN and field data comparison.

<table>
<thead>
<tr>
<th>Set #</th>
<th>Field Data</th>
<th>DFN Model Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Trace Length (m)</td>
<td>$P_{21}$ (m$^{-1}$)</td>
</tr>
<tr>
<td>1</td>
<td>4.4</td>
<td>0.08</td>
</tr>
<tr>
<td>2</td>
<td>2.1</td>
<td>0.01</td>
</tr>
<tr>
<td>3</td>
<td>2.6</td>
<td>0.09</td>
</tr>
<tr>
<td>4</td>
<td>4.0</td>
<td>0.06</td>
</tr>
</tbody>
</table>
Once the joint size distribution is determined, a similar process is used to calibrate the $P_{32}$. The model $P_{21}$ is compared to the field observed $P_{21}$, and the input $P_{32}$ is adjusted according to the comparison. As can be seen in Table 5-3 and Table 5-4, there is a good agreement between the DFN modelling results and the mapped field data. As a DFN model is a stochastic model, once the $P_{32}$ is determined, several generations of the joint sets were created to ensure that the $P_{21}$ remained matched. Figure 5-5 shows a comparison of the joint orientations measured in the field and those of the DFN model. A good agreement between the orientation and concentration of the joint sets can be seen in the stereonets (Figure 5-5). These results show that the DFN model was calibrated and can be considered representative of the rock mass at Bowmanville and Central pits.

Figure 5-5: Stereonets showing the a) Bowmanville field mapping data, b) Bowmanville DFN model data, c) Central pit field mapping data, and d) Central DFN model data.
Since the DFN generations were considered suitable representations of the rock mass at the mine sites, an estimation of IBSD was conducted using both the Ray Cast Volume and Fragmentation Grid methods. These different methods yielded similar IBSDs. The results of the analysis are presented in Figure 5-6 as solid lines.

![Block Size Distributions](image)

**Figure 5-6**: IBSD (solid line) and BBSD (dashed line) of the Central (blue), Bowmanville (green), and Lupita (red)

The IBSD of Lupita and Bowmanville pits are very similar, with a $P_{80}$ of approximately 6.5 m and 6.8 m respectively. The Central pit has a significantly larger in-situ block size distribution with a $P_{80}$ of approximately 18.7 m as well as less than 1% of blocks smaller than 1 m. This difference in block size between the areas of El Gallo was visually observed during the field campaigns: the rock mass in the Central pit was blockier than in the Lupita pit. At Bowmanville, the existence of the persistent bedding planes and jointing is the main factor contributing to the reduction of the IBSD. The regular interval at which these planes occur prevents the formation of large blocks.

### 5.2.2 Assessing Blast Fragmentation

The following section provides a brief overview of the blasting fragmentation assessments. The blasted block size distribution (BBSD) is used to estimate the efficiency of blasting, thereby giving feedback for subsequent blasting operations. Fragmentation performance affects downstream processes (e.g. loading, hauling, and milling), and knowing the BBSD allows calculating broken
muck pile density, adjusting crusher settings, determining % oversize, and assessing secondary blasting requirements (Mosher, 2011). Optimal truck and shovel performance also relies on good fragmentation results to ensure higher fill factors are achieved. Accordingly, a means of measuring the fragmentation is required.

Visual inspection, sieve analysis, and 2D and 3D image analysis are used to estimate BBSD of muck piles (Bamford et al., 2018). Visual inspections are the quickest and easiest to perform; however, they are highly subjective and therefore, unreliable. Moreover, they only allow for a qualitative description of the fragmentation. Sieve analysis gives the most accurate and consistent results (Han and Song, 2016). Sieve analysis is a labour and time-intensive procedure and is not practical for mining operations where large volumes of rock are blasted. Hence, these two methods are inadequate for fragmentation analysis, which needs to be conducted frequently and objectively to gain meaningful results.

As a result, image analysis methods have become more prevalent in mining operations to estimate BBSD because they are practical, fast, and provide relatively accurate measurements (Sanchidrián et al., 2009). Image analysis techniques have several limitations, including a limit in measurement resolution and rock segmentation accuracy (Bamford et al., 2017; Sanchidrián et al., 2009). Both image system resolution and segmentation accuracy can have a significant impact on the accuracy of the BBSD estimate. 3D imaging and analysis methods have eliminated the need for placement of objects to set image scale, thereby reducing the error associated with using a constant scale to represent an uneven muckpile surface (Campbell and Thurley, 2017; Onederra et al., 2014). While by using 3D imaging some of the limitations have been reduced, the principal drawback to these methods is that only the muckpile surface BBSD is captured, while the internal distribution remains unknown (Onederra et al., 2014).

As discussed previously, multiple methods exist for estimating the BBSD, and this work focuses on image-based techniques. Images of blasted muck piles collected from Lupita, Central and Bowmanville were used to estimate the BBSD using image analysis techniques. Due to the limited field time for collecting post-blast data at Central pit, it was not possible to capture an orthophoto of the blasted muck pile with the UAV, hence the images of the muckpile in Central pit had to be collected using a terrestrial camera. The terrestrial images in Central pit had an average GSD of 0.13 cm/pixel. At Bowmanville, the DJI Matrice 600 Pro was used to collect 38 images of a blasted
muckpile with the Olympus M.Zuiko 45mm/1.8 lens to generate an orthophoto with a GSD of 1.5 cm/pixel. Similarly, in the Lupita pit an orthophoto was created using 20 images, captured by the DJI Phantom 4 Pro, with a 1.3 cm/pixel resolution. The orthophoto is considered a better product to use in image analysis for BBSD estimation because it is a composite of collected images corrected to have a fixed scale. This fixed scale results in a map of the muckpile without the perspective and lens distortion which might be present in a single image. Figure 5-7 shows the image and orthophotos used for image analysis. Some pre-processing was required to mask the areas outside of the muckpile of interest, as shown in cyan (Figure 5-8), to eliminate them from the analysis.

![Images from a) Central pit, b) Bowmanville, and c) Lupita produced for image analysis of the blasted muckpiles](image)

Figure 5-7: Images from a) Central pit, b) Bowmanville, and c) Lupita produced for image analysis of the blasted muckpiles

The images were then imported into Split-Desktop by Split Engineering LLC (Split Engineering LLC, 2018) for image analysis to estimate BBSD. GSDs were used to set image scale so that measurements can be assigned to rock fragments. The software used the input images to delineate the rock fragments using image segmentation. Extensive manual editing of the rock fragment delineation was required to improve the rock segmentation process. The delineation network of rock fragments was overlaid on the original images in Figure 5-8. Figure 5-6 plots the BBSD produced by the image analysis for each site.
Figure 5-8: Rock fragment delineation for a) Central pit, b) Bowmanville and c) Lupita. The colour cyan is the masked area, blue outlines the rock fragment boundaries and the red regions represent fines

5.2.3 Analyzing the Blasting Efficiency

The amount of powder used to blast rock can influence fragmentation; however, the effective use of explosive energy depends on multiple factors. Appropriate drill hole placement is required for proper distribution of explosive energy (Onederra and Chitombo, 2007). Moreover, poor stemming or lack of stemming can allow gases to escape. Several measurements can be used to assess the quality of blasting: muckpile profile, displacement, volume, swell and face profile (Berkhimer, 2011; Thornton, 2009). However, these measurements do not provide information on whether a suitable powder factor was used. Empirical relationships such as those discussed by J. Latham, Meulen, and Dupray (2006) can be used to verify if the powder factor used in a blast is appropriate for a target fragmentation. These relationships are typically based on the Bond work index of the rock, IBSD of the rock mass, and the type of explosive used. One version of these relationships developed by Kahriman et al. (2001), is based on 14 case studies, relating the powder factor of a blast to the IBSD, BBSD and the intact rock properties through the following equation:

\[ q_B = 10 \, W_i \left\{ \left( \frac{1}{\sqrt{D_{b80}}} \right) - \left( \frac{1}{\sqrt{D_{i80}}} \right) \right\} K \]

\[ K = \left( \frac{860}{912} \right) \times \rho_{rock} \]
Where $W_i$ is Bond’s work index for the particular rock type, $D_{880}$ and $D_{80}$ are 80% passing for BBSD and IBSD respectively (in micrometre). $K$ is a conversion constant relating the energy used in Bond’s work index (1 kWh = 860 kcal), the energy of ANFO (1 kg of ANFO = 912 kcal) and the specific gravity of the rock ($\rho_{\text{rock}}$) by Equation 5-2.

Use of these models to determine the powder factor (the explosive energy used to break rock) can be successfully implemented if the IBSD is known. The target fragmentation size is particularly important as it affects many operations at a mine: drilling, loading, hauling, crushing, grinding, and milling. Determining the optimal fragmentation also impacts the cost of blasting, as higher fragmentation requires more drilling and explosive, thereby increasing blasting costs.

The analysis of the IBSD and BBSD plots presented in Figure 5-6 shows that there is a size reduction due to blasting in all the pits. The IBSD $P_{80}$ is reduced to the BBSD $P_{80}$ from 18.7 m, 6.5 m, and 6.8 m to 0.29 m, 0.37 m, and 0.69 m for the Central, Lupita and Bowmanville pits, respectively. Significant fines (blocks less than 1.5 cm in size) were created by blasting at the Central pit, with 34% of the material being fines. The Lupita and Bowmanville pits had produced 23% and 11% fines, respectively. The relatively low percentage of fines generated for Bowmanville quarry is expected for an aggregate operation where fines can negatively affect economics. The different objectives are also reflected by the lower powder factor used at Bowmanville, contributing to the larger BBSD. These results from the plot (Figure 5-6) are then used to calculate the theoretical powder factors using Equations 5-1 and 5-1. Table 5-5 presents the required parameters used in equations 8 and 9, the resulting theoretical powder factor, and the actual powder factor used at the mines.

Table 5-5: Table of required parameters, the resulting theoretical powder factors compared to actual powder factor used.

<table>
<thead>
<tr>
<th>Mine Site</th>
<th>$D_{880}$ (m)</th>
<th>$D_{80}$ (m)</th>
<th>$\rho_{\text{rock}}$ (kg/m$^3$)</th>
<th>$W_i$ (kWh)</th>
<th>Theoretical Powder Factor (kg/t)</th>
<th>Actual Powder Factor (kg/t)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>Standard Deviation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central</td>
<td>0.29</td>
<td>18.7</td>
<td>2,520</td>
<td>16.30</td>
<td>0.25</td>
<td>0.21</td>
</tr>
<tr>
<td>Lupita</td>
<td>0.37</td>
<td>6.5</td>
<td>2,520</td>
<td>16.30</td>
<td>0.19</td>
<td>0.20</td>
</tr>
<tr>
<td>Bowmanville</td>
<td>0.69</td>
<td>6.8</td>
<td>2,750</td>
<td>14.95</td>
<td>0.12</td>
<td>0.16</td>
</tr>
</tbody>
</table>
The Bond’s work index and density for the El Gallo complex were obtained from the resources estimate for the El Gallo Complex (Read and Willis, 2013) by McEwen Mining. Site personnel provided the Bond’s work index and density at Bowmanville. The actual powder was calculated based on one month of blasting data from each of the Lupita and Central pits, and 74 blasts at Bowmanville.

5.2.4 Results and Discussion

The blasting at each site is generally in line with the theoretical powder requirements, especially in the case of Lupita blasting. Blasting at Bowmanville uses a lower powder factor, but the more uniform blasting (lowest powder factor deviation) occurs here. The results also suggest that there could be inefficiencies with the blasting program at Bowmanville as the theoretical powder requirement is 0.04 kg/t lower than the actual. These inefficiencies are an area of potential improvement at the operation.

The relatively high standard deviation of the powder factor at the El Gallo complex, which ranged from 0.13 to 0.31 kg/t, was identified as a possible issue. This variation may account for the field observations of flyrock, back break into the catch benches, and blast damage to the final pit walls. A catch bench analysis at Central pit of area mapping suggests that only 61% of catch bench area is maintained. The catch bench width histogram (Figure 5-9) shows that the designed bench width of 7.5 m with an expected 70% reliability of achieving 5.7 m (Cylwik et al., 2016) has not been achieved.

Furthermore, the BFA achieved is over 15° shallower than the designed BFA of 75° in some areas. Figure 5-10 shows a slope model of the analyzed sector of the central pit. The dominant colour is blue and purple indicated that slope achieved is between 52° and 68°, which is supported by section A-A’ (see Figure 5-11) showing a BFA of 61° and 63°. A comparison of the as-built catch bench and the planned catch bench areas show a 39% loss of design. These results indicate that the blasting and wall control practices in this particular area were inadequate for maintaining the required catch bench and achieving the desired face angle. This type of information is essential for site personnel and can be used to identify areas of improvements. In particular, there could be more focus on blasting close to the final walls to ensure better results. However, it should be noted that the area analyzed in Central pit had multiple wedge failures, which were the reason it was selected
for mapping. These geotechnical issues could have contributed to the poor bench performance results, and they might not be representative of the whole Central pit.

Central Pit Catch Bench Analysis

Figure 5-9: Catch bench width analysis at the Central pit.

Figure 5-10: BFA analysis of a sector of Central pit.
5.3 Kinematic Slope Stability Analysis

Designing slopes is one of the most significant challenges in open pit mines. It is favourable for slopes to be as steep as possible while also ensuring that their stability is not compromised. This reduces the stripping required and has positive financial implications. The overall process for slope design has been relatively well established over the last 35 years. The expectation is that slopes remain stable over the life of mine and beyond (Read and Stacey, 2011). This requires on-going slope monitoring and analysis as conditions of slope can change during the life of mine by pushing back the pit slopes, exposing new discontinuities on the wall or due to weathering of rock material. One of the tools available to engineers to evaluate the stability conditions of rock slopes is conducting kinematic stability analyses.

The interaction of joints with the surface of a surface or underground excavation can create rock block failure: blocks that have the potential to slide along a joint or multiple joints. Using stereonets, it is possible to identify whether joints that can cause failure are present and thus examine the direction and likelihood of slope failure (Wyllie and Mah, 2005). This rather simple approach has been extensively covered in the literature and books, notably in Guidelines for Open
Pit Slope Design (Read and Stacey, 2011) or Rock Slope Engineering (Wyllie and Mah, 2005). In this work, the UAV collected data from Top2B pit was used to build a DFN model of the rock slope, replicating the mapped joints in the slope within their exact location and orientation (semi-deterministic), and creating a conditional DFN model. Subsequently, stochastic joints were added to the DFN model, behind the pit wall. This model is used to see if the conditioned and stochastic joints can account for the failures observed at Top 2B pit. These DFN results were compared to those of a simple kinematic analysis.

5.3.1 Generating a DFN

The DFN model for the kinematic analysis was generated based on the physical locations of the joints mapped using an aggregate approach, where all the joints were modelled as a single set. The joint trace centroids, trace lengths, their dip and dip directions, and joint plane normals, mapped on the Top 2B pit were exported from the point cloud model generated in CloudCompare. These traces were directly imported into FracMan and inserted on the surveyed pit wall surface to replicate the mapping joints (Figure 5-12).

The resulting trace map is used to generate semi-deterministic joints in the DFN model. It is important to note that the joints generated based on the traces are not fully deterministic; the joints generated have a known orientation, trace length and trace location but the joint radius is unknown. Furthermore, the traces could be formed by the center of the joint radius, an edge, or a chord, so analytical estimations of the joint radius are required (Rogers et al., 2017). Various analytical methods have been developed to estimate the joint radius from the trace length data, as discussed in the literature (Tonon, 2007; Villaescusa and Brown, 1992; Zhang et al., 2002). Due to the ease of implementation, the method discussed by Zhang, Einstein, and Dershowitz (2002) was used to estimate the joint radius size.
Figure 5-12: Trace map of joints identified during mapping on the Top 2B wall as-built imported into FracMan.

The joint radius of the mapped data at Top 2B pit was fit by a log-normal distribution with a mean trace length of 2.88 m and a standard deviation of 2.74 m, with a significance of 99%. The simulated traces (following the log-normal distribution) are shown against the actual trace data in Figure 5-13. This distribution was used to generate the joint radius in the DFN model. For the semi-deterministic model, the size and center of the joints were stochastically generated while adhering to the determinist constraint that each joint had to fit onto a mapped trace, such that all the mapped traces were replicated.
In order to generate joint sets within the rock mass, behind the pit wall surface, the semi-deterministic DFN model was further populated with stochastic joints by bootstrapping from the mapped joint data. Bootstrapping is a statistical procedure that draws values from the existing data, with replacement, rather than a fitted distribution (Golder Associates Ltd, 2018b). The intensity of jointing was set using the iterative process of picking an arbitrary $P_{32}$ and adjusting it until the $P_{21}$ of the model on the Top 2B slope matched the field $P_{21}$. Ten stochastic DFN models were generated. For each of the ten stochastic DFN generations, a subset was created where the joints intercepting the pit surface were removed, since those were conditioned based on the tracemap. These subsets were considered the stochastically generated sets and were combined with the joints generated by using the traces. The result was ten semi-deterministic and stochastic (Det-Sto) DFN models. Figure 5-14 shows a representation of the DFN model for the Top 2B pit wall.
5.3.2 Kinematic Slope Stability Analysis using Deterministic-Stochastic DFN Models

The pit wall design surface was loaded into the 3D DFN models to conduct a kinematic slope stability analysis. A wedge analysis was conducted for each DFN model to investigate the size and number of the wedges formed on the slope surface. The FracMan rock wedge tool was used to conduct the kinematic analysis. The tool works based on key block theory developed by Goodman and Shi (1985) and uses the fracture network geometry to identify blocks formed on the slope surface. The stability of each block is then assessed using the Mohr-Coulomb failure criterion for sliding. The rock at Top 2B pit has a density of 2.7 kg/m$^3$ and a conservative friction angle of 27° was used for the joints and they were assumed to be cohesionless. The stable and unstable blocks were identified and their volumes were recorded. Figure 5-15 shows the unstable (red) and stable (green) wedges formed behind the pit wall in one of the DFN models. There are relatively few wedges formed in this model.
Figure 5-15: View of unstable (red) and stable (green) wedges formed in one DFN model generation and the fault zone in red.

The wedge analysis results are plotted in Figure 5-16 as cumulative distributions of the wedge volume. The P80 varied from 12 m$^3$ to approximately 71 m$^3$, with an average of 31 m$^3$. Only two DFN models had a larger P80 than the average. A kinematic analysis of the wedges determined that there were on average ten unstable or failed wedges in each model. A histogram of the aggregated failed wedge volumes of all the model runs is presented in Figure 5-17. Volumes smaller than 1 m$^3$ accounted for 85% of all the failures; suggesting that the mode of failure is not purely kinematic at Top 2B northeastern wall. Moreover, none of the models replicated a visually observed failure in the wall.
Figure 5-16: Size distribution of all the wedges generated by using the deterministic-stochastic model

Figure 5-17: Histogram of failed wedge volumes from the semi-deterministic and stochastic models
5.3.3 Discussion

Most of the failure in the mapped area of the Top 2B pit wall occurred along the major fault, as can be seen from the DEM model (Figure 5-18). Visual observations suggest that this was a wedge failure, in particular, the wedge form against the joint highlighted in red; however, the DFN model results do not corroborate this observation. In order to test this, the wedge failures were modelled in SWedge (Rocscience, 2018b). This is a tool that allows the evaluation of surface wedges in slopes between two joints. Five SWedge analyses were conducted: the stability of each of the four joint sets and joint identified in on bench 4 (Figure 5-18 in red) were assessed against the major fault (85°/052°, dip/dip direction). The highlighted joint had an orientation of 54°/149°.

![Figure 5-18: DEM model of Top 2B pit showing wedge failures with a modelled joint identified in red.](image)

Similarly to the DFN model, the friction angle was assumed to be 27°. One of the assumptions of SWedge is that the joints are continuous and persistent; however, they can be scaled to match the trace lengths mapped. In the analyses, the joint set trace lengths (abbreviated to TL in Table 5-6)
were unscaled (TL_{unscaled}), and scaled to the maximum (TL_{max}) and average (TL_{avg}) mapped trace length of each set. Figure 5-19 shows the SWedge analysis conducted for joint set #2 with the scaled wedges. There is a 98.5% reduction in wedge volume from the unscaled to the TL_{max} scaled wedge, and a further 100% reduction when scaled to TL_{avg} (making the wedge negligible). The dispersion of each set was described by the K Fisher Constant, which determined a probability of failure (PoF). A deterministic factor of safety (FoS) was also used to describe the stability of the wedges formed. The results of the completed SWedge calculations are presented in Table 5-6.

Figure 5-19: SWedge analysis of the major fault and joint set 2 showing a) an unscaled trace length wedge, b) a wedge scaled to the largest mapped trace length, and c) a wedge scaled to the average trace length of set 2.

The analysis of the joint identified (54°/149°) and the fault (85°/052°) in SWedge showed that no wedge was formed; the visual observation led to an incorrect assumption regarding the failure mechanism. This is an example of why visual observations can be subjective and unreliable, and why objective collection and processing of reliable data is required. Table 5-6 shows the results of the analysis. The PoF and FoS are presented and show that the probability of failure is low for all sets; however, the FoS of set #2 and #3 is below the threshold of 1.2 discussed in Section 2.3.1. Considering the size of the wedge formed by set #3, set #2 was classified as a critical set. It is very
unlikely that a 1,332 m$^3$ wedge is formed, due to the fact the joint persistence required for this has not been observed in the field. Furthermore, the presence of other fractures behind the wall is likely to limit the maximum wedge size as seen in Figure 5-16 and Figure 5-17. The scaled results of the $SWedge$ analysis support the results obtained by the DFN modelling, i.e. that the average scaled wedges are typically between 0 and 1 m$^3$ in size.

Table 5-6: Kinematic analysis results using SWedge

<table>
<thead>
<tr>
<th>Joint set #</th>
<th>PoF</th>
<th>FoS</th>
<th>Trace Length (m)</th>
<th>Volume (m$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Req. for largest Wedge</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Measured Max.</td>
<td>Measured Avg.</td>
</tr>
<tr>
<td>1</td>
<td>0.04</td>
<td>6.2</td>
<td>36.0</td>
<td>33.0</td>
</tr>
<tr>
<td>2</td>
<td>0.00</td>
<td>0.3</td>
<td>149.9</td>
<td>36.4</td>
</tr>
<tr>
<td>3</td>
<td>0.00</td>
<td>0.6</td>
<td>38.7</td>
<td>9.4</td>
</tr>
<tr>
<td>4</td>
<td>0.02</td>
<td>1.4</td>
<td>86.6</td>
<td>12.2</td>
</tr>
</tbody>
</table>

The results of the DFN and $SWedge$ analysis indicate that sliding wedge failure is an unlikely cause of the failure identified. An alternative explanation for the failure was sloughage due to the weak and highly weathered rock surrounding the fault. The weak rock sloughed when excavated until it reached a stronger rock unit contact which prevented further unravelling, thereby making it seem like a wedge failure. This theory is supported by the large volume of loose and smaller material located at the base of the failures (see Figure 4-19 and Figure 5-18). These results demonstrate how advanced data collection methods can provide additional information for understanding the rock mass.

5.4 Summary

This chapter presented how the UAV collected data could be used to supplement the collection of the high quality input data required to build a DFN model and its uses. The methodology for generating a DFN model was described for both calculating the IBSD and conducting a kinematic stability assessment. Two different approaches were used. For the IBSD estimation, the joints were grouped into sets and generated using a disaggregated approach. The advantage of this approach is that each set can have a unique joint radius, and its orientation specified. For the kinematic analysis, the fracture network was created using a single generation through bootstrapping. In bootstrapping, original mapping data set is sampled, with replacement, to generate the joint
orientation resulting in a stereonet that replicates the original data. During this process, the sampled values can be matched exactly or some variance can be introduced to ensure each generation produces a different fracture model. As this is a partial aggregate approach, the joint diameter is modelled by a single distribution. Only the overall joint radius will be recreated, and there may not be a difference between the sets. Overall, both methods produced a DFN that matched the field observations and was suitable for the analysis.

Three blasting field studies were presented; two at the El Gallo complex and one at the Bowmanville quarry to showcase the advantages of using UAVs to collect pre- and post-blast data. DFN models were generated for the pit walls and the IBSD was estimated for the rock mass in each case study. UAV images of post-blast muckpiles were used to estimate the blast-induced rock fragmentation. The results of this analysis were used to estimate the optimum powder factor for rock fragmentation. The results indicated that both mines have some inefficiencies in blasting. At the El Gallo complex, the variation in the powder factor may be the cause of some blast induced damage observed on the pit walls. However, the typical amount of explosive used is in line with the theoretical powder factor values. Implementation of a more consistent blasting program could have positive outcomes on the final pit walls and catch benches. At Bowmanville, the results suggest that a consistently higher powder factor is used. This may be attributed to some blast energy loss caused by gas escaping through the well developed joint sets.

A kinematic stability analysis was conducted at the Top 2B pit using a conditional DFN model based on semi-deterministically and stochastically generated joints. The model reproduced the visible traces on the wall while stochastic joints populated the volume behind the wall creating a more representative model of the rock mass seen at Top 2B. Ten of these DFN models were generated for the stability analysis. None of the models reproduced the failure observed on the Top 2B pit walls. The failed wedges were generally between 0 and 1 m³. The DFN results were supported by the kinematic analysis conducted in SWedge, which showed the average wedge size formed is also between 0 and 1 m³. The alternative theory proposed is that the rock surrounding the fault zone is likely weaker and highly altered, causing it slough until a stronger rock lithology contact is reached. Therefore, the failures may be a combination of material weakness with the interaction of contacts or joints.
This chapter demonstrated the advantage of using UAVs to collect additional data for advanced modelling. Data that would have been unavailable is used to develop advanced models to assess the blasting and slope stability at open pits. Furthermore, the data can be quickly reviewed and revisited to confirm the model results, as was done in the case of the Top 2B stability analysis to verify the sloughed material volume.
Chapter 6
Conclusions

6 Conclusions

Mining is becoming a more complex process; easily accessible and higher grade reserves are depleted, resulting in open-pits going deeper and a higher need for operational excellence. This has made the stability of slopes both critical and more complicated, creating a need for advanced modelling and increasing the emphasis on design compliance. This thesis focused on presenting a UAV approach for collecting geotechnical data that keeps mine personnel safe while also improving the data quality collected. The methods described can be used to collect geotechnical information, ensure design compliance, and as the basis for advanced modelling. This work aims to contribute to the integration of UAV technology into routine open pit operations, improving data collection and worker safety.

This final chapter presents a summary, conclusions, and recommendations for further study of this research.

6.1 Summary

The existing literature was reviewed to identify the current gap in research. While the use of UAVs and photogrammetry has been a topic of research, there were relatively few practical guidelines for its implementation in routine mine operations. The research was generally done at sites in relatively simple geological settings or for identifying large scale structure, but not at the bench scale operating mines require. The use of UAVs as a tool to supplement or replace the current pit wall mapping techniques at mines with complicated geology was identified as a gap. Furthermore, this work intended to showcase how the UAV collected data can be used for operational compliance monitoring or as input data for DFN modelling, which can consequently be used for blast optimization and slope stability assessments.

The data were collected in four different mines in diverse geological settings. Each of the sites presented different challenges. At the Bald Mountain and Bowmanville regulatory requirements made planning more complicated, whereas at the El Gallo and Tasiast sites the heat, dust, and
weather conditions caused flight issues. For all the mine sites, geotechnical data was collected from inaccessible pit wall areas, such as the upper benches, significantly increasing the quantity of data available for analysis. In addition to pit wall mapping, UAVs were used to map blasted muckpiles at the mine sites to assess the blast induced rock fragmentation. The fragmentation data collection had minimal impact on operations because the loading and hauling operations did not need to be stopped. The field time spent collecting data over large areas was also drastically reduced. The equations for flight planning were provided, along with an example of their application, to ensure the desired quality of data was obtained.

For all the sites, the data and the resulting point clouds were of very high quality, with most having a resolution higher than 2 cm/pixel. At those resolutions, it was possible to identify joints as small as 10 cm in length, while also enabling the identification of large multi-bench features. It was possible to obtain these results by using cameras with high resolutions sensors; however, the use of the right lens was an important factor. Lenses with long focal lengths make it possible to capture more detailed images, thus using these lenses improves the mapping results. Manual, semi-automated and fully-automated methods were used in CloudCompare to map discontinuities of the pit wall 3D point cloud. Both the fully-automated and semi-automated algorithms performed better with very high-resolution point clouds. Nevertheless, having a cloud of high quality increased the computational power required, slowing down the overall mapping process. Therefore, a balance between the desired mapping scale and point cloud quality needs to be achieved for optimal mapping. The information collected from the virtual mapping of the 3D point cloud was used for further analysis, including:

- Measuring dip and dip direction of joints;
- Measuring joint trace lengths and the coordinates of their centroids;
- Measuring pre-split blasting half cast length and orientation;
- Generating DEM and slope models; and
- Calculating slope orientations and angles.

Also, by reducing the time required in the field, more time can be spent on post-processing and analyzing the data. Making the data permanently available for virtual mapping allows for
significantly more detailed mapping. This additional available time for mapping is significant because areas with intense jointing require more time and detailed mapping than is typically done using conventional techniques (Tuckey et al., 2016). This has a direct impact on the subsequent modelling results since more robust data is used.

3D point cloud models that are developed from the UAV images of pit walls allow characterizing discontinuities, pre-split hole half-casts, and slope geometries. This information can be used to control the quality of final wall blasting by establishing site-specific relationships between the fracture intensity (P_{21}) of the rock mass and the results of pre-split blasting. The results of the study, conducted at two mine sites, demonstrated that increased fracture intensity has a negative impact on the pre-split deviation, pre-split half-cast factor (HC_{10}) and the slope back break.

In Section 4.3, DEMs were developed using the photogrammetry data to assess the design compliance of Top 2B pit. The results of the analysis demonstrated that the blasting requires some refinement at Top 2B, in particular, the buffer and pre-split blasting. The design BFA is achieved in some areas; however, there is significant variation in the results, as seen in Figure 4-16. The bench width results also vary significantly, with only one bench achieving the target width. This noncompliance can be attributed to the fault running through the pit wall, and to the significant sloughage of altered rock material along the benches. The methodology presented in this study can be easily implemented to ensure the as-built pit walls comply with the design requirements. Moreover, the UAV can be flown over the same areas even if access to the benches is lost, to monitor any changes to the pit wall and rock mass condition and provide high temporal resolution data.

The joint data collected from different mine sites were used as input to generate DFN models of the rock mass for Lupita, Central, Bowmanville, and Top 2B pits. The DFN was used to estimate the IBSD at Lupita, Central and Bowmanville operations as part of a blast optimization program. The IBSD was related to the BBSD through the empirical relationship proposed by Kahriman et al. (2001), and the results of the analyses were compared to the actual powder factor used at the mine sites. The significant variation in powder factor at the El Gallo complex might have accounted for the reduced catch bench and the lower pit slope angles observed in the Central Pit.

At the Top 2B pit, a kinematic stability analysis was conducted using the DFN model. The DFN model was generated by conditioning the joints to the observed traces on the wall so that the
simulated joints exactly replicated the traces. This set was considered semi-deterministic since the joint orientation, trace location and trace length were known; however, the joint size and centroid in space were unknown. Subsequently, a stochastic joint set was generated behind the pit wall based on bootstrapping samples from the mapped data. This combined semi-deterministic and stochastic model was used to conduct a wedge and stability analysis. The results of the DFN model, supported by the SWedge results, demonstrated that wedge failures were not the cause of the failures observed on the pit walls.

The thesis demonstrated the potential value of using UAVs as a platform for data collection. It was shown that UAV use can increase worker safety and the quantity and quality of collected data, while reducing field time and disruptions to mine operations.

6.2 Limitations

As previously discussed, there are limitations to UAV data collection methods. The wall orientation bias still exists within the data if the data is only collected from one section of the wall. The results also need to be validated in the field (Read and Stacey, 2011). The placement of suitable GCPs is a challenge. If the GCPs or systems like PPK are not used, the resulting point cloud accuracy can be negatively impacted. Inaccurate point clouds cannot be used for any subsequent data analysis.

The weather and lighting conditions have a significant impact on UAV use. If there is glare, the captured image quality is reduced, which will reduce the quality of the point cloud. Furthermore, the presence of glare might require manual post-processing of the images to exclude low-quality ones from the image set. Dust conditions can also have an adverse effect on data collection; dust in the air or covering the pit walls reduces the image quality and feature matching effectiveness, and it can impact the UAV causing overheating, blocking moving parts, and damaging electronic components. Furthermore, UAVs cannot be used in rain, snow, or heavy winds. Working in mines, it is not possible to avoid some of these hostile work environments; however, intelligent flight planning and careful handling of the UAV can mitigate some of these limitations.

The local geology also plays a role in the time required for mapping joints as well as the required GSD for the photogrammetry processes. Rock masses with higher intensities of small fractures require a smaller GSD, which increases both cloud generation and mapping time. Careful
consideration needs to be given to the desired GSD to ensure optimal results in terms of time and quality. Significant time has to be spent processing the data to reconstruct a 3D point cloud, and the GSD directly influences this. Most of the methods used in this work are computationally intensive. Therefore, powerful computers are required to generate, manipulate and analyze the point clouds efficiently.

6.3 Major Contributions

The main contributions of this work are:

- Providing a general framework for integrating UAVs into open pit operations to capture high-quality pit wall images for photogrammetry reconstructions, producing 3D point clouds used to conduct geotechnical mapping.

- Highlighting the importance of UAV equipment selection and matching. The equations for generating appropriate flight plans are given and explained in detail.

- Explaining virtual point cloud mapping, including the difference between the available methods. The results of this are explored by comparing the $P_{21}$ results to the BFA and $HC_{10}$ factor, and site-specific relationships can be developed between these parameters.

- Presenting a methodology for assessing blast performance which can be implemented to improve blasting results or help site personnel identify areas of concern.

- Discussing methods for generating a combined semi-deterministic and stochastic DFN model using the UAV collected data. This combined model can increase the reliability of results as the field observations are more accurately represented.

6.4 Future Work

During the development of this work several areas of improvement and further research were identified:

- In this study, GCPs were only used at one mine site (Top 2B pit) to improve the accuracy of the point cloud model. The influence of placing GCPs on the mapping pit wall on the accuracy of the 3D point cloud model and measured structural and geometrical data needs
to be further investigated. In the Top2B pit case, slope monitoring prisms were used as GCPs for the model calibration, however, developing other methods for safely placing GCPs on the highwall would significantly improve the accuracy and confidence of aerial mapping results.

- The relation between the fracture intensity ($P_{21}$), pre-split half-cast factor ($HC_{10}$), and the bench face angle needs to be further investigated in different geological settings to develop technical guidelines for improving the quality of pre-split blasting.

- Developing UAV based solutions for differentiating between natural and blast-induced discontinuities on the pit wall would be very useful and could reduce post-processing time. For this purpose, a combination of UAV-photogrammetry and UAV-hyperspectral imaging can be used.

- Finally, the integration of UAV technology for geotechnical data collection in underground mines (GPS denied environments), required further investigation. This can significantly improve safety and increase the quality of the collected data in underground mines.
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