



Newcastle University

A Multiscale Investigation of Fracture Networks Interpreted from Aerial and Drone Imagery

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Abstract

This PhD thesis focuses on advancing the understanding and characterization of geological fracture networks using aerial and drone imagery, and automated fracture extraction methods. The research addresses three primary questions: the reliability and robustness of automated fracture extraction methods when applied to decimeter resolution aerial imagery, the effects of varying imaging resolutions on the interpretation of fault and fracture networks, and how spatial and resolution-dependent variability in fracture networks impacts geological interpretations. The studies carried out throughout this research employ a multiscale approach, using datasets of varying resolutions, from aerial imagery at 0.2 m/px to field imagery at 0.002 m/px, to quantify the information loss across different resolutions. Automated extraction methods, specifically the Complex Shearlet Transform and Binary Thresholding Method, were tested for their reliability and reproducibility. Results reveal that currently, automated fracture extraction methods face challenges, specifically with the reliable extraction of fractures from low-resolution datasets. It was found that the accuracy and reliability of these methods are significantly impacted by the resolution of the input data and by exposure continuity. Reliability was quantified by measuring the Root Mean Square Error (RMSE) of fracture lengths between different automated approaches, which revealed significant discrepancies, indicating that these methods often produce inconsistent results when applied to the same datasets. The impact of image resolution on fracture network properties was investigated and quantified using manual approaches. High-resolution imagery (0.02 cm) captures fine-scale features but is limited by area-bound censoring. Medium-resolution (2 cm) imagery offers a balanced view, identifying a broad range of fracture lengths and characteristics. Low-resolution imagery (20 cm) covers extensive areas

but often misses finer fractures, leading to severe fine-scale fracture censoring. A multiscale approach and rigorous tracing methodology are essential for accurate geological analysis. Finally, a case study on the granitic rocks of west Hitra Island, Norway, using imagery at three different scales (regional, local, and outcrop scales) demonstrates that accurate geological interpretations are possible using imagery alone. This study also stresses the importance of applying clearly defined criteria when using manual methods with decimeter-resolution imagery to ensure reliable results.

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Contents

Abstract	i
Acknowledgments.....	iii
List of Figures	x
List of Tables.....	xvi
List of Abbreviations.....	xvii
Chapter 1 Introduction.....	19
1.1 Fracture Interpretation from Imagery.....	19
1.1.1 Remote Sensing in structural geology	23
1.1.2 Interpretation Methods	26
1.1.3 Reliability and Reproducibility	27
1.1.4 Applications of Fracture Analysis.....	29
1.2 Aims, Objectives and Scope of This Research	31
1.2.1 Research Questions	31
1.2.2 Research Aims and Objectives.....	31
1.3 Thesis Structure and Chapters Outline	32
Chapter 2 Literature Review	35
2.1 Introduction	35
2.2 Manual and Automated Fracture Interpretation	36
2.2.1 Fracture Networks and Outcrop Studies.....	36
2.2.2 Limitations and Innovations.....	38
2.2.3 Reproducibility and Reliability of Geological Investigations	46
2.3 Image Capture Techniques for Geological Fracture Mapping.....	50
2.4 Use of UAVs in Geology	56
Chapter 3 Data and Methodology	59
3.1 Criteria for Study Area Selection	59

3.2 Geological Setting.....	61
3.2.1 Gillet Mountain, California, USA	61
3.2.2 Salt Valley, Utah, USA	64
3.2.3 Havmyran, Hitra, Norway	67
3.2.4 Craginaw, Galloway, Scotland	69
3.3 Datasets.....	70
3.3.1 Aerial Imagery	71
3.3.2 Drone Imagery	72
3.3.3 Data Quality and Accessibility	73
3.4 Fracture Interpretation and Characterization	74
3.4.1 Manual tracing	75
3.4.2 Automated fracture tracing-Complex Shearlet Transform	76
3.4.3 Automated fracture tracing- Binary thresholding method	82
Chapter 4 Reliability of Contrast-Based Automated Fracture Detection from Decimeter Resolution Aerial Imagery.....	84
Abstract	84
4.1 Introduction	86
4.2 Methodology & Data	88
4.2.1 Data and Setting	91
4.2.2 Workflow.....	94
4.3 Results and Observations	99
4.3.1 Characteristics of Extracted Networks – Shearlet Method	99
4.3.2 Characteristics of Extracted Networks – Binarization Method	111
4.3.3 Network and Image Characteristics	116
4.4 Discussion	120
4.4.1 Effects of contrast on fracture network properties	120

4.4.2 Effect of vegetation and exposure continuity.....	122
4.4.3 Effects of lighting	124
4.4.4 Challenges and Recommendations for Automated Lineament Detection Using Contrast-Based Methods	126
4.5 Conclusions.....	127
Chapter 5 Quantifying Differences Between Fracture Networks Characterized on Different Resolution Datasets	129
Abstract	129
5.1 Introduction	131
5.2 Methodology.....	134
5.2.1 Imagery and Datasets	134
5.2.2 Aerial Imagery	134
5.2.3 Field data acquisition	136
5.2.4 Drone Imagery	136
5.2.5 Fracture Interpretation	137
5.2.6 Surface Fracture Width	140
5.3 Results and Observations	141
5.3.1 Impact of Resolution on Interpreted Fracture Networks.....	142
5.3.2 Orientation, Connectivity, and Intersection Angles.....	146
5.3.3 Surface Width, Length and Intensity	151
5.4 Discussion	161
5.4.1 Impact of Surface Expression and Resolution on Reliable Fracture Tracing	162
5.4.2 Impact of Resolution on Topology in Fracture Network Characterization	164
5.4.3 Variability of Networks Across Resolutions and Practical Implications....	167
5.5 Conclusions.....	170

Chapter 6 Characterization of the Deformation Patterns in the Granitic Rocks of	
Hitra: A Multiscale Analysis.....	172
Abstract	172
6.1 Introduction	174
6.2 Study Area	177
6.3 Geological Background.....	179
6.3.1 Batholith Composition	180
6.4 Data and Methodology	181
6.4.1 Data Acquisition.....	181
6.4.2 Remote Sensing and Datasets	182
6.4.3 Fracture Interpretation	182
6.5 Results and Observations	185
6.5.1 Regional Scale Structural Analysis.....	186
6.5.2 Local Scale Structural Analysis – from 1.35 meters to over 3,240 meters	191
6.5.3 Outcrop Scale Structural Analysis – from 0.07 meters to 65 meters.....	192
6.5.4 Cross-Cutting Relationships Across Scales.....	193
6.5.5 Topology	194
6.5.6 Kinematic Evidence	196
6.5.7 Fracture Length Distribution	200
6.6 Discussion and Conclusions	202
6.6.1 Brittle Deformation Patterns.....	203
6.6.2 Regional Considerations.....	208
6.7 Conclusions.....	210
Chapter 7 Discussion and Conclusions	213
7.1 Summary of Findings.....	213
7.2 Considerations in Fracture Interpretations	216

7.2.1 Reliability, Reproducibility, and Replicability of Automated and Manual Approaches	219
7.2.2 Impact of Exposure Extent and Continuity on Fracture Interpretations..	222
7.2.3 Impact of Resolution on Fracture Interpretations	225
7.3 Implications of Findings	229
7.4 Future Research	232
References	235

List of Figures

Figure 1.1 Illustration of the three fracture modes: Mode I – Tensile; Mode II – Shearing fractures; Mode II – Tearing fractures (Rountree et al., 2002)

Figure 1.2 Picture of a DJI Phantom 4 (RTK) equipped with a high-resolution camera

Figure 1.3 Chart showing the percentage of scientific articles where software is identified, not identified, or where software is potentially not applicable (e.g., review articles)

Figure 2.1 Graphical representation of sharp edge (left) and boundary recognition (right).

Figure 3.1 Location map for the areas of interest: A. Yosemite, California, USA; B. Salt Valley, Utah, USA; C. Havmyran, Hitra, Norway; D. Cragshaw, Galloway, Scotland.

Figure 3.2 Geological map of the area of Yosemite – Gillet Mountain, together with area of interest, in red (U.S. Geological Survey, 2024).

Figure 3.3 Geological map of the area of Arches National Park, together with area of interest, in red (National Park Service, 2021).

Figure 3.4 Geological map of the area of West Norway, together with area of interest, in red (Norwegian Geological Survey (NGU), 2024).

Figure 3.5 Geological map of the area of South Scotland, together with area of interest, in red (EDINA, 2024).

Figure 3.6 A. Flight path followed for acquiring data; B. Quality of data expressed in number of images per area.

Figure 3.7 Full workflow followed for automated fracture extraction in Chapter 4.

Figure 3.8 A. Mexican wavelet; B. Morlet wavelet; C. Schematic representation of Shearlets.

Figure 3.9 Visual representation of the complex shearlet transform workflow.

Figure 3.10 Visual representation of the binary thresholding workflow.

Figure 4.1 Full-color images of the four study areas: A. Gillet Mountain, Yosemite, USA; B. Salt Valley, Utah, USA; C. Havmyran, Hitra, Norway; D. Cragshaw, Galloway, Scotland. The red box in each image indicates the areas used for automated extractions.

Figure 4.2 Workflow (Simplified) followed throughout the study. Shearlet Method is in black, Binarization Method is in red.

Figure 4.3 – 4.3A Visual representation of the contrast thresholds for each ensemble. Green lines and numbers represent the different thresholds used. Figure 4.3B shows how the foreground/background thresholds were varied, and what portions of the grayscale spectrum were subsequently used to trace lineaments (foreground)

Figure 4.4 This image caption describes automated interpretations using the Shearlet Method across different case studies, with Ensemble 1 in green and Ensemble 5 in red. In Yosemite (A and B), high rock mass contrast highlights fractures, though Ensemble 1 misses some high-intensity features (pointed by black arrow). In Utah (C and D), lower contrast reveals wider fractures, but vegetation causes some interference. In Hitra (E and F), extensive vegetation leads to non-geological interpretations. Similarly, in Cragshaw (G and H), vegetation and shadows compromise the reliability of lineament tracing.

Figure 4.5 Scatterplots showing the relationship between feature length and contrast across varying thresholds for each dataset. Panels C, F, I, and L illustrate how the same features are interpreted in Ensemble 1 (green) versus Ensemble 5 (red).

Figure 4.6 Rose diagrams illustrating orientation of lineaments from different iterations of automatically extracted fracture networks. Main orientations are consistent among all the ensembles. Plots J and K however show that there is a significant difference between features traced solely in vegetation and features traced solely in rock mass.

Figure 4.7 Length distribution plots showing variability between ensembles. As rock mass continuity decreases, length distribution becomes more spread and less reliable. The Root Mean Square Error was calculated to measure the reproducibility between distributions for the four study cases.

Figure 4.8 Results from four iterations (A, B, C, D) using the binary thresholding method. Overall, numerous non-geological features and circular artifacts can be seen, underscoring the method's general unreliability.

Figure 4.9 Scatter plots of length against average feature contrast. Red line is average rock mass contrast, at a value of 209; green line is average vegetation contrast, at a value of 105. Figures show the relative percentages of features above, between, and below vegetation and rock mass contrast for Iterations A (19.34%, 79.98%, 0.51%), B (0.58%, 97.84%, 1.53%), C (6.01%, 92.72%, 1.07%), and D (0%, 94.6%, 5.29%).

Figure 4.10 Rose diagrams of the lineaments extracted using the binarization method for four different iterations. The major difference amongst plots A, B, C, and D is frequency. This highlights how sensitive this automated process is to parameter changes.

Figure 4.11 Cross plot analysis of lineament network characteristics influenced by varying contrast; (S) stands for skeletonized, (B) stands for binarized, (F%) stands for foreground percentage.

Figure 5.1 Study area in Hitra across different resolutions. A. shows the location in low-resolution imagery (20 cm/px), B. in medium-resolution (2 cm/px), B1 shows the location where field measurements were taken, C. in high-resolution (0.2 cm/px), and D. is a zoomed view of the high-resolution imagery. E is a graphical representation of overlapping areas across resolutions.

Figure 5.2 At the center of the image there is an example of fractures with just one edge exposed (A.) and how they were interpreted (B.). This fracture was formed by two edges, but one was likely lost due to weathering.

Figure 5.3 A. Low-resolution, 222 features identified; B. Medium-resolution, 3,449 features identified; C. High-resolution, 1,591 features identified.

Figure 5.4 Topology characterized at the three resolutions of interest. Low-resolution is the most disjointed one, with it gradually increasing at medium- and high-resolution. Low-resolution shows 74% isolated nodes (I), medium has 60% (I), and high-resolution records 57% (I). Connectivity increases with resolution.

Figure 5.5 Comparative analysis of fracture networks across different resolutions. A) High-resolution displays consistent feature detection across datasets. B) Medium-resolution shows potential false positives and missing connections. C) Low-resolution mostly lacks visible features, indicating limited detail capture.

Figure 5.6 Intensity maps for low (5A) and medium (5B) resolution imagery. While 5A presents low intensities (0-0.6 F/m), 5B shows a broader range (0.2-2 F/m). Despite differences in fracture counts, both show heightened intensities in the northeast and south regions of the exposure.

Figure 5.7 Fracture orientations across varying resolutions: high (A), medium (B), and low (C). All datasets consistently show dominant N-S, NE-SW, and NW-SE trends.

Figure 5.8 A and C show medium-resolution imagery, displaying a lower degree of interaction and complexity compared to B, and D, which feature high-resolution imagery, where the network is clearly more complex and interconnected.

Figure 5.9 Intersection angles at high resolution (A) measured at 67°, compared to 65° at medium resolution (B). Several features present at high resolution are absent at medium resolution.

Figure 5.10 A. and B Fractures observed at medium and high resolution, respectively, together with segments used to measure surface fracture width. The red arrow points to the same feature interpreted at both medium and high resolution, appearing continuous at medium resolution but revealed as multiple merging fractures at high resolution. C. shows how length varies across the different datasets.

Figure 5.11 Lognormal distribution of fracture lengths across different resolutions. A and B show low-resolution imagery, C and D medium-resolution, E and F high-resolution, G and H field data. The plots show a close alignment with the 95% confidence interval of a lognormal distribution, particularly evident as the fracture lengths approach the Y-axis, indicating shorter fractures are more commonly detected at higher resolutions. Probability plots confirm the expected distribution of lengths, underscoring the consistency and reliability of the data.

Figure 5.12 Comparison of average lengths, intensity, and density for medium- and low-resolution imagery. Medium-resolution generally shows larger ranges in length and higher intensity and density values compared to low-resolution, suggesting that features are better represented in medium-resolution compared to low-resolution.

Figure 5.13 Comparison of lengths, intensities, and densities between medium and high-resolution images. Medium-resolution shows a wider spread in length (e.g., 0.44m-2.2m) than high-resolution (e.g., 0.41m-1.1m). High-resolution has higher values for intensity and density, showing it captures more details.

Figure 6.1 (A) Location map of the general area of investigation (EF89-32N), together with the MTFC. (B) Simplified Geological map of the island of Hitra and Froya, with two faults belonging to the Møre-Trøndelag Fault Complex (dashed red lines). Highlighted to the left are the areas of investigation, which cover mostly granite, and tonalite.

Figure 6.2 Maps showing fracture patterns traced in the western region of Hitra Island at different scales and interpretations using RGB images. (A) Overview map at 1:55,000 scale showing general fracture orientations. (B–D) Detailed zoom-ins of selected areas, highlighting differences in fracture orientations and densities.

Figure 6.3 Fracture intensity maps (m/m^2) for all areas of investigation, showing how fracture intensity varies across different scales. 3A. intensity for regional-scale features. Intensity is highest in the southwestern part of the island; 3B. Intensity for local-scale features, showing clusters of high fracture intensity, juxtaposed with

patches of lower intensity, attributed to vegetated areas; 3C. Intensity for outcrop-scale features (West outcrop), which are generally quite low across the exposure; 3D Intensity for outcrop-scale features (East outcrop), showing patches of high and moderate fracture intensity.

Figure 6.4 Four rose diagrams showing fracture orientation distributions at different scales: (A) 320 fractures ranging from 34 m to 14 km, showing orientations ENE-WSW and NE-SW; (B) 3,124 fractures ranging from 1.35 m to over 3,000 m, confirming similar orientations; (C) and (D) 3,490 and 1,423 fractures respectively, with lengths ranging from 0.07 m to ~65 m, highlighting dominant fracture sets.

Figure 6.5 Length-weighted spatial variability of fracture orientation. The shift toward ENE-WSW is clearly visible.

Figure 6.6 The triangular plot shows the distribution of I, Y, and X nodes for regional-, local- and outcrop-scale features. For outcrop-scale features I nodes dominate due to fractures terminating without intersections, often attributed to exposure or resolution limits. For local scale, I nodes decrease, and Y nodes increase to ~32%. For regional scale features, I nodes further decrease, Y nodes become most prevalent, and X nodes increase slightly, indicating improved traceability and interaction of fractures at larger scales.

Figure 6.7 Shear zone that is hypothesized to affect the area between the three dashed red lines. The dashed red lines mark a distinct ENE/WSW-oriented shear zone where fractures are consistently NE/SW, indicating dextral movement. The gradual change in fracture orientation from NE/SW to ESE/WNW toward the MTFC suggests stress field rotation and adaptation to sinistral movement. The ESE/WNW orientations near the MTFC show the effect of the fault zone's sinistral movement on the region.

Figure 6.8 (A) Low-resolution aerial imagery of the area with no fractures traced. (B) The same area with interpreted fractures and inferred fault planes (based on visible offsets and alignments), suggesting eastward displacement consistent with local left-lateral shear movements in later stages of the MTFC. (C) A view just east of areas A and B, where additional signs of fracture displacement are observed.

Figure 6.9 Fractures selected for relative-age analysis to determine the chronological sequence of fracture formation.

Figure 6.10 Cumulative distributions of length for the three resolutions of interest.

Figure 7.1 Qualitative radar (spider) plot comparing manual fracture extraction vs. two automated approaches. Each axis ranges from 0% (lowest) to 100% (highest). The plot highlights how automated approaches rank highly in reproducibility but require

careful parameter tuning to achieve high reliability. Manual approaches score lower in reproducibility yet can be quite reliable, especially when guided by expert insight.

Figure 7.2 Example of feature being interrupted by a vegetated patch, which brings uncertainty and bias to the interpretation

Figure 7.3 A. Fractures seen at high-resolution; B. Fractures traced manually; C. Granularity of high-resolution imagery posing problems for correct identification of fracture connections.

List of Tables

Table 3.1 Entries used for WebODM parameterization.

Table 4.1 Image properties for each locality used in the study.

Table 4.2 Parameters used in the different ensembles of the Shearlet Method for extracting features.

Table 4.3 Parameters used for extracting networks automatically via ImageJ.

Table 4.4 Table of properties of networks extracted automatically with the shearlet method

Table 4.5 Table of properties of networks extracted automatically with the binarization method.

Table 5.1 Parameters and criteria for fracture identification and tracing in high, medium, and low-resolution imagery, including guidelines for merging, snapping, and setting zoom levels.

Table 5.2 The table presents surface width measured for four features in common between medium- and high-resolution imagery. Measurements were taken at 20%, 50%, and 80% of feature lengths in both medium- and high-resolution imagery. Measurements vary across features, with high-resolution imagery capturing a broader range of aperture values for selected features compared to medium-resolution.

Table 6.1 Criteria followed for manual fracture tracing across all scales.

Table 6.2 Younging table summarizing relative age relationships among fracture sets. "+" indicates a younger fracture, "-" an older one, "o" an unconfirmed relationship, and "Ø" no observed relationship.

Table 7.1 Proposed workflow for automated contrast-based fracture extraction, summarizing key steps and considerations to enhance reliability and reproducibility of fracture network interpretations.

List of Abbreviations

Px: Pixels

UAV: Unmanned Aerial Vehicle

LiDAR: light detection and ranging

GIS: Geographic Information Systems

DEM: Digital Elevation Model

DSM: Digital Surface Model

DTM: Digital Terrain Model

DFN: Discrete Fracture Network

VTOL: Vertical Take Off and Landing

RGB: Red, Green and Blue

GSD: Ground Sampling Distance

Hahog: Hessian Affine Harris Oriented Gradient

RMSE: Root Mean Square Error

CDF: Cumulative Distribution Function

MTFC: Møre–Trøndelag Fault Complex

CNN: Convoluted Neural Network

Chapter 1 Introduction

1.1 Fracture Interpretation from Imagery

One of the most significant applications of modern imaging techniques is in the detailed mapping and analysis of fracture networks within geological formations. Fractures in geological formations are mechanical breaks or discontinuities that separate a rock body into two or more parts (Gudmundsson, 2011). These features are the most common outcrop-scale structures in the Earth's crust (Gudmundsson, 2011) and play crucial roles in various geological processes and applications. For instance, they control fluid flow in hydrocarbon reservoirs and aquifers (Sarkar et al., 2004), which has a considerable impact on resource extraction and groundwater management (Bratton et al., 2006). Fractures also have implications in the mining and civil engineering sectors, specifically they play a crucial role in slope safety and stability, tunneling, and foundations (Hoek and Bray, 1981). Fracture mapping has historically been an activity that is strongly reliant on fieldwork (e.g., Agosta et al., 2010; Narr and Suppe, 1991; Olkiewicz, 1979), where geologists manually study fractures, faults, and other geological structures directly in the field using established surveying methods (e.g., Watkins et al., 2015). These methods often involve detailed measurements of fracture orientations, spacings, lengths, and topology. Fieldwork provides critical ground-truth data that are essential for understanding the geological history of an area, the mechanical properties of rocks, and potential resource exploration or hazard assessments. Traditional fieldwork-based fracture mapping is often time-consuming, labor, financially intensive, and limited by accessibility issues in remote or hazardous areas. This limitation is however being addressed by the development of new technologies, such as remote sensing, drone surveys, and digital mapping tools, which have started to transform this practice. These technologies

allow for the collection of high-resolution data (< 2 cm) over large areas more efficiently and safely, reducing the reliance on direct field observations. Structural geology, and fracture mapping specifically, has benefited greatly from remote sensing (Mwaniki et al., 2015).

There are three different types of fractures: mode I (tensile fractures), mode II (shear fractures), and mode III (tearing fractures) (Figure 1.1).

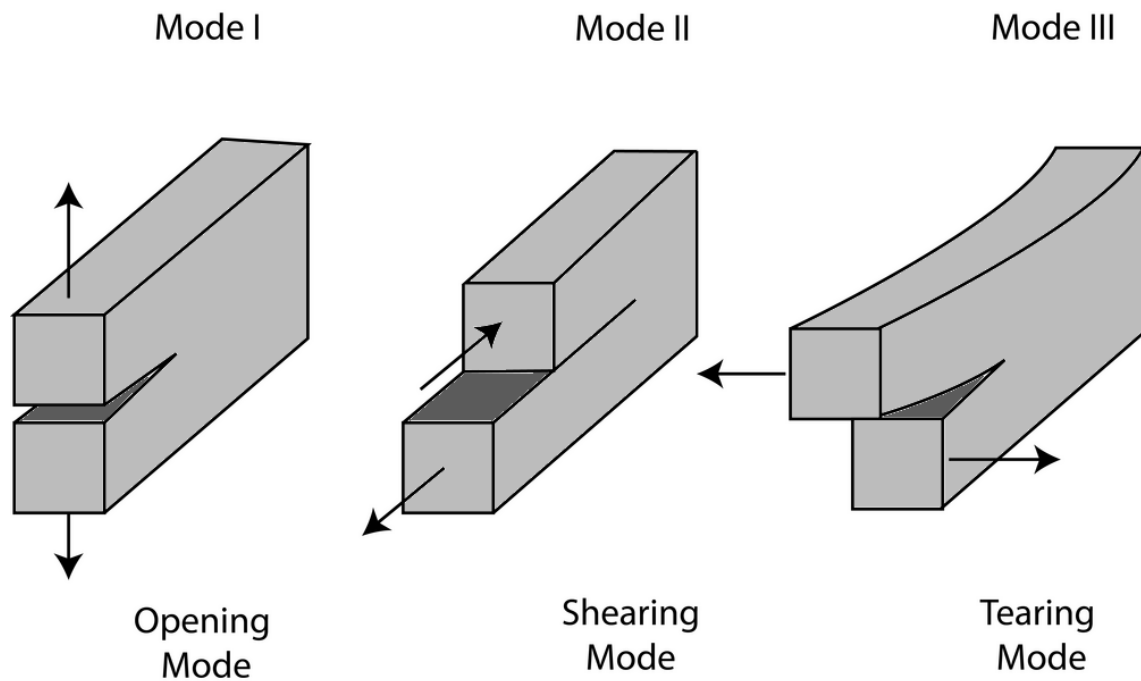


Figure 1.1 Illustration of the three fracture modes: Mode I – Tensile; Mode II – Shearing fractures; Mode III – Tearing fractures (Rountree et al., 2002)

Mode I fractures, also known as joints, are characterized by the rock being extended perpendicularly to the fracture surface due to tensile stress (Twiss and Moores, 2007). These fractures form when the tensile stress exceeds the tensile strength of the rock (Dutler et al., 2018), causing it to crack open. Mode I fractures are typically planar and can occur on a variety of scales, from microscopic cracks to large joint systems visible in outcrops (Bonnet et al., 2001). They are important in geological studies because they often act as pathways for fluid flow, also impacting rock strengths (Bonnet et al.,

2001). Mode II fractures, also known as shear fractures, occur due to shear stress acting parallel to the fracture surface (Twiss and Moores, 2007). This causes lateral displacement along the fracture plane. Shear fractures are characterized by a rough surface texture and can also occur on various scales (Biswas et al., 2023). They often occur in conjunction with mode I fractures, contributing to the complexity of fracture networks (Atkinson, 1987). Mode III fractures, also referred to as tearing fractures, instead are formed due to tearing or twisting stress, causing displacement parallel to the fracture front (Twiss and Moores, 2007). These fractures are less common than mode I and mode II but are significant in the context of complex stress fields and rock deformation. The different modes of fractures provide insights into the stress conditions of the geological region where they form. Mode I fractures indicate areas subjected to tensile stress, where the rock is separated into upper and lower surfaces (Feng et al., 2019). These tensile stresses can result from various geological processes, including tectonic plate movements, thermal expansion, and fluid pressures. Mode II fractures reveal the presence of shear stress, where rocks experience sliding or lateral displacement (Ghamgosar and Doğan, 2015). This type of stress is often associated with faulting and tectonic shearing processes (Bonnet et al., 2001). Mode III fractures, on the other hand, suggest areas experiencing out-of-plane shear stresses.

Regions experience changes in stress regimes over long periods of time, which leads to the development of fractures. These fractures are usually grouped up by sets, which are often divided based on timing and/or geological events. For example, an area may first be subjected to stress with a specific orientation, resulting in the formation of fractures labeled as Set 1. Changes in tectonic conditions can later introduce a new stress orientation, forming another set of fractures (Set 2) with a different orientation. These different sets can be identified through orientation

changes, cross-cutting relationships, and carbon dating, which allows geologists to establish the relative timing and sequence of geological events. These multiple fracture sets can interact, creating complex networks with various topological connections (Gillespie et al., 1993). The greater the interconnection of fractures from different sets, the higher the permeability of the host rock (Sibson, 1996), especially in crystalline rocks (Berkowitz, 2002). This interconnectedness is crucial for the migration of groundwater, hydrocarbons, and hydrothermal fluids. Fractures can evolve and grow over time through mechanisms such as coalescence, where smaller fractures link up to form larger, more continuous fractures (McBeck et al., 2020). This process can occur due to continued stress application, leading to the extension and interconnection of existing fractures. As fractures coalesce, they create more extensive and integrated networks, which can significantly impact the mechanical and hydraulic properties of the rock mass (e.g., Wang, 2019). Coalescence is a critical process in the evolution of fracture systems, influencing the overall permeability of geological formations.

Understanding how fractures from different sets connect is key, as it may influence the ability of fluid to flow through a rock (Alvarez et al., 2021). Topology refers to the connectivity and spatial arrangement of fractures (Sanderson and Nixon, 2015). Understanding the topology of fracture networks not only is crucial for determining how fluids move through the rock mass, but it also contributes to understanding how rocks respond to stress. Conversely, poor connectivity can impede fluid movement, affecting resource extraction and waste disposal. The topology of fracture networks influences the mechanical behavior of the rock mass. Well-connected fracture networks can weaken the rock, making it more susceptible to deformation and failure under stress. This has implications for the stability of slopes, tunnels, and other engineering structures. Understanding fracture topology is also vital for environment

protection purposes, as it plays a crucial role in predicting the movement of contaminants and designing effective remediation strategies (National Research Council, 1996).

Fractures can form through various processes, such as lithostatic and tectonic stresses (mode I), thermal stresses from cooling and contraction of igneous rocks (mode I), high fluid pressures (mode I and II), and fluid erosion (mode II and III) (Jinghong et al., 2011; Zhou et al., 2023).

1.1.1 Remote Sensing in structural geology

Advances in remote sensing and imaging technologies have revolutionized mapping, allowing for the analysis of larger areas with greater efficiency and accuracy (Nex and Remondino, 2014). Aerial photography provided a new perspective, allowing geologists to map large areas more accurately and efficiently than ground-based methods (Hansman and Ring, 2019). This method made it easier to identify large-scale geological structures including folds, fractures, and fault lines. The introduction of photogrammetry further enhanced these capabilities, which allowed for the creation of three-dimensional models from two-dimensional images, which allowed for even more detailed and accurate geological interpretations (Wolf and Dewitt, 2000).

The advent of satellite imagery in the late 20th century marked a significant milestone in geological imaging (Gupta, 2017). Satellites equipped with multispectral and hyperspectral sensors provided data across various wavelengths, allowing geologists to analyze surface composition, vegetation cover, and mineralogy from space (Sabins, 1999). This development opened new avenues for remote sensing in geology, providing comprehensive coverage and the ability to monitor changes over time. The integration of Geographic Information Systems (GIS) with remote sensing data has enabled the computer-based characterization of large datasets, allowing them to be

stored, manipulated, and visualized using GIS. This has facilitated complex spatial analyses and the production of detailed geological maps (Burrough et al., 2015). The combination of GIS and remote sensing provided a powerful tool for geological research, improving the acquisition process of various data types and the development of predictive models. In recent decades, the use of UAVs has further revolutionized geological imaging. UAVs equipped with high-resolution cameras offer unparalleled detail and accessibility to difficult-to-access areas (Figure 1.2).



Figure 1.2 Picture of a DJI Phantom 4 (RTK) equipped with a high-resolution camera

Drones can quickly cover vast, frequently inaccessible areas, and they can provide high-resolution imagery that increases the accuracy and thoroughness of geological surveys (Nex and Remondino, 2014).

Fracture mapping has become increasingly important, especially for applications such as resource extraction, geological storage, and environmental management. Advanced imaging technologies, such as UAV-based photogrammetry, LiDAR, and high-resolution satellite imagery, provide the necessary data to accurately map and

analyze these fracture networks. By using data from LiDAR or photogrammetry it is possible to generate DEMs (Digital Elevation Model), which represent the shape of the bare ground. There are two kinds of DEMs: DTMs (Digital Terrain Model) which represent the bare ground surface without any objects like vegetation or buildings, and DSMs (Digital Surface Model) which include all surface features and objects on the ground (Brovelli et al., 2004). DTMs, by providing a clean, unobstructed view of the ground surface, are particularly useful for geological applications where the presence of vegetation or man-made structures could obscure key features such as fault lines or subtle topographical discrepancies indicative of underlying structures. DTMs are often described as 2.5D because they represent terrain as a 2D surface embedded in 3D space, where each (x, y) location has a single height (z). This approach, used in GIS software, limits the representation of real-world features like vertical surfaces, overhangs, and caves. Essentially, while they offer an x and y coordinate for every point, they only provide one z-value (elevation) for each of these points, which is why they are not considered fully three-dimensional (Weibel, 1993). The improving imaging technologies have also helped with the development of automated methods for fracture extraction and analysis. Machine learning algorithms and computer vision techniques are increasingly being used to automate the detection and mapping of fractures from high-resolution images. These methods can process large datasets quickly and accurately, reducing the time and effort required for manual mapping (Faiq Adenan et al., 2024). One of the primary research questions in this study is the reliability and robustness of automated fracture extraction methods when applied to imagery with different resolutions. These techniques aim to reduce the time-consuming and laborious aspects of manual mapping, offering a quicker and more efficient option that also minimizes human bias (Prabhakaran et al., 2019). However, the effectiveness of these automated

methods can vary depending on the resolution and quality of the input data. UAV-captured high-resolution images have the potential to improve the precision of these automated methods by identifying smaller fracture features, which are essential for thorough geological analyses. The resolution of imagery, in fact, significantly impacts the interpretation of fault and fracture networks (Prabhakaran et al., 2019). High-resolution images provide more detailed information about fracture apertures, lengths, and orientations, which are essential for accurate geological modeling. Lower-resolution images may censor these details as below detection limits, leading to less accurate interpretations.

1.1.2 Interpretation Methods

Fractures from imagery can be interpreted in three different ways, each of which has its strengths and weaknesses: 1) Traditional manual approaches, where it is the expert that interprets fractures from imagery, completely relying on their experience and knowledge throughout the process. The biggest advantage that this method has is the fact that it has the potential to be the one with the highest precision and accuracy, however, the biggest limitation of this approach is its inherent subjectivity, which implies problems from a point of view of reproducibility and reliability; 2) Semi-automated approaches, which combine human expertise with computational tools, and has started being adopted for 2.5D and 3D datasets (e.g. (Thiele et al., 2017; Vasuki et al., 2014)). These approaches use the least-cost-path algorithm and interpolate structural features between manually defined control points in the cloud point and raster data. These approaches have the potential to improve reproducibility compared to fully manual methods, as the computational tools provide a more consistent framework for identifying fractures. However, they still face some reproducibility challenges because they require the expert to manually pinpoint the beginning and end of the fracture. 3) Fully automated approaches have

only recently appeared in the world of science, and extract entirely based on algorithms. In this research, two contrast-based approaches are used. These approaches have the ability to process large datasets in a very time-effective way. The results produced using these approaches are highly reproducible; however, their reliability has not been effectively quantified.

1.1.3 Reliability and Reproducibility

Whether performed manually or automatically, fracture tracing from imagery has become a standard in the scientific community. However, there is an ongoing concern about the reproducibility and reproducibility of scientific results. In recent years, more attention has been given to issues of reproducibility, including data availability, across various scientific disciplines (Ireland et al., 2022). The concepts of reliability and reproducibility are very important as they are indicators of how good results are. Specifically, reliability refers to the consistency of a measure and indicates how accurately a measurement can be replicated using the same dataset but with a different approach or workflow. Reproducibility, on the other hand, involves the ability to exactly replicate a measurement using the same approach or workflow. These two concepts should be the backbone of credible scientific research. Although manual methods have long played vital roles in science, with automated approaches now emerging as newer tools in the scientific world, reliability and reproducibility are often overlooked. Many studies do not clearly state the parameters followed for taking measurements, and they often fail to make the datasets and software used for measurements and analyses available. This omission represents a significant limitation, as it outright removes the possibility of reproducing the results (Andrews et al., 2019; Ireland et al., 2022). Additionally, there is a "paywall" effect as much of the software used for measurements and analyses in scientific research is often

subscription-based or requires a one-off payment for access. Moreover, many scientific articles fail to specify the software used in the research (Figure 1.3).

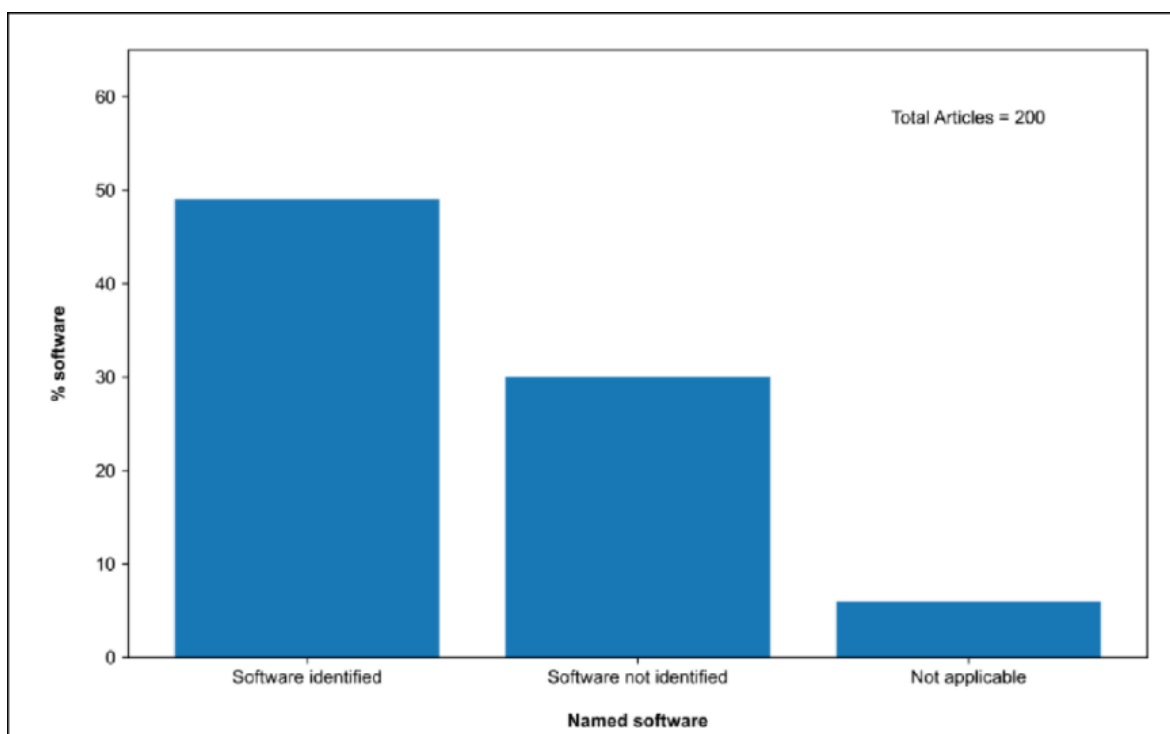


Figure 1.3 Chart showing the percentage of scientific articles where software is identified, not identified, or where software is potentially not applicable (e.g., review articles)

All this further restricts reproducibility, as it limits access to the necessary tools and resources needed to reproduce and verify results. Furthermore, reliability is particularly problematic with automated methods. Until specific studies were carried out in this thesis, there has not been an established method to objectively measure the reliability of measurements made using automated techniques. It is important to emphasize that this observation is not intended to undermine the valuable research conducted so far. However, these properties, reliability, and reproducibility, are the backbone of credible science, and at the current state of things, they are often overlooked.

1.1.4 Applications of Fracture Analysis

Fracture analyses have many applications in the industry. In hydrogeology, fractures control the movement and storage of groundwater (Zhou et al., 2023). For instance, the productivity of aquifers in fractured rocks depends largely on the density and connectivity of the fractures (Maréchal et al., 2004). In petroleum geology, fractures can significantly impact hydrocarbon reservoirs (Bratton et al., 2006). Fractured reservoirs are often more productive because the fractures provide pathways for oil and gas to migrate towards production wells (Bratton et al., 2006). Accurate characterization of fracture networks in these reservoirs can lead to more efficient extraction techniques and improved recovery rates (Kharrat and Ott, 2023). In mining, understanding the distribution and properties of fractures is crucial for both resource extraction and safety. Fractures can control the stability of mine walls and roofs, and their presence can either facilitate or hinder mining operations (Bai and Tu, 2019). Similarly, in civil engineering, fractures in rocks can affect the stability of foundations, tunnels, and other structures (Wang, 2019). Knowledge of fracture networks can help engineers design safer and more efficient structures by predicting potential failure zones and optimizing excavation methods. Environmental geology also benefits from the study of fracture networks, particularly in understanding and mitigating the movement of contaminants through fractured rocks. Contaminants can travel quickly along fractures, posing a risk to groundwater resources and requiring careful management to protect the environment (Odling and Roden, 1997). In addition to contaminant transport, fractures influence the storage and migration of radioactive waste. Geological repositories for radioactive waste rely on the integrity of host rocks to isolate waste from the biosphere. Fractures in these rocks can compromise the repository's safety by providing pathways for radionuclide migration (Vandergraaf et al., 1997). Detailed fracture mapping and understanding of fracture properties are

crucial for assessing the suitability of potential repository sites and ensuring long-term containment (Seetharam et al., 2014). Fracture networks also play a role in carbon sequestration efforts, where CO₂ is injected into deep geological formations for long-term storage. The success of carbon sequestration projects depends on the ability to predict and manage the movement of CO₂ within the storage formation, which is influenced by the presence and characteristics of fractures (Iding and Ringrose, 2010). High-resolution imaging and modeling of fracture networks help in evaluating the storage capacity, leakage risks, and overall feasibility of sequestration sites (Rizzo et al., 2024). Moreover, fracture studies contribute to geothermal energy extraction by enhancing the permeability of geothermal reservoirs. Fractures facilitate the circulation of water through hot rock, improving heat transfer and increasing the efficiency of geothermal energy production (Cao and Sharma, 2023). Characterizing properties of fractures such as density, orientation, and connectivity, is essential for optimizing geothermal well placement and maximizing energy extraction (Cao and Sharma, 2023).

Overall, the study of fracture networks is integral to various geological and engineering applications, influencing the management of natural resources, mitigation of environmental hazards, and development of sustainable energy solutions. By interpreting fractures from imagery, geologists can gain valuable insights into the structural integrity and behavior of geological formations. This knowledge is essential for informed decision-making in fields such as resource management, environmental protection, and engineering, ultimately contributing to safer and more sustainable practices.

1.2 Aims, Objectives and Scope of This Research

1.2.1 Research Questions

This research seeks to address several key questions fundamental to the understanding and characterization of geological fracture networks using advanced imaging techniques:

- 1) How reliable and robust are automated fracture extraction methods when applied to decimeter resolution aerial imagery, and how do different methods compare in terms of accuracy and efficiency in detecting and characterizing fracture patterns?
- 2) What are the effects of varying imaging resolutions on the interpretation of fault and fracture networks in granitic rocks?
- 3) How do the spatial and resolution-dependent variability of fracture networks affect the interpretation of geology?

1.2.2 Research Aims and Objectives

The primary aim of this research is to enhance the understanding and characterization of fracture networks in geological formations using advanced imaging techniques and automated extraction methods. This will be achieved with the following specific objectives:

- 1) Using Complex Shearlet Transform and Binary Thresholding Method for extracting features from decimeter resolution aerial imagery to quantify reliability and reproducibility of automatically extracted fracture networks.
- 2) Conduct a comparative analysis of fracture networks extracted manually using a dataset with different resolutions (20 cm/px, 2cm/px, 0.2cm/px) to quantify the amount of information being lost when investigating at certain resolutions.
- 3) Analyze the variability in fracture network properties across different scales and resolutions.

- 4) Multiscale fracture investigation for characterizing geology from regional to outcrop scales, while assessing the impact of spatial and resolution-dependent variability on the interpretation of regional geology, connectivity, and overall network characteristics.

1.3 Thesis Structure and Chapters Outline

Chapter 2 reviews the evolution of manual and automated fracture interpretation techniques in geology, highlighting advancements in imaging technologies and identifying key limitations in current methods, particularly concerning reproducibility, reliability, and the impact of image resolution.

Chapter 3 explains the reasoning behind selecting study areas, acquiring data, and analyzing fracture networks. It describes the basic principles behind both manual and automated fracture extraction techniques, and also outlines how imaging resolution influences the accuracy and reliability of measurements. The chapter also summarizes the geological settings of the study sites and how data was processed.

Chapters 4, 5, and 6 represent the three research chapters and have been written as scientific publications. Each chapter is ready for review in peer-reviewed journals. Each chapter comes with the following sections: Introduction, Data and Methodology, Results and Observations, Discussion, Conclusions, and all address the research question and aims.

Chapter 4 is the first research chapter, and investigates the reliability of currently available contrast-based automated approaches for extracting fracture networks from imagery and the reproducibility of their results. The work is titled *“Reliability of*

Contrast-Based Automated Fracture Detection from Decimeter Resolution Aerial Imagery" and is planning to be published in the Journal of Computers and Geosciences. I estimate that ~85% of the manuscript is my own work, while my supervisors Ireland and Davie contributed mostly with corrections, comments, and some edits that helped me refine my work.

Chapter 5 explores the impact of varying image resolutions on fracture network characterization using a multiscale approach. It quantifies the information loss at different resolutions by analyzing the physical and network properties of fractures, such as length, orientation, density, intensity, and topology. The work is titled *"Quantifying Differences Between Fracture Networks Characterized on Different Resolution Datasets"* and like for Chapter 5, is also planned to be published in the Journal of Computers and Geosciences. Here too, ~90% of the manuscript is my own work, while my supervisors Ireland and Davie contributed mostly with corrections, comments, and some edits that helped me refine my work.

Chapter 6 investigates the fracture patterns in the granites of west Hitra Island using aerial and drone imagery at three different scales, focusing on the deformation styles linked to the tectonic history of the Norwegian passive margin. The work is titled *"Characterization of the Deformation Patterns in the Granitic Rocks of Hitra: A Multiscale Analysis"*. Like the previous two papers, ~90% of the manuscript is my own work, while my supervisors Ireland and Davie contributed mostly with corrections, comments, and some edits that helped me refine my work.

Chapter 7 is the culmination of this thesis, and brings together the conclusions from Chapters 4, 5, and 6, showing how they collectively address the research aims and questions.

Chapter 2 Literature Review

2.1 Introduction

This section outlines the critical role of both manual and automated fracture interpretation techniques in geological studies. It delves into the historical context and limitations of traditional manual approaches. Furthermore, it discusses the evolution and innovations brought about by advanced imaging technologies, such as drone-based photogrammetry, and high-resolution orthoimagery, which have significantly enhanced the precision and scalability of fracture network analysis.

Multiscale approaches for characterizing fractures play a crucial role in geology by enabling the understanding of the spatial variability of fracture networks (Chabani, 2021). By analyzing fractures at different scales, such as long regional fractures and local-scale networks (under tens of meters) (e.g., Bertrand et al., 2015; Tartaglia et al., 2022), geologists can better comprehend how these features interact and compare across various spatial extents. The field of remote sensing has recently witnessed major innovations that have been translated to Earth science applications (Booyesen et al., 2019). When adopting imagery for geological characterization of sites, the extent to which resolution at each scale of investigation affects geological interpretation remains unclear, representing a major gap in the literature. While it is known that resolution impacts the objectivity of an investigation (D. Peacock et al., 2019; Weismüller et al., 2020), the specific ways this influences broader geological investigations and geological understanding need further exploration. Understanding how different resolutions affect the interpretation of geological features is crucial for accurate and reliable geological assessments.

The section identifies key gaps in current literature, particularly concerning the reliability and reproducibility of automated methods and the impact of resolution on geological interpretations. It also highlights the importance of multiscale approaches in understanding the spatial variability of fracture networks, thereby emphasizing the need for comprehensive studies that integrate various imaging techniques to improve geological assessments and applications in geoenergy.

2.2 Manual and Automated Fracture Interpretation

2.2.1 Fracture Networks and Outcrop Studies

Fractures and fracture networks are the result of brittle deformation in geological formations (Twiss and Moores, 2007), and a fracture network is formed when fractures that are arranged spatially interact with each other (Peacock et al., 2018). Fractures with similar properties (fracture type, mineral filling, etc.), and with specific ranges of orientations, are usually grouped into sets (Peacock et al., 2018). As previously mentioned, understanding fracture networks is essential for various applications, from geology to engineering. For instance, in geothermal energy exploration, fractures facilitate the circulation of geothermal fluids, affecting heat extraction efficiency (e.g., Siratovich et al., 2015). Moreover, fractures also play a significant role in geotechnical engineering, where they affect the stability of slopes, tunnels, and foundations (e.g., Bäckblom and Martin, 1999; Hoek and Bray, 1981). Usually, the simplest and most common way to understand fracture networks affecting an area of interest is by studying fractures exposed at an outcrop. Historically, outcrops are fundamental for the characterization of fracture networks (e.g., Harder, 1910; Matson, 1905), since they provide direct access to the geometrical and spatial properties of fractures. Outcrops can serve as natural laboratories since they allow for direct observations of fracture interactions, terminations, and cross-

cutting relationships (e.g., Bonato et al., 2022; Heggernes et al., 2023). However, while outcrop studies provide invaluable data, with a level of detail that is very difficult to match with remote-based analyses, they come with limitations. First of all, outcrops can be very difficult to access, which is why the use of drones is becoming so widespread in geology. Then, outcrop observations are inherently limited to accessible scales, making it very hard to capture the full extent of fracture networks, which might span several orders of magnitude (e.g., Tartaglia et al., 2022; Walter et al., 2022); another limitation of outcrop-based studies is the inherent bias that comes with manual sampling. Data collected from outcrops may be biased due to the selective sampling of well-exposed areas or the preferential measurement of prominent fractures, potentially skewing the statistical representation of the network (Murphy et al., 2023; D. C. Peacock et al., 2019). Additionally, geological campaigns can be very expensive, and financial constraints could further exacerbate this bias. Despite these limitations, outcrops remain invaluable as analogs for subsurface geology (Howell et al., 2014), particularly in the geoenergy sector (e.g., Bowman M. B. J. and Smyth Helen R., 2016). They in fact provide insights into the characteristics of reservoir rocks and fracture networks that would be otherwise inaccessible. Outcrops allow geoscientists to observe and measure geological features at a scale and resolution that inform models of subsurface reservoirs used in hydrocarbon exploration and geothermal energy projects (Bowman M. B. J. and Smyth Helen R., 2016). For instance, carbonate outcrops have been subject of extensive studies to understand how fracture distribution and connectivity impact fluid flow in oil and gas reservoirs (Bratton et al., 2006). Similarly, granitic outcrops serve as analogs for enhanced geothermal systems, where understanding the natural fracture networks is critical for optimizing heat extraction (e.g., Klee et al., 2020). The integration of outcrop data with subsurface geophysical data and numerical models can produce

more accurate predictions of reservoir behavior, while also reducing uncertainty and improving the efficiency of energy extraction processes (Howell et al., 2021). Therefore, outcrops play a crucial role in bridging the gap between surface observations and subsurface applications in energy resource development. Moreover, fracture networks in geological formations are critical pathways for the underground migration of water. The permeability and connectivity of these networks, which can vary significantly based on fracture size, orientation, and density, directly influence the fluid flow patterns within the rock mass (Reeves et al., 2012; Seetharam et al., 2014). Detailed knowledge of these fracture networks is essential in geoenergy to understand how fluids (i.e., geothermal brines) migrate over time (Miranda et al., 2018; Pruess and Narasimhan, 1982) and assess how long plants can operate.

2.2.2 Limitations and Innovations

The analysis of fracture networks in geological formations has long been regarded as a critical element of geology, as it acts as a window into the subsurface and behavior of rock formations (e.g., Sanderson, 2016). Understanding fracture networks is critical for predicting fluid flows, assessing rock stability, and evaluating resource potential in various geological settings, such as hydrocarbon reservoirs, groundwater aquifers, and geothermal systems (Bossennec et al., 2022; Merembayev and Amanbek, 2022). Historically fracture mapping was an activity that was mostly carried out through field-based methods, involving manual observations and measurements of fractures at outcrops (e.g., Olson et al., 1998; Schopf, 1960; Watkins et al., 2015). However, there are major limitations to manual approaches, including: 1) high cost associated with field activity, 2) areal limitations, 3) time-consuming processes, 4) potential to be biased and not reproducible. In recent years, technological advancements in imaging

have revolutionized fracture analysis, enabling more precise and detailed remote characterization of fracture networks (e.g., Booysen et al., 2021; Tartaglia et al., 2022; Zimik et al., 2023). High-resolution imaging techniques, such as drone-based photogrammetry, LiDAR, and high-resolution orthoimagery, have enabled geologists to capture and analyze fractures at various scales with greater accuracy (Bistacchi et al., 2015). The resolution of world imagery now mostly ranges between 20 to 50 cm (Toth and Józków, 2016; Trollvik, 2014), providing consistently high-quality data for various applications. Fracture interpretation from imagery has a long history in geological studies. It has become of vital importance in geological studies, particularly for analyzing fracture networks in regions that are difficult to access. Such interpretations can be carried out from datasets like orthoimagery (satellite and aerial), or photogrammetric models (e.g., Tartaglia et al., 2022; Uotinen et al., 2020). The interpretation of fractures from imagery allows geologists to gain insights into the geometry, orientation, and connectivity of fracture networks across large-scale areas. Manual fracture tracing can produce very reliable results at the expense of time (Weismüller et al., 2020) and reproducibility (Andrews et al., 2019). Although remote sensing technology is enabling ultra-high-resolution imagery (Singh and Hoskere, 2023), and is enabling the advancement of remote fracture characterization, fieldwork remains an essential part of geology, and cannot be entirely replaced (Casini et al., 2016). For instance, there are already examples in the literature of scientists performing activities that were once exclusively carried out in the field entirely remotely, using high-resolution imagery and DTMs/3D models. (e.g., Bertrand et al., 2015; Massaro et al., 2024; Tartaglia et al., 2022). In geology, datasets can be categorized into 2D, 2.5D, and 3D, each offering different levels of spatial information. A 2D dataset represents geological features in two dimensions, typically as maps, orthoimagery, or cross-sections. A 2.5D dataset adds limited depth

information, such as elevation, creating a surface model (e.g., Digital Elevation Models). In contrast, 3D datasets provide full volumetric data, capturing length, width, depth, (i.e., 3D seismic, DFN modelling) which allows for detailed analysis of subsurface structures like rock layers and faults. Although fieldwork remains essential for collecting data that is challenging to obtain from 2D, 2.5D, and 3D datasets, such as detailed planes of features near the resolution limit, and for capturing high-resolution imagery, the overall fracture analysis process is becoming increasingly time and cost-efficient (Palamakumbura et al., 2020). This is largely due to the integration of high-resolution cameras with drones and aircrafts, and the optimization of workflows.

Digital or automated feature recognition is a field with roots that extend well beyond geological fracture detection. Early foundations can be traced back to seminal works in image processing and pattern recognition from the 1960s and 1970s (Rosenfeld, 1976). These early studies introduced fundamental concepts in digital image analysis, such as edge detection, region-based segmentation, and pattern classification. Researchers like Haralick and Shapiro (1985) further refined these methodologies, providing comprehensive frameworks for computer vision tasks. They elaborated on morphological and statistical techniques for edge detection and region-based segmentation, as well as texture-based feature extraction. These methods were then picked up and further refined by John F. Canny in 1986, who developed a tool that carries his name. The method applies a noise reduction filter to the image using a Gaussian filter and uses a Sobel operator for gradient calculation, highlighting regions with high spatial derivatives, and non-maximum suppression to refine edges (Canny, 1986). Moreover, it uses double thresholding to classify strong and weak edges, followed by edge tracking by hysteresis to ensure continuity. Another example of the pioneer methods for edge detection is the Laplacian method. The latter detects edges

by first smoothing the image with a Gaussian filter to reduce noise, then applying the Laplacian operator to highlight regions of rapid intensity change. Edges are identified at the zero-crossings of the Laplacian (Torre and Poggio, 1983; Ziou and Tabbone, 1993). While these traditional edge detection methods have long been foundational in image processing, and are valuable for detecting sharp changes in edge gradients (e.g., Ding and Goshtasby, 2001; Mlsna and Rodríguez, 2009), they struggle with boundary recognition and truncation (Figure 2.1), which is the reason why more complex methods such as deep learning methods, and the shearlet method were developed.

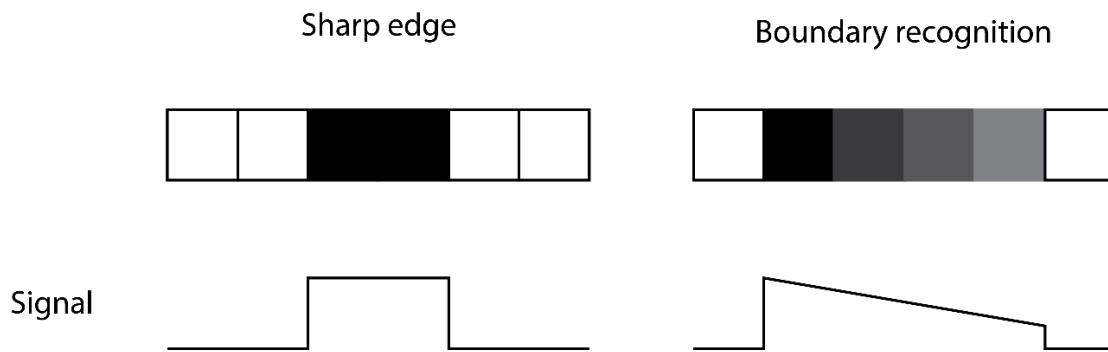


Figure 2.1 Graphical representation of sharp edge (left) and boundary recognition (right).

Over the past decade, several automated and semi-automated fracture tracing techniques have started to emerge in science (e.g., Nhat-Duc et al., 2018; Prabhakaran et al., 2019; Thiele et al., 2017), further enhancing the efficiency and accuracy of geological investigations. Seemingly they set out to solve the three major issues of manual approaches: 1) reproducibility, 2) time efficiency, and 3) bias. In medical imaging, extensive research has evaluated the reliability and accuracy of automated image analysis methods used in computer-aided diagnoses. Studies focus on quantifying algorithm performance using standardized metrics like sensitivity, specificity, and inter-observer agreement, ensuring reproducibility and clinical

reliability (e.g., Litjens et al., 2017). To address this issue, advanced methods incorporating machine learning and contextual information have been developed to improve the accuracy of image-based diagnoses (e.g., Esteva et al., 2017; Litjens et al., 2017). One example is the YOLACT++ segmentation model (Ji et al., 2024), which automates rock fracture detection using a ResNet-101 backbone and deformable convolutional layers (Ji et al., 2025). Unlike contrast-based methods that rely on grayscale intensity differences, YOLACT++ learns fracture patterns from data, making it more adaptable to different levels of lighting and noise. It integrates prototype masks and multi-scale recognition to improve accuracy (Ji et al., 2025).

Validation with benchmark datasets and protocols is common practice in the medical field. However, in geological applications, such systematic assessments of automated fracture extraction methods are non-existent, which highlights a significant gap, as the geological field lacks standardized measures to evaluate the reliability and accuracy of automatically extracted fracture networks from imagery. Moreover, automated methods have typically been tested on high-quality, continuous datasets with minimal noise (e.g., Prabhakaran et al., 2021, 2019; Weismüller et al., 2020). While these conditions help demonstrate the potential of automated approaches, they may not fully address the challenges these methods could face when applied to more complex, real-world geological settings with lower-quality data. Data used for automated approaches usually has very high resolution, in fact, Prabhakaran et al., (2019, 2021) and Weismüller et al., (2020) used imagery that ranged from 0.18mm to 40.1 mm. Automated methods are often tested on high-resolution imagery, but it's not yet fully understood how their performance scales with lower-resolution data. This is a substantial limitation because world imagery currently ranges between 20 to 50 cm in resolution (Toth and Jóźków, 2016; Trollvik, 2014). Another significant limitation of automated methods for fracture trace extraction is their inability to

interpret complex geological features critically, as is possible with manual methods. In manual analyses, geologists can compare their interpretations against the original images to validate whether a fracture terminates or intersects and continues (e.g., Leta et al., 2013), providing the contextual understanding that automated approaches lack unless they incorporate elements of machine learning and training algorithms. This ability to cross-verify and adjust interpretations based on visual confirmation makes manual methods particularly reliable. Automated approaches, on the other hand, are limited to interpreting features without the ability to perform such comparative validation; it is the expert that performs comparative validation on a network that was extracted automatically, reintroducing bias into the analysis.

Another important limitation arises from the inherent differences between surface and subsurface fracture networks. Fractures observed in outcrops at the Earth's surface often experience exhumation or uplift histories distinct from deeper rock layers, frequently resulting in fracture patterns that diverge significantly from subsurface counterparts (Nelson, 1985; Schofield et al., 2021). In addition, near-surface rocks can undergo additional fracturing due to environmental processes (Hynek et al., 2017), such as glacial loading and unloading, which leads to “relaxation” and fracture propagation. Because these processes do not occur at depth, fracture patterns in outcrops may not accurately mirror the conditions of deeper systems. Compounding this issue is the lack of a deterministic “ground truth” for subsurface fractures: direct observations at depth are sparse, and validation often relies on indirect measures, such as matching permeability or fluid pressures. As a result, fracture analyses depend solely on surface-based data to infer deeper geologic structures, there is an unavoidable degree of uncertainty—making it impossible to confirm with complete confidence that the identified fracture patterns accurately characterize the subsurface.

The process of cross-verification is completely absent in contrast-based automated methods, as they are entirely based on colorimetry and pixel values of the image (Lei and Fan, 2024). Usually, contrast-based automated approaches use binary segmentation methods like Otsu thresholding (Balabanian et al., 2017). However, For instance, automated systems often fail to distinguish between actual fractures and environmental elements such as shadows or cliffs, as the quality of an automated extraction is greatly impacted by shadows and lighting conditions (Guo et al., 2018). While human experts can leverage their experience and contextual knowledge to make these distinctions, automated systems rely purely on pixel-level data, which can lead to misinterpretations. After the extraction process, significant postprocessing is required (e.g., Weismüller et al., 2020; Zeng et al., 2020), and most of this is performed by the expert that supervises the operation, leading to the reintroduction of subjectivity and potential biases into the workflow. This involvement of experts in postprocessing reduces the advantages of automated approaches, as the final interpretations are still influenced by individual judgment. Consequently, the reproducibility and objectivity of the automated methods are compromised. Despite their advanced capabilities, these newer automated methods still face challenges in maintaining reliability across different datasets. Deep learning methods, for instance, are highly dependent on the quality of the training data. If the training dataset is poor or biased, the resulting models may be unreliable and fail to generalize well to new or varied geological settings (Chen et al., 2021). Similarly, shearlet-based methods require careful parameterization. The choice of parameters can significantly affect the method's performance, and determining the optimal values is not straightforward, which can limit their applicability across different datasets (Prabhakaran et al., 2019).

Although there are some contrast-invariant automated methods (e.g., Kovessi, 1999; Vasuki et al., 2014), most automated techniques identify contrast in images, specifically, the shadows cast within cracks, or fracture fillings such as vegetation, all based on contrast differences (Ozturk and Saricam, 2017; Prabhakaran et al., 2019), and tend to trace pixels arranged in linear patterns. Despite the abundance of studies on automated methods, there is minimal discussion on how resolution impacts the reliability and reproducibility of fracture networks extracted using these techniques, as well as how parameterization and training data influence their reliability. There is a lack of clarity on the preparatory work users need to undertake prior to adopting automated approaches, such as understanding the dataset requirements and defining the objectives of the analysis. There is also insufficient information on the minimum resolution requirements and the characteristics of fracture sets and images necessary for reliable automated fracture tracing, as the current prevailing assumption generally adheres to the notion that “the higher the resolution, the better” (e.g., Gavazzi et al., 2023; Kanoun et al., 2022; Prabhakaran et al., 2019). Moreover, these methods lack robust benchmarks to assess the reliability and accuracy of fracture extraction across diverse geological environments, which is also a serious limitation. To ensure that the extracted information is reliable, it is crucial to develop a measurement that accurately quantifies the reliability of automated fracture detection methods. Current validation methods predominantly rely on comparisons with manual interpretations, which, despite their inherent biases, are considered the gold standard for accuracy (Jannin et al., 2006).

While the reliability of automated approaches must be established through initial validation—often involving manual cross-checking—this process doesn't need to be repeated exhaustively for every new dataset. Unlike manual interpretations, which inherently carry subjective biases and yet are trusted for their expert judgment,

validated automated methods can consistently produce reliable results without continual manual oversight. Automated approaches are intended to save time and reduce bias (Gavazzi et al., 2023; Zhang et al., 2021), and their efficiency becomes more tangible once they are proven reliable. This implies the need to assure reliability through robust initial validation, thereby enabling their efficient application without extensive ongoing manual validation. As previously mentioned, automated approaches set out to reduce bias, while also improving time efficiency and reproducibility. As stated by Prabhakaran et al. (2019), in order to achieve optimal results using the contrast-based, shearlet-based automated method they developed, “a carefully chosen fractured outcrop that is relatively free of noise” is required. This requirement significantly limits the applicability of the method to only ideal, noise-free conditions, thereby failing to account for the complexities and variabilities present in more typical, real-world geological settings. As a consequence, there is a risk of sampling bias, as highlighted by Zhu et al. (2022), because imagery used for automated fracture extraction is often selected from regions with well-developed fractures and minimal noise, which are preferred for automated sampling. This selective data usage means that the method may not accurately represent fracture networks in more complex or noisy environments.

2.2.3 Reproducibility and Reliability of Geological Investigations

The reproducibility and reliability of geoscience studies have been the focus of recent work (Ireland et al., 2022; Steventon et al., 2022; Tedersoo et al., 2021). The two main issues with manual and automated approaches are their reliability and reproducibility. A reliable interpretation implies that findings are not dependent on the specifics of the programming language, equipment, or methodology used, and similar outcomes are obtained when different workflows are applied to the same

dataset to answer the same research question (Ireland et al., 2022). Manual approaches rely heavily on the expert's judgment and contextual understanding, which can provide detailed and nuanced interpretations of fracture networks. However, studies have shown that these approaches suffer from significant issues with reliability and reproducibility. Andrews et al. (2019) found that different geoscientists interpreting the same dataset often produced varying results, highlighting the inherent subjectivity in manual interpretations. This variability arises because manual methods depend on individual expertise and personal biases, leading to inconsistencies in how fractures are identified and characterized. Consequently, while an individual geoscientist may produce consistent results using their own methods, the lack of standardized procedures makes it difficult to reproduce results across different analysts, compromising the overall reliability of manual approaches. However, the inherent subjectivity of manual approaches makes them hardly reproducible because they rely heavily on the individual expertise and interpretation of the geologist, leading to variations in how fractures are interpreted (Andrews et al., 2019). Fracture network interpretations, whether manual or automated, inevitably involve different forms of uncertainty (Guerriero et al., 2010; Peacock et al., 2019). Two main categories are commonly recognized: parameter uncertainty and model structural uncertainty (Briggs et al., 2012). Parameter uncertainty arises when different parameter choices, such as contrast thresholds, zoom levels, and key imaging properties like resolution and inherent image contrast (Andrews et al., 2019), lead to varying fracture network interpretations from the same dataset. Automated methods that use fixed analytical parameters often produce identical outputs when the same dataset is reprocessed, leading to highly reproducible outcomes. However, when small adjustments in parameters, potentially necessitated by variations in image quality or resolution, cause significant changes in

the interpreted fracture network, the reproducibility of the method is compromised. This uncertainty is considered a subset of the overall interpretation uncertainty since it is directly linked to the sensitivity of the final interpretation to the analytical setup, including how well the image captures the necessary geological detail. Importantly, the properties of the image itself, such as resolution, constitute a form of measurement uncertainty. Lower resolution images may blur fracture edges or lower contrast, thereby affecting the parameterization process. In these cases, experts may need to select different parameter values to compensate for the image limitations, introducing a degree of bias where the “optimal” parameter set is partially determined by subjective expert judgment. While manual interpretations are shaped by human judgment and subjectivity, automated methods are influenced by how parameters are defined, making parameter choices one of the key ways interpretation uncertainty enters automated workflows. Model structural uncertainty (related to reliability) reflects the possibility that the interpreted fracture network itself is incorrect, for instance by missing critical fractures or misrepresenting their connectivity (Weismüller et al., 2020). Even if a method is highly reproducible, its outputs can still be unreliable if they fail to represent the true geological reality. It is useful to distinguish two additional concepts here. Reproducibility denotes producing the same results from the same dataset when identical analysis steps are applied. Reliability concerns whether the method’s interpreted fracture network genuinely captures real-world geological features. The primary goal for geological applications is reliability, since subsurface management or hazard assessments depend on correct fracture interpretations, but reproducibility remains essential to ensure that once a method is validated, it can be applied consistently without repeated manual recalibration (Ireland et al., 2022).

Andrews et al. (2019) found that subjective biases significantly influence data collection, with participants' personal characteristics affecting fracture data. Major fracture sets were consistently identified, but smaller-scale features varied, affecting fracture statistics like trace length and density. This behavior underscores the potential for subjective biases to introduce uncertainty and compromise the reproducibility of geological studies, particularly in manual approaches. Reproducibility, as defined by Ireland et al. (2022) is the consistent production of the same results when identical analysis steps are applied to the same dataset. Structural analysis requires the accurate measurement of features such as lengths and connectivity within fracture networks. However, factors like resolution, geological conditions, exposure, methods, and analyst variability can significantly reduce measurement precision and accuracy, implying that there is also a reduction in the reproducibility, and arguably reliability, of measurements (D. Peacock et al., 2019). Peacock et al. (2019) found that interpreting fractures near image resolution limits severely impacts measurement accuracy. Currently, there are significant gaps in characterizing fractures manually at multiple scales. While high-resolution imagery from drones has revolutionized fracture characterization, the literature lacks comprehensive studies comparing fracture network properties using different resolution data. Specifically, there is insufficient quantitative analysis on how varying image resolutions affect the interpretation of fracture networks, which is crucial for accurate and reliable geological modeling. Most existing studies focus on the benefits of high-resolution data but do not address the challenges and limitations, such as the inability to detect fractures below the resolution limit and the variability introduced by different analysts and methods. These gaps highlight the need for multiscale approaches and more detailed investigations to ensure robust and consistent fracture characterization.

Automated approaches aim to address reproducibility issues by providing consistent and objective workflows (Casini et al., 2016). They rely on predefined algorithms and processing steps, which should theoretically yield the same results when applied to the same dataset (e.g., Chen et al., 2021; Prabhakaran et al., 2019; Vasuki et al., 2014). However, the reliability of these approaches can be compromised by factors such as the quality of input data, the resolution of imagery, and the specific parameters used in the algorithms. Most existing studies focus on the qualitative quality and efficiency aspects of automated approaches, with little concern about their limitations. Addressing these limitations is crucial for understanding the current constraints of automated methods and improving their reliability and reproducibility.

2.3 Image Capture Techniques for Geological Fracture Mapping

Imagery plays a crucial role in fracture mapping, providing detailed visual data essential for analyzing geological features. Image acquisition is a fundamental step that sets the foundation for subsequent image processing and analysis (Schöberl et al., 2009). Light, the primary medium through which we gain information from the environment, is captured by cameras to create images of scenes. This process begins when light photons travel from a source, reflect off objects, and enter the camera through the lens system (Rowlands, 2020). Inside the camera, the lens focuses these incoming light rays onto a photosensitive surface, such as film in analog cameras or an electronic sensor in digital cameras (Physics LibreTexts, 2024). This interaction begins when light photons travel from the source, reflect off objects, and then enter the camera. Here the capture of light and its conversion into imagery occurs through three components: lens, shutter, and image sensor (Physics LibreTexts, 2024). The lens system in a camera is responsible for directing photons towards the image sensor (Rowlands, 2020). By focusing the light, the lens ensures that the reflected

light rays bend to form a clear image. Image sensors then produce an electronic signal in proportion to the light they receive, typically arranged as pixel arrays in two dimensions. These sensors capture images by employing on-chip amplification and analog-to-digital conversion (Jayasuriya, 2021). Image sensors are controlled through electronic shutters. The shutter regulates the duration for which light is allowed to hit the sensor. This exposure time is crucial for determining how much light is captured. Shutter speed (also known as exposure time) controls the length of time for which the sensor of a digital camera is exposed to the incoming light (Simon et al., 2022), influencing the brightness and overall exposure of the image. In cameras with mechanical shutters, the exposure time is determined by two moving shutter curtains, placed in front of the focal plane. However smaller and inexpensive digital cameras nowadays use electronic shutters, with no mechanical parts; here, the light sensor is switched on and off for the time of the exposure (Simon et al., 2022).

The entire process of imagery capture thus revolves around the physics of light, influencing factors such as image clarity, color fidelity, and contrast. Understanding the behavior of light as it interacts with the camera system is essential for optimizing geological imagery and extracting valuable information from it. Light, as electromagnetic radiation exhibits wave-like properties as it propagates through space (Al-Azzawi, 2018). The wavelength of light (measured in nanometers) determines its color, with shorter wavelengths corresponding to blue and violet tones, and longer wavelengths associated with red and orange (Nassau, 1980). The nature of light, however, can be altered by optical materials, which can absorb, reflect, or transmit light (Al-Azzawi, 2018). In the context of geological imagery, the spectral sensitivity of the camera sensor, for example, influences its ability to detect and record different wavelengths of light, which influences the color reproduction and

spectral accuracy of the captured images. As stated by Akkaynak et al., (2014), the intensity recorded at a sensor is a function of the light that illuminates the object of interest, the light that is reflected from the object toward the sensor, the spectral sensitivity of the sensor, and optics of the camera. The interaction of light with the camera lens is governed by principles of geometric optics. Geometrical optics use rays to represent the propagation of light as it traces paths through the optical system (Rowlands, 2020). The bending of these rays, critical for focusing and image clarity, is governed by Fermat's principle, which suggests that light rays will opt for a path between two points that is a minimum with respect to adjacent hypothetical paths (Jenkins and White, 1976). If a light ray travels more slowly in one medium compared to another, the quickest path may result in a change of direction. This bending phenomenon of light is known as refraction.

Refraction is mainly caused by the density difference between two contacting media and occurs when a light ray passes the interface plane (Kwon and Casebolt, 2006). The extent of refraction depends on the media involved. For example, when light passes from air into the glass of a camera lens, the extent of refraction depends on both the difference in refractive indices of the media and the angle of incidence of the light ray (Kwon, 1999). Snell's law states that the ratio of the refractive index of each of the media is proportional to the ratio of the incident and refractive angle of the light ray:

$$\frac{n_1}{n_2} = \frac{\sin \beta}{\sin \alpha} \quad [2.1]$$

Where n_1 is the incident light, n_2 is the refracted light, α is the incident angle and β is the refracted angle.

The camera lens employs the principles of refraction to make light rays converge at a specific point on the camera's image sensor, the focal point. Focusing involves adjusting the distance between the lens and the sensor, allowing for the precise alignment of the focal point with the sensor plane (Krotkov, 1988).

The behavior of light, however, is also influenced by the surrounding environment, including atmospheric conditions, surface properties, and illumination angles. Atmospheric scattering, for example, causes light to scatter in all directions as it passes through the Earth's atmosphere. The sunlight entering the atmosphere is scattered or absorbed by air molecules, aerosol, and ozone layers (Nishita et al., 1993). The characteristics of scattering depend on the size of particles in the atmosphere: scattering by small particles such as air molecules is called Rayleigh scattering and causes distant objects to appear hazier and less saturated, while scattering by aerosols such as dust is called Mie scattering and affects all wavelengths more equally (Nishita et al., 1993). Any interaction with the processes of reflection, transmission, or scattering can induce polarization (Goldstein, 2017). Polarization can be defined as the description of the vibration of the electric field component of light waves (Goldstein, 2017). Light waves can oscillate in various orientations, and when these oscillations are in a specific direction, the light is said to be polarized. Sunlight, for example, is unpolarized as it can vibrate in multiple directions and the plane of vibration alternates many times per second (Konnen, 1985). However, upon reflecting, refracting, or scattering, light can become polarized (Goldstein, 2017). For instance, light reflecting off a non-metallic surface, such as water or glass, tends to become horizontally polarized (Konnen, 1985). Polarizing filters, commonly used in photography and optical instrumentation, use this principle by selectively blocking certain orientations of light waves. These filters are made of materials that allow to

transmit either 1) the light of only one direction of vibration or 2) the light of one sense of rotation (Konnen, 1985), effectively reducing glare and enhancing contrast. This is particularly useful in outdoor settings, where reflected light from surfaces like water bodies, rocks, or vegetation can create unwanted glare. Therefore, by using polarizing filters, clearer imagery can be obtained. Surface properties, such as reflectivity, texture, and color, also affect how light interacts with media. Whether a light ray is reflected, transmitted, or absorbed depends on the angle of incidence but also the refractive index of the encountered material (Rost et al., 2018). For example, when a stream of photons encounters a medium with a change in the index of refraction some are reflected and some are refracted into the medium (Clark, 2020). Reflectivity determines the amount of light that is reflected versus absorbed, while texture affects the scattering and diffusion of light. For instance, smooth surfaces like polished rocks reflect light in a more specular manner, whereas rough surfaces scatter light diffusely (Rost et al., 2018). These interactions influence the appearance of rocks, minerals, and terrain surfaces in captured images, making it then possible to trace various geological characteristics.

Understanding the principles of light and its interaction with the camera sensor lays the foundation for orthoimagery processing. Orthoimagery refers to aerial photographs that have been geometrically corrected (orthorectified) to create a uniform scale (Baltsavias, 1996), which allows interpretation and mapping (Zhang et al., 2023). Since large areas cannot usually be covered by a single photograph at the desired scale and resolution, a series of aerial photographs need to be converted into orthoimagery (Kerschner, 2001). Orthoimagery integrates the information obtained from images with the geometric properties of maps, allowing them to be easily combined with additional information from geographic information systems (GIS) to

create an orthoimage map (Kerschner, 2001). In orthoimagery processing, advanced algorithms and software are employed to align multiple images, correct distortions, and improve image quality. This correction allows orthoimages to be used as precise base maps for GIS, enabling detailed analysis of geological features and accurate fracture mapping (Baltsavias, 1996). The process of orthoimage generation mainly consists of two aspects: orthorectification and orthoimage mosaic (Zhang et al., 2023). The entire process usually starts with camera pose measurement between each aerial image; then, each pixel of aerial frames will be ortho-rectified by using computed inter-frame poses. Finally, a complete digital orthoimage is generated according to the given range of all rectified images by image mosaic methods (Zhang et al., 2023). There are two main categories of orthoimagery: aerial and satellite. Aerial orthoimagery is captured using cameras mounted on aircraft or UAVs (unmanned aerial vehicles), which fly over the area of interest. These images are typically of higher resolution due to the closer proximity of the camera to the ground, providing a more precise geometrical description of objects compared with satellite images (Ma et al., 2013). Satellite orthoimagery, on the other hand, is obtained from satellites orbiting the Earth. Although satellite images generally have lower resolution compared to aerial images and are more sensitive to the absorption and scattering of atmospheric elements, their scanning band is significantly wider and they can cover much larger ground areas (Ma et al., 2013). Nowadays, photogrammetric processing software such as Agisoft Metashape (formerly Photoscan), Pix4Dmapper, and OpenDroneMap (WebODM) are commonly used to generate detailed spatial data from images acquired by UAV drones (Tsai and Lin, 2017). These software packages process aerial photographs to produce photogrammetric outputs, including point clouds, digital surface models, and orthomosaic images. An orthomosaic is a geometrically corrected (orthorectified) image that stitches together multiple aerial

photographs into a single, uniform-scale image free of distortions. GIS software like QGIS, ArcGIS, and ArcMap can then be used to visualize, analyze, and integrate these orthoimages with other geospatial data for applications such as detailed geological mapping and fracture analysis.

2.4 Use of UAVs in Geology

Over the past decade, the use of Unmanned Aerial Vehicles (UAVs), commonly referred to as drones has significantly revolutionized scientific research across multiple disciplines, including geology (Carrivick et al., 2013) (Carrivick et al., 2013; Madjid et al., 2018). However, their adaptation for civilian use began in earnest in the 1980s when the first UAVs were produced in Japan at the request of the Minister of Agriculture, Forests, and Fisheries, primarily to aid in agricultural tasks (Kardasz et al., 2016). Unlike their military counterparts, civilian drones are generally smaller, powered by electric motors, and predominantly deployed for photography and data collection (Kardasz et al., 2016). The widespread adoption of UAV technology in civilian applications has led to significant advancements in environmental monitoring and geological data collection (Manfreda et al., 2018). In geology, drones have become indispensable for tasks such as mapping, surveying, and conducting detailed geological investigations, thanks to their ability to operate at low altitudes and manoeuvre over terrain that is otherwise difficult to access (Carrivick et al., 2013). This capability allows them to collect data that is both precise and comprehensive, covering extensive areas that would otherwise be challenging and costly to survey using traditional ground-based or manned aerial methods (Nex and Remondino, 2014; Shakhathreh et al., 2019).

Furthermore, data collected using UAVs can be analyzed using Geographic Information Systems (GIS) and image processing software has transformed the way

geological data is analyzed and used (Nex and Remondino, 2014). UAV-collected data can be processed to create detailed 3D models and high-resolution maps that are invaluable for environmental management strategies, including the assessment and mitigation of environmental hazards (Giordan et al., 2017; Gomez and Purdie, 2016). This technology provides more extensive and comprehensive datasets, particularly in 3D, which significantly enhances geological surveys. Traditionally, the gathering of 3D information in the field has relied on more limited ground-based observations and manual data collection techniques, which are often time-consuming (Nex and Remondino, 2014). Drones equipped with high-resolution cameras and sensors can rapidly cover large areas, providing detailed visual data that is crucial for analyzing fracture networks in rock formations (Nex and Remondino, 2014). This capability enhances various geological applications, including the investigation and management of subsurface reservoirs (Lepillier et al., 2020).

UAVs facilitate geological surveys and detailed mapping. By employing UAV imagery, it is possible to capture high-resolution data that reveals the complex geometries of fracture networks (Nex and Remondino, 2014).

As imaging technology continues to improve, its integration with other geological assessment tools promises to further refine our understanding of fracture networks and consequently of fluid dynamics in geological formations. Advancements in imaging technology are crucial for enhancing geoenergy applications, such as geothermal energy extraction and deep radioactive waste disposal, by improving our ability to effectively manage subsurface environments across various geological contexts. Imaging plays a pivotal role in characterizing fracture networks within rock masses (Nex and Remondino, 2014), which is essential for assessing site suitability for these projects (Reeves et al., 2012). As technology continues to evolve, the applications of imaging tools in geology continue to expand, promising even greater

contributions to scientific research and environmental management. The flexibility, cost-effectiveness, and data richness offered by imaging technology make them indispensable tools, reshaping how geological research is conducted and applied in the real world.

Chapter 3 Data and Methodology

This section introduces the methodologies and data that were used in the thesis. It outlines the criteria for selecting study areas, the data acquisition and processing techniques, and the methods used for fracture interpretation and characterization. The methodologies described here provide a comprehensive framework for assessing the reliability and reproducibility of automated fracture extraction methods, investigating the impact of imaging resolution on fracture network analysis, and comparing different automated methods for detecting and characterizing fracture patterns.

3.1 Criteria for Study Area Selection

The selection process of the study areas was based on:

1. Data accessibility – Data should be easily accessible. Study areas were chosen based on the availability of easily accessible, publicly available low-resolution imagery. Specifically, the data needed to be within the resolution range of 20 cm to 50 cm (Esri, 2023), which is typical for readily available datasets. This criterion ensures that the datasets can be easily obtained and used by other researchers, facilitating reproducibility and validation of the study's findings. For instance, imagery for Havmyran (Norway) was captured directly in the field and will be made publicly available for others to use. Havmyran (Norway) is the only site where imagery was captured directly in the field, and imagery used for analyses will be made publicly available for others to use (Section 3.3).
2. Exposure continuity – A key criterion for selecting study areas was the level of exposure continuity, specifically the degree to which rock outcrops are free from vegetation and other obstructions. Study sites were chosen to represent

a spectrum of exposure levels, ranging from areas with minimal vegetation cover (approximately 98% exposure) to those with significant vegetative obstruction (down to about 16% exposure). This deliberate selection allows for a systematic investigation into how varying degrees of exposure continuity impact the effectiveness of automated fracture extraction methods. By analyzing outcrops across this range, the study aims to quantify the extent to which vegetation affects automated feature detection and to establish the minimum exposure continuity necessary for reliable fracture network analysis. This approach addresses a notable gap in existing literature, where the impact of vegetation on automated extraction has been acknowledged but not thoroughly quantified (e.g., Hashim et al., 2013; Prabhakaran et al., 2019).

3. Literature coverage – Given the mostly remote-based nature of this study, one key factor in selecting the investigation sites was their extensive coverage by previous field-based studies, particularly at the Hitra site. This provided a well-documented baseline for testing and validating manual feature extraction methods at multiple scales. The multiscale investigation used low-resolution (plane) and medium- to high-resolution (drone) imagery, which allowed the characterization of geology from regional to local scales. This approach allowed for assessing how spatial and resolution-dependent variability influences the interpretation of regional geology and overall network characteristics.

All these criteria combined provided a robust and comprehensive basis for achieving the research aims proposed in this thesis, and allowed for a comparative analysis of fracture networks using advanced imaging techniques.

3.2 Geological Setting

This thesis focuses on four key study areas: Gillet Mountain in Yosemite, USA; Salt Valley in Utah, USA; Havmyran in Hitra, Norway; and Craignaw in Galloway, Scotland. Figure 3.1 presents the location maps for the selected investigation sites. Each site is described extensively in the following sections.

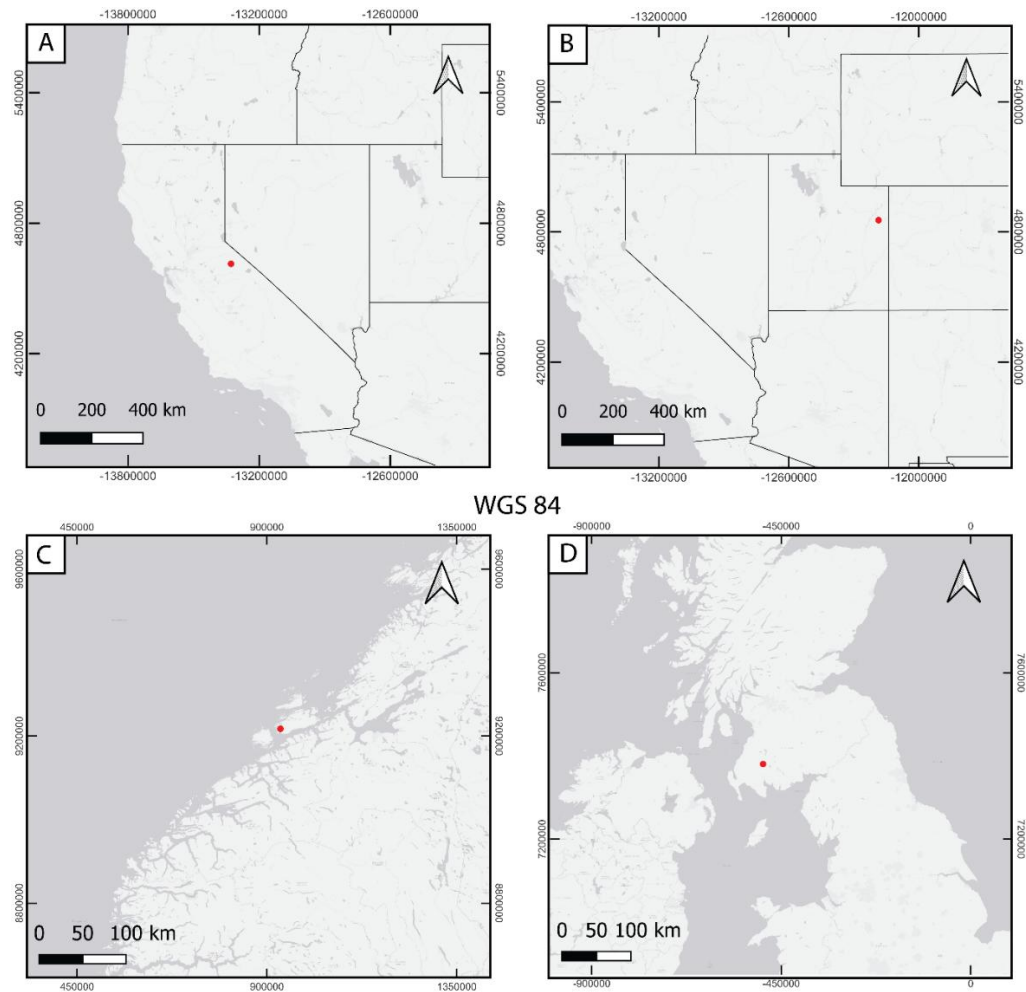


Figure 3.1 Location map for the areas of interest: A. Yosemite, California, USA; B. Salt Valley, Utah, USA; C. Havmyran, Hitra, Norway; D. Craignaw, Galloway, Scotland.

3.2.1 Gillet Mountain, California, USA

Rocks outcropping in Gillet Mountain are part of the Sierra Nevada Batholith, and parallel the Pacific Coast of California about 150 miles inland (Christensen, 1966). The Sierra Nevada has undergone significant tectonic activity, including uplift and faulting, particularly during the Cenozoic Era (Unruh, 1991). The batholith itself was uplifted during the Nevadan orogeny in the Late Jurassic to Early Cretaceous periods, leading to extensive erosion and the exposure of deep crustal rocks (Bateman, 1992). The present-day topography of the Sierra Nevada is, thus, a direct result of both tectonic uplift and subsequent erosional processes (Bateman, 1992; Christensen, 1966). This results in elevations ranging from about 2,000 meters to over 3,000 meters.

It features a rock composition ranging from quartz diorite to granite, emplaced during the Mesozoic era (Bateman and Eaton, 1967). The Sierra Nevada batholith is located in the central part of a complex, faulted synclinorium, which aligns with a downfold in the Mohorovicic discontinuity and in the P-wave velocity boundaries within the crust (Bateman and Eaton, 1967). As suggested by Bateman et al. (1963), the batholith primarily comprises quartz-bearing granitic rocks, varying from quartz diorite to alaskite, interspersed with smaller masses of older plutonic rocks and remnants of metamorphosed sedimentary and volcanic rocks (Bateman et al., 1963). Specifically, the area of interest, Gillet Mountain, is primarily composed of the Johnson Granite Porphyry, which is one of the major components of the Late Cretaceous Sierra Nevada Batholith (Coleman and Glazner, 1997). This granite porphyry is characterized by its fine-grained texture, miarolitic cavities, pegmatite veins, and abundant xenoliths. The Johnson Granite Porphyry was emplaced as a shallow, tabular intrusion extending to about 1.5 km in depth, influenced by regional shear zones that played a significant role in its emplacement (Titus et al., 2005). The specific rock composition includes a fine-grained matrix of quartz, K-feldspar, plagioclase, and

minor biotite/opaques, along with phenocrysts of quartz and feldspar, and megacrysts of K-feldspar (Bateman, 1992).

Dating back approximately 85.4 ± 0.1 million years, the Johnson Granite Porphyry is one of the youngest plutons within the Tuolumne Intrusive Suite (Coleman and Glazner, 1997). The Gillet Mountain site, with its composition dominated by this granite porphyry, provides an excellent setting for examining fracture networks and understanding the geological processes associated with this structurally complex formation.

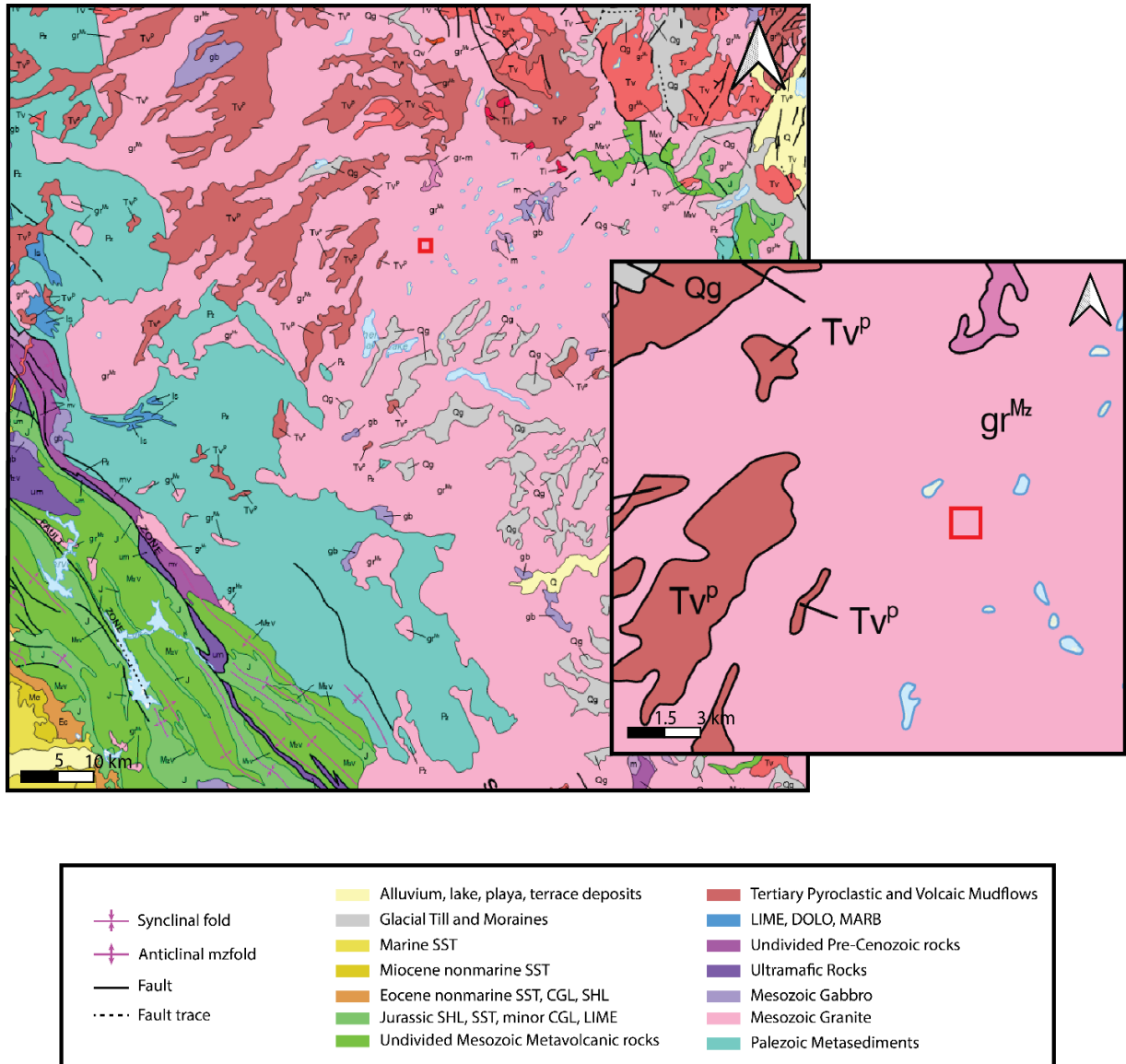


Figure 3.2 Geological map of the area of Yosemite – Gillet Mountain, together with area of interest, in red (U.S. Geological Survey, 2024).

3.2.2 Salt Valley, Utah, USA

Salt Valley, situated in the Arches National Park, features outcrops that are part of the Curtis Formation, part of the Upper Jurassic San Rafael Group (Gilluly and Reeside Jr., 1928). The Curtis Formation is a shallow marine sandstone (Anderson and Lucas, 1992), characterized by siltstone and sandstone in different proportions across

different regions (O'Sullivan, 1981). The formation consists of mostly very fine-grained sandstone to siltstone with only four clean partly cross-bedded sandstone units (O'Sullivan, 1981). The specific area of interest, highlighted in Figure 3.3, lies on the limbs of Salt Valley anticline, which is a northwest-trending diapiric structure composed of Mesozoic sedimentary rocks arching over a thick core of salt from the Paradox Member of the Middle Pennsylvanian Hermosa Formation (Gard, 1976). As explained by Gard (1976), this salt began migrating shortly after deposition, likely due to faulting, causing upwelling that formed a linear positive area; this upwelling induced increased sediment deposition in adjacent areas, further enhancing salt migration. By the late Jurassic, salt flowage had slowed, allowing the deposition of Morrison and younger formations across the salt well, with a thick cap of insoluble residue forming from ongoing salt dissolution (Baars and Doelling, 1987; Doelling, 1985; Gard, 1976).

This salt tectonism has resulted in the formation of prominent anticlines and synclines, which are a defining feature of the region's geology (Baars and Doelling, 1987). Today's topography of Salt Valley is, thus, heavily influenced by underlying salt tectonics, particularly the dissolution and movement of salt layers, leading to subsidence and faulting (Doelling, 1985). The interplay between sedimentary processes and tectonic activity has created a varied topography, with significant aeolian landforms and structural features (O'Sullivan, 1981).

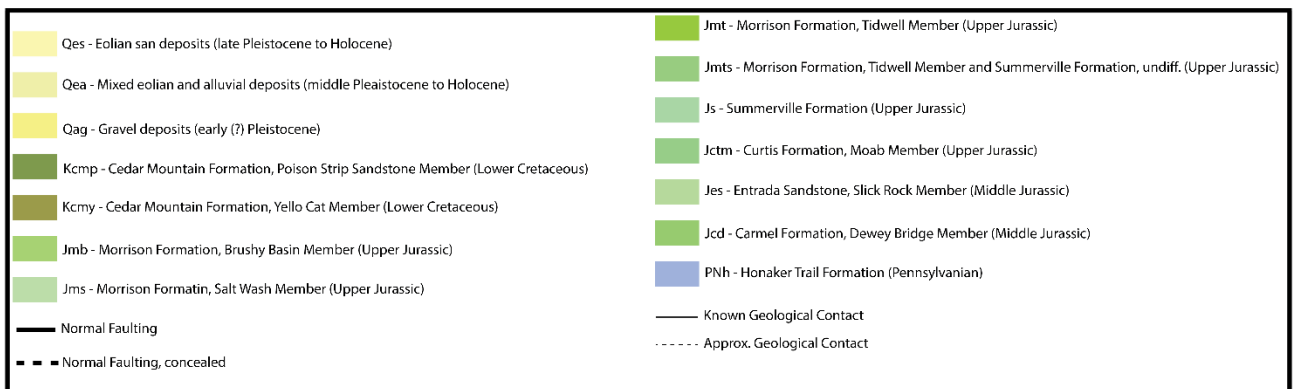
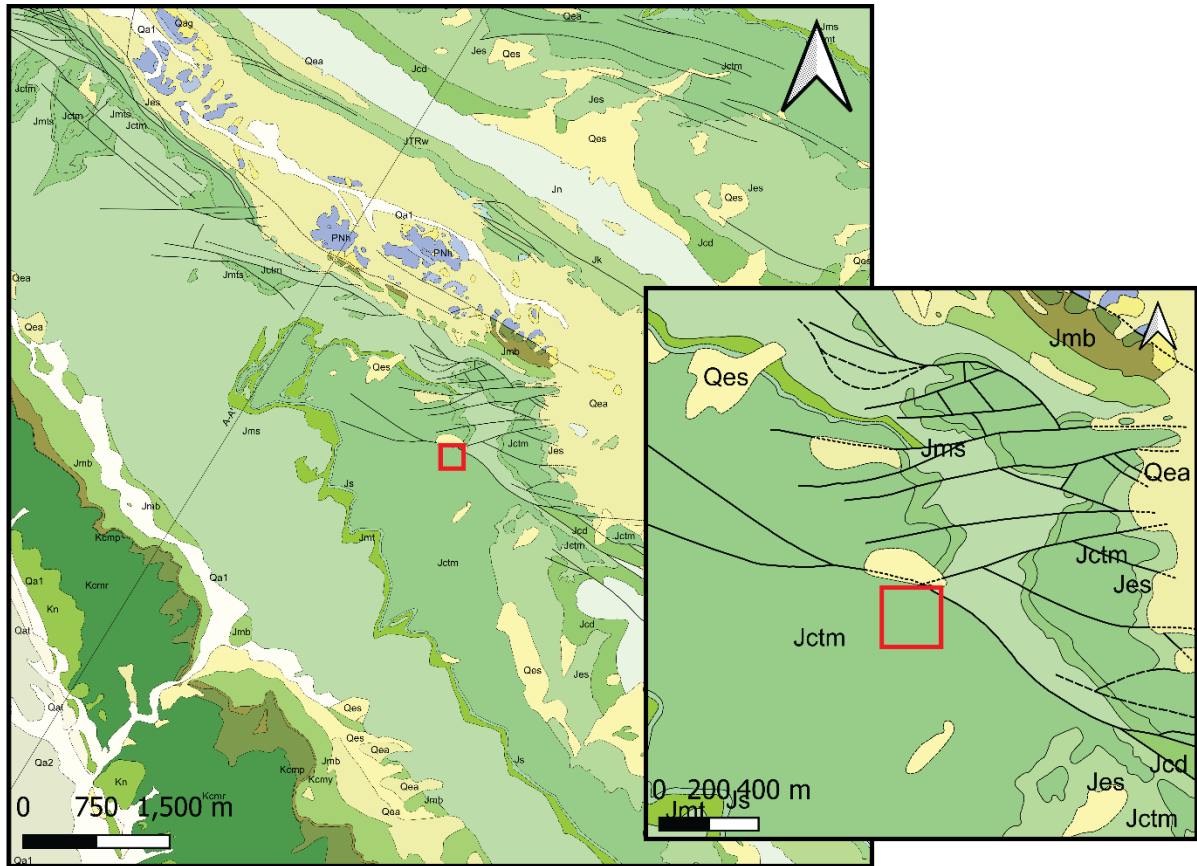


Figure 3.3 Geological map of the area of Arches National Park, together with area of interest, in red (National Park Service, 2021).

3.2.3 *Havmyran, Hitra, Norway*

Havmyran, located on Hitra Island, Norway, is part of the Smøla-Hitra Batholith. The island lies off the coast of Trøndelag, in central Norway, and represents one of the primary plutonic complexes in the Upper Allochthon of the Norwegian Caledonides (Gautneb and Roberts, 1989). With pluton emplacement occurring from the Mid Ordovician to early Silurian periods (Bøe et al. 2005), the Smøla-Hitra Batholith exhibits composition variations from granitic to granodiorite/tonalite (Gautneb and Roberts, 1989). The closure of the Iapetus Ocean was crucial in shaping the geological history of the Scandinavian Caledonides, including Hitra and Frøya. This event occurred from the Late Ordovician to Early Silurian as the Baltica, Laurentia, and Avalonia plates converged, leading to the Caledonian orogeny, one of the major mountain-building events in geological history (Mark et al., 2020; Peron-Pinvidic and Osmundsen, 2020).

The continental collision caused deformation, metamorphism, and magmatic activity, forming extensive thrust sheets and complex fault systems, like the Møre-Trøndelag fault complex (Peron-Pinvidic and Osmundsen, 2020).

These tectonic events are evident in the structural features and lithological diversity of Hitra and Frøya (e.g., Gautneb and Roberts, 1989; Peron-Pinvidic and Osmundsen, 2020; Tartaglia et al., 2022). Studying these areas provides insights into the tectonic evolution of the Scandinavian Caledonides and the mechanisms driving orogenic processes and subsequent rifting events (Mark et al., 2020).

The study area for this thesis is located 7.5 km SSW of Kvenvær. The granitoids in southwestern Hitra are medium-grained and equigranular, primarily composed of plagioclase, biotite, hornblende, and quartz (Nordgulen et al., 1995). Minor interstitial microcline and accessory minerals such as apatite, epidote, titanite, zircon, opaques, and chlorite are also present. The rocks are intersected by aplite and pegmatite dykes

and a weak mineral alignment can be observed in certain areas (Nordgulen et al., 1995). Topographically, Hitra island features rugged terrain, with 16 peaks generally ranging from sea level to around 300 meters (Mindat.org, 2024).

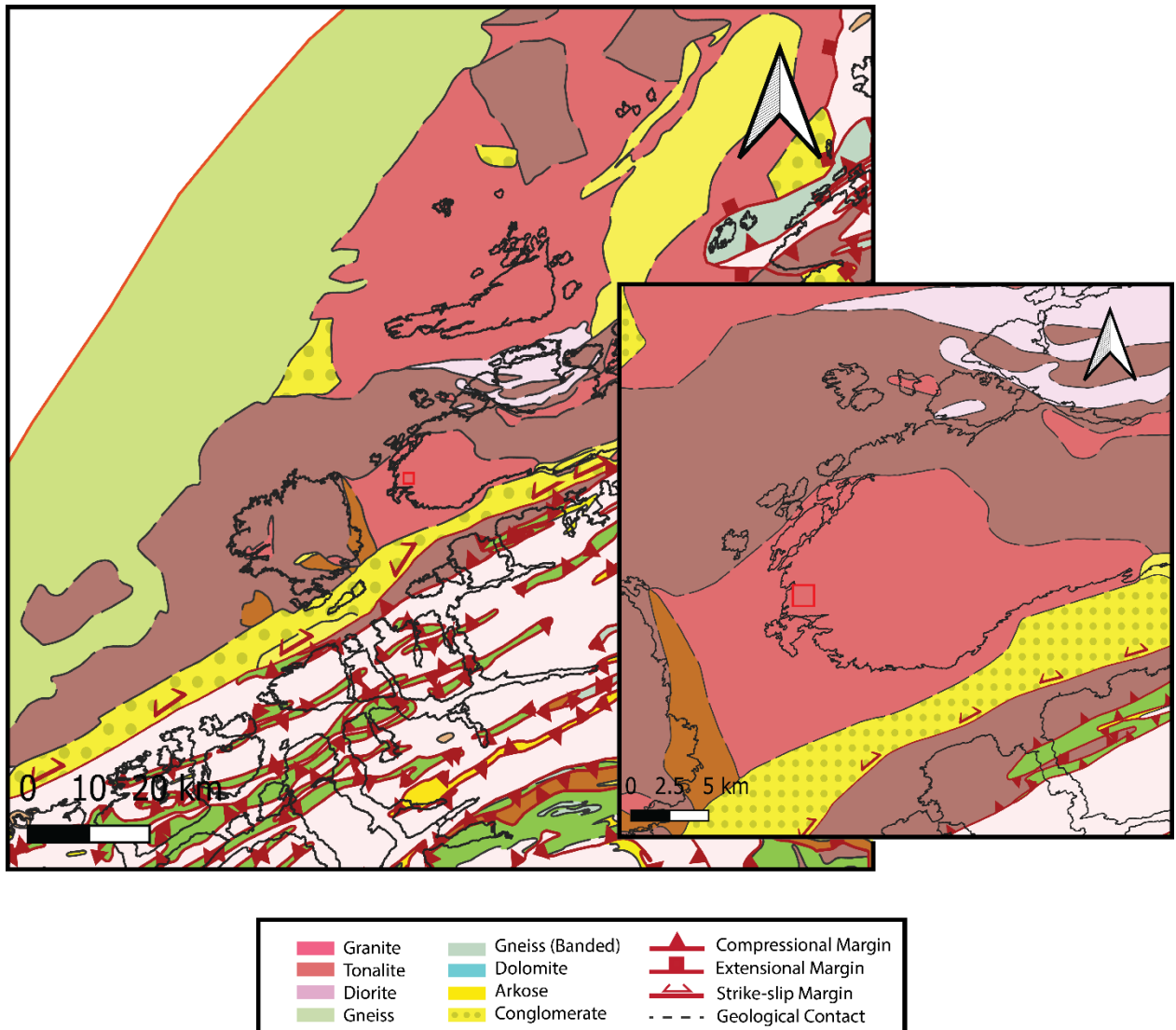


Figure 3.4 Geological map of the area of West Norway, together with area of interest, in red (Norwegian Geological Survey (NGU), 2024).

3.2.4 Craginaw, Galloway, Scotland

Craginaw, located in Galloway, Scotland, is geologically significant as it forms part of the Loch Doon Pluton. This pluton was emplaced during the Devonian period, approximately 408 million years ago, during the late stages of the Caledonian orogeny (Tindle and Pearce, 1981). The Loch Doon pluton is part of the Southern Uplands Terrane and is characterized by a coarse-grained texture and complex intrusion history, including the presence of multiple generations of granite and associated dykes (Hines et al., 2018). It formed during the late stages of the Caledonian orogeny (Tindle and Pearce, 1981), a period of significant mountain-building that affected much of present-day Scotland. Following its emplacement, the region underwent substantial erosion and uplift, particularly during the Carboniferous and Permian periods (Piper, 2007). More recently, during the Pleistocene, the area was heavily glaciated, which significantly influenced its current topography (Ballantyne, 2021). Glacial activity during the Pleistocene carved out deep valleys and left behind distinctive features such as cirques and moraines (Ballantyne, 2021). The Loch Doon Pluton is a complex, zoned granitic intrusion ranging in composition from hypersthene diorite at the margins through quartz diorite and granodiorite to granite and cordierite microgranite at its core (Gardiner and Reynolds, 1932; Tindle and Pearce, 1981). It comprises three primary igneous facies—granite, tonalite, and norite—forming a concentrically zoned pluton with a granite core that transitions into tonalite through intermediate facies (Piper, 2007). This zonation reflects the different stages of magma cooling and crystallization, with earlier-formed minerals located at the periphery and later-formed, more evolved minerals concentrated toward the center (Hines et al., 2018).

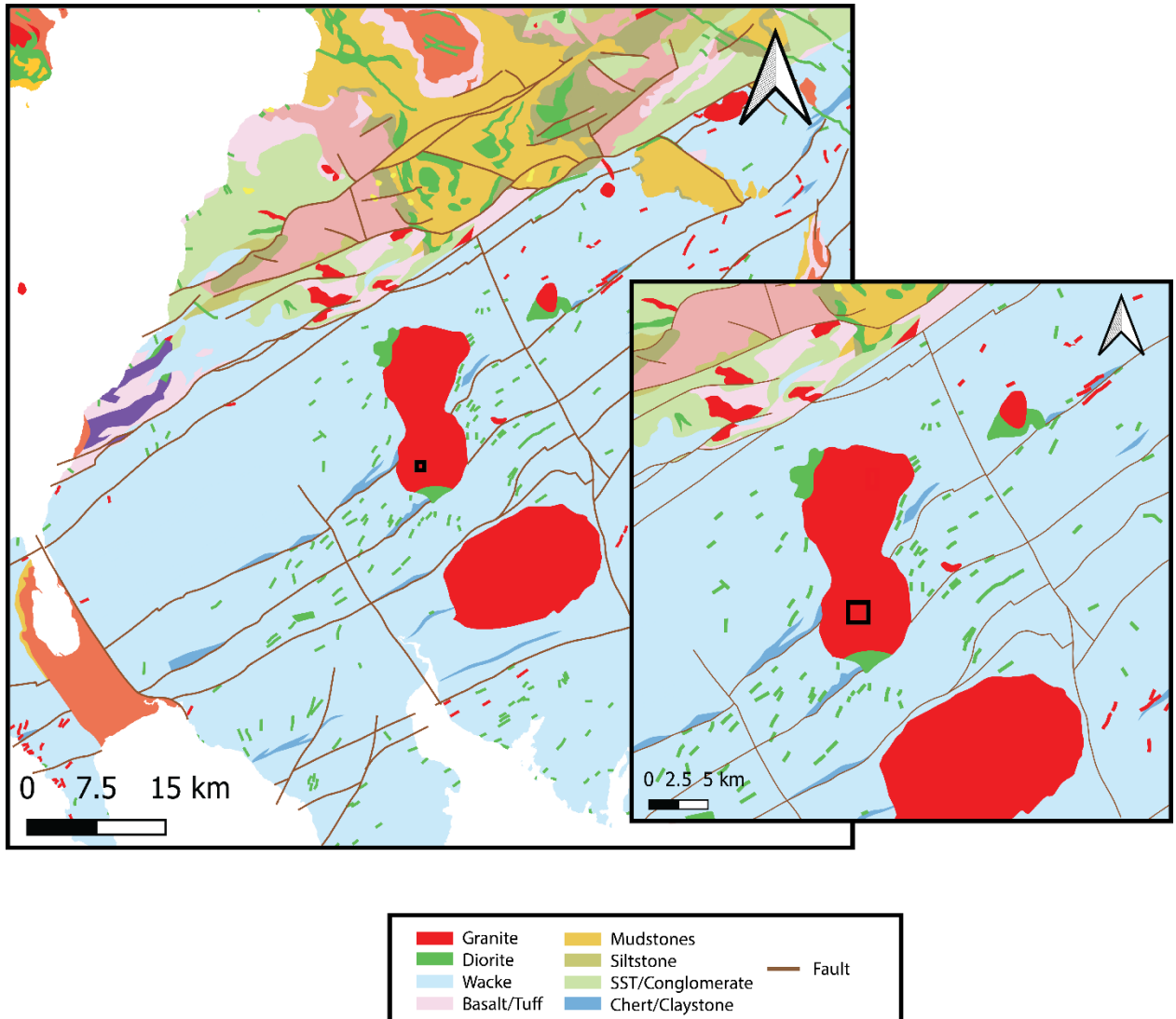


Figure 3.5 Geological map of the area of South Scotland, together with area of interest, in red (EDINA, 2024).

3.3 Datasets

The imagery used throughout this thesis was initially full-color (RGB), but in Chapter 4 it was converted to grayscale to support contrast-based analyses. The low-resolution imagery used in Chapters 4, 5, and 6 was acquired through pre-existing surveys, while medium- and high-resolution imagery used in Chapters 5 and 6 was collected during a geological field campaign using a DJI Phantom 4 drone. For Gillet

Mountain (USA), Utah (USA), and Cragshaw (Scotland), only aerial imagery was available. In contrast, for Hitra (Norway), where fieldwork was conducted, drone flights were carried out at different altitudes to produce imagery at spatial resolutions ranging from 0.02 m (medium resolution) to 0.002 m (high resolution). The aerial imagery for each dataset was obtained from the following sources: 1) Yosemite and Utah: World Map Service (WMS) layers in QGIS, which use satellite basemaps similar to Google's terrain imagery; 2) Hitra (Norway): The "Ortofoto Hitra Frøya Agdenes 2015" dataset, available through the Norwegian Mapping Authority (Kartverket); 3) Cragshaw (Scotland): aerial imagery was downloaded via EDINA's DigiMap service, which provides orthorectified aerial photography for the UK.

3.3.1 Aerial Imagery

1. Yosemite, USA: Imagery was sourced from Airbus Imagery, using Maxar Technology, and was downloaded in QGIS via Webmap Services. The satellite imagery, acquired in 2023, has a resolution of 25 cm/px. The area of interest spans 0.063 km².
2. Utah, USA: Imagery was sourced from Airbus Imagery, using Maxar technology in collaboration with Geospatial Enterprise Operations, Farm Production and Conservation, and the United States Department of Agriculture. Data has a resolution of 25 cm/px. The area of interest spans 0.07 km².
3. Hitra, Norway: The aerial imagery used for this study was sourced from Kartverket and was acquired as part of a 2015 survey over the islands of Hitra and Frøya. The imagery, following the "Orthophoto 20" standard, specifies properties such as overlap, altitude, and sensor specifications. The survey used an UltraCam X digital camera, with a Ground Sample Distance (GSD) of 20-25 cm, and a side overlap of 20% (Trollvik 2014; Lauritsen et al. 2019). For the

specific outcrops studied, the imagery has a resolution of 21 cm/px and covers an area of 0.045 km²

4. Craginaw, Scotland: Imagery was sourced from DigiMap. The 2013 survey data has a resolution of 25 cm/px, covering 0.064 km².

3.3.2 Drone Imagery

3.3.2.1 Data Acquisition

The drone imagery for the Hitra study area was captured using a DJI Phantom 4®, equipped with a 1/2.3" CMOS, 12.4 MP sensor. During this acquisition, two distinct datasets were collected, consisting of medium-resolution and high-resolution images. The medium-resolution dataset involved capturing images at altitudes ranging between 25 and 35 meters. During this process, the camera settings were configured with an exposure time of 1/500s, an ISO speed of 100, and a focal length of 9mm. The resulting imagery had a resolution of 2 cm/px, and a total of 420 images were collected for the area. The high-resolution imagery was captured at a much lower altitude of 4 meters above the ground. The camera settings for this high-resolution dataset included an exposure time of 1/800s, an ISO speed of 100, and a focal length of 9mm. The resulting images had an impressive resolution of 0.2 cm/px. A total of 16 high-resolution photos were taken, focusing on specific areas where logistical conditions allowed, even though the original traverse lines could not be strictly followed. Nevertheless, these images still provided valuable data for the study.

3.3.2.2 Data Processing

Once the imagery was collected, it was processed into an orthophoto using WebODM software, using parameters in Table 3.1. The processing combined the 420 photos from the medium-resolution dataset into a single composite orthophoto with a final

resolution of 2 cm/px. The orthophoto processing involved using specific algorithms for feature matching and detection. For feature matching, the Brute force method was employed. This algorithm compares each feature in the first set with all other features in the second set by calculating the distance between them. The closest match is returned. Although effective, this method can be time-consuming, particularly when working with large datasets, as it exhaustively searches for matches across all features (OpenCV, 2024). For feature detection, the Hahog algorithm (an acronym for Hessian Affine Harris Oriented Gradient) was used. This method combines the Hessian Affine feature point detector with the Histogram of Oriented Gradients (HOG) descriptor, allowing for accurate feature detection and description in the images.

Resize Image (px)	Auto Boundary	DEM Res.	D S M	D T M	Feature Quality	Feature Type	Ign. GSD	Matcher-Neighbors	Matcher Type	Mesh Size	ODS	Ortho. Res. (cm)	PC Filter	PC Quality	PC Rectify	SFM Algorithm
N	T	0.4	T	T	U	Hahog	T	Def	Flann	4M	T	2	0	U	T	Incremental

Table 3.1 Entries used for WebODM parameterization.

3.3.3 Data Quality and Accessibility

Accessibility of data was facilitated by using established repositories and open-source platforms. Aerial imagery from Yosemite, Utah, and Craginaw was sourced from the Open Geospatial Consortium and DigiMap, ensuring reliable and consistent data availability. For Hitra, data was obtained from Kartverket and processed using WebODM, an open-source photogrammetry tool, promoting transparency and reproducibility. The orthoimagery has a geolocation error of 0.89 m. Overlap was kept between 60 to 80%, and flight path followed for acquiring data is visible in Figure 3.6A. In terms of quality, the quality of the survey was good, with 3 to 5 in a unit area (Figure 3.6B).

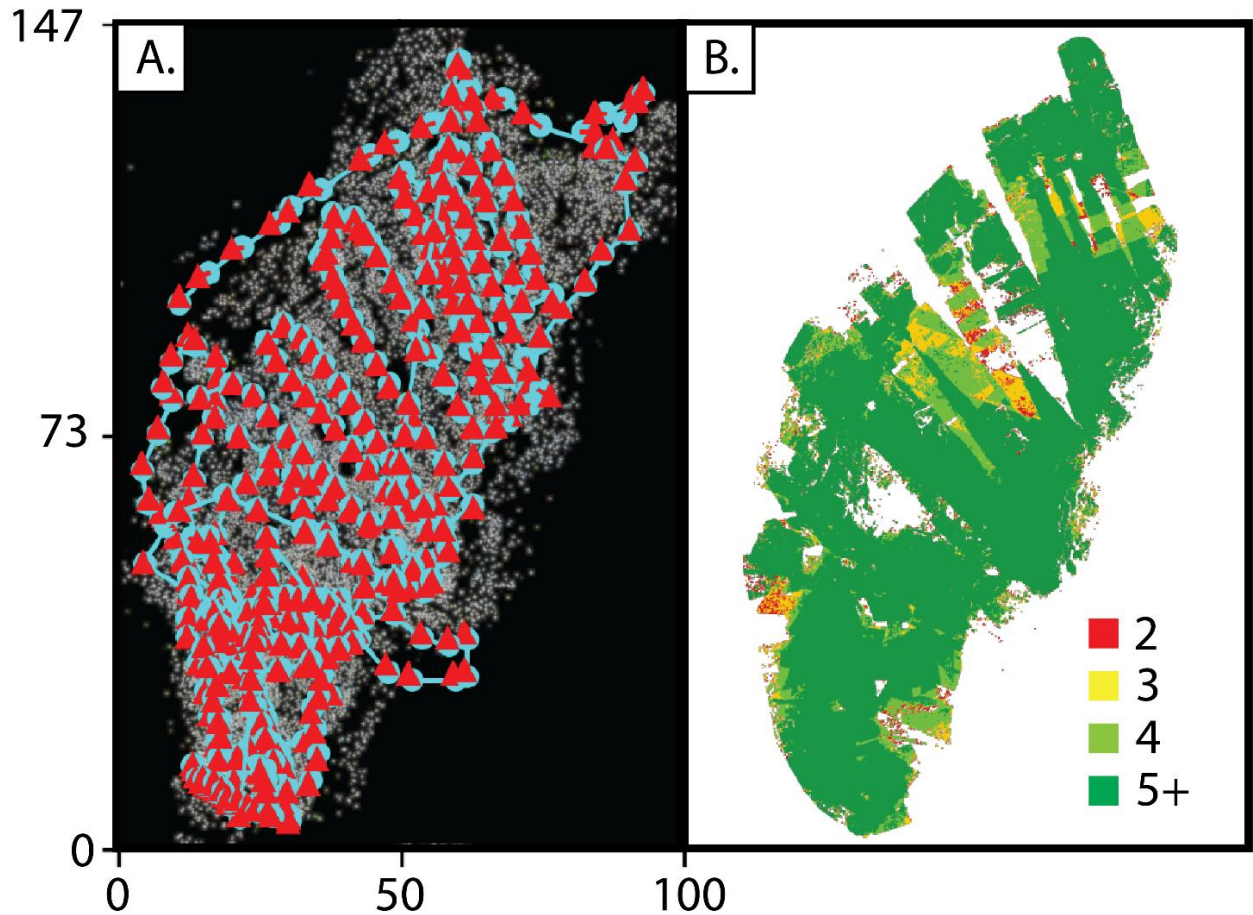


Figure 3.6 A. Flight path followed for acquiring data; B. Quality of data expressed in number of images per area.

Ensuring data quality and accessibility is crucial for the reliability and reproducibility of this research. Data quality was maintained by implementing strict guidelines for tracing features and adhering to them consistently throughout the study. All datasets were stored and managed in a GIS database, allowing for efficient data retrieval and analysis.

3.4 Fracture Interpretation and Characterization

In this study, two fracture interpretation methods were used: manual and automatic. Manual fracture interpretation involves expert analysis of fracture patterns based on

geological knowledge and guidelines that were designed to improve reproducibility and reproducibility of manual approaches. On the other hand, two contrast-based automated methods were also used, specifically one used Shearlets (Labate, 2005) to trace features using multiple contrast thresholds, and the other one used a single threshold to binarize and skeletonize an image.

3.4.1 Manual tracing

To characterize the fracture networks, fractures were manually interpreted. To ensure the interpretations are reproducible and reliable, criteria for the interpretation of fractures were defined. These criteria are one of the most important aspects around which this research revolves. The key to mitigating limitations of manual approaches, such as bias, lies in employing rigorous criteria for fracture identification. In the imagery used, fractures are interpreted as near-linear features of dark pixels that form a discontinuity/gap within, or at the edge of the rock mass. It was ensured following the same consistent approach to interpreting fractures to improve the reliability and limit human bias (Andrews et al. 2019). Fracture tracing and analyses were performed using QGIS®, and all the analyses of fracture characteristics were performed with NetworkGT (Nyberg, Nixon, and Sanderson 2018). This tool performs all the essential analyses necessary to describe a network of fractures, including calculating feature lengths, generating orientation plots, classifying fractures into sets with expert input, and conducting topological investigations. The topology tool in NetworkGT specifically classifies network topology according to Sanderson and Nixon (2015). Throughout this thesis, interpretations were carried out at three zoom levels, a process that others have adopted for the interpretation of remote sensing data (e.g., Andrews et al. 2019). Fractures were traced along their center, and if only one edge was visible, the line

was traced along the only visible edge. Where fractures intersect vegetated areas, interpolation was carried out across these areas only where they were separated by $<2\text{m}$ for low-resolution imagery (equivalent to 10 px) or 20cm for high-resolution imagery (equivalent to 10 px) and $<2^\circ$ change in angle. In cases of fractures filled with vegetation, if the separation between the two edges exceeded 0.5m, the line was traced along the center, equidistant from both edges. The detection limits for fractures were 0.044m in high-resolution, 0.4m in medium-resolution, and 1m in low-resolution imagery, corresponding to 2 pixels in high and medium resolutions, and 4 pixels in low resolution. For one fracture to have an intersection with another, a maximum snapping distance of 3 pixels was set. Each fracture trace is defined by a minimum of 3 vertices.

3.4.2 Automated fracture tracing-Complex Shearlet Transform

The full workflow followed for automated tracing is presented in **Error! Reference source not found..** The same QGIS-based workflow that was applied to analyzing fractures traced manually, was also applied to fractures extracted using automated methods.

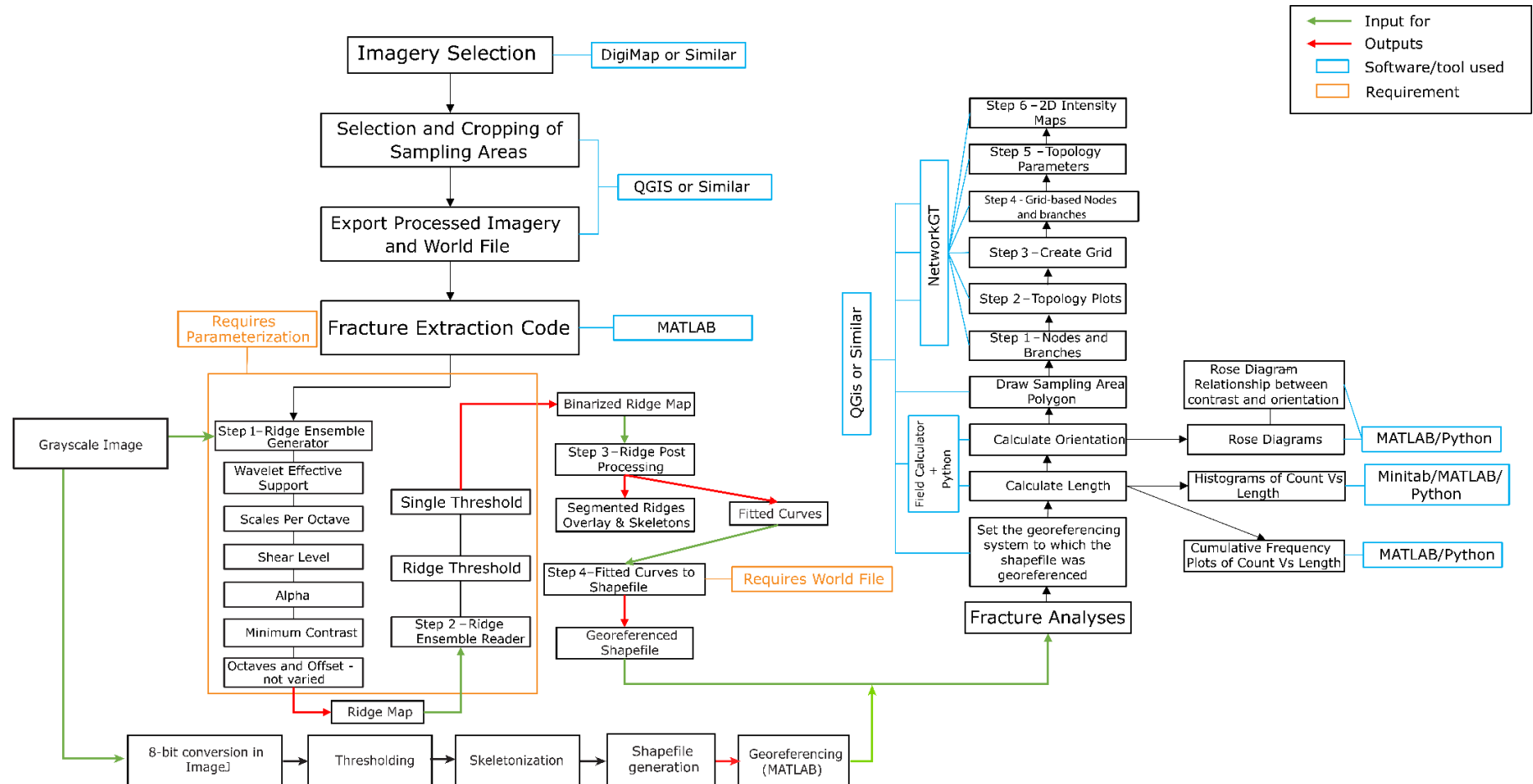


Figure 3.7 Full workflow followed for automated fracture extraction in Chapter 4.

The Shearlet method developed by Prabhakaran et al. (2019) is based on the concept that data from the real world usually display abrupt changes in contrast, and it is within those changes that key information is stored. Generally speaking, automated approaches are very time-efficient, and are generally less subject bias. The code is based on the concept of the complex shearlet system theorized by Labate and Kutyniok (2005), which is in turn an expansion of the wavelet theory. Wavelets are rapidly decaying wave-like oscillation that has zero mean. Oppositely to sine waves, wavelets have a finite duration, which is the peculiar characteristic of this type of wave. Wavelets are characterized by two main concepts: 1) scaling and 2) shifting. Scaling [eq. 3.1] refers to the process of stretching or shrinking a signal over time, and is expressed with

$$\psi\left(\frac{t}{s}\right) \quad s > 0 \quad [3.1] \text{ (Labate, 2005)}$$

where ψ represents the mother (or prototype) wavelet, t is time, and s is the scaling factor. The scale factor (s) shows how much a signal is scaled in time, and is inversely proportional to frequency. Provided that there is a constant of proportionality, there will be a reciprocal relationship between scale and frequency, and this constant of proportionality is called center frequency. The center frequency can be used to calculate the equivalent frequency [eq. 3.2], which is expressed as

$$F_{eq} = \frac{C_f}{\delta t} \quad [3.2] \text{ (Labate, 2005)}$$

where F_{eq} is the actual (or equivalent) center frequency, C_f is the dimensionless center frequency, s is the scaling factor and δt is the sampling interval. Therefore, the wavelet is being scaled by a factor of 2, and the equivalent frequency will be reduced by an octave. A large-scale factor s will result in the wavelet having a lower frequency, whilst a smaller scale factor s will result in the wavelet having a higher frequency. This is important as low and high-frequency wavelets are most effective

in identifying different types of signals. For instance, a low-frequency wavelet helps capture quickly varying changes in a signal.

Shifting [eq. 3.3] means delaying or advancing the onset of the wavelet along the length of the signal and is expressed by

$$\phi(t - K) \text{ [3.3](Labate, 2005)}$$

Where ϕ , is the scaling function, t is time and K is the translation (or shift). The equation simply means that the center of frequency of the wavelet will be moved to K .

Wavelets however have a fundamental issue: as previously mentioned, wavelets move along the length of the signal and are therefore monodirectional [eq. 3.4]. In fact, for traditional wavelets, dilation matrices are diagonal:

$$\begin{bmatrix} a & 0 \\ 0 & a \end{bmatrix} : a > 0 \text{ [3.4](Labate, 2005)}$$

The matrix in Equation 3.4 represents an isotropic dilation; a is a scaling factor. If $a > 1$, the transformation is an expansion; if $0 < a < 1$, it is a contraction; if $a = 1$ there is no scaling. Although similar to wavelets, there are substantial differences between the two. While the forming matrix for wavelets are simple dilation matrices, shearlets have upper triangular matrices [eq. 3.5]:

$$M_{as} = \begin{bmatrix} a & \sqrt{a}s \\ 0 & \sqrt{a} \end{bmatrix} : a > 0 \cup s \in R \text{ [3.5](Labate, 2005)}$$

And M_{as} is the result of the product between a shear transformation and an anisotropic dilation [eq. 3.6]:

$$M_{as} = \begin{bmatrix} 1 & -s \\ 0 & 1 \end{bmatrix} \begin{bmatrix} a & 0 \\ 0 & \sqrt{a} \end{bmatrix} = \begin{bmatrix} a & \sqrt{a}s \\ 0 & \sqrt{a} \end{bmatrix} \text{ [3.6](Labate, 2005)}$$

Noting that $\sqrt{a}$ can be replaced by any $0 < \alpha < 1$.

Shearlets can be applied to image analysis due to their ability to represent anisotropic features such as edges. Unlike traditional wavelets, which are isotropic and often

struggle to represent directional information, shearlets offer a multidirectional and anisotropic framework. This makes them more effective at detecting and representing features with sharp edges, and ridges, like fractures in rock masses. The main differences between shearlets and wavelets are summarized in Figure 3.8.

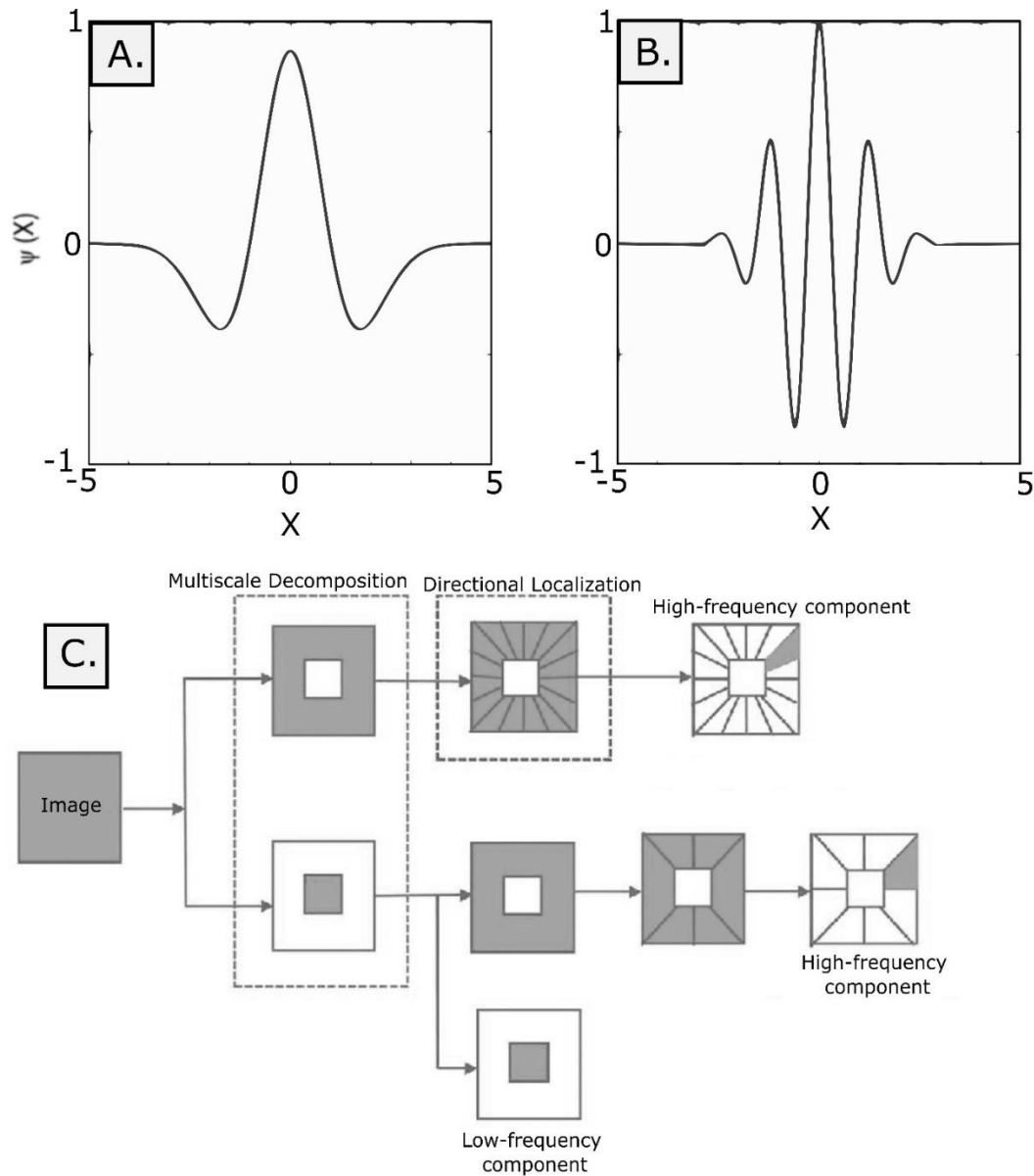


Figure 3.8 A. Mexican wavelet; B. Morlet wavelet (Chitsaz et al., 2016); C. Schematic representation of Shearlets (Liu et al., 2020).

The continuous shearlet transform depends on three parameters: a (the scaling factor), s (the shear parameter), and t (the translation parameter), which allows for a more flexible and anisotropic analysis of data compared to traditional wavelets (Kutyniok and Labate, 2012). This flexibility enables the shearlet transform to capture directional features in signals or images more effectively compared to wavelets, making it particularly useful for identifying edges, ridges, and other geometric structures that may not be well-represented by wavelets alone.

While shearlets are theoretically advantageous for tracing geological features from imagery due to their ability to capture and represent directional and anisotropic features with higher precision than traditional wavelets (Prabhakaran et al., 2019), it is important to acknowledge the limitations and sensitivities of this technique. Chapter 4 of this thesis explores these limitations in detail, highlighting how the effectiveness of shearlets can be influenced by various parameters, and discussing the broader challenges inherent in automated approaches. Geological formations, such as fractures, faults, and strata, often exhibit complex, contrasting, multi-directional patterns that traditional multiscale methods struggle to accurately trace. The shearlet transform developed by Prabhakaran et al. 2019 transforms uses grayscale images as the basis for fracture extraction and then makes each image into a ridge probability map representing an ensemble of possible features, with five iterations per ensemble. The resulting ensemble was converted into a skeletonized image, thinning detected ridges into single-pixel clusters (Prabhakaran et al. 2019). Polylines were then fitted through the skeleton image and converted into a georeferenced shapefile for quantifying and characterizing the fracture network. To assess the impact of varying contrast thresholds, the minimum contrast threshold was varied for each ensemble, while other parameters remained constant. The minimum contrast can be any value between 0 to 255. In all the images used in this

study, faults and fractures are most likely represented by low contrast values (<235), with the unfractured rock mass mostly represented by higher contrast values. The complex shearlet transform workflow is summarized in Figure 3.9.

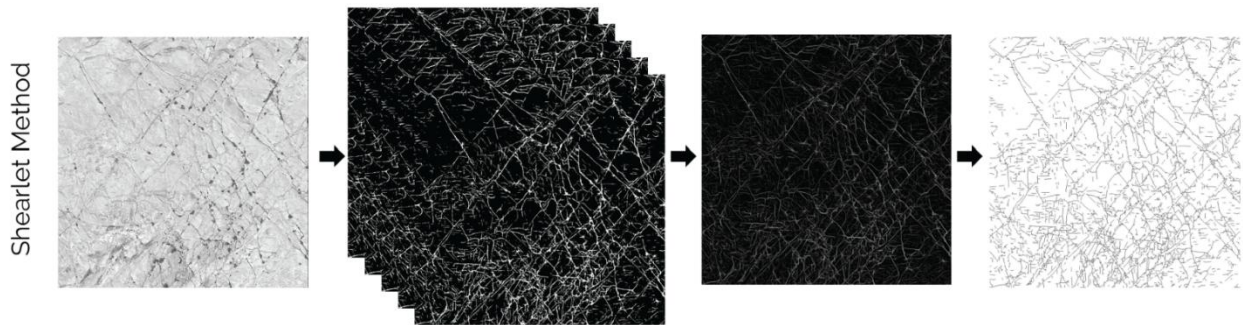


Figure 3.9 Visual representation of the complex shearlet transform workflow.

3.4.3 Automated fracture tracing- Binary thresholding method

The binarization method was implemented using ImageJ (v. 1.53t). This workflow adopts two key steps: 1) thresholding, which produces a binarized image, and 2) skeletonization, which simplifies areas identified via the thresholding method into 1-pixel lines. The binarization function in ImageJ uses a threshold to distinguish between the foreground and background (ImageJ, 2023), whilst skeletonization adopts the Zhang-Suen thinning algorithm, which iteratively reduces the foreground features to a skeletal representation (ImageJ, 2024a). The binary thresholding workflow is represented in Figure 3.10. The same grayscale image used in the shearlet method was employed for consistency. Using the same grayscale image for both automated methods ensured that any differences in the results were due to the methods themselves rather than variations in the input data. This method was only applied to the Yosemite dataset and with four iterations. For example, a contrast threshold of 175 means that pixels with an intensity value lower than 175 are identified as part of the foreground, and pixels with intensity values greater than 175 are designated as background. Parameters used for each of the binarizations are

shown in Table 2. In each resulting binary image, pixels have a value of either zero (black), which represents the foreground, or one (white), which represents the background. The binary thresholding method does not preserve the topology of the networks automatically extracted, meaning that, despite lines being effectively snapped, they do not form nodes where they intersect. To address this, it was assumed that features within a proximity of 0.000001m (or 1 micrometer) were connected. Selective removal of features based on length and circularity was performed in ImageJ using the Analyze Particles tool with the parameters listed in Table 2. Circularity was calculated in ImageJ directly. The final skeletonized image was converted into a shapefile using the Raster to Polyline tool in ArcGIS (Esri, 2024).

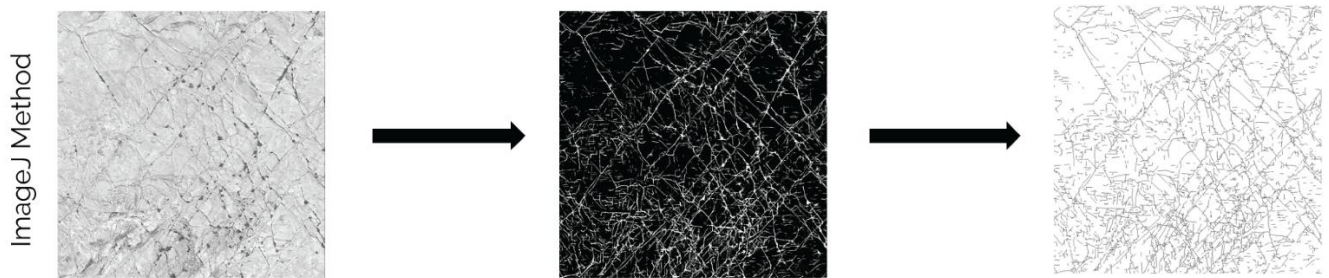


Figure 3.10 Visual representation of the binary thresholding workflow.

Chapter 4 Reliability of Contrast-Based Automated Fracture Detection from Decimeter Resolution Aerial Imagery

Abstract

Aerial imagery that captures outcrop exposures of rocks enables the characterization of structural discontinuities such as faults and fractures across large and difficult-to-access areas. These datasets provide an opportunity to analyze the characteristics of fault and fracture networks as analogs for the subsurface. Automated interpretation methods have the potential to reduce subjectivity, increase efficiency, and improve reproducibility. While these methods are commonly used with high-resolution images, the widespread availability of decimeter-resolution imagery means that demonstrating the reliability of automated methods with decimeter-resolution data could significantly extend their application.

This study investigates the reliability of two automated fracture detection methods using decimeter resolution imagery and specifically the sensitivity to contrast between rock mass and fractures. The results indicate that: 1) at lower contrast thresholds, the average feature length increases while the number of feature intersections decreases; 2) extracted features demonstrate reduced robustness in discontinuous outcrop exposures. It is crucial to note that these findings presume a scenario where the rock mass exhibits high contrast, and fractures are characterized by low contrast. The findings demonstrate that automated feature detection is reproducible, but currently produces very unreliable results. The use of these methods requires a detailed understanding of how image properties and the parameters defined in the detection method impact the resultant features detected.

The use of automated methods with decimeter resolution imagery requires clearly defined criteria to quality check the results.

4.1 Introduction

Faults and fracture networks in rock masses influence both the storage and flow of fluids and serve as important indicators of stress and strain histories (Gudmundsson 2011). These networks can both facilitate and hinder fluid flow (Miranda et al. 2020) and reliably characterizing these networks is crucial in hydrogeology and geoenergy, especially for rocks with low matrix permeability (Berkowitz 2002). This includes applications such as geological disposal of radioactive waste and identifying pathways for contaminants (Bear 1993; Witherspoon, Cook, and Gale 1980), as well as geothermal energy where fracture networks act as permeability pathways for brines (Pruess and Narasimhan 1982; Singhal and Gupta 2010).

Outcrops provide invaluable analogs for in-situ rocks at depth enabling detailed characterization of fault and fracture networks (e.g., Howell, Martinius, and Good 2014). By studying exposed rock formations, geologists gather critical geometric data often limited in subsurface studies, improving the accuracy of geological models (Bertrand et al., 2021). These analogs offer insights into the spatial relationships and connectivity of fractures, supplementing sparse subsurface data from wells and seismic surveys, and are essential for understanding reservoirs and predicting fluid flow (J. and M., 2016). Images of outcrops provide therefore a unique dataset from which to interpret fault and fracture networks (e.g., Castaing et al. 1996; Gabrielsen and Braathen 2014; Tartaglia et al. 2022). Image analysis involves various techniques and processes aimed at extracting meaningful information from images (e.g., Voorn et al., 2013; Weismüller et al., 2020). It plays a critical role in fields like geology, where it identifies and characterizes features such as faults and fractures. The development of remote sensing acquisition technologies such as drones has profoundly transformed the ability to capture and use imagery, enabling the characterization of structural features across large areas of exposure and in traditionally inaccessible

locations (Saibi et al. 2018). However, the proliferation of such data has made manual extraction of geological information increasingly impractical (Thiele et al. 2017) and the use of automated interpretations offers improved efficiencies (Chen et al. 2021; Prabhakaran et al. 2019) and can mitigate the subjective bias of manual interpretations (Andrews et al. 2019; Bond et al. 2007; Wilson, Bond, and Shipley 2019). An early example of image processing for feature detection is the Canny edge detection method (Canny 1986), and this was followed by advancements in edge detection algorithms and the integration of rudimentary machine learning techniques (Cracknell and Reading 2014; Harvey and Fotopoulos 2016; Kozlovskaya et al. 2023). The use of automated techniques for extracting features from imagery has been applied to satellite imagery (e.g., Hung, Batelaan, and Smedt 2005; Sarp 2005) and increasingly drone imagery (Prabhakaran et al. 2019; Weismüller et al. 2020). Lower-resolution imagery (~25 cm), referred to as 'decimeter-resolution imagery,' is more readily available (Santos and Rapp 2019; Taylor and Lovell 2012). The availability and accessibility of open license aerial imagery varies worldwide, averaging 0.3m for selected metropolitan areas, 0.5m across the US and Europe, and 0.6-1.2m elsewhere (Esri 2023b). While decimeter resolution imagery has limitations for cm-scale detail, its availability and accessibility make it valuable for mapping meter-scale features, which is useful for applications such as mapping regional geological structural trends and reconnaissance work (Njue 2010; Ray 1960). Although automated detection methods have proven effective with high-resolution imagery (e.g., Prabhakaran et al., 2019, 2021; Weismüller et al., 2020), their effectiveness with decimeter-resolution imagery has received minimal attention.

This work investigates the reliability and reproducibility of automated feature extraction from decimeter-resolution aerial imagery. It evaluates the use of two

existing contrast-based automated feature detection methods with decimeter-resolution imagery.

4.2 Methodology & Data

Throughout the study, four different outcrop exposures covered by aerial imagery with comparable resolutions were used to investigate the reproducibility and reliability of automated detection methods (Figure 4.1A, B, C, and D).

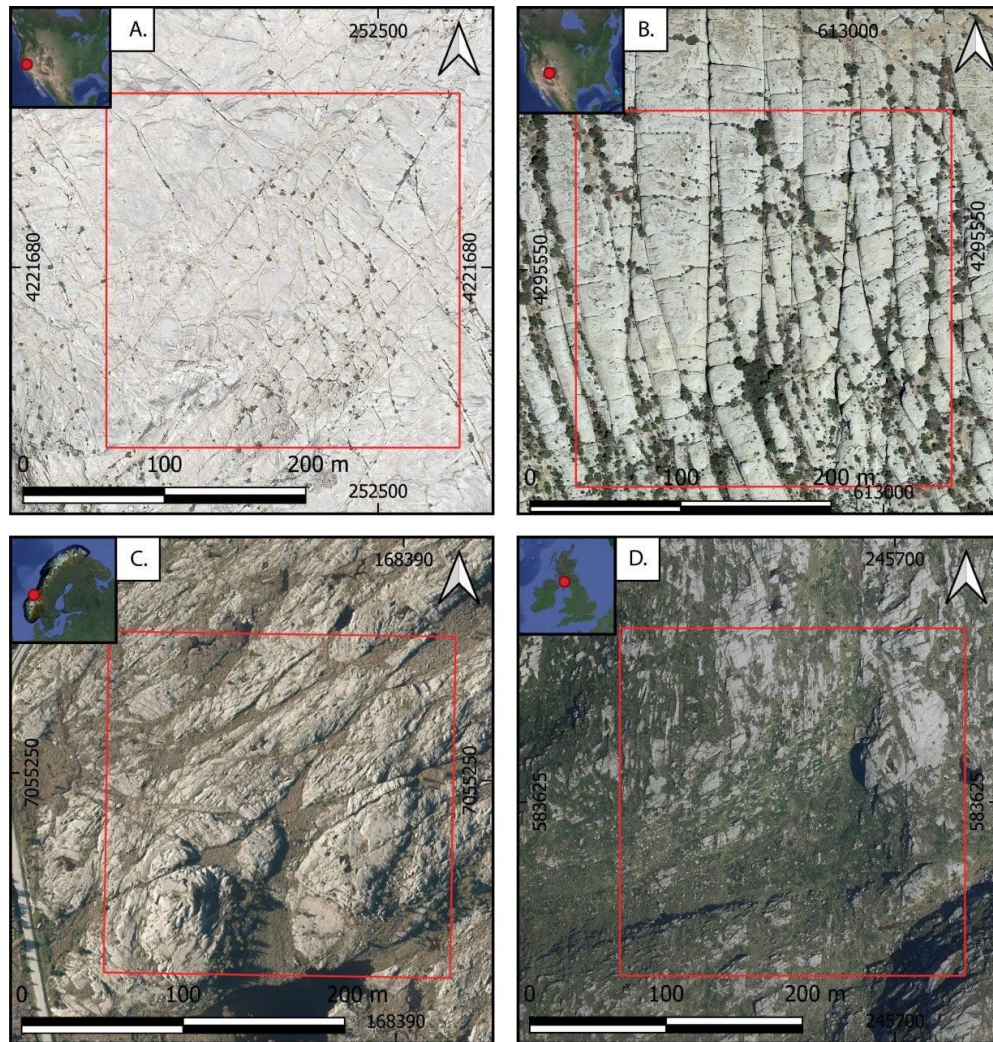


Figure 4.1 Full-color images of the four study areas: A. Gillet Mountain, Yosemite, USA; B. Salt Valley, Utah, USA; C. Havmyran, Hitra, Norway; D. Craignaw, Galloway, Scotland. The red box in each image indicates the areas used for automated extractions.

Fracture networks were extracted using two different automated methods. Image properties at each locality were quantified using Photoshop and QGIS. Multiple iterations of fracture networks were extracted to investigate the impact of varying key parameters. Similar to other studies examining fault and fracture network characteristics (e.g., Alexandersen & Andreassen, 2020; Alvarez et al., 2021; Sanderson & Nixon, 2018), properties including fracture length, orientation, and network topology were quantified.

In this study, two fracture detection methods were used: 1) the shearlet-based method developed by Prabhakaran et al. (2019), which detects contrast differences between the rock mass and fractures, and 2) a binary method implemented in ImageJ (Rueden et al. 2017) that differentiates fractures based on contrast. In both cases, a single raster image with dimensions of 1000px-by-1000px was used as input. The workflow adopted for both methods and used throughout this investigation is summarized in Figure 4.2.

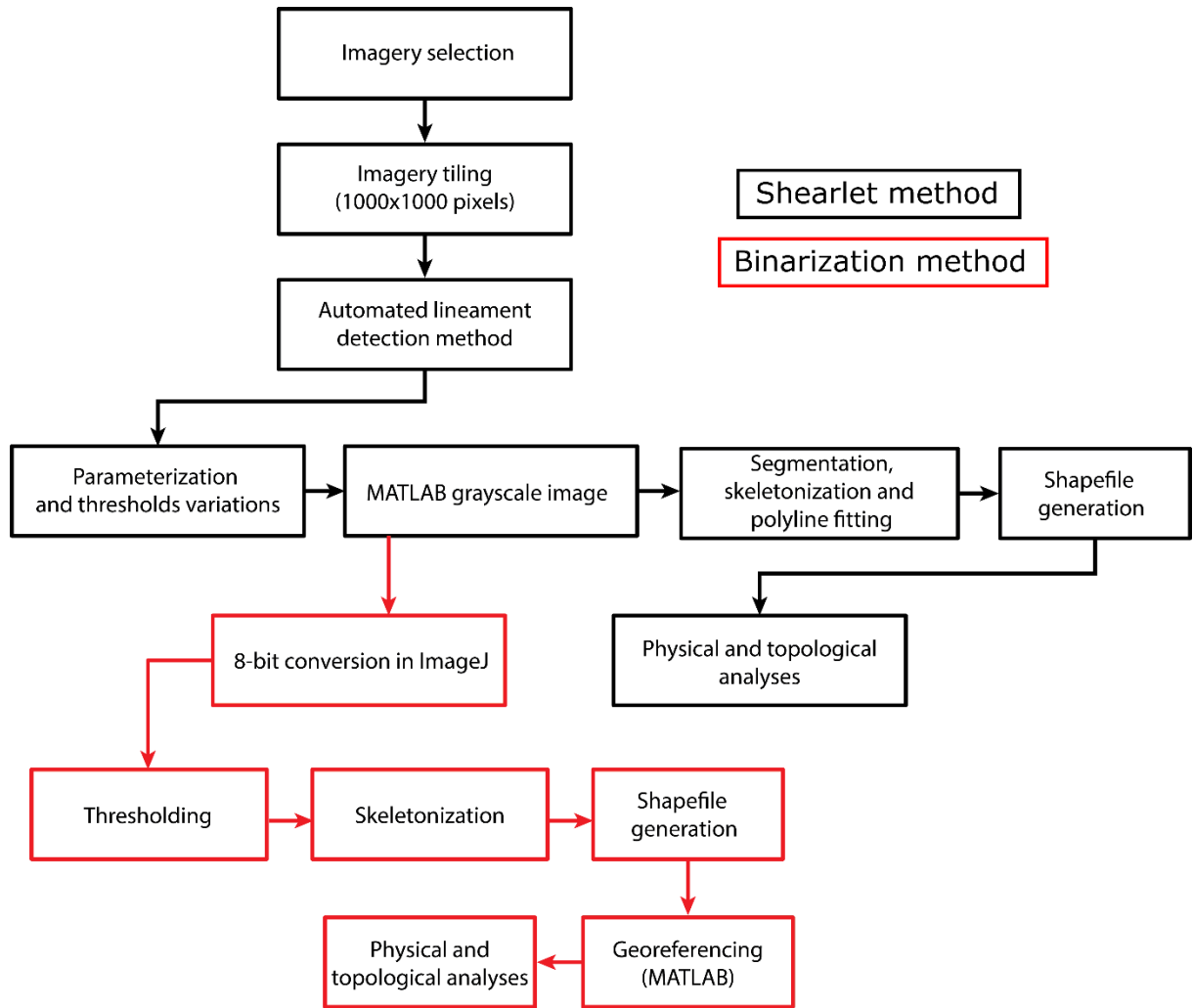


Figure 4.2 Workflow (Simplified) followed throughout the study. Shearlet Method is in black, Binarization Method is in red.

The shearlet method by Prabhakaran et al. (2019) is implemented in MATLAB and uses the complex shearlet ridge and edge measure (CoShREM) method described by Reisenhofer et al. (2016), incorporating Otsu thresholding (Otsu, 1979). This method was demonstrated using high-resolution drone imagery. The binary method in ImageJ uses a threshold value to differentiate between foreground and background pixels, considering pixels with intensity greater than the threshold as foreground and those with less intensity as background. Fractures extracted in both methods are

represented as lines, a common representation of geological features like faults and fractures in images and maps (Soller, Lindquist, and Matti 2002). Both methods employ a skeletonization process to convert raster representation of features into 1-pixel-wide lines (Rakesh and Rajpreet 2008).

4.2.1 Data and Setting

Outcrop exposures from four locations are used in this study (Figure 4.1): Gillet Mountain, Yosemite, USA (Tile A); 2) Salt Valley, Utah, USA (Tile B); 3) Havmyran, Hitra, Norway (Tile C) and 4) Craginaw, Galloway, Scotland (Tile D). Full-band color imagery for each location is shown in Figure 4.3, with summarized image properties provided in Table 4.1. See Data Availability for original imagery sources.

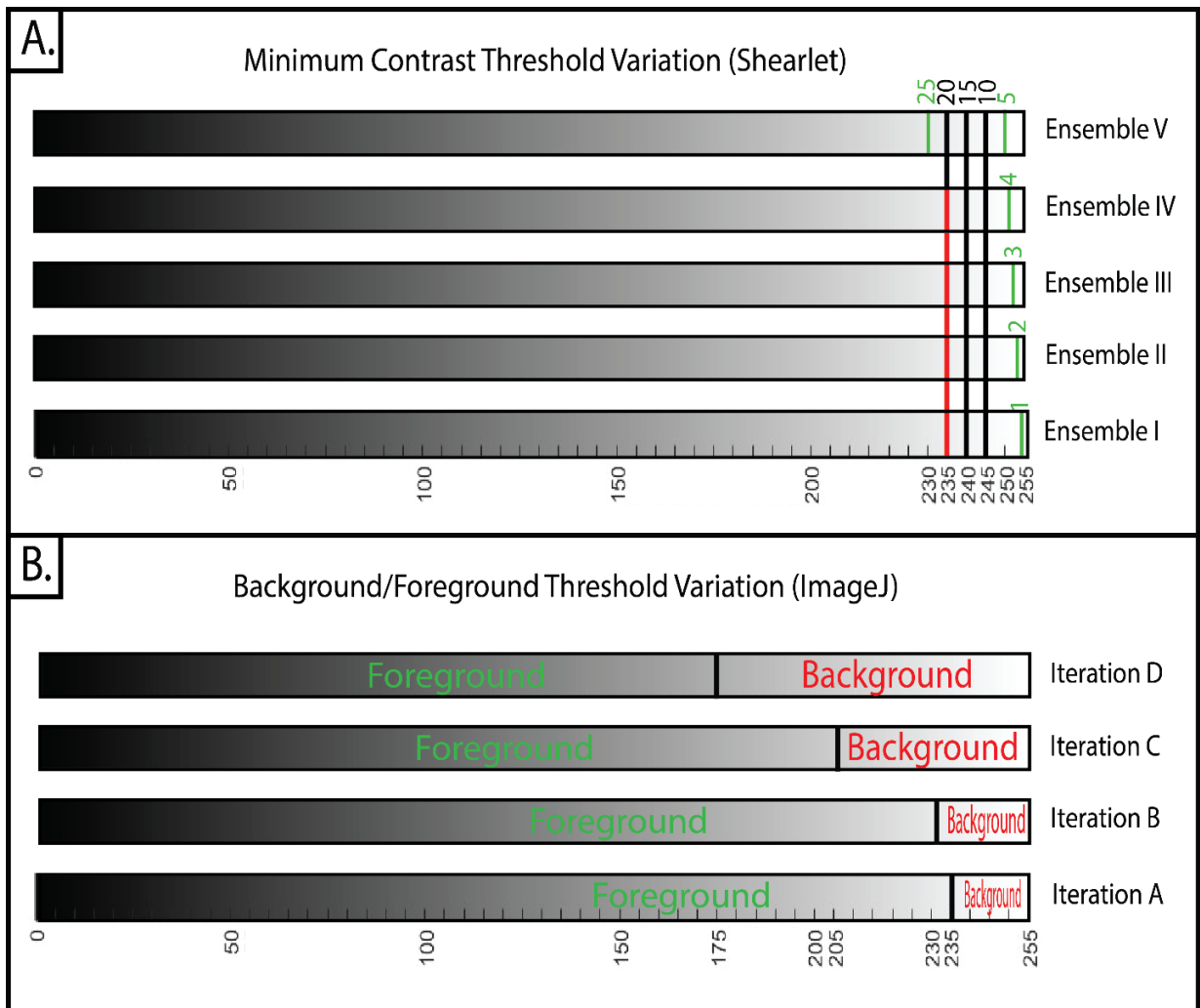


Figure 4.3 – 4.3A Visual representation of the contrast thresholds for each ensemble. Green lines and numbers represent the different thresholds used. Figure 4.3B shows how the foreground/background thresholds were varied, and what portions of the grayscale spectrum were subsequently used to trace lineaments (foreground)

Location	Image res. [Cm/pp]	Type of acquisition	Original image	Adjusted	Size (px)	Area (km ²)	Dominant rock type	Exposed rock %	Average image contrast	Average rock mass contrast	Average vegetation contrast
Yosemite	25	Aerial Survey	RBG	Grayscale	1000x1000	0.063	Granite	98.3	209	209	105
Utah	25	Aerial Survey	RBG	Grayscale	1000x1000	0.07	Sandstone	73.8	162	193	72
Hitra	21	Aerial Survey	RBG	Grayscale	1000x1000	0.045	Granite	51.6	133	175	107
Craignaw	25	Aerial Survey	RBG	Grayscale	1000x1000	0.064	Granite	15.6	99	163	81

Table 4.1 Image properties for each locality used in the study.

Gillet Mountain, Yosemite, constitutes part of the Sierra Nevada Batholith, featuring a rock composition ranging from quartz diorite to granite, emplaced during the Mesozoic (Bateman and Eaton 1967). The exposure in Salt Valley, Utah, belongs to the Curtis Formation, a component of the Upper Jurassic San Rafael Group (Gilluly and Reeside Jr. 1928). Havmyran, Hitra, is associated with the Smøla-Hitra Batholith, with pluton emplacement occurring from the Mid Ordovician to early Silurian (Bøe et al. 2005), exhibiting composition variations from granitic to granodiorite/tonalite (Gautneb and Roberts 1989). Caignaw, Galloway, pertains to the Loch Doon pluton, emplaced during the Devonian (late Caledonian) (Tindle and Pearce 1981), showcasing a composition ranging from granitic to granodioritic (Gardiner and Reynolds 1932; Hines et al. 2018).

4.2.2 Workflow

4.2.2.1 Image Preprocessing

All images, which were originally three-band color images (RGB), were converted to grayscale, with pixel values ranging from 0 (black) to 255 (white), using the `im2gray` function in MATLAB (MathWorks 2023b), which performs a weighted sum of the RGB values from each band. Grayscale images were then cropped into 1000x1000 pixel tiles using Adobe Photoshop (v. 24.3.0). The file format for images remained .TIF throughout the study.

4.2.2.2 Image Analysis

To investigate the influence of image properties and outcrop characteristics on extracted feature networks, the following aspects were quantified: 1) percentage of vegetation cover, 2) continuity of the exposed rock area, representing the degree to

which exposure of rock can be traced continuously over an area without being interrupted by vegetation, 3) percentage of foreground pixels (based on the total number of pixels above the defined threshold) and 4) pixel connectedness. The percentage of vegetation cover was quantified using ArcMap 10.8.2's Image Classification Tool. Ten training polygons were traced over vegetated areas to guide the classification algorithm in identifying and extracting vegetated pixels across the image. To quantify the foreground percentage in binary images produced by both approaches, the 'Raster Layer Unique Values Report' function in QGIS was used to compute the count of unique pixel values within the image and then calculate the proportion of foreground to background pixels for both the binarized and skeletonized images. Pixel connectedness in binary and skeletonized images produced using both approaches was determined using MATLAB's Depth-First Search (DFS) function, which calculates the number of connected regions in a two-dimensional matrix (MathWorks, 2023a).

4.2.2.3 Shearlet Method

The Shearlet Method, based on the complex shearlet transform method developed by Prabhakaran et al. (2019), is designed to interpret fractures in rock exposures by detecting linear features, or 'ridges,' in an image. Each image is transformed into a ridge probability map representing an ensemble of possible features, with five iterations per ensemble (see Table 1). The resulting ensemble is converted into a skeletonized image, thinning detected ridges into single-pixel clusters (Prabhakaran et al. 2019). Polylines are then fitted through the skeleton image and converted into a georeferenced shapefile for quantifying and characterizing the fracture network.

To assess the impact of varying contrast thresholds, the minimum contrast threshold was varied for each ensemble (see Table 4.2), while other parameters remained unchanged. The minimum contrast can be any value between 0 to 255.

Parameters	Values	
Wavelet effective support	5, 8, 10, 12, 15	Base-case Parameters
Scales per octave	1, 2, 3, 4	
Alpha	0, 0.25, 0.5, 0.75, 1	
Offset	0.001, 0.01, 0.1, 1, 2	
Octaves	3.5	
Minimum Contrast		Modified Parameters
Ensemble I	1, 5, 10, 15, 20	
Ensemble II	2, 5, 10, 15, 20	
Ensemble III	3, 5, 10, 15, 20	
Ensemble IV	4, 5, 10, 15, 20	
Ensemble V	5, 10, 15, 20, 25	

Table 4.2 Parameters used in the different ensembles of the Shearlet Method for extracting features.

In all the images used in this study, faults and fractures are most likely represented by low contrast values (<235, see Figure 4.3A), with the unfractured rock mass mostly represented by higher contrast values. The contrast thresholds used in this method

are listed in Table 4.2. Contrast thresholds used for Ensemble I to IV are shown in Figure 4.3A. The upper threshold was kept constant at 235 for the first four Ensembles. In Ensemble V, the upper threshold was set at 230, while the lower threshold was set at 250.

4.2.2.4 Binarization Method

To evaluate the reliability of the Shearlet Method the results were compared to the Binarization Method implemented using ImageJ (v. 1.53t). Only the image from Yosemite was used for this comparison; the same grayscale image used in the shearlet method was used for consistency. The method separates pixels above and below a defined threshold value (see Figure 4.3B) to distinguish between foreground and background (ImageJ 2023). For example, a contrast threshold of 175 means that pixels with an intensity value lower than 175 are identified as part of the foreground, and pixels with intensity values greater than 175 are designated as background. Four different contrast thresholds were evaluated, which are shown in Table 4.3.

Iteration #	Contrast Threshold
A	210
B	205
C	195
D	175

Table 4.3 Parameters used for extracting networks automatically via ImageJ.

In each resulting binary image, pixels have a value of either zero (black), which represents the foreground, or one (white), which represents the background. Skeletonization of the binarized image then fitted lines along the foreground features

(ImageJ, 2024). The Binarization Method does not preserve topology of the networks automatically extracted, meaning that, despite lines being effectively snapped, they do not form nodes where they intersect. To address this, it was assumed that features within a proximity of 0.000001m (or 1 micrometer) were connected.

4.2.2.5 Fracture Network Analysis

To characterize the automatically extracted networks, the following properties were determined for each iteration: 1) number of features, 2) length of each feature, 3) orientation of each feature, 4) density and intensity of the network, and 5) network topology. This analysis was conducted in QGIS using the NetworkGT plugin (Nyberg, Nixon, and Sanderson 2018), which provides functionality for characterizing fault and fracture networks (Nyberg et al. 2018). Length and orientation were calculated using the field calculator in QGIS. Throughout the study, Root Mean Square Error (RMSE) was used to measure the reliability of automated methods. RMSE was calculated between the normalized fracture length distributions of automatically extracted networks, indicating how much variability exists across different ensembles and iterations. It provides a quantitative measure of how accurately automated methods detect and trace features compared to a known standard or reference. Lower RMSE values indicate higher reliability and accuracy of the automated method, as they reflect smaller differences between the predicted and observed feature detections. However, in this study, no manual interpretation is used as a reference. Instead, the outputs from each parameter set or distinct automated method are compared directly with one another, and each acts as a standalone baseline. The RMSE therefore quantifies how the key fracture property of length differs across these automated outputs, again, with each output effectively serving as a baseline in turn.

Consequently, lower residuals between RMSE indicate that an automated method produce more reliable results. In our analysis, the fracture length from each ensemble were represented using step histograms, and the counts were normalized to a common scale for reliable comparisons. The differences between the normalized histograms were quantified by calculating the root mean square error (RMSE) for each pair of ensembles.

4.3 Results and Observations

4.3.1 Characteristics of Extracted Networks – Shearlet Method

The results of the Shearlet Method for each area of interest are summarized in Figure 4.4.

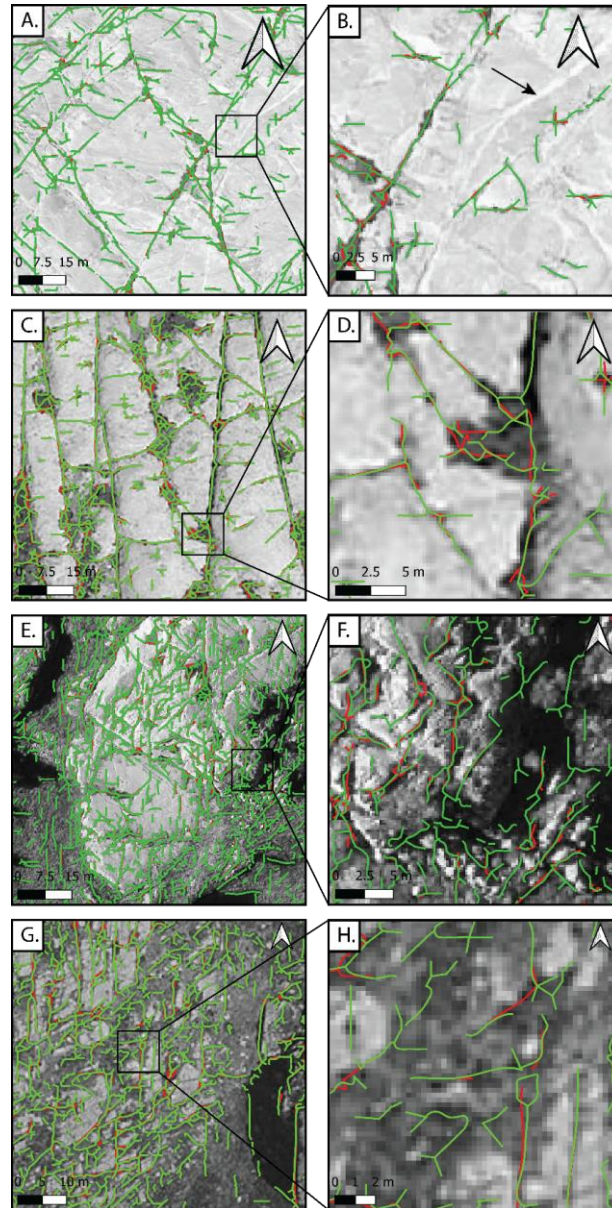


Figure 4.4 Automated interpretations using the Shearlet Method across different case studies, with Ensemble 1 in green and Ensemble 5 in red. In Yosemite (A and B), high rock mass contrast highlights fractures, though Ensemble 1 misses some features, including high-intensity ones (pointed by black arrow). In Utah (C and D), lower contrast reveals wider fractures, but vegetation causes some interference. In Hitra (E and F), extensive

vegetation leads to non-geological interpretations. Similarly, in Cragshaw (G and H), vegetation and shadows compromise the reliability of lineament tracing.

While some features were identified (Figure 4.4A, B, C, and D), others were missed by the method, as shown in Figure 4.4B and Figure 4.4D. Additionally, there is a significant presence of non-robust geological interpretations, such as features inaccurately traced in shadows and vegetation, particularly evident in Figure 4.4E, F, G, and H. Figure 4.5C, F, I, L show the effect of thresholding on fracture length in all four case study areas. Fractures appear more broken down with lower thresholds, indicating that the extraction is more sensitive and results in more connections (Figure 4.5C, green lines, Ensemble I). In Ensemble B (Figure 4.5C, red lines, Ensemble 5), the exact same feature is interpreted as continuous, demonstrating how varying thresholds can significantly alter the interpretation of geological features. This highlights the importance of selecting appropriate thresholds to ensure accurate and consistent feature extraction in automated geological analysis.

4.3.1.1 Yosemite – Effect of Multi-Contrast Thresholds on Fracture Networks

Ensemble I identified 6,471 features with an average length of 2.17 m, density of 0.103, and 2D intensity of 0.217. In Ensemble II, features decreased by 11.3% to 5,738, with an average length of 2.21 m. Density and 2D intensity decreased to 0.091 and 0.202, respectively. Ensemble III saw a further 8.6% reduction to 5,244 features, with average length increasing to 2.23 m, and density and 2D intensity decreasing to 0.083 and 0.185. Ensemble IV reduced features by 7.97% to 4,836, with an average length of 2.25 m, and density and 2D intensity down to 0.077 and 0.172. In Ensemble V, features sharply decreased by 50.37% to 2,395, with average length increasing to 2.49 m, and density and 2D intensity dropping to 0.038 and 0.095. Topology analysis

showed a reduction in nodes from 6,421 in Ensemble I to 2,702 in Ensemble V (Table 4.4).

In Ensemble I, 4.4% of features had contrast above average rock mass contrast, 91.7% between rock mass and vegetation contrast, and 3.9% below vegetation contrast (Figure 4.5A). In Ensemble V, 1% were above rock mass contrast, 88.3% between rock mass and vegetation contrast, and 10.8% below (Figure 4.5B). Major trends (NS and EW) persisted across all ensembles (Figure 4.6A, B). In Ensemble I, the average feature contrast was 170, which decreased to 169 in Ensemble II. This trend of decreasing contrast continues with Ensembles III and IV, where the average feature contrast was 167 and 165, respectively. By Ensemble V, the average feature contrast significantly dropped to 149 (Table 4.4).

The statistics for Yosemite align with expectations, indicating fewer features when lowering contrast thresholds. Interestingly, as shown in Figure 4.7A, length distribution varies very little, between the Ensembles. While tracing fewer features results in fewer nodes, lower density, and lower intensity, the increase in feature length can be explained by two factors.

Firstly, there is a continuous decrease in the number of short features traced using high-intensity pixels (closer to 250) from Ensemble I to Ensemble V. High-intensity pixels tend to break up fractures more frequently because they are interpreted as separate features (Figure 4.5C). This also contributes to an increase in nodes from ensemble to ensemble, as longer features are interrupted by numerous shorter features, creating more connections and intersections within the fracture network. Secondly, as contrast thresholds are lowered, the length trend shifts toward the right side of the plot, which indicates longer features throughout the network. This is attributed to the fact that lower contrast thresholds result in fewer breaks caused by

high-intensity pixels, which are otherwise interpreted as separate features. Moreover, the relatively low variability of RMSE observed between ensembles (Table 4.4) suggests minimal differences in the length distributions across the five ensembles (Figure 4.8A, 7E). This consistency across parameterizations is used here as an indicator of reliability, the rationale for which was discussed previously. The high consistency correlates well with the continuous exposure of the Yosemite study area, which is 98.3%. The continuous exposure provides less opportunity for non-geological interpretation of features, leading to similar length distributions and a low RMSE (3.56).

4.3.1.2 Utah – Effect of Multi-Contrast Thresholds Variation on Fracture Network

For Utah, Ensemble I identified 10,751 features with an average length of 1.83 m, density of 0.173, and 2D intensity of 0.281. Ensemble II reduced features by 6.2% to 10,085, with an average length of 1.86 m, density of 0.162, and 2D intensity of 0.268. Ensemble III saw a further reduction to 9,366 features, an average length of 1.89 m, and density and 2D intensity of 0.151 and 0.254. Ensemble IV identified 8,912 features, with an average length of 1.91 m, and density and 2D intensity of 0.143 and 0.243. Ensemble V saw a significant drop to 4,440 features, with an average length of 2.24 m, and density and 2D intensity decreasing to 0.071 and 0.153. Topology analysis showed a reduction in nodes from 9,401 in Ensemble I to 4,733 in Ensemble V (Table 4.4).

In Ensemble I, 1.7% of features were above average rock mass contrast, 66.6% between rock mass and vegetation contrast, and 31.7% below vegetation contrast (Figure 4.5D). Ensemble V had <1% above rock mass contrast, 62.1% between rock

mass and vegetation contrast, and 37.6% below (Figure 4.5E). Major trends (NS and EW) persisted across all ensembles (Figure 4.6C, D).

The average feature contrast decreased from 100 in Ensemble I to 89 in Ensemble V (Table 4.4). Length variation is more pronounced for the Utah case study, as shown in Figure 4.7B. Average feature contrast goes down as contrast thresholds are lowered, which is an expected behavior since at lower thresholds the software becomes less sensitive to high-intensity pixels. Interestingly, the length distributions between the ensembles start to spread out (Figure 4.7B), with RMSE between ensembles becoming larger. The calculated average RMSE of 5.20 (Table 4.4) is higher than the one for Yosemite (3.56) (Figure 4.7E), which corroborates the theory that as the percentage of continuity decreases, the reproducibility of the automated extraction also decreases, resulting in more varied lengths. Overall, there is still a good degree of similarity between the Ensembles for Utah, meaning that the method is still tracing features reliably and maintains a consistent length across ensembles.

4.3.1.3 Hitra – Effect of Multi-Contrast Thresholds on Fracture Networks

In Hitra, Ensemble I detected 14,652 features averaging 1.47 m in length, with a density of 0.326 and 2D intensity of 0.478. Ensemble II reduced features to 13,440, with an average length of 1.50 m, and density and 2D intensity of 0.299 and 0.447. Ensemble III identified 12,353 features, with an average length of 1.54 m, and density and 2D intensity of 0.275 and 0.422. Ensemble IV reduced features to 11,471, with an average length of 1.57 m, and density and 2D intensity of 0.255 and 0.400. Ensemble V saw a significant drop to 5,621 features, with an average length of 1.98 m, and density and 2D intensity of 0.125 and 0.232. Topology analysis showed a reduction in nodes from 12,836 in Ensemble I to 5,739 in Ensemble V (Table 4.4).

In Ensemble I, 1.7% of features were above average rock mass contrast, 45.5% between rock mass and vegetation contrast, and 52.8% below vegetation contrast (Figure 4.5G). In Ensemble V, 1% were above rock mass contrast, 42% between rock mass and vegetation contrast, and 57% below (Figure 4.5H). Major trends (NS and NESW) persisted across all ensembles (Figure 4.6E, F).

The average feature contrast decreased from 107 in Ensemble I to 103 in Ensemble V (Table 4.4). This higher vegetation percentage introduces more noise and less distinct geological features into the dataset. As visible in Figure 4.7C, the spread between trendlines starts to be considerable, and again this aligns with our expectations. Rock mass continuity across the Hitra case study is much lower compared to the previous two cases, with a continuity of 51.6%. In fact, the RMSE average for Hitra was 6.16, which is higher than the previous two cases (Figure 4.7E). This again further confirms that reproducibility of automated methods decreases as rock mass continuity decreases.

4.3.1.4 Craignaw – Effect of Multi-Contrast Thresholds on Fracture Networks

For Craignaw, Ensemble I identified 11,276 features with an average length of 1.77 m, density of 0.192, and 2D intensity of 0.339 (Figure 4.6A to Figure 4.6F). Ensemble II reduced features by 7.5% to 10,426, with an average length of 1.81 m, and density and 2D intensity of 0.163 and 0.296. Ensemble III detected 8,912 features, with an average length of 1.87 m, and density and 2D intensity of 0.139 and 0.261. Ensemble IV reduced features to 7,542, with an average length of 1.98 m, and density and 2D intensity of 0.118 and 0.233. Ensemble V saw a significant drop to 2,398 features, with an average length of 2.74 m, and density and 2D intensity decreasing to 0.037 and

0.103. Topology analysis showed a reduction in nodes from 11,701 in Ensemble I to 3,142 in Ensemble V (Table 4.4).

Almost no features in Ensemble I had an average contrast above rock mass (0.3%), while 46.8% were between rock mass and vegetation contrast, and 51.9% below vegetation contrast (Figure 4.5J). In Ensemble V, no features were above rock mass contrast, 51.2% were between rock mass and vegetation contrast, and 48.8% below (Figure 4.5K). Major trends (NS, EW, NESW) persisted across all ensembles (Figure 4.6G, 6H).

The average feature contrast in Cragshaw ranged from 82 in Ensemble I to 84 in Ensemble IV, with a slight decrease back to 82 in Ensemble V (Table 4.4). These fluctuations highlight the challenges posed by high vegetation percentage and low rock mass continuity, which is only 15.6%. The average feature contrast being close to the average vegetation contrast (81) rather than the rock mass contrast (163) indicates that the automated detection method often traces features in vegetated areas rather than in the rock mass. Lastly, for Cragshaw, although fewer features were traced compared to previous cases, a much larger spread of length distributions can be observed (10.04) (Figure 4.7D). In fact, given the very low rock mass continuity in this case study, the very significant spread between RMSEs indicates higher variability and lower reproducibility in the fracture length measurements. The low continuity is contributing to the increased difficulty in consistently tracing features, leading to greater discrepancies in the length distributions across different ensembles (Table 4.4). Following trends from previous case studies, this study confirms the hypothesis that rock mass continuity is the greatest contributing factor to reliable fracture tracing.

Location	Contrast Thresh. Max/min	# of fractures	Avg Length (m)	RMSE Ens. I/II Ens. I/III Ens. I/IV Ens. I/V Avg RMSE	# of nodes	Topology (%)	Density (F/m ²)	2D Intensity (Σ Length /m ²)
Yosemite								
Ensemble I	254/235	6,471	2.17	-	6,421	I:73; Y:23; X:4	0.103	0.217
Ensemble II	253/235	5,738	2.21	1.86	5,709	I:74; Y:23; X:3	0.091	0.202
Ensemble III	252/235	5,244	2.23	2.79	5,118	I:75; Y:23; X:2	0.083	0.185
Ensemble IV	251/235	4,826	2.25	2.29	4,858	I:75; Y:22; X:3	0.077	0.172
Ensemble V	250/230	2,395	2.49	6.18 3.56	2,702	I:80; Y:18; X:2	0.038	0.095
Utah								
Ensemble I	254/235	10,751	1.83	-	9,401	I:66; Y:30; X:4	0.173	0.281
Ensemble II	253/235	10,085	1.86	1.28	8,846	I:66; Y:30; X:4	0.162	0.268
Ensemble III	252/235	9,366	1.89	1.92	8,331	I:67; Y:29; X:4	0.151	0.254
Ensemble IV	251/235	8,912	1.91	2.07	8,088	I:68; Y:29; X:3	0.143	0.243
Ensemble V	250/230	4,440	2.24	11.10 5.20	4,733	I:75; Y:23; X:2	0.071	0.153
Hitra								
Ensemble I	254/235	14,652	1.47	-	12,836	I:66; Y:30; X:4	0.326	0.478
Ensemble II	253/235	13,440	1.50	1.28	11,964	I:67; Y:29; X:4	0.299	0.447
Ensemble III	252/235	12,353	1.54	2.42	11,263	I:69; Y:28; X:3	0.275	0.422
Ensemble IV	251/235	11,471	1.57	3.20	10,609	I:70; Y:27; X:3	0.255	0.400
Ensemble V	250/230	5,621	1.98	13.75 6.16	5,739	I:79; Y:20; X:1	0.125	0.232
Craignaw								
Ensemble I	254/235	12,276	1.77	-	11,701	I:71; Y:25; X:4	0.192	0.339
Ensemble II	253/235	10,426	1.81	2.15	10,055	I:73; Y:25; X:2	0.163	0.296
Ensemble III	252/235	8,912	1.87	2.98	8,825	I:75; Y:24; X:1	0.139	0.261
Ensemble IV	251/235	7,542	1.98	5.51	7,792	I:76; Y:21; X:3	0.118	0.233
Ensemble V	250/230	2,398	2.74	22.48 10.04	3,142	I:86; Y:13; X:1	0.037	0.103

Table 4.4 Table of properties of networks extracted automatically with the shearlet method.

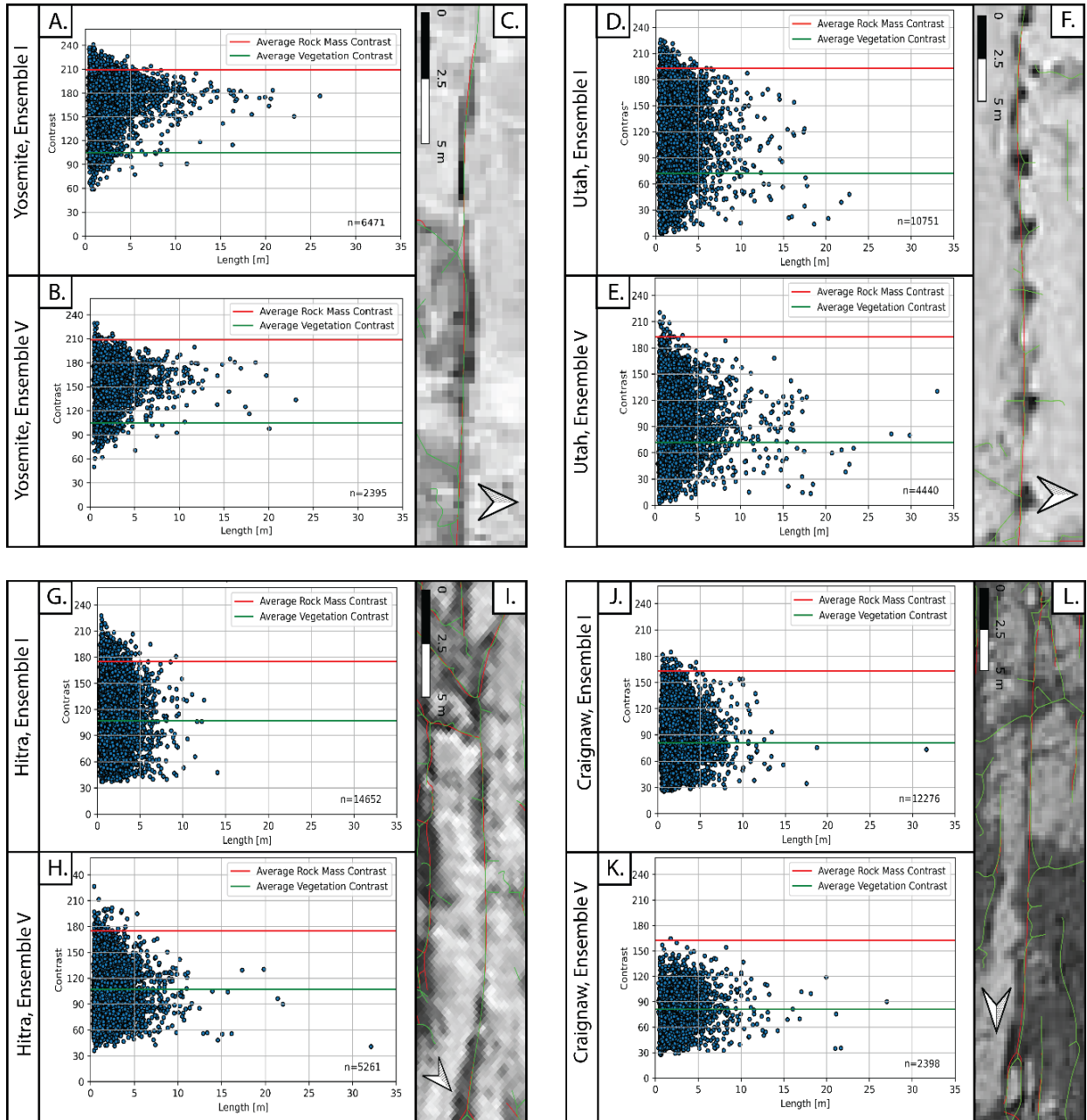


Figure 4.5 Scatterplots showing the relationship between feature length and contrast across varying thresholds for each dataset. Panels C, F, I, and L illustrate how the same features are interpreted in Ensemble 1 (green) versus Ensemble 5 (red).

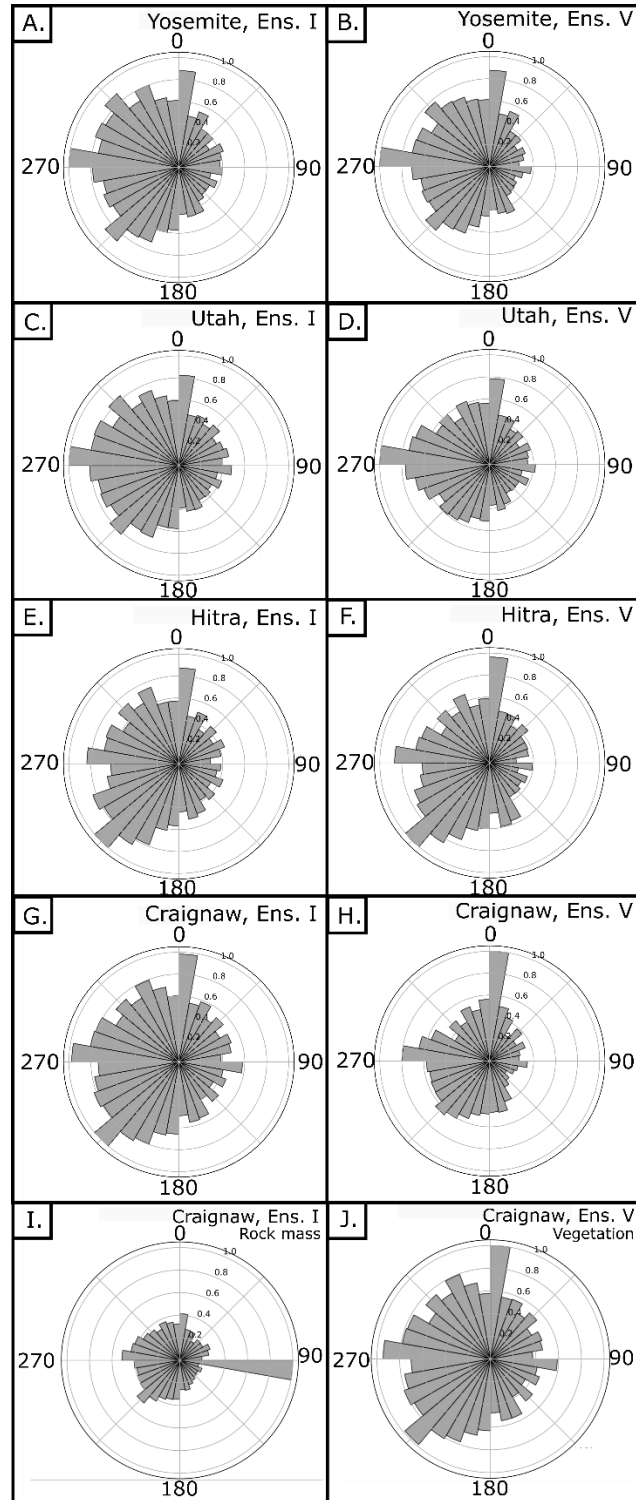


Figure 4.6 Rose diagrams illustrating orientation of lineaments from different iterations of automatically extracted fracture networks. Main orientations are consistent among all

the ensembles. Plots J and K however show that there is a significant difference between figures traced solely in vegetation and features traced solely in rock mass.

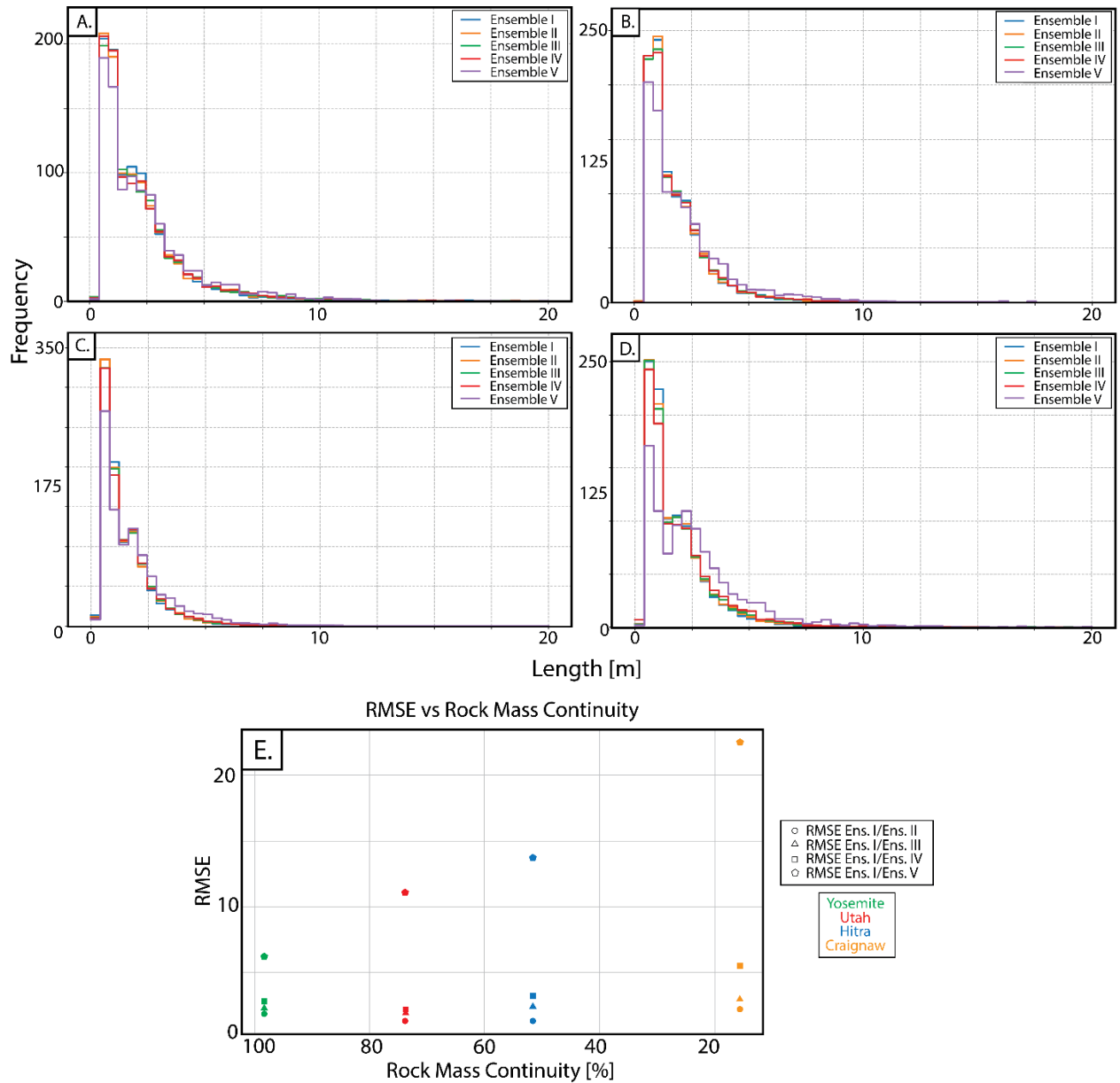


Figure 4.7 Length distribution plots showing variability between ensembles. As rock mass continuity decreases, length distribution becomes more spread and less reliable. The Root Mean Square Error was calculated to measure the reproducibility between distributions for the four study cases.

4.3.2 Characteristics of Extracted Networks – Binarization Method

Figure 4.8 presents the results for Iterations A to D. Using the Binarization Method often results in numerous non-geological interpretations and circular artifacts (Figure 4.8), indicating the overall unreliability of the method. As the thresholds are lowered in the Binarization Method, results become increasingly comparable to those of the Shearlet Method.

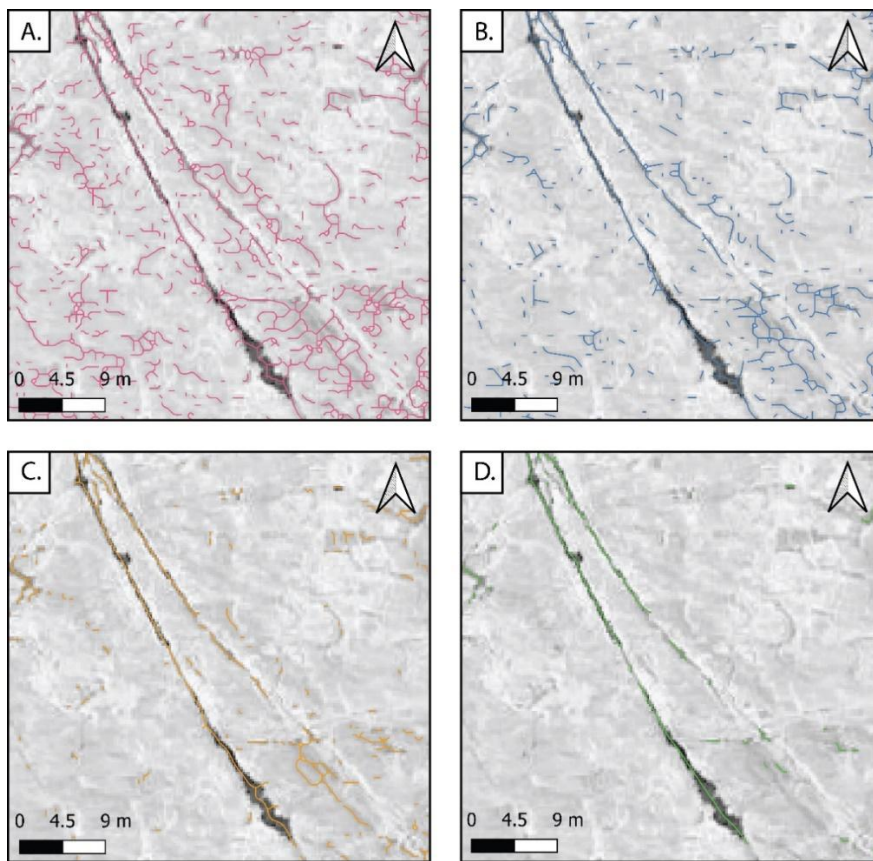


Figure 4.8 Results from four iterations (A, B, C, D) using the binary thresholding method. Overall, numerous non-geological features and circular artifacts can be seen, underscoring the method's general unreliability.

However, the Binarization Method still struggles to maintain feature continuity at higher contrast thresholds, which often results in broken features that should be continuous for accurate geological interpretation.

4.3.2.1 Yosemite – Effect of Single-Contrast Threshold on Fracture Networks

Results are summarized in Table 4.5.

Iteration #	Contrast Threshold	AVG Feature Contrast	# of fractures	AVG Length (m)	# of nodes	Topology (%)	Density (F/m ²)	2D Intensity (Σ Length/m ²)
Iteration A	210	194	45460	2.07	42337	I:43; Y:55; X:2	0.70	0.67
Iteration B	205	184	30851	1.93	32418	I:55; Y:44; X:1	0.49	0.48
Iteration C	195	183	18840	1.82	23065	I:69; Y:31; X:0	0.29	0.32
Iteration D	175	151	8319	1.46	12720	I:85; Y:15; X:0	0.13	0.14

Table 4.5 Table of properties of networks extracted automatically with the binarization method.

In Iteration A, 45,460 features were extracted with an average length of 2.07 m, a density of 0.70, and a 2D intensity of 0.67. Feature count decreased by 33.1% in Iteration B to 30,851, with density and 2D intensity dropping to 0.49 and 0.48, respectively. Iteration C recorded 18,840 features, with density and 2D intensity further reduced to 0.29 and 0.32. Iteration D traced 8,319 features, with density at 0.13 and 2D intensity at 0.14 (Table 4.5).

Feature contrast analysis (Figure 4.9A to D) shows that in Iteration A, 19.34% of features were above the average rock mass contrast of 209, 79.98% were between 209 and 105, and 0.51% were below 105. Iteration B had 0.58% above 209, 97.84%

between 105 and 209, and 1.53% below 105. Iteration C recorded 6.01% above 209, 92.72% between 209 and 105, and 1.07% below 105. Iteration D had no features above 209, with 94.6% between 209 and 105, and 5.29% below 105. Fewer features were identified as contrast thresholds increased (Table 4.5).

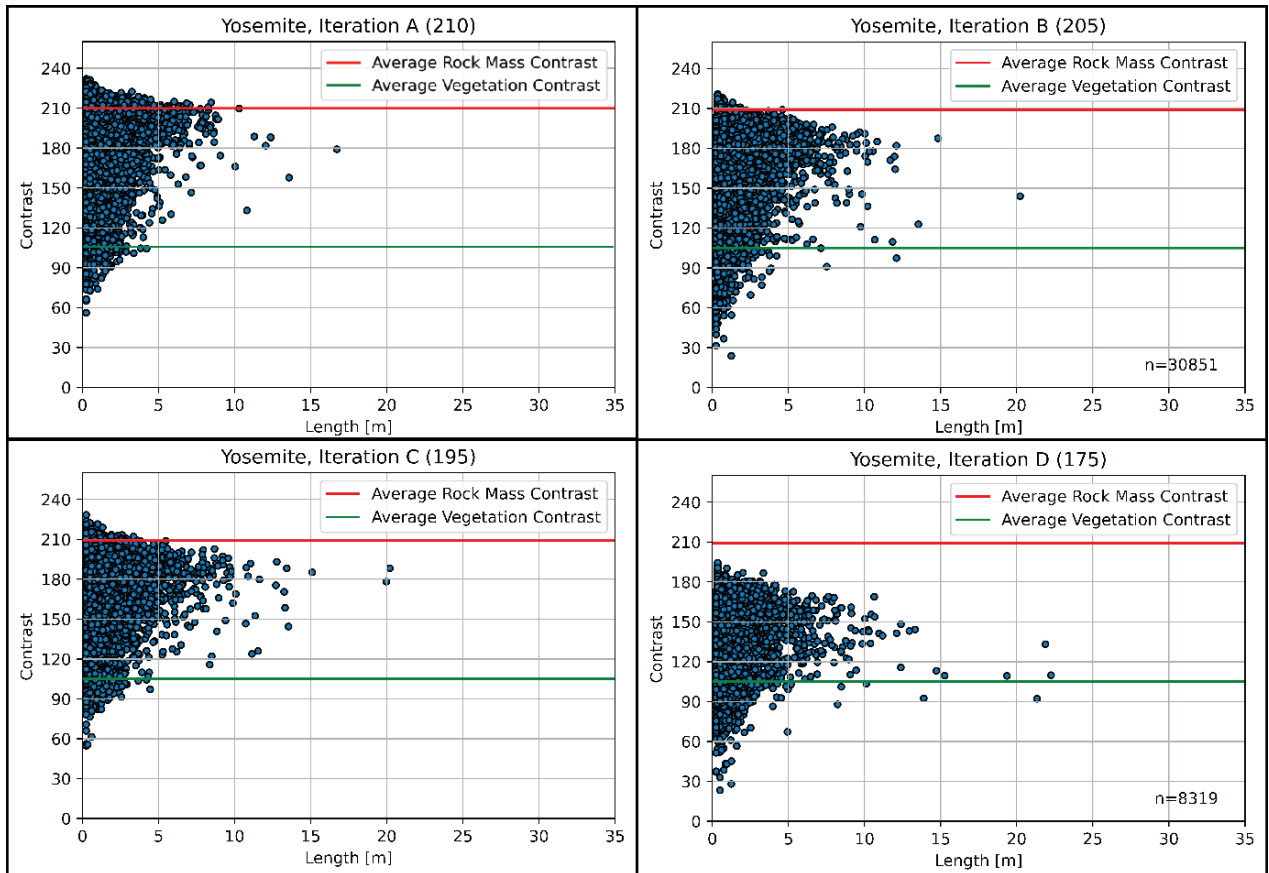


Figure 4.9 Scatter plots of length against average feature contrast. Red line is average rock mass contrast, at a value of 209; green line is average vegetation contrast, at a value of 105. Figures show the relative percentages of features above, between, and below vegetation and rock mass contrast for Iterations A (19.34%, 79.98%, 0.51%), B (0.58%, 97.84%, 1.53%), C (6.01%, 92.72%, 1.07%), and D (0%, 94.6%, 5.29%).

Topology results (Table 4.5) indicate that in Iteration A, the network comprised 42,337 nodes with 43% I nodes, 55% Y nodes, and 2% X nodes. The node count decreased to

32,418 in Iteration B, with 55% I nodes, 44% Y nodes, and 1% X nodes. Iteration C had 23,065 nodes with 69% I nodes and 31% Y nodes. Iteration D had 12,720 nodes with 85% I nodes and 15% Y nodes.

The NS and EW orientations dominated across all iterations (Figure 4.10A to D), with consistent patterns suggesting potential extraction artifacts. The results show that increasing contrast thresholds (from Iteration A to D) significantly reduces the number of detected features and alters their properties. Higher thresholds filter out lower-intensity pixels, representing smaller or less distinct features, leading to a more fragmented and simplified network. This is evidenced by the decrease in feature count, density, and 2D intensity, and the shift in node proportions.

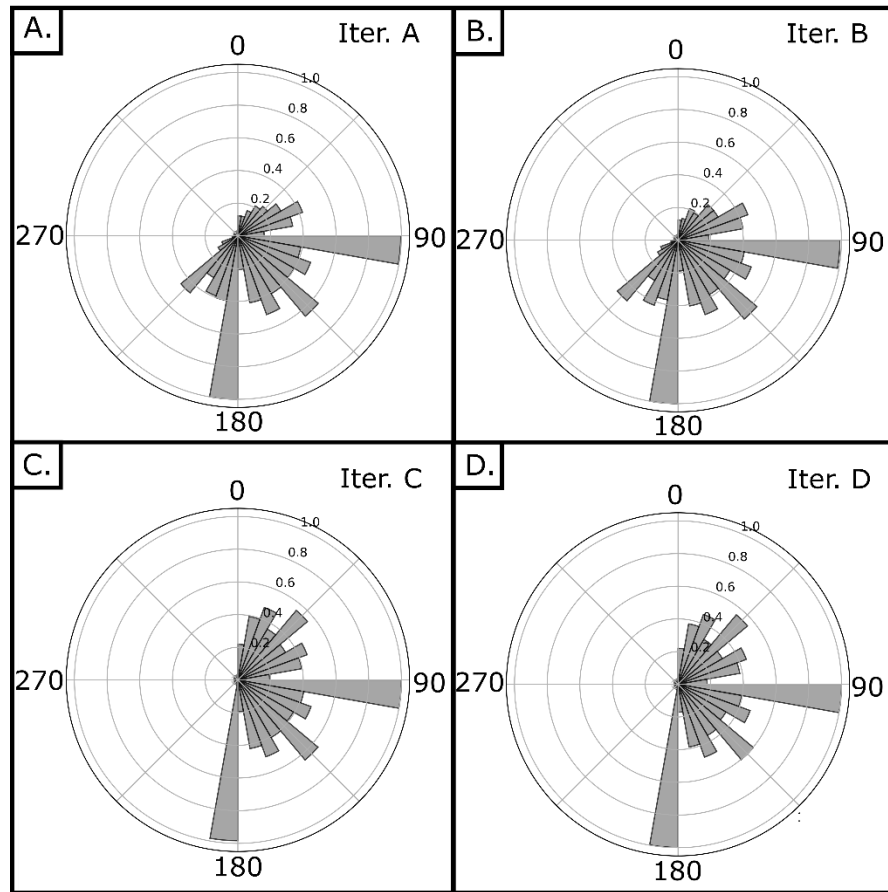


Figure 4.10 Rose diagrams of the lineaments extracted using the binarization method for four different iterations. The major difference amongst plots A, B, C, and D is frequency. This highlights how sensitive this automated process is to parameter changes.

The comparison of average feature contrast supports these observations. As contrast thresholds increase from Iteration A to D, the average feature contrast decreases from 194 to 151. Moving to Iteration D, the Binarization Method, similar to the Shearlet Method, is increasingly restricted to using darker pixels (low intensity). This means that fewer short, high-contrast features, which are often noise and non-geological, are detected. Consequently, only the longer, linear features, which are more likely to be geological, remain (Table 4.5).

This shift causes the average feature contrast to move further away from the average rock mass contrast (209), as the software primarily uses dark pixels to trace features. In terms of reliability, upon comparing results to the network extracted using the Shearlet method for Yosemite, the Binarization Method was found to be much more unreliable, with a calculated average RMSE of 40.22, which is even higher than the RMSE for Cragshaw. The RMSE between ensemble I and Iteration A was 39.78. This was expected, as the ImageJ method is considered a more "out-of-the-box" approach and is not as specialized as the Shearlet Method. This underlines the significant impact of the chosen image processing technique on the reliability of fracture length measurements.

4.3.3 Network and Image Characteristics

Figure 4.11 shows crossplots of how fracture network characteristics change as a consequence of using different contrast thresholds.

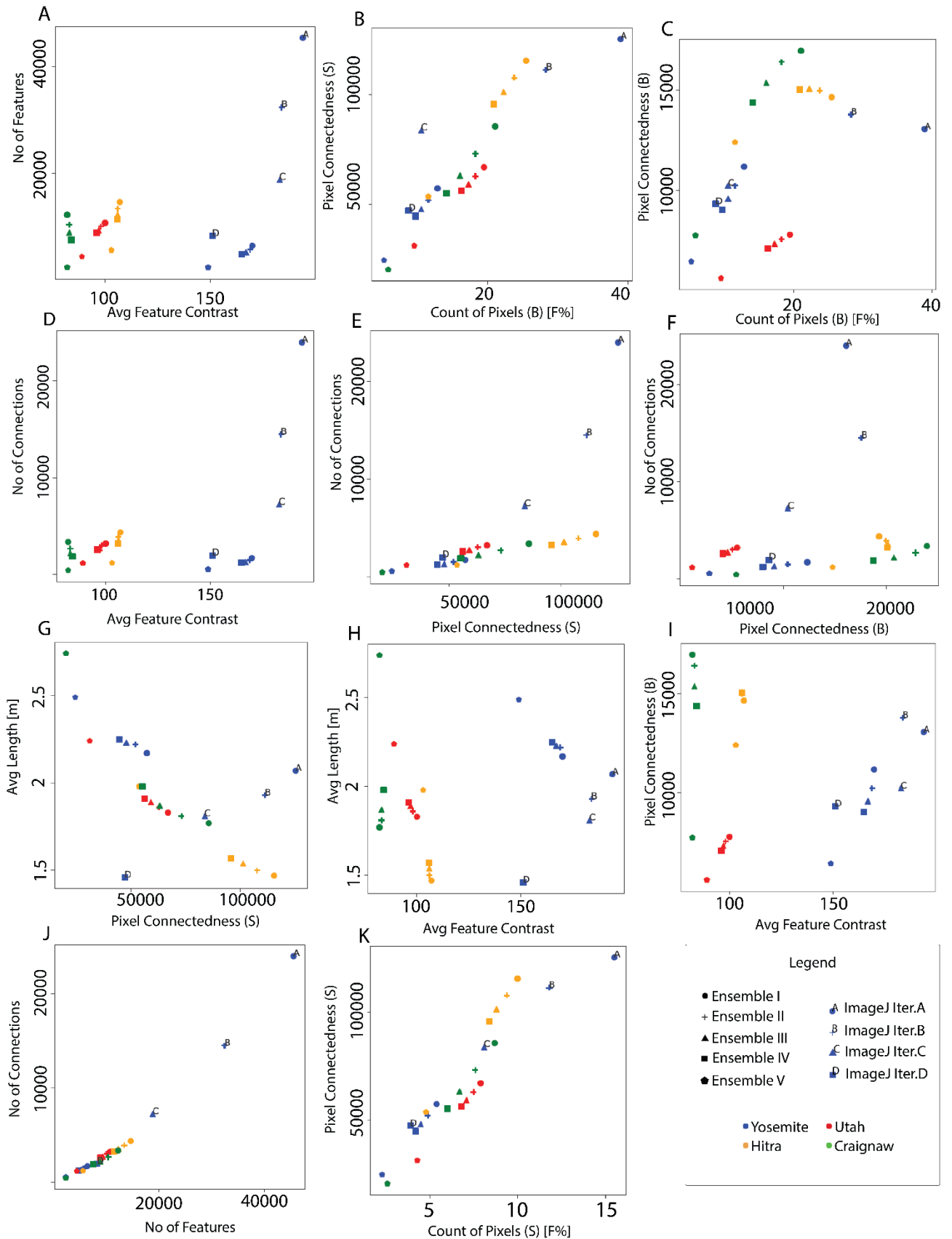


Figure 4.11 Cross plot analysis of lineament network characteristics influenced by varying contrast; (S) stands for skeletonized, (S) stands for skeletonized, (B) stands for binarized, (F%) stands for foreground percentage.

Figure 4.11B is significant in that it points to the role of exposure continuity in automated approaches. Hitra and Craignaw are the cases with the most fractures identified and are also the ones with the highest percentage of vegetation (48.8% and 84.4%, respectively). Because of the contrast similarity between fracture and vegetation, this has been translated to a very high foreground percentage, interpreted as features after skeletonization. As average feature contrast decreases, so does the total number of nodes (Figure 4.11D). This relationship occurs because lowering the contrast threshold causes the code to trace pixels with lower intensities (darker pixels), effectively meaning the number of I nodes is increasing (Table 4.5). As a result, the average feature contrast becomes closer to zero, and the code increasingly restricts its tracing to darker pixels. Continuous exposures like Yosemite and Utah show a strong positive correlation between node count and average feature contrast, the number of features extracted decreases as contrast thresholds are lowered from Iteration A through D, which is in line with the Shearlet method. The features traced across all iterations exhibit increasingly lower average feature contrast from Iterations A to D, implying that as the contrast thresholds are lowered (moving toward zero), the ImageJ method, which relies solely on pixel intensity, limits itself to tracing darker pixels (Figure 4.11A). The study that narrow, high-contrast regions typically result in more robust feature extraction (Figure 4.11A).

Given the negative trend observable in Figure 4.11A, it can be concluded that there is a correlation between average feature contrast and the number of features.

Specifically, as the contrast thresholds are lowered (leading to lower average feature contrast), the number of features traced also decreases. This correlation is expected as the binarization method is increasingly restricted to darker pixels as the threshold is lowered, naturally resulting in fewer detectable features. In terms of reliability and reproducibility, this means that both methods' ability to consistently detect features is influenced by the contrast threshold setting, with lower thresholds potentially compromising the reliability of feature detection by excluding high-intensity pixels, hence resulting in a more broken-down network. A negative correlation between pixel connectedness and average feature length (Figure 4.11G) indicates that higher contrast thresholds may fragment longer features into shorter ones by excluding low-contrast pixels, whereas lower thresholds capture longer, more complete features but risk including non-meaningful ones.

The conversion from binarized to skeletonized images in both methods is reproducible and reliable, indicated by the positive linear correlation between binarized and skeletonized pixel connectedness (Figure 4.11B, C). Figure 4.11E and Figure 4.11F show a linear correlation between the number of connections and pixel connectedness in both skeletonized and binarized images for both Shearlet method ensembles and Binarization method iterations. This indicates that an increase in pixel connectedness corresponds to more connections within the network, further confirming the reliability of the conversion from binarized images to skeletonized images.

4.4 Discussion

The results presented demonstrate that fractures interpreted automatically from imagery are very sensitive to contrast thresholding, and that simplified single contrast thresholds are less reliable than the more complex Shearlet Method.

The results demonstrate that for outcrops with a high level of exposure continuity (e.g., Yosemite and Utah, Figure 4.1A, B), the two automated methods can produce reliable results (Figure 4.11B, C), as there is a lower chance of identifying features in vegetation. However, as contrast thresholds are lowered with a low-continuity exposure (Hitra and Craginaw, Figure 4.1C, D), the automated methods are more likely to identify features within extensive darker areas of the imagery, which in grayscale often correspond to vegetation (Figure 4.11I). This tendency increases the likelihood of wrongly identifying geological features in vegetated areas (Table 4.4).

4.4.1 Effects of contrast on fracture network properties

The variability in fracture network properties due to different contrast thresholds highlights the critical role of image contrast in automated feature extraction methods. Figure 4.11A, Table 4.4, and Table 4.5 illustrate significant changes in detected network properties as contrast thresholds are lowered. Lower thresholds (Ensemble I) capture more connections and shorter, fragmented features, while higher thresholds (Ensemble V) result in longer, more continuous features (Figure 4.5C, F, I, L), as also suggested by the negative correlation between pixel connectedness and average feature length (Figure 4.11G). In Ensemble I, using lower contrast thresholds, the networks show numerous connections and shorter feature lengths, as seen in the green lines in Figure 4.11C, F, I, L. As contrast thresholds increase towards Ensemble V, networks become more continuous, indicated by the

red lines, capturing brighter, more distinct features. This is supported by the decrease in the number of detected features and the increase in average feature length as thresholds rise (Figure 4.11A).

Higher thresholds exclude darker pixels, reducing detectable features and increasing the percentage of I-Nodes, which signifies shorter features with fewer interactions (Table 4.5). The reliability of the conversion from binarized to skeletonized images is supported by the positive correlation between pixel connectedness in both forms (Figure 4.11B, C), and the linear relationship between the number of connections and pixel connectedness (Figure 4.11E, F).

The impact of contrast thresholding is also evident across different geological settings. In Yosemite and Utah, with higher rock mass exposure, the initial average feature contrast is higher, resulting in more geological features. In Hitra and Cragshaw, with higher vegetation percentages and lower rock mass continuity, the average feature contrast is closer to vegetation contrast, complicating the distinction between geological features and noise, which also results in the identification of more features.

Iterations A to D in the Binarization Method show similar trends to the Shearlet Method. Lowering thresholds from Iteration A to D results in fewer, fragmented features, mirroring the shearlet method observations. The consistency of these effects across different methods highlights the crucial role of contrast, and contrast thresholding in automated feature extraction. This implies that regardless of the specific technique used, careful calibration of contrast thresholds is essential for accurate and reliable geological feature detection.

4.4.2 Effect of vegetation and exposure continuity

Vegetation and exposure continuity significantly affect the reliability of automated feature detection. Non-robust geological interpretations, such as features inaccurately traced in shadows and vegetation were observed (Figure 4.4E, F, G, H, Figure 4.10B, Table 4.4, Table 4.5), underscoring how different environments can lead to incorrect detections. In grayscale images, vegetation, shadows, and water bodies have similar contrast levels (60-150) to structural discontinuities, as shown in Figure 4.4 and Table 4.3. Both methods often detect features along the edges of these elements. In regions with dense vegetation, automated methods, particularly at lower contrast thresholds, struggle to differentiate between vegetation and actual geological features in grayscale images due to similar pixel intensities. With higher contrast thresholds in the Shearlet Method, there is an increasing number of detected features in both the vegetation and the rock mass. Upon visual inspection, many of these features do not appear to correspond to actual fractures (for instance, lines traced in/through vegetation or regions of the rock where no discernible fracture is visible), and are thus considered false positives (Figure 4.4). In no cases fractures should be traced in areas that are not rock exposures. Although no formal ground-truth dataset is used for verification, these observations provide a practical check to distinguish real fractures from artifacts introduced by the automated process. The results show that two out of the three main identifiable trends (Figure 4.6I, J) may not be reliable, as they are solely traced in areas of vegetation and not in rock mass. Features traced solely on rock mass mainly trended EW (Figure 4.6I). In Ensemble I for Cragshaw, the total number of traced features was 12,276, yet 9,854 features were traced on vegetation, accounting for approximately 78% of the total features, indicating suboptimal results. Therefore, the degree of pixel connectedness

and the reliability of feature tracing are influenced by the contrast threshold levels, as higher pixel connectedness often correlates with more continuous and reliable features. Figure 4.11C shows that, in all Ensemble Vs for each case study, an increased contrast threshold corresponds to lower levels of pixel connectedness. This occurs because higher thresholds classify pixels with intensities above the threshold as background, causing the automated method to break up features and resulting in interrupted and fragmented features. Conversely, lower thresholds allow the method to trace darker features more continuously. After analyzing the low RMSE values from Figure 4.7 in relation to rock continuity parameters (Table 4.3), it is possible to observe that high RMSE values correspond with high rock mass exposure in Yosemite and Utah. This reinforces the reproducibility of automated feature detection in well-exposed geological settings. Conversely, Hitra and Cragshaw show lower rock continuity and higher RMSE values, indicating decreased reproducibility and highlighting the method's sensitivity to environmental conditions. Linear relationships between rock mass continuity and RMSE were hypothesized because the minimum contrast parameters were increased linearly during the analysis. This linear increase implies that features were traced using increasingly restricted portions of pixels with lower intensity (darker). As the contrast threshold rises, the set of detectable pixels changes predictably because each incremental change in the threshold systematically excludes the pixels with lower contrast. This systematic exclusion impacts the length of features, number of features, pixel connectedness, and other related metrics in a consistent and measurable manner. Our results supported this hypothesis. The relationships between these parameters and the contrast threshold tend to exhibit linearity due to the controlled and gradual nature

of the threshold adjustments, further validating the observed correlations in well-exposed geological settings like Yosemite and Utah.

The study reveals limitations in using decimeter-resolution imagery with automatic methods for extracting features. The low RMSE in regions with a substantial percentage of continuous rock exposure, such as Yosemite and Utah, indicate that automated methods are more reproducible in these settings. However, this does not necessarily imply a reliable tracing of geological features. In areas with continuous exposures, the reduced presence of vegetation lowers the chance of tracing non-geological features, improving the method's effectiveness. Conversely, in settings like Cragshaw with minimal rock exposure, lower RMSE values point toward the potential misidentification of features due to the increased percentage of vegetation, which leads to the introduction of non-robust geological interpretation due to linear patterns being identified in vegetation. Moreover, the RMSE between Ensemble I using the Shearlet Method and Iteration A using the binarization method was 39.78, which provides a definitive measure of the unreliability of these automated approaches. This measure of RMSE serves as a critical indicator of the need for ongoing refinement and validation of automated techniques in geological analysis. These findings underline that, while automated feature extraction can reduce interpretation time and improve reproducibility, their reliability on decimeter-resolution imagery heavily depends on exposure continuity. Decreased continuity directly impacts the network reliability extracted by automated methods, making the methods highly sensitive to image properties such as contrast levels and thresholds. Therefore, while automated methods work better with continuous exposure, the reliability of the features traced remains a primary concern.

4.4.3 Effects of lighting

The albedo of the rock mass, a measure of the amount of light reflected by a surface (e.g., Bemis et al., 2014), likely impacts the effectiveness of automated feature detection. High albedo can lead to overexposure in photographic or satellite imagery, obscuring detailed texture necessary for accurate feature identification, while low albedo can result in underexposure, diminishing contrast and making subtle features difficult to detect (e.g., Maerz, Franklin, and Bennett 1990). Granitic rocks typically exhibit albedo ranging between 30% and 35%, reflecting approximately one-third of the incident sunlight while the remainder is absorbed (Rees, 2013; Trimble, 1987). Dry desert sandstones, instead, have lower albedo, ranging between 20% and 32% (Craft and Horel, 2019; Henderson-Sellers and Wilson, 1983). The high albedo of rock mass at Yosemite (Figure 4.3A) compared to Utah (Figure 4.3B) may reduce the contrast between features and rock mass. Fractures often appear as shadows due to the lack of incident light. If exposed, fracture surfaces would have a similar albedo to the rock mass. Additionally, clean fractures with no gap between edges can be obscured by the highly reflective rock surface. Features filled with material similar to the surrounding rock also have similar albedo, making detection challenging. Thus, high albedo can obscure both exposed fractures and tightly aligned breaks, reducing feature visibility. The combination of narrow feature apertures and high rock albedo can make contrast-based approaches more challenging, particularly in characterizing intersections due to the high reflectivity of the rock, which often masks narrow terminations.

The angle of light incidence with exposed rock when the image is acquired also plays a key role in the correct extraction of features (e.g., Jaud et al., 2019; Sekrecka, Wierzbicki, and Kedzierski, 2020; Walker and Trexler, 1977). For instance, as highlighted by the red box in Figure 4.4G, it is clear that the dark area is just a shadow

of a cliff. Yet, when looking at the same picture in grayscale, the automatic methods mistook it for a geological feature because the shadow and the rock look similar in terms of lightness and darkness. Moreover, when the sun is low, it can cast shadows on the rocks, making them look like geological features to the automatic methods. Low light can also make real features hard to see and trace (Creus, Sanislav, and Dirks 2021).

4.4.4 Challenges and Recommendations for Automated Lineament Detection Using Contrast-Based Methods

The findings of this study suggest that, while automated fracture detection methods relying on contrast differences in grayscale images to trace features are highly reproducible, they cannot always be considered reliable. In discontinuous exposures, it can be challenging for automated methods to reliably interpret features through areas with vegetation cover. The same challenge applies to the edges of outcrop exposures, which could be structural features. Automated methods accurately trace outcrop edges, but these may not represent geologically meaningful features and require careful validation. In contrast to image classification methods that use training data and machine learning (e.g., Harvey and Fotopoulos 2016; Reinhardt et al, 2022), contrast-based methods cannot incorporate prior geological information. Grayscale images have fewer unique values compared to three-band color images, potentially complicating accurate feature detection (Petrushan et al., 2023).

To optimize reliability and robustness of automated feature extraction it is recommended that:

- a) The sensitivity of feature networks to threshold parameters, such as contrast is evaluated and a rigorous quality control (QC) workflow post-extraction is established.
- b) Inaccurate interpretations can be mitigated by either a) conducting image pre-processing to exclude vegetation by assigning null values to vegetated areas or implementing image post-processing, which requires selective feature removal based on defined criteria, involving user expertise.

4.5 Conclusions

The study reveals limitations in using decimeter-resolution imagery with automatic methods for extracting features. The reliability and reproducibility of contrast-based methods are highly sensitive to image properties such as contrast levels and contrast thresholds. Additionally, outcrop characteristics like exposure continuity and vegetation percentage significantly impact the effectiveness of these methods. Exposure continuity in decimeter-resolution aerial imagery also impacts feature detection reliability. While automated feature extraction methods reduce interpretation time, and subjective biases, and improve reproducibility, their reliability on decimeter-resolution imagery depends widely on exposure continuity, as decreased continuity was observed to directly impact network reliability extracted by automated methods.

Understanding how contrast changes across an image, together with environmental factors like vegetation cover and exposure continuity, is crucial for accurate and reliable automated fracture detection. These findings can be extended to any automated contrast-based approach currently available, emphasizing that while

automated methods can significantly aid geological investigations, their reliability is highly contingent upon appropriate parameter settings and image characteristics. The workflow presented throughout this paper serves as a measure of the reliability of automated methods when applied to low-resolution imagery, and highlights their limitations and challenges. This study underscores the necessity of considering image properties and environmental conditions to ensure meaningful geological interpretations. By providing a detailed analysis of the impact of various parameters, this study offers valuable insights into optimizing automated fracture detection methods and improving their application in geological research.

Chapter 5 Quantifying Differences Between Fracture Networks Characterized on Different Resolution Datasets

Abstract

The interpretation of fracture networks varies across different resolutions, and while it is well understood that resolution impacts the ability to map fractures, the specific differences in how various resolutions affect fracture characterization still remain unclear. The increased availability of imagery facilitates the characterization of regions that were once challenging to access. However, often the resolution of commonly available imagery is insufficient for accurately characterizing fracture networks, and the extent of information loss at varying resolutions has not been quantified yet. This paper sets out to investigate and quantify the impact of varying resolutions on the characterization of fracture networks. This was achieved using three datasets: aerial imagery (referred to as low-resolution with 0.2m/px), drone imagery (medium-resolution at 0.02m/px), and field imagery (high-resolution at 0.002m/px). In order to quantify the network properties that are being lost in resolution, fractures' physical properties such as length and orientation, and network properties such as density, intensity, and topology are characterized. The study concluded that resolution and surface width play a critical role in fracture network characterization. Varying resolutions capture distinct levels of detail, which profoundly affects the accuracy of subsequent analyses and interpretations. Specifically, low-resolution data often yields generalized information that might gloss over finer details. Medium-resolution, offers an optimal balance between detail and

coverage, making it particularly valuable for comprehensive analyses. In contrast, high-resolution data, while capturing finer details in imagery, often misses the broader geological context. This paper emphasizes the need for a multiscale approach to effectively characterize complex geological features remotely and provides a clearer understanding of the limitations and capabilities inherent in different resolutions.

5.1 Introduction

Fractures that form networks may act as both fluid flow pathways and as barriers to flow in geological materials (Berkowitz, 2002) and their accurate characterization has applications and implications in geoenergy, especially for low permeability rocks such as granites (Berkowitz, 2002). Fracture patterns observed at outcrops provide an analog of the subsurface (Zimik et al., 2023). Fracture traces in outcrops are interpreted as the surface manifestation of underlying fracture zones (Lattman and Parizek, 1964) and aerial imagery provides an invaluable tool for characterizing remote and hard-to-access geological sites (Saibi et al., 2018). Aerial images from manned aircraft surveys have long been a standard for geological analyses (O'Connor et al., 2017), and are key for obtaining geospatial data across large areas. Fixed-wing aircraft, such as Cessnas, and helicopters are commonly used for these surveys, which can cover extensive areas using medium- and large-format cameras and hyperspectral imaging systems (GeoInformatics, 2024; IntelliSpatial, 2024; Williams et al., 2014). Medium-format cameras, with sensors larger than 35mm but smaller than large format, offer superior image quality and dynamic range. Large-format cameras feature even larger sensors, typically 4x5 inches or more, providing exceptional detail for high-resolution photography. Recently, drones have gained popularity in geoscience due to their cost-effectiveness for carrying low-payload equipment (<20 kg). Drones initially began gaining traction for scientific applications in the 1990s, primarily with fixed-wing models (e.g., Nyquist 1996). However, fixed-wing drones, while effective for extensive surveys, are somewhat limited in their versatility, as they are less manoeuvrable, are not capable of Vertical Take-off and Landing (VTOL), and cannot maintain stationary position. Rotary-wing drones have become widely used

due to their ability of flying at much lower altitudes than larger piloted fixed-wing aircraft, and can also hover in place, making them ideal for detailed and more localized surveys, especially in areas with complex terrains and/or obstacles. Rotary-wing drones have only gained popularity in the last 10 years (e.g., Carrivick et al. 2013), enabling the collection of data with much higher resolution (Hunt Jr et al., 2010; Scaioni et al., 2009). High-resolution imagery acquired using drones has enabled data collection that was previously not possible, leading to the proliferation of high-quality data for fracture interpretations (Booyesen et al., 2021). A constraint on the accuracy and precision of characterizing fracture networks using any remote sensing images is image resolution (Bonnet et al., 2001; Faleide et al., 2021). Any fractures below the imagery resolution will not be interpretable. The determination of an appropriate resolution often depends on the specific characteristics and requirements of the study, as well as the particular fractures being investigated (Cihlar et al., 2003; D. Peacock et al., 2019; Xie et al., 2008).

The scaling relationships of fault and fracture systems are well documented (e.g., Bonnet et al., 2001) and the importance of multiscale characterization is widely recognized (e.g., Bertrand et al., 2015; Chabani, 2021). However, less attention has been given to the quantitative analysis of the differences in fracture networks interpreted from different resolution datasets. This study sets out to investigate the differences in interpreted fracture networks from a granitic exposure in Havmyran Natural Reserve in Norway, using three differing resolutions of imagery. By interpreting, analyzing, and comparing the networks interpreted at three different resolutions we highlight and identify limitations of each, and emphasise the value of

multi scale analysis. It examines the impact of image resolution on the reliability and reproducibility of observed fracture network trends.

Fracture networks show complex spatial variability, with fractures ranging from nanoscale to macroscale. The transition from distributed small-scale fractures to a localized, interconnected system is a key aspect of structural geology, influencing fluid flow and mechanical properties of the rock mass (Rizzo et al., 2017). This transition is scale-dependent, meaning that different imagery datasets with different resolutions have varying degrees of fracture connectivity, length distributions, and topology. Previous studies have demonstrated that abrupt changes in fracture patterns correspond to a shift from diffuse microcracking to macroscopic failure (Lockner et al., 1991; Rizzo et al., 2017), a process that is critical for understanding rock deformation, reservoir permeability, and seismicity. By analyzing fracture networks across multiple resolutions, this study aims to quantify how different scales impact the interpretation of network properties, connectivity.

Using three images of the same location with different resolutions allows for direct comparisons in 17 overlapping areas. This study highlights the critical role of multiscale approaches to effectively characterize geological fracture networks from remote imagery. By analyzing fracture properties at three resolutions, it was demonstrated that each scale offers unique insights that are crucial for a comprehensive understanding of fracture networks. Findings emphasize that integrating data across scales is essential for mitigating the limitations inherent to any single resolution.

5.2 Methodology

5.2.1 Imagery and Datasets

For this study, all images used are full-color images. Images are from two different acquisition systems: aerial photography that provides low-resolution imagery, with the most extensive coverage, and drone-based imagery for both medium and high-resolution datasets.

5.2.2 Aerial Imagery

The aerial imagery used was acquired as part of a 2015 survey over the islands of Hitra and Froya. The resolution of the survey varies from 20 to 50cm (Trollvik, 2014). This imagery was acquired following the "Orthophoto 20" standard, which specifies properties related to overlap, altitude, and sensor specifications. Key details of the 2015 survey over Hitra and Froya include an overlap of 20% and a Ground Sample Distance (GSD) of 20-25 cm for digital cameras, with UltraCam X being used (Lauritsen et al., 2019). The area of interest (Aoi) for the specific outcrops in the study has a resolution of 21 cm per pixel. Throughout the study, this data is referred to as low-resolution (Figure 5.1A).

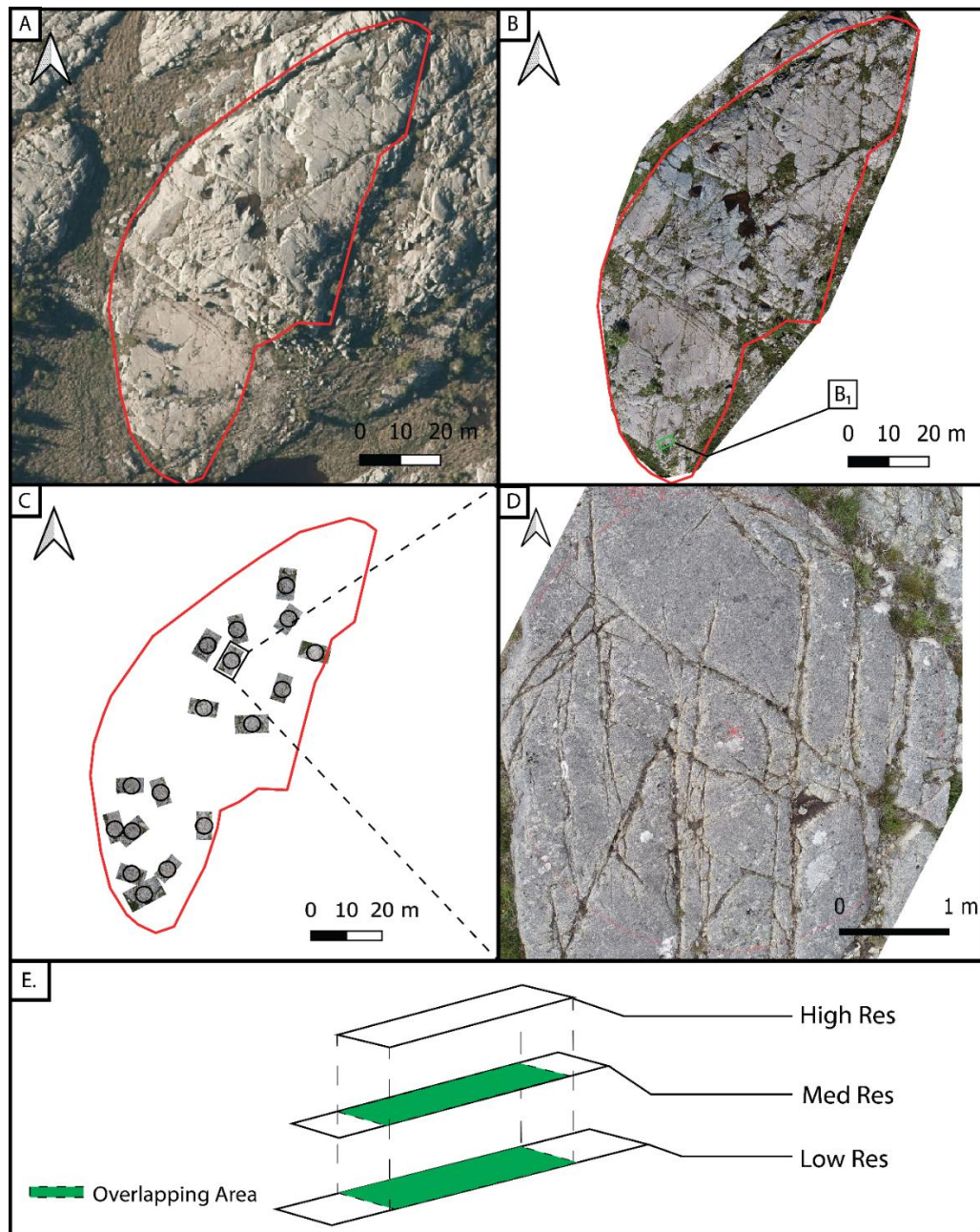


Figure 5.1 Study area in Hitra across different resolutions. A. shows the location in low-resolution imagery (20 cm/px), B. in medium-resolution (2 cm/px), B1 shows the location where field measurements were taken, C. in high-resolution (0.2 cm/px), and D. is a zoomed view of the high-resolution imagery. E is a graphical representation of overlapping areas across resolutions.

5.2.3 Field data acquisition

To compare data extracted from high-resolution imagery with real-world data, field measurements were conducted on 25 distinct fractures. Measurements were taken in one location in close proximity to one of the circles used throughout the analysis, highlighted in Figure 5.1B₁. These features, ranging in length from 1 cm to 10 cm, were thoroughly analyzed for orientation, dip, and strike using a Silva Ranger S geological compass. Additionally, surface apertures were measured with a tape measure. However, intersections among the fractures were not characterized in this study. This approach ensured a precise comparison between the high-resolution images and the actual geological data measured directly in the field.

5.2.4 Drone Imagery

Medium-resolution imagery was acquired using a DJI Phantom 4® equipped with a 1/2.3" CMOS, 12.4 MP sensor. The altitude during the acquisition ranged between 25 and 35 meters, with an exposure time, ISO speed, and focal length of 1/500s, ISO-100, and 9mm, respectively. Overlap was between 55% to 65%. The original images were processed in an orthophoto using WebODM. The resulting orthoimage is a composite of 420 photos, with a final resolution of 2 cm/px (Fig.1B). Key parameters for the creation of the orthophoto included: an orthophoto resolution of 2 cm/px, "Bruteforce" as matcher type, and "Hahog" as feature type, covering a total area of approximately 5,975m². High-resolution imagery for sampling circle analyses was acquired using the same DJI Phantom 4®. The altitude was 4 meters above the ground surface. ISO speed was 100, focal length 9mm, and the exposure time was set to 1/800s. This imagery has a 0.2cm/pixel (Figure 5.1C, D). In field, 17 sampling circles, each 4 meters in diameter with an error margin of ± 4 cm, were traced to guide data

acquisition. For each circle, unlike the medium-resolution imagery, the one at high-resolution was single frame imagery, and not a mosaic, and was captured from a perfectly perpendicular angle to minimize distortion and ensure the accuracy of fracture details. The circular scanline method is an effective method for characterizing fracture networks when it is not practical, for instance when time and resources are limited, to map continuous areas of exposure (e.g., Mauldon et al., 2001; Rohbaugh, 2002; Watkins et al., 2015).

5.2.5 Fracture Interpretation

To characterize fracture networks, fractures were manually interpreted. In the imagery used, fractures are interpreted as near-linear features that form a discontinuity within or at the edge of the rock mass. It was ensured that a consistent approach to interpreting fractures was followed in order to improve the reliability and limit bias (Table 5.1) (e.g., Andrews et al. 2019).

Criteria	Low-resolution Imagery	Medium-resolution Imagery	High-resolution Imagery
Line tracing	Center of the feature/along the only exposed edge		
Min Length [px]	4	2	
Angle for interpolation across veg. areas	+/- 2°		
Max separation for interpolating across vegetation	2m	20cm	

Max narrow vegetated areas	0.5m. Beyond that, trace along the closest and clearest edge from the start of the fracture		
Maximum zoom	1:60	1:15	1:4
Working zoom	1:120	1:30	1:8
Minimum zoom	1:240	1:60	1:20
Minimum number of vertices per feature	3	3	3
Max snapping pixels	3	3	3

Table 5.1 Parameters and criteria for fracture identification and tracing in high, medium, and low-resolution imagery, including guidelines for merging, snapping, and setting zoom levels.

Fracture tracing and analyses were performed using QGIS®, and length, orientation, and topology were calculated using NetworkGT (Nyberg et al., 2018). Topology, as described by Sanderson and Nixon (2015), classifies fracture network intersections (or nodes) as I (Isolated tips), X (Crossings), and Y (Abutments), which describe the connections and interactions between fractures.

The interpretation was undertaken at three zoom levels (see Table 1), a process that others have adopted for the interpretation of remote sensing data (e.g., Andrews et al. 2019). Fractures were traced along their centerline. When only one edge is visible, tracing followed the discernible rock boundary adjacent to non-rock areas, assuming this boundary represents a fracture discontinuity (Figure 5.2).

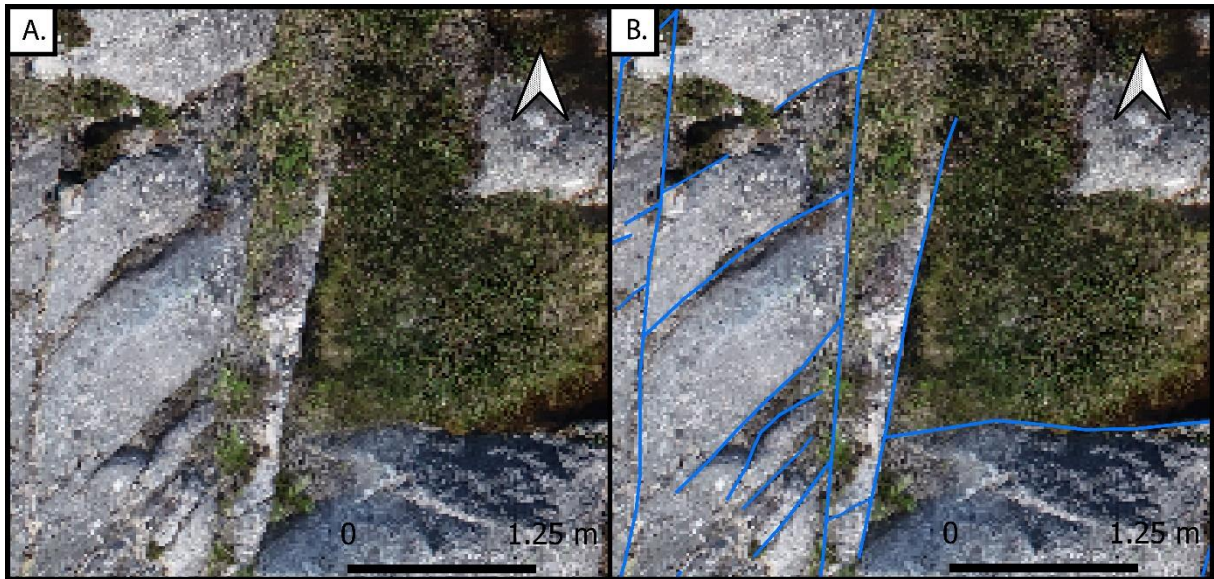


Figure 5.2 At the center of the image there is an example of fractures with just one edge exposed (A.) and how they were interpreted (B.). This fracture was formed by two edges, but one was likely lost due to weathering.

The detection limits are 0.044 meters for high-resolution imagery, 0.4 meters for medium-resolution imagery, and 1 meter for low-resolution imagery, corresponding to 2 pixels in both high and medium resolution and 4 pixels in low resolution. For one fracture to have an intersection with another, a maximum snapping distance of 3 pixels was set. Each fracture trace is defined by a minimum of 3 vertices.

Where fractures intersect vegetation, they were only interpolated across these areas where they were separated by <10 px, which is <2 m for low-resolution imagery or <20 cm for high-resolution imagery, and $<2^\circ$ change in angle. Across all resolutions, in cases of fractures filled with vegetation, if the separation between the two edges exceeded 0.5 m, the line was traced along the center, equidistant from both edges.

The use of the circular scanline method, described by Watkins et al. (2015), for high-resolution imagery, necessitated manual calculations of properties such as density

and intensity within localized areas. For the low- and medium-resolution imagery, which covered broader areas, NetworkGT was used to analyze the entire region. This dual approach allowed us to directly compare the localized detail captured in high-resolution imagery with the broader trends observed in lower resolutions, highlighting the importance of integrating different methods for a comprehensive understanding of fracture networks.

Using the interpreted fractures, it is then possible to calculate the fracture density [eq. 5.1], intensity [eq. 5.2], and mean trace length [eq. 5.3].

$$\sigma = \frac{n}{A} \text{ [5.1] (Mauldon et al., 2001)}$$

$$I = \frac{L}{A} \text{ [5.2] (Mauldon et al., 2001)}$$

$$\mu = \left(\frac{\pi r}{2}\right) \left(\frac{n}{m}\right) \text{ [5.3] (Watkins et al., 2015)}$$

Where μ is average length, I is intensity, σ is density, n is number of fractures intersecting with the circle, m is the number of fracture terminations within the circle, r is the circle radius, L is total length. These formulas are consistent with those used in NetworkGT, although they were manually applied to the high-resolution dataset in this study.

5.2.6 Surface Fracture Width

Fracture width refers to the opening width of a fracture normal to the strike direction (Waldron and Snyder, 2020). At the surface, the measured width is likely greater than the width in the subsurface (Stock and Frampton, 2023). In this study, surface width was measured to investigate the minimum width necessary for a feature to be interpreted reliably. Widths were measured manually at six overlapping areas (Figure

5.1E). Surface width was measured for selected fractures only. For each feature at 20%, 50%, and 80% along its length the apparent width of the fracture was measured. In cases where defining the aperture was challenging due to ambiguous fracture edges or visibility of only one edge, the aperture was measured at the nearest section where both fracture edges were clearly visible and could be accurately determined.

5.3 Results and Observations

The following subsections will describe the length, intensity, orientation, connectivity, intersection angles, and surface width of fractures, and how surface width affects detectability at each resolution. Figure 5.3 shows the interpretations of fracture sets at the three resolutions of interest. From this figure, it is possible to see how much more complex fracture networks become just by increasing resolution, together with also the area-related censoring effects. Fractures are very different across the three resolutions of interest. Specifically, fractures at low resolution tend to be very linear when compared to fractures traced at medium and high resolution, as visible in Figure 5.3A, B, C. Another big difference is the number of fractures identified across the dataset, going from 222 fractures at low-resolution, to 3,449 fractures at medium-resolution and 1,591 at high-resolution. The average number of connections per branch is ~1.05 for the network identified using low-resolution imagery, 1.8 using medium-resolution imagery, and 2 using high-resolution imagery. The average line length is 5.18 meters for the low-resolution network, 1.31 meters for the medium-resolution network, and 0.48 meters for the high-resolution network.

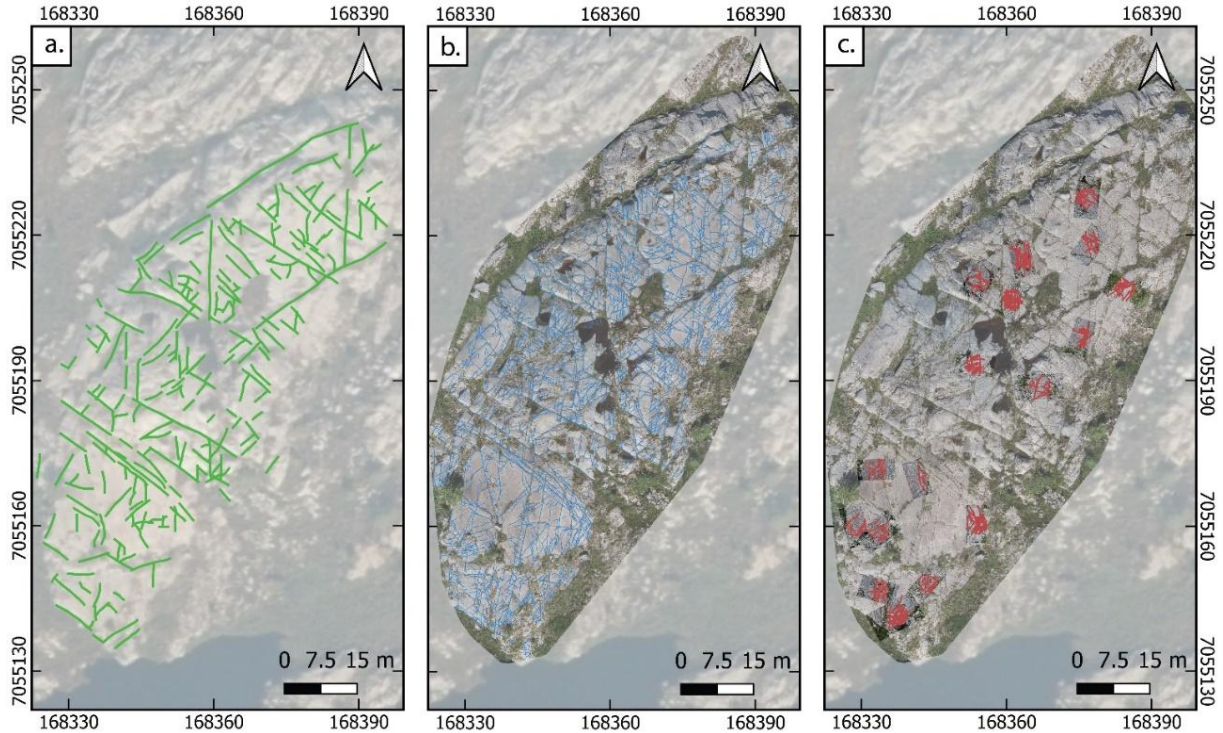


Figure 5.3 A. Low-resolution, 222 features identified; B. Medium-resolution, 3,449 features identified; C. High-resolution, 1,591 features identified.

5.3.1 Impact of Resolution on Interpreted Fracture Networks

Fracture network complexity is simplest in the lowest resolution, indicated by fewer topological connections and fewer recognizable fractures (Figure 5.4 & Figure 5.5). As visible in both Figure 5.4 and Figure 5.5, with high-resolution imagery, finer details of fracture networks become visible (Figure 5.5A), which are not discernible in low and medium-resolution images (Figure 5.5B, C). One example is that where in the high-resolution images three fractures can be interpreted, in the medium-resolution images these fractures are interpreted as single features and are indistinguishable from one another, whilst at low-resolution fractures are completely indiscernible (Figure 5.5).

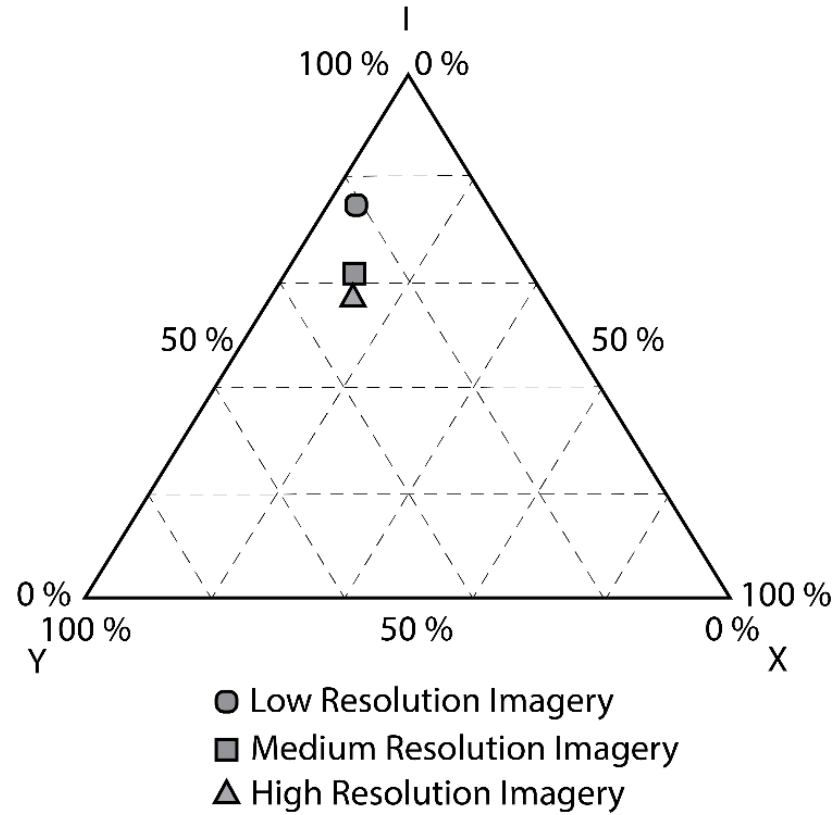


Figure 5.4 Topology characterized at the three resolutions of interest. Low-resolution is the most disjointed one, with it gradually increasing at medium- and high-resolution. Low-resolution shows 74% isolated nodes (I), medium has 60% (I), and high-resolution records 57% (I). Connectivity increases with resolution.

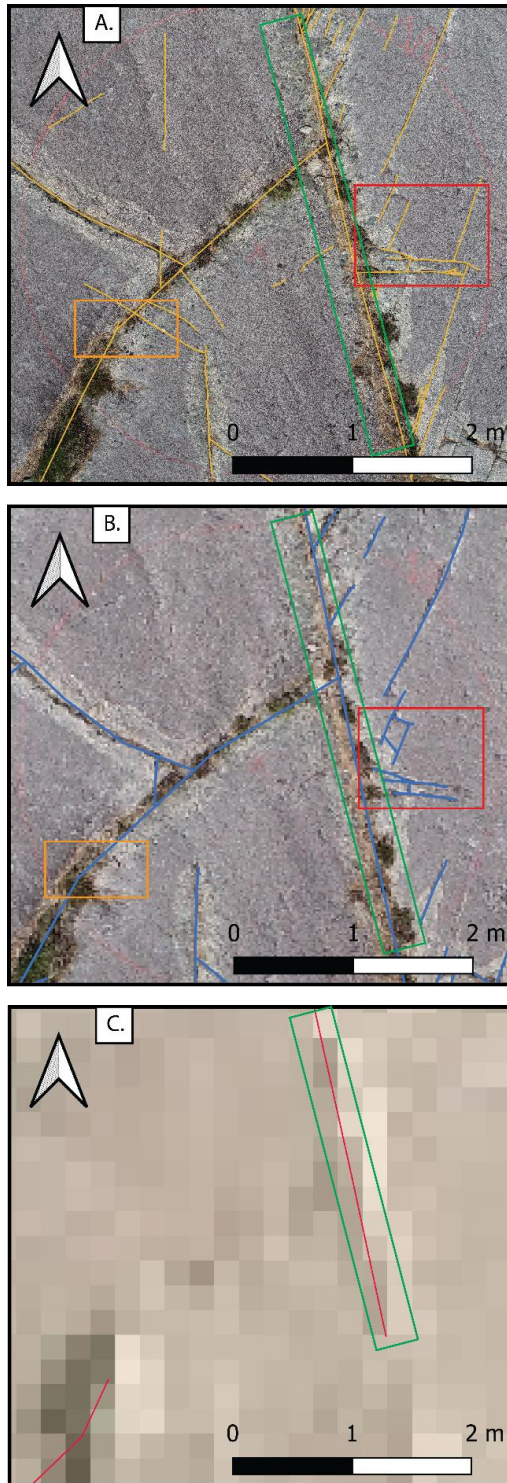


Figure 5.5 Comparative analysis of fracture networks across different resolutions. A) High-resolution displays consistent feature detection across datasets. B) Medium-resolution

shows potential false positives and missing connections. C) Low-resolution mostly lacks visible features, indicating limited detail capture.

31% of fractures can be observed at both medium and high resolution, meaning that 69% of the fractures detected in the high-resolution imagery are not visible or are missed in the medium-resolution imagery. However, the most significant difference observed is the presence of intersections between different fractures. Specifically, 88.3% of the fractures in high-resolution images show intersections, compared to 15% in medium- and 32.4% low-resolution images, respectively. Some fractures (Figure 5.5), while visible at both medium and high resolutions, appear as separate clusters that do not interact as they appear using medium resolution. The network of fractures traced using the high-resolution images is more complex; a total of 2,479 nodes were identified using high resolution, whereas within the same circles, only 661 nodes are present at medium resolution. The number of nodes identified within one circle is relatively close to the number identified using the drone dataset, which is 7,706. However, considering the total area covered using high-resolution data, which is approximately 214 m², compared to the area covered by medium-resolution data, which is 4,617 m², the proportion of nodes identified is significantly higher in the high-resolution dataset. In high-resolution data, these two clusters are connected. Fracture intensity is highest toward center-north-east and south/center-south-east (Figure 5.6). Interpretations from the low-resolution imagery have a lower fracture intensity, ranging from 0.1 to 0.6 F/m, compared to the interpretations from medium-resolution 0.2 to 2 F/m (Figure 5.6A, B). The intensity varies similarly, with higher intensities in the northeast and southern regions of the exposure.

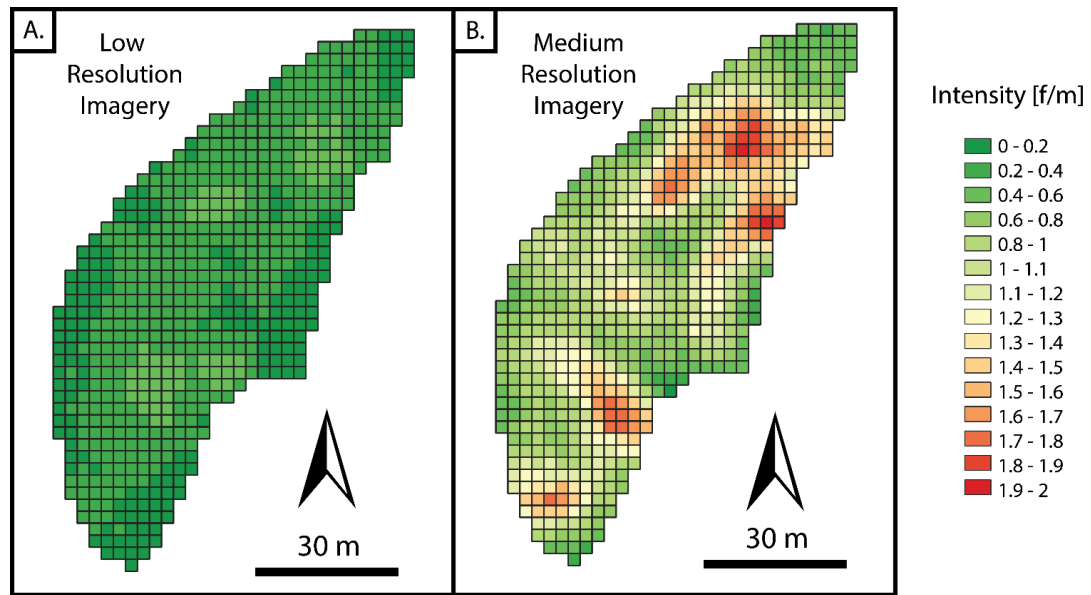


Figure 5.6 Intensity maps for low (5A) and medium (5B) resolution imagery. While 5A presents low intensities (0-0.6 F/m), 5B shows a broader range (0.2-2 F/m). Despite differences in fracture counts, both show heightened intensities in the northeast and south regions of the exposure.

5.3.2 Orientation, Connectivity, and Intersection Angles

While there are differences between the number of fractures interpreted in low, medium, and high-resolution images, the dominant orientations are very similar (Figure 5.7).

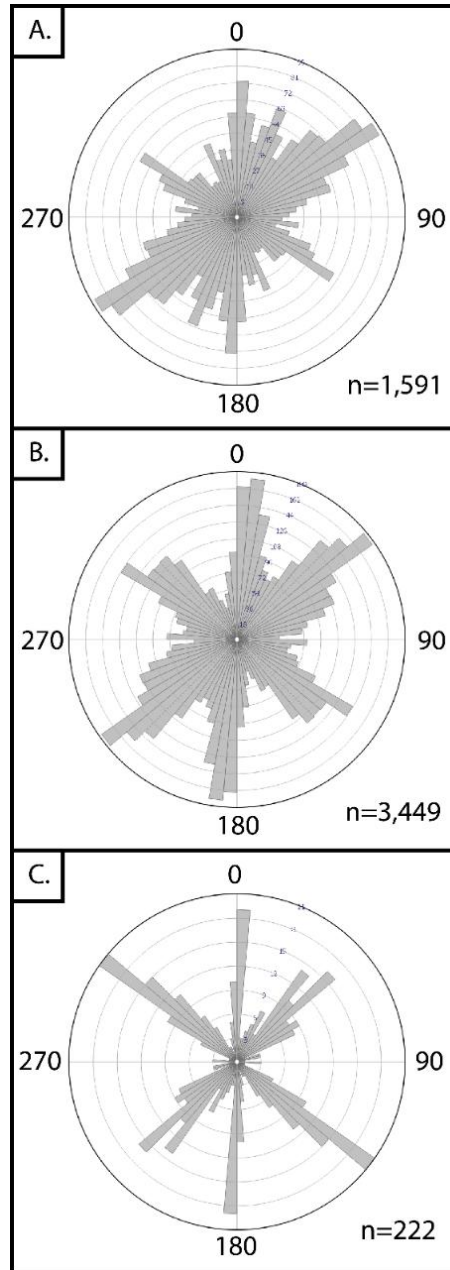


Figure 5.7 Fracture orientations across varying resolutions: high (A), medium (B), and low (C). All datasets consistently show dominant N-S, NE-SW, and NW-SE trends.

From the analysis of the rose plots at different resolutions, the northwest-southeast (NW-SE) orientation appears dominant, particularly in the low-resolution data. However, this apparent dominance is reduced when high-resolution data is

considered. This observation is not inherently incorrect but rather indicative of a resolution effect on data interpretation. In the low-resolution imagery, NW-SE orientations account for 39 fractures. However, in the high-resolution data, there are 109 fractures identified with this orientation. The key difference lies in the increased detection of fractures with orientations other than NW-SE in the high-resolution data. This implies that a significant amount of fracture data, particularly those with different orientations, is lost or obscured in lower-resolution images (Figure 5.7). These frames may not contain as many NW-SE oriented fractures, resulting in an overrepresentation of the north-south (N-S) and northeast-southwest (NE-SW) trends. Additionally, from the high-resolution data, there might be a higher occurrence of fractures with N-S and NE-SW orientations.

The interpreted connectivity changes significantly between the different interpretations from the low, medium, and high-resolution images, and therefore so does the topology (Figure 5.8A and B).

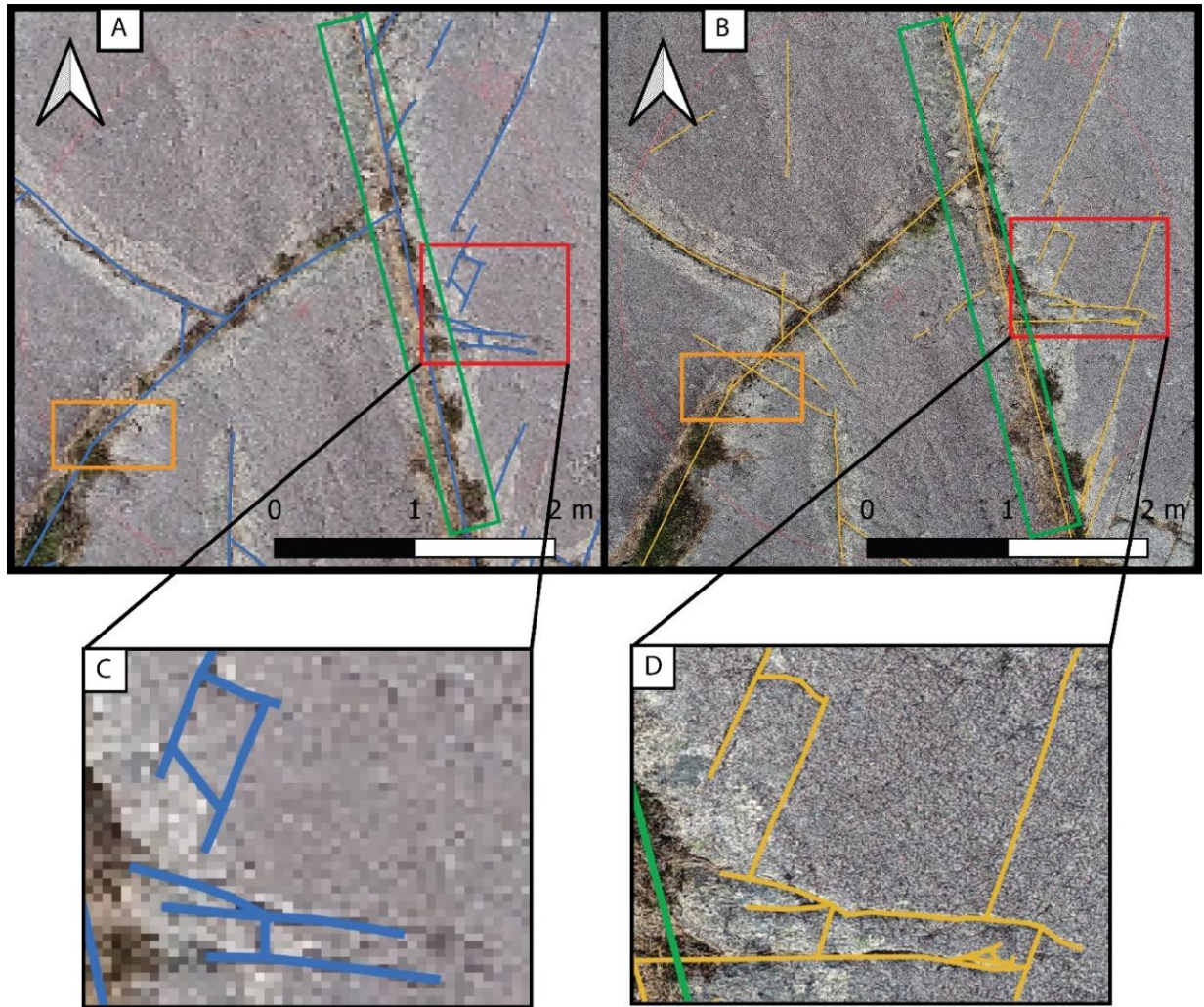


Figure 5.8 A and C show medium-resolution imagery, displaying a lower degree of interaction and complexity compared to B, and D, which feature high-resolution imagery, where the network is clearly more complex and interconnected.

Interpretations from low-resolution imagery exhibit the lowest connectivity, with 74% of I-nodes, 21% Y-nodes, and 5% X-nodes. Interpretations from medium-resolution imagery have higher connectivity, with 60% isolated nodes, 28% terminating nodes, and 12% crosscutting nodes. Interpretations from high-resolution data have the greatest connectivity, with 57% isolated nodes, 30% terminating nodes, and 13%

crosscutting nodes (Figure 5.8). Fracture intersection angle was also measured for the same two features but at different resolutions (Figure 5.9A, B).

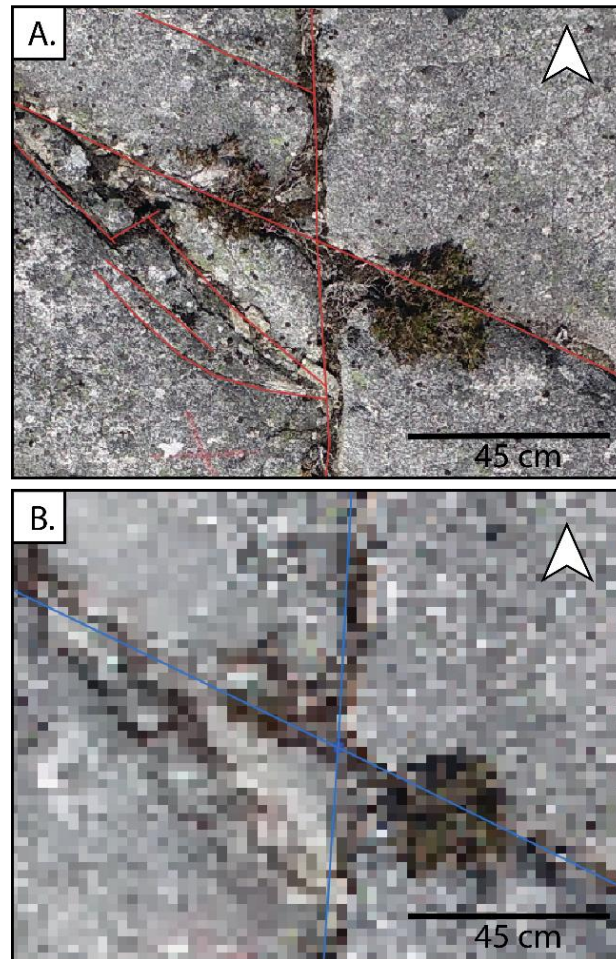


Figure 5.9 Intersection angles at high resolution (A) measured at 67°, compared to 65° at medium resolution (B). Several features present at high resolution are absent at medium resolution.

At medium resolution, the intersection angle between the two selected fracture features was measured to be 66 degrees. At high resolution, however, the same

features showed a larger intersection angle of 67 degrees. This discrepancy shows how resolution can influence the interpretation of fracture geometries. The difference suggests that higher resolutions may capture finer details and changes along fractures in a network that lower resolutions might smooth over or miss, leading to variations in the interpreted geometry. Moreover, as visible in Figure X, most features that are present in Figure 5.9A at high resolution, are completely absent in Figure 5.9B, which is another effect of features impossible to trace as below the detection limit.

5.3.3 Surface Width, Length and Intensity

Surface fracture widths interpreted vary significantly between the different resolution images, as summarized in Table 5.2

Medium Resolution						High Resolution						
Feature ID	Surface Width						Surface Width					
	20%		50%		80%		20%		50%		80%	
	[m]	[px]	[m]	[px]	[m]	[px]	[m]	[px]	[m]	[px]	[m]	[px]
0	0.019	1	0.078	4	0.068	4	0.195	98	0.042	21	0.056	28
1	0.051	3	0.075	4	0.063	3	0.028	14	0.062	31	0.05	25
2	0.062	3	0.055	3	0.031	2	0.007	4	0.023	12	0.015	8
3	0.02	1	0.038	2	0.036	2	0.014	8	0.016	8	0.01	5

Table 5.2 The table presents surface width measured for four features in common between medium- and high-resolution imagery. Measurements were taken at 20%, 50%, and 80% of feature lengths in both medium- and high-resolution imagery. Measurements vary across features, with high-resolution imagery capturing a broader range of aperture values for selected features compared to medium-resolution.

Figure 5.10A and B show two examples of the same fractures observed in the medium and high resolutions respectively.

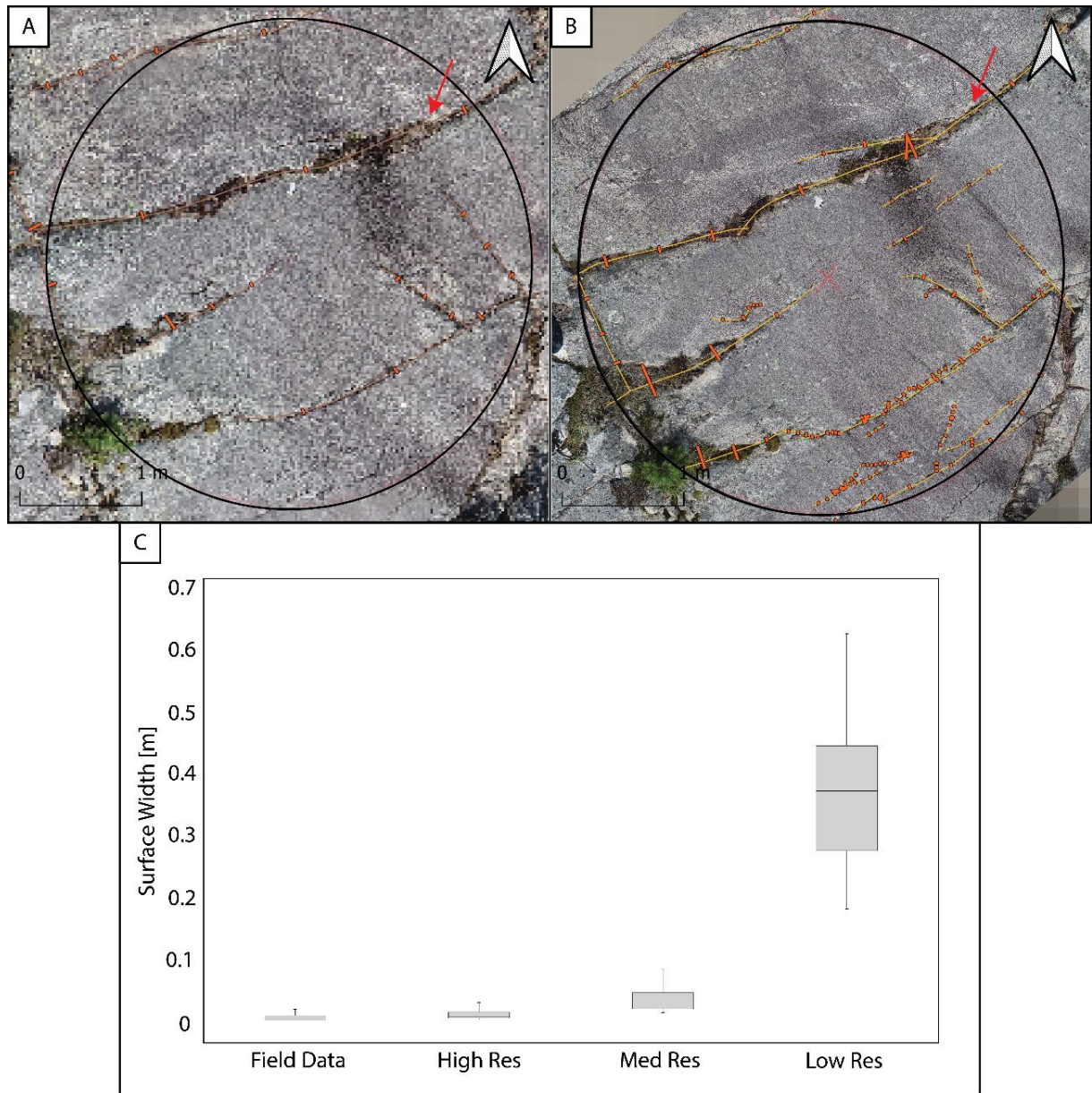


Figure 5.10 A. and B Fractures observed at medium and high resolution, respectively, together with segments used to measure surface fracture width. The red arrow points to the same feature interpreted at both medium and high resolution, appearing continuous

at medium resolution but revealed as multiple merging fractures at high resolution. C. shows how length varies across the different datasets.

Highlighted in Figure 5.10A, a single continuous fracture is interpreted with a measured surface width of 2 pixels (or 0.046 meters). The same fracture at high resolution (Figure 5.10B) is interpreted as being the result of two fractures that coalesced into one, with a measured width between the two of 43 pixels (or 0.086 meters). Overall, high-resolution imagery provides the most detailed surface width measurements, with widths ranging from 0.004 to 0.076 meters (15 pixels per feature on average). Medium-resolution imagery captures surface widths ranging from 0.02 to 0.08 meters (2.1 pixels per feature on average). Low-resolution imagery shows the least detailed measurements, with surface widths ranging from 0.357 to 0.42 meters (1.7 pixels per feature on average) (Figure 5.10C).

The standard deviation of fracture lengths varies significantly across different resolutions and quantifies the variation in fracture sizes across different resolutions. High-resolution imagery has the lowest standard deviation (0.68) with a fracture length range of 0.008 to 7.57 meters, which indicates that measurements of length are more consistent across high-resolution imagery. Medium-resolution imagery shows a higher standard deviation (1.67) and a broader length range (0.03 to 31.7 meters). Low-resolution imagery exhibits the highest standard deviation (4.54) with a limited length range (0.98 to 4.53 meters), reflecting less consistency and a narrower detection range. High-resolution imagery measured surface widths ranging from 0.001 meters to 0.08 meters. These measurements align with field data shown in Figure 5.10C. Medium-resolution imagery captured a broader range of apertures but aligned well with those taken in-field.

The cumulative distribution functions (CDF) for fracture lengths reveal distinct patterns for each resolution, fitting well against a lognormal distribution overall (Figure 5.11A, C, E). As of Figure 5.11G, H, a total of 25 fracture length measurements were collected in-field. Therefore, given the limited data, a definitive assessment of the distribution's adherence to a specific model remains challenging. While the data generally aligns with a lognormal distribution, the limited field measurements introduce some uncertainty, making it difficult to fully validate the observed trends across all resolutions.

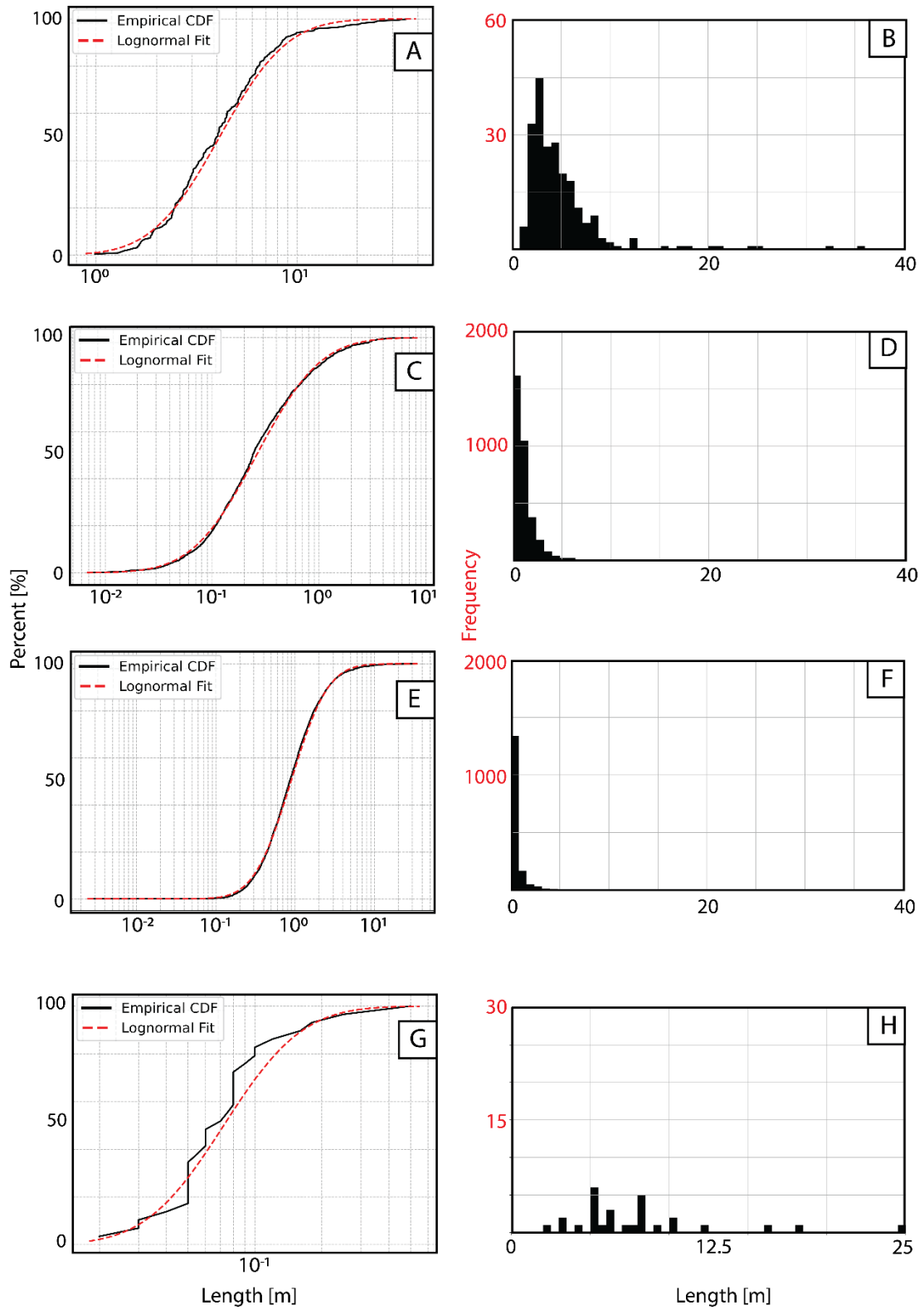


Figure 5.11 Lognormal distribution of fracture lengths across different resolutions. A and B show low-resolution imagery, C and D medium-resolution, E and F high-resolution, G

and H field data. The plots show a close alignment with the 95% confidence interval of a lognormal distribution, particularly evident as the fracture lengths approach the Y-axis, indicating shorter fractures are more commonly detected at higher resolutions. Probability plots confirm the expected distribution of lengths, underscoring the consistency and reliability of the data.

The R^2 values for the lognormal fits are as follows: 0.9913 for low-resolution, 0.9982 for medium-resolution, and 0.9970 for high-resolution, indicating a strong fit for all datasets. The lower R^2 value for the low-resolution imagery (Figure 5.11A) corroborates the theory that low resolution is less effective when the area is restricted. However, low-resolution imagery is still relatively effective for identifying mid-range fractures (1.2m to 8m), provided that fractures have a large surface aperture (>40cm) (Figure 5.10C, Figure 5.11B). In contrast, medium-resolution data has the highest R^2 value among the three (Figure 5.11), making it very effective in identifying fractures of various lengths, with 83.2% of lengths in the range from 0.3m to 3m (Figure 5.11D, Figure 5.12A, D), despite the relatively restricted area.

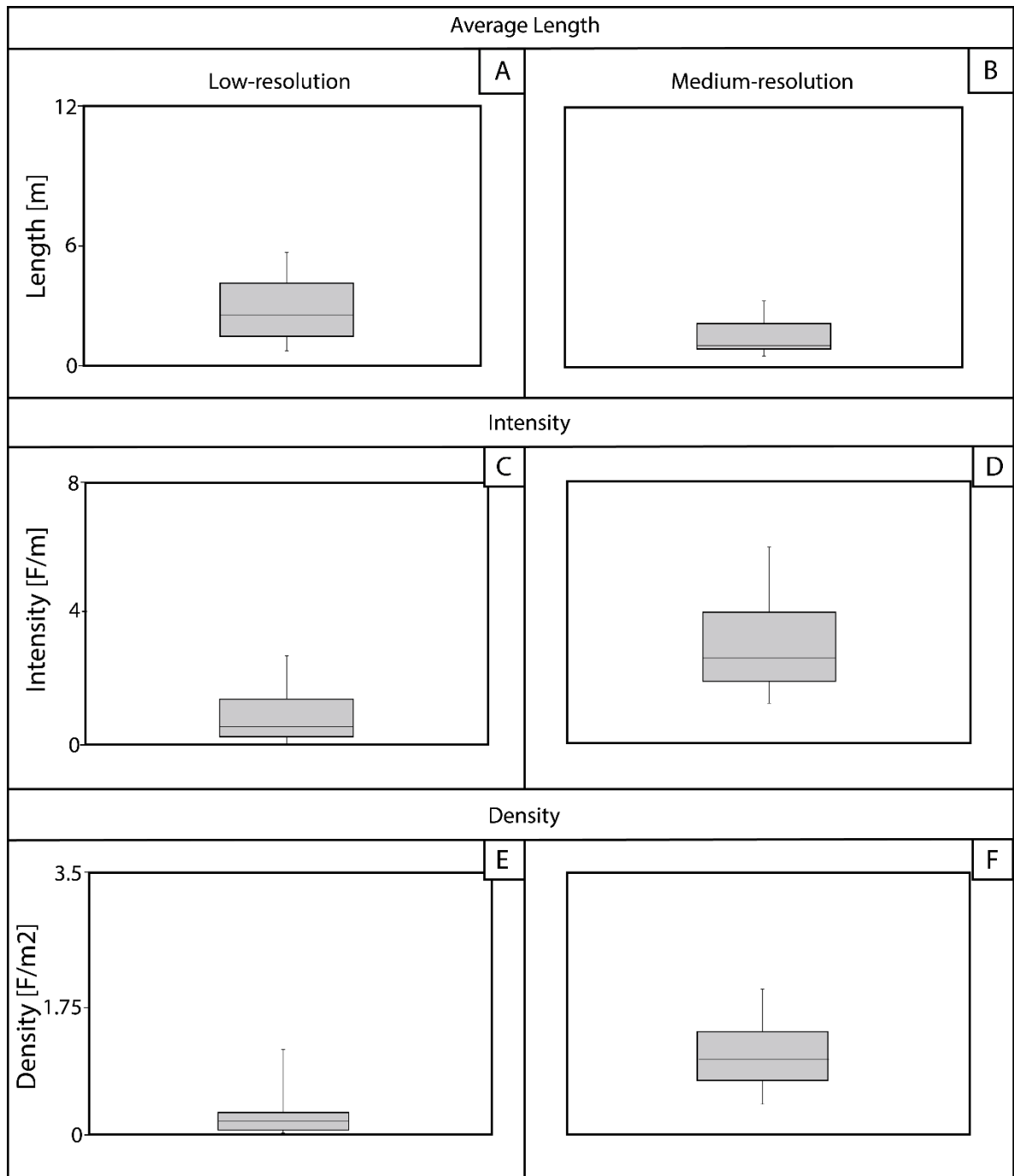


Figure 5.12 Comparison of average lengths, intensity, and density for medium- and low-resolution imagery. Medium-resolution generally shows larger ranges in length and higher intensity and density values compared to low-resolution, suggesting that features are better represented in medium-resolution compared to low-resolution.

High-resolution imagery also shows a strong fit to the lognormal distribution (Figure 5.11E). However, it is limited by the size of the image, which means that fractures longer than a certain length cannot be fully captured and interpreted. Nevertheless, it proved to be suitable for tracing fractures with lengths ranging from 0.004 m to 1.1 m, capturing finer details than the two lower resolutions missed. Although high-resolution data enabled the interpretation of the shortest fractures (up to 0.4cm), the one that most closely aligned with the manual fracture length measurements taken in the field, which averaged 9cm, with a minimum of 2cm, was medium-resolution imagery. The ranges of length of fractures interpreted along traverse lines vary significantly, with low-resolution imagery showing lengths from 0.25m to 6.3m, medium-resolution from 0.3m to 3m, and high-resolution imagery from 0.0041m to 1.1m.

Intensity is lower for low-resolution (0.25 to 2.0 F/m) compared to medium-resolution (1.9 to 4.6 F/m) and high-resolution (1.9 to 6.0 F/m) (Figure 5.6; Figure 5.12C, D; Figure 5.13C, D). Density also follows a similar pattern, with low-resolution showing 0 to 0.3 F/m², medium-resolution showing 0.6 to 1.5 F/m², and high-resolution showing 1.3 to 2.1 F/m² (Figure 5.12E, F; Figure 5.13E, S). This is expected for both density and intensity because higher-resolution imagery captures finer details and a greater number of smaller fractures, leading to higher fracture counts per unit area. In contrast, low-resolution imagery merges smaller fractures, resulting in fewer detectable features and consequently lower intensity and density values.

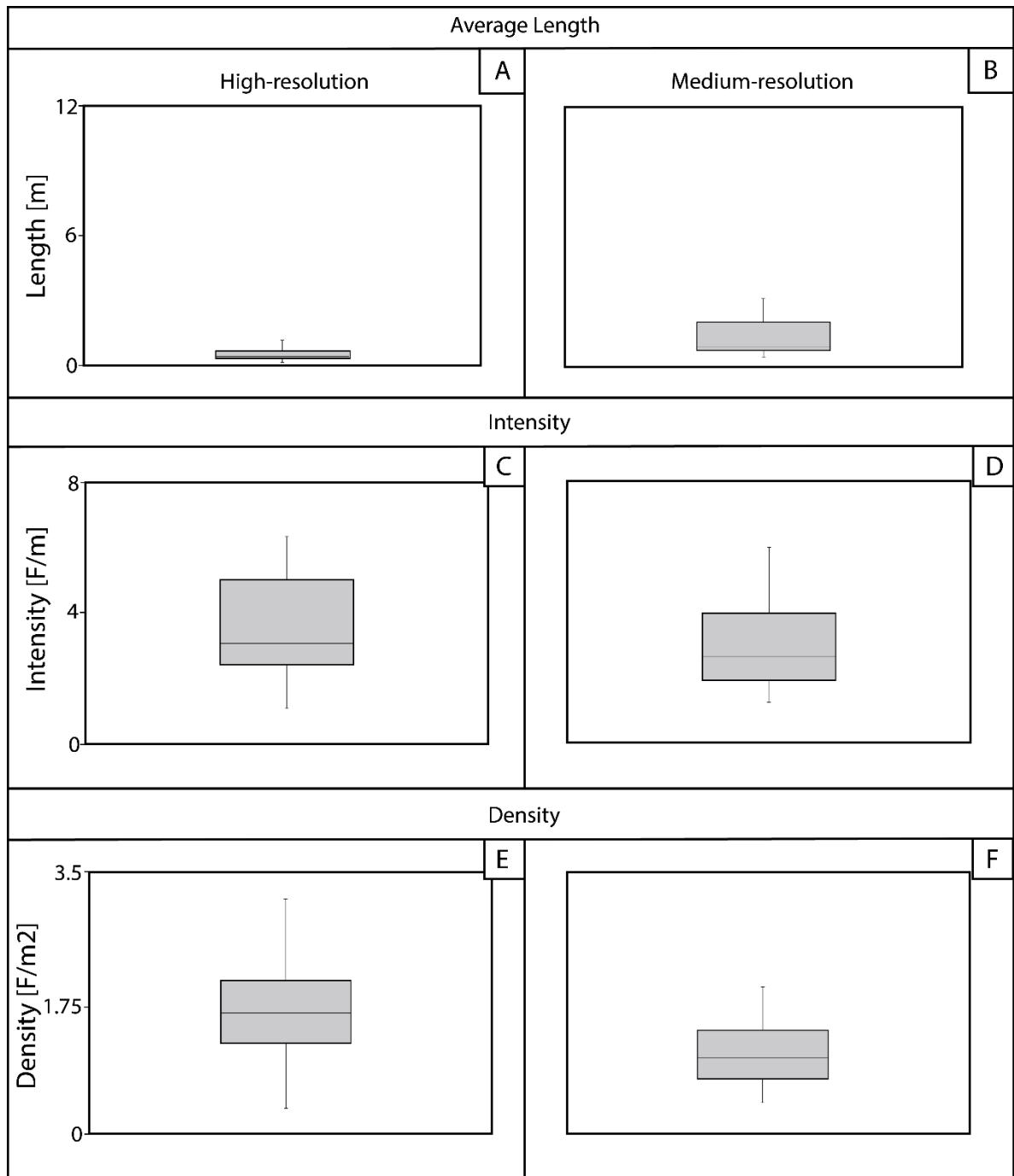


Figure 5.13 Comparison of lengths, intensities, and densities between medium and high-resolution images. Medium-resolution shows a wider spread in length (e.g., 0.44m-2.2m) than high-resolution (e.g., 0.41m-1.1m). High-resolution has higher values for intensity and density, showing it captures more details.

5.4 Discussion

The multiscale analysis of fracture networks demonstrates the significant differences in fracture interpretations from different resolution imagery. High-resolution imagery provided the most detailed, reliably characterizing fracture widths that closely matched field data, and revealed higher connectivity within fracture networks. Medium-resolution imagery offered an optimal mix between details and context, whilst covering also the entire surface area. Low-resolution imagery provided the least detailed measurements because it lacked the ability to capture finer features within the fracture network. This resulted in a more limited and generalized representation, where only the most prominent fractures were visible, and smaller or below detection limit features were either merged or entirely missed. Therefore, the overall representation of the fracture network was simplified, losing the complexity and detail that higher-resolution imagery could provide. In terms of orientation, datasets consistently showed a dominant N-S fracture orientation, which indicates the consistency and reliability of data collected across the three different resolutions.

The comparison between low and medium-resolution data reveals significant differences in both the range and consistency of fracture lengths. Low-resolution imagery captures fractures up to 4.53 meters, whereas medium-resolution is up to 31.7 meters, which indicates that medium-resolution is far more effective at identifying longer fractures. Medium-resolution imagery provides a more accurate representation of features at its scale, which allows for a clearer visual identification and subsequent feature tracing, whereas the same features in low-resolution imagery may fall below the detection threshold due to insufficient surface aperture. In terms of minimum lengths, all features are similar in pixel count, with each ranging between 2 to 4 pixels long across all resolutions. This limited subset contributes to

the inability to distinguish whether fractures are single entities or the result of coalescence. This highlights the limitations of low-resolution imagery and underscores the need for higher-resolution imagery to accurately interpret fracture lengths and interactions.

5.4.1 Impact of Surface Expression and Resolution on Reliable Fracture Tracing

High-resolution imagery is essential for precise measurements of surface widths, critical for understanding fracture geometry, and ensuring the reliability of interpretations. In fact, when compared to measurements taken in field (Figure 5.10C), which ranged between 0.001 meters to 0.08 meters, high-resolution imagery aligns very closely with these. Medium-resolution imagery, while still providing a reasonable alignment with field data, offers an advantageous balance between detail and area coverage. This resolution is particularly valuable for extensive yet detailed geological analysis, facilitating a broader yet substantial understanding of fracture networks without the need for the ultra-fine detail that high-resolution provides. In contrast, low-resolution imagery often exaggerates surface widths due to its broader pixel size, highlighting its limitations in capturing detailed fracture geometry. The average surface width used for tracing features in low-resolution imagery is approximately 2 pixels, which is on the borderline of the threshold defined for accurate feature tracing. This limitation significantly impacts the ability to reliably interpret longer lineaments, especially in areas where the fracture's surface width falls below the detection limit, leading to interruptions and incomplete traceability. The tendency of low-resolution imagery to misrepresent surface widths underscores the importance of choosing the appropriate resolution based on the specific requirements of the geological study. For detailed geological studies where precision is paramount, high-resolution imagery is indispensable. However, for broader

geological surveys where extensive area coverage is more critical than minute detail, low-resolution imagery may still serve as a valuable tool, despite its limitations.

Surface expression of fracture width is probably the most important factor that influences the ability of an expert to trace a fracture reliably when performing image-based fracture mapping.

This study found that fractures narrower than 2 pixels are undetectable across all resolutions, as shown in Figure 5.10C. The identification of a detection limit stresses the importance of planning drone data acquisition according to the known smaller widths of fractures observed during field visits, which ensures that the resolution is sufficient to detect and trace fractures accurately. This is critical for the comprehensive characterization of fracture networks. Moreover, this also highlights the importance of adopting multiscale approaches, as higher resolutions complement gaps that affect lower resolutions, and ensures a comprehensive fracture network characterization.

Surface width measurements taken at high resolution align closely with field observations, which further corroborates the accuracy and reliability of high-resolution imagery in representing geological features, making it essential for detailed geological studies. Medium-resolution imagery (2 cm/px) offers valuable insights but may underestimate surface widths due to its limited pixel resolution, as highlighted in Table 2. Although this underrepresentation necessitates the integration of high-resolution data for more accurate measurements, the fracture tracing process remained overall reliable. Moreover, by strictly adhering to the guidelines outlined in Table 5.1, the reproducibility of the analyses was maximized. The average surface width above the 2 px threshold served as a consistent criterion, ensuring that detected features were identifiable and traceable across different datasets, thereby minimizing variability and enhancing reproducibility. In contrast,

low-resolution imagery (21 cm/px) shows the smallest widths, averaging 2 pixels, making it the most unreliable and difficult to reproduce for detailed geological studies. Using low-resolution data for characterizing fractures in small areas is particularly limiting because the main advantage of low-resolution imagery lies in its coverage over extensive areas spanning tens or even hundreds of kilometers. Therefore, in smaller, restricted areas, the reliability of these measurements is reduced as low-resolution imagery is not meant to be used for that purpose, and it may fail to capture the necessary detail for accurate geological analysis. Consequently, both the restricted area and low-resolution result in very little usable data for accurate geological interpretation. However, for larger areas and fractures, low-resolution imagery could still be a very strong option.

5.4.2 Impact of Resolution on Topology in Fracture Network Characterization

The variability of the networks identified across the three resolutions indicates that a considerable amount of information is being lost, particularly when fracture connections become indistinguishable at lower resolutions, and are close to the detection limit. Our multi-resolution analysis shows that high-resolution imagery captures more short fractures and yields more accurate topological details, whereas medium-resolution imagery often merges or omits those subtle connections. Consequently, for studies focusing on fracture network topology or the detection of small-scale features, high-resolution data are essential. On the other hand, if the study's primary goal is to identify major structural trends, orientations, or large-scale connectivity, medium resolution may prove sufficient and more cost-effective.

One crucial finding is that connections within fracture networks must be represented by at least 2 pixels to be considered reliable across all resolutions. This finding is supported by the surface width measurements (as detailed in Table 5.2 and Figure

5.10), which show that fractures narrower than 2 pixels are undetectable, leading to incomplete network representations. The differences in cumulative distribution functions (CDFs) for fracture lengths, as shown in Figure 5.11, indicate that higher resolutions capture shorter fractures, which are often missed in lower resolutions. This is further evidenced by variations in fracture intensity across resolutions detailed in Figure 5.13, where higher resolutions display increased intensity due to detecting smaller fractures. These missing fractures in lower-resolution data lead to simplified network representations and reduced complexity and connectivity, highlighting the limitations of lower resolutions in accurately capturing the full extent of fracture networks. If a connection cannot be represented by this minimum threshold, it becomes unreliable and difficult to reproduce. This threshold is evident from the absence of fractures with an aperture below 2 pixels in all datasets, as shown in Figure 8. High-resolution data provides the most consistent and dependable connections, while medium and low resolutions may fail to capture finer interactions, leading to less reliable interpretations. Moreover, the results point toward a clear scale-dependent transition in fracture network complexity. As resolution increases, finer details of the network become visible, leading to higher measured fracture density and increased connectivity. This is particularly evident in the transition from low- to medium- and high-resolution datasets, where previously indistinguishable fractures become traceable, and their intersections become more apparent. The increase in detected fracture intersections at higher resolutions suggests that connectivity and network topology are strongly resolution-dependent rather than purely geological. While previous experimental studies have shown that fractures can evolve from distributed damage to localized structures under stress (Rizzo et al., 2017), this study instead has shown how different resolutions impose limitations on the observed network properties.

Bias can be introduced by the analyst's interpretation (e.g., Andrews et al. 2019), especially for near-resolution interpretations, such as fracture connectivity. One might argue that mapper-to-mapper inconsistencies could overshadow the influence of resolution. While these sources of uncertainty can indeed be large, resolution fundamentally dictates whether certain fractures are visible in the first place. If a fracture aperture is below the detection limit, no amount of consistent interpretation or optimal imaging conditions can compensate. Conversely, higher-resolution imagery inherently reduces ambiguity by capturing finer details. Consequently, even when other uncertainties exist, resolution remains a primary factor in controlling fracture detectability and measurement accuracy. In our experience, when features approach the detection limit, their identification becomes more subjective because features started to be interpreted in a way that made sense geologically rather than based strictly on visual evidence, as different experts can bring varied experiences to the interpretation. Given the subjectivity in interpreting connectivity, especially near resolution limits, it is essential to establish clear rules and guidelines for fracture tracing to minimize bias, as outlined in Table 5.1. Understanding the dataset and the specific objectives of the study is crucial for selecting the appropriate resolution and ensuring reliable results, as also pointed out by Andrews et al. (2019). If the focus of the study is to determine fracture connectivity, prioritizing the highest resolution data possible is critical. By combining high, medium, and low-resolution datasets, researchers can achieve a comprehensive understanding of fracture networks, balancing detail and coverage to minimize the effects of resolution constraints and enhance the overall reliability and reproducibility of the analysis.

5.4.3 Variability of Networks Across Resolutions and Practical Implications

While the networks identified at medium and high resolutions generally display similar fracture properties, the low-resolution network significantly differs, not only by missing shorter features but also by failing to detect narrower fractures, regardless of their length. This results in a loss of both fine and extensive details that are present in the higher resolution datasets. An increasing percentage of sub-cm fractures is being traced with higher resolution datasets, which is further corroborated in Figure 5.11's histogram: the high-resolution data shows a concentration of fractures in the range going from 0 and 0.5m. In contrast, medium-resolution has fewer fractures in this range but more fractures spanning up to 5m. This can be explained by the “aggregation effect” (Figure 5.5A, B), where features that appear as a single, continuous fracture at medium resolution are actually comprised of several shorter, isolated fractures that are only discernible at high resolution. Medium-resolution imagery provides a good balance, offering enough detail and coverage to characterize the geology of the area effectively. Low-resolution imagery, while extensive, often misses many fractures due to the generalization of information. Acquiring large-scale, high-resolution imagery (<0.2 cm), while it would be invaluable for capturing fine-scale features and topology, can be logistically challenging. This is due to limitations in data acquisition capabilities such as flight time and battery life, storage capacity, and processing power. As a result, while high-resolution imagery provides unparalleled detail, it is typically restricted to smaller areas of a few thousand square meters at best (e.g., Bemis et al. 2014; Prabhakaran et al. 2021), making it difficult to capture and interpret larger-scale geological trends comprehensively. This underscores the importance of carefully selecting the appropriate resolution based on the specific needs and goals of a study, and highlights the value of a multiscale approach for a comprehensive understanding.

Fracture length also demonstrates the limitations and strengths of each resolution. The lower R^2 value for the low-resolution data (Figure 5.11A) suggests that the fracture lengths captured at this resolution deviate from the expected log-normal distribution, likely due to the resolution's inability to accurately capture the full range of fracture sizes, particularly the smaller or narrower fractures that are more readily identified at higher resolutions. The strong area-bound censoring is clearly visible in Figure 5.11A, C, E, where distributions move closer to the Y-axis as the resolution increases, indicating that the fracture lengths (on the X-axis) become increasingly smaller with higher resolutions. This is also visible in the histograms in Figure 5.11B, D, F. High-resolution imagery captures the finest details, and on average is close to the lower end of the field measurements. Medium-resolution imagery also aligns very well with the field data, capturing a broad range of typical fracture widths. Low-resolution imagery, however, tends to overestimate surface widths, highlighting its limitation in capturing detailed fracture geometry. Due to the extensive coverage area of low-resolution imagery, using a restricted area for analysis often results in truncation/interruption of longer fractures. In contrast, medium-resolution imagery still experiences truncation for features larger than the covered area, but captures a broader range of fracture lengths, offering a balance between capturing both short and intermediate-length fractures. This makes medium-resolution data particularly valuable for studies that require a comprehensive overview of fracture networks over larger areas.

Intensity and density change greatly between datasets. As seen in Figure 5.12C, D, E, F, density is highest in networks extracted from high-resolution imagery; it decreases in medium-resolution imagery and is lowest in low-resolution imagery. This shows that while high-resolution captures many details, the broader networks are more clearly represented in medium-resolution, with low-resolution missing most of the

fractures in the rock mass. Fracture intensity, as visible in Figure 5.11C, D, tends to be higher in medium and low-resolution datasets, and lower in high-resolution datasets which is expected. The relationship between density, intensity, and connectivity of fracture networks is confirmed in the observed variations across different resolutions, where higher resolutions capture more complex and interconnected networks, while lower resolutions result in sparser, less connected networks Figure 5.8. Networks extracted from high and medium-resolutions demonstrate much more complex topologies, indicating higher complexity and connectivity. In contrast, the low-resolution network appears sparse and disconnected. This highlights a significant detail loss at lower resolutions and underscores the importance of data integration. Based on the threshold of at least 2 pixels for reliable fracture tracing, the intensity map can be interpreted as both a map of surface width and a reliability map. High intensity areas indicate a higher concentration of fractures that meet the minimum width threshold of 2 pixels, suggesting these regions have more reliably detectable fractures. Conversely, low intensity areas may indicate lower fracture intensity, but at the same time also implies that fewer fractures meet the 2 pixels threshold, highlighting areas where the detection of fractures is less reliable.

Orientation varies significantly across different resolutions, directly impacting network interpretations. As shown in Figure 5.7, while the major trends remain relatively consistent, the range of orientations identified differs significantly between low-resolution and medium/high-resolution datasets. This variation underscores the importance of using a multiscale approach for accurate geological interpretations. By integrating data from multiple resolutions, researchers can cross-validate findings, ensuring that key fractures are consistently identified across different scales. This cross-validation enhances the reliability of geological analyses because it confirms that different workflows applied to the same dataset yield qualitatively similar results.

While the consistent major orientations across resolutions demonstrate the reliability of the findings, the reproducibility of results might be challenged, especially with low-resolution imagery. Throughout this study, analyses on low-resolution data produced hard-to-reproduce networks due to the average surface width being below the two-pixel threshold necessary for accurate fracture tracing. This emphasizes the importance of using higher-resolution imagery to achieve reproducible results in geological studies.

5.5 Conclusions

The multiscale analysis of fracture networks conducted in the Havmyran Natural Reserve underscores the critical importance of resolution in remote geological characterization. High-resolution imagery provides exceptional detail, uncovering complex and reliable connections within fracture networks. However, it can miss the broader geological context due to its limited coverage and may be subject to statistical biases such as truncation. Medium-resolution imagery strikes a balance, offering both a clear overview and significant detail, making it ideal for comprehensive geological analysis. In contrast, low-resolution imagery is effective for capturing broader geological trends across large areas but often overlooks finer details, making it less reliable for studies focused on restricted areas.

Low-resolution imagery, effective for surveying extensive areas, generally captures only large, visible fractures, overlooking finer structural details. This limitation often results in a generalized and less reliable depiction of fracture networks, particularly in studies that require detailed analysis within confined areas. Findings, particularly the significant variance in fracture identification, from 222 features in low-resolution up to 3,449 in medium and 1,591 in high-resolution imagery, underline the

importance of resolution in defining the clarity and utility of geological interpretations.

Moreover, the study demonstrated that a minimum feature width of 2 pixels is necessary to maintain accuracy and consistency across all resolutions, ensuring that fracture networks are not only visible but also reliably traced and analyzed. The analysis showed that high-resolution imagery closely matched field-measured attributes, reinforcing its essential role in detailed geological studies where precision is critical.

In conclusion, adopting a multiscale approach offers significant benefits for achieving a more comprehensive understanding of fracture networks. Each resolution level contributes to the overall analysis, provided it aligns with its intended purpose, whether capturing larger-scale structural trends or resolving finer-scale fracture details. By integrating data from multiple resolutions, researchers can balance coverage with detail, leading to geological interpretations that are both more reliable and more complete.

Chapter 6 Characterization of the Deformation Patterns in the Granitic Rocks of Hitra: A Multiscale Analysis

Abstract

This study investigates the fracture patterns in the granitic rocks of west Hitra Island, Norway, to understand the deformation styles associated with the region's complex tectonic history. Using aerial and drone imagery fractures ranging from 0.07 meters to 14 kilometers in length were analyzed.

The analysis revealed extensive brittle structures with varied orientations across all scales. Two primary fracture sets were identified: NE-SW/ENE-WSW and NW-SE striking features, which align closely with the orientation of the Møre-Trøndelag Fault Complex (MTFC). Relative-age analysis, based on cross-cutting relationships, suggests that the NW-SE fractures are the oldest, while the ENE-WSW fractures are the youngest.

Power-law analysis of fracture lengths indicates self-similar fracturing processes influenced by consistent tectonic stresses across different scales. The study also observed that fracture intensity increases with finer scales, and the topology of fracture networks varies with scale, reflecting changes in fracture connectivity and interaction.

The multiscale approach used for this study highlights the dynamic and sequential nature of tectonic stress and its impact on granitic rock deformation. The findings emphasize the importance of integrating multiscale analyses to advance the understanding of structural discontinuities in granitic contexts. This work contributes to a more comprehensive view of how past geological processes shape present-day

rock deformation patterns, underlining the role of structural inheritance and regional stress regimes in fracture development.

6.1 Introduction

Fracture patterns in rocks are fundamental to understanding geological processes and have significant implications for both natural and engineered barriers (Berkowitz, 2002). These fractures, which form in response to applied stress, can range from simple, isolated cracks to complex, interconnected networks. In geological media, fractures develop due to brittle failure and can be classified into joints and faults (Gillespie et al., 1993). Fractures initiate and propagate when the applied stress exceeds the rock's inherent strength, causing the rock to fail either in tension or shear. This leads to the development and extension of cracks under continued stress (Ghasemi et al., 2020; Hoek and Bieniawski, 1965).

Fractures in granite may occur for several reasons; as granitic plutons cool and solidify deep within the Earth's crust, they crystallize under high and relatively uniform lithostatic pressure conditions (Nédélec and Bouchez, 2015). Tectonic uplift and erosional processes can progressively remove the overlying rock layers, bringing the granitic plutons closer to the surface (Hilley et al., 2005). This exhumation results in a significant decrease in confining pressure, leading to stress imbalances within the rock mass (Molnar et al., 2007). Additionally, thermal contraction during the cooling of the pluton can generate internal stresses that contribute to fracturing (Nasser et al., 2009). The combined effects of thermal contraction and decreased confining pressure promote the development of various fracture types in granitic rocks. Common fractures include extension fractures, which occur perpendicular to the minimum principal stress direction and are characterized by tensile opening modes; shear fractures, which develop when differential stresses exceed the shear strength of the rock, leading to displacement along fracture planes; and hybrid fractures, which exhibit both extensional and shear characteristics due to complex stress conditions (Liu et al., 2022). The formation of these fractures is influenced by

factors such as the rate of stress application, the mechanical anisotropy of the granite, and the prevailing tectonic stress regime.

Discontinuities such as faults, fractures, and shear zones play a crucial role in geology since they significantly affect fluid flow in petroleum and groundwater reservoirs. These features range from microscopic cracks and millimeter-scale fractures to kilometer-scale faults and can either enhance permeability by providing pathways for fluids or act as barriers that impede flow, depending on their characteristics and connectivity (Barton et al., 1995; Siler et al., 2018; Yuguchi et al., 2021). In limestones and crystalline rocks, highly permeable fracture zones facilitate fluid movement, while in some hydrocarbon reservoirs, fault structures can seal and compartmentalize fluids, influencing reservoir performance and management strategies (Abelin et al., 1991; Schultz, 2019).

Understanding the spatial distribution of fracture networks in granitic rocks is essential due to their significant influence on geological processes and fluid flow. However, traditional field methods face limitations in capturing these features over large areas and multiple scales. To address this, remote sensing techniques, particularly aircraft and drone imagery, have become invaluable tools for effectively identifying and analyzing fractures across extensive regions. Remote sensing techniques, specifically aircraft and drone imagery, have become vital tools for identifying and analyzing discontinuities over extensive areas (e.g., Samsu et al., 2020; Tartaglia et al., 2022). While imagery provides a powerful tool for structural analysis, the reliability of results extracted from remote sensing depends on factors like image resolution, data processing, and interpretation methods (e.g., Xie et al., 2008). High-resolution imagery allows for detailed mapping of fracture networks, but challenges such as vegetation cover, shadow effects, and scale limitations can affect the accuracy of interpretations (e.g., Bemis et al., 2014; Xie et al., 2008). Previous studies have

demonstrated that integrating remote sensing data with field observations enhances the reliability of structural analyses (e.g., Bertrand et al., 2015; Tartaglia et al., 2022). Acknowledging the limitations of imagery and validating results through complementary methods are essential for accurate geological interpretations. Moreover, relying on a single resolution for remote geological characterization can be insufficient due to the scale-dependent nature of geological features (Bertrand et al., 2015a; Bonnet et al., 2001). Geological structures, such as fractures and faults, exhibit characteristics that vary significantly across spatial scales—from microscopic cracks to regional fault systems. Using only one resolution may result in missing critical information about the fracture network, such as small-scale fractures that influence fluid flow or large-scale structures that control regional stress fields (Drury, 1987). Multiscale analyses integrate data from various resolutions, providing a more comprehensive understanding of geological formations and processes (Turner, 2006). For example, Turner (2006) highlights that multiscale modeling allows for capturing both the detailed local geology and the broader regional context, which is essential for accurate structural interpretations. Therefore, employing multiple resolutions is crucial for a holistic and accurate characterization of geological structures.

A significant aspect of fracture systems that are extensive across large areas is their relationship with structural inheritance, where pre-existing faults and fabric in the basement influence the shape, orientations, and location of fracture systems (Samsu et al., 2020). For example, Samsu et al., 2020 demonstrated that the orientations of fractures within the Gippsland Basin showed significant influence from underlying pre-rift basement structures, which affected both their initial formation and subsequent reactivation patterns across different scales.

The aim of this research is to characterize the fracture patterns in the granitic rocks of west Hitra Island, Norway, across multiple length scales—from centimeters to kilometers—to understand the deformation styles associated with the region's complex tectonic history. Using a combination of aerial and drone imagery, fractures ranging from 0.07 meters to 14 kilometers in length were analyzed. A key aspect of this study is to demonstrate that relying on a single dataset or scale is insufficient for accurate geological characterization, highlighting the necessity of multiscale analysis. The objectives of this study are to: 1) interpret faults and fractures across different scales using remote sensing data; 2) investigate the scaling relationships and self-similarity of fracture networks at regional, local, and outcrop scales; 3) characterize the connectivity and topology of fractures across these scales; and 4) show how multiscale datasets provide a more comprehensive understanding compared to single-scale analyses.

This study emphasizes the importance of integrating observations of fractured rock masses multiple scales as part of accurately characterizing the deformation patterns in granitic rocks.

6.2 Study Area

Hitra Island is located on the western coast of Norway Figure 6.1A. It is part of the Trøndelag county and is situated west of Trondheim. The study focuses on the granitic rocks in the western and south-western parts of Hitra Island (Figure 6.1B).

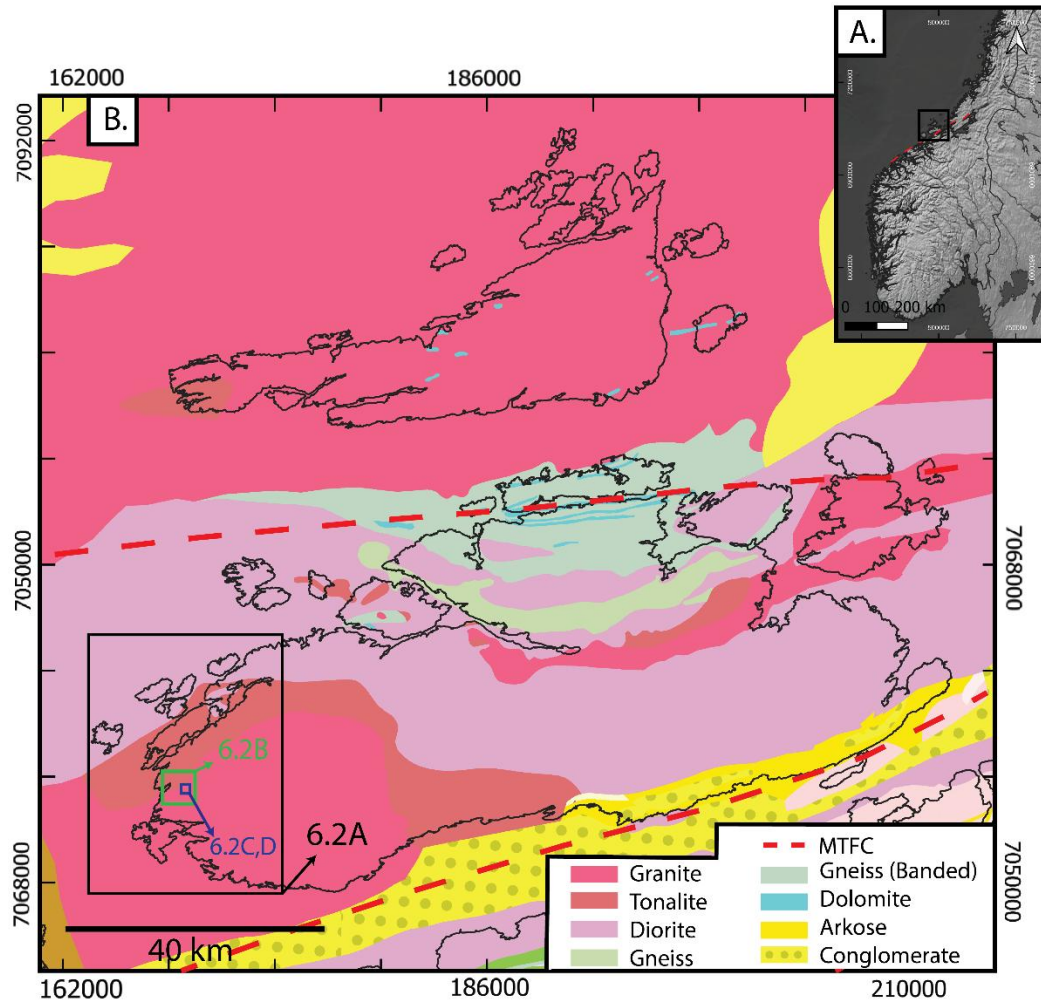


Figure 6.1 (A) Location map of the general area of investigation (EF89-32N), together with the MTFC. (B) Simplified Geological map of the island of Hitra and Froya, with two faults belonging to the Møre-Trøndelag Fault Complex (dashed red lines). Highlighted to the left are the areas of investigation, which cover mostly granite, and tonalite.

The study area covers approximately 131 km² in the western and southwestern parts of Hitra. More detailed analyses were conducted on a smaller, 4.4 km² section within this area. Additionally, for even more focused investigations, high-resolution orthoimagery collected in the field, covering a total area of 0.018 km² was used. This

comprehensive approach allows for an intricate examination of the deformation patterns in the granitic rocks across different parts of Hitra Island.

6.3 Geological Background

The geological history of the Scandinavian peninsula is closely linked to the closure of the Iapetus Ocean. This closure involved a series of events that resulted in a complex subduction system dominating the Baltoscandian margin of continental Baltica during the Ordovician (Gee et al., 2013). This process led to a collision with Laurentia in the Silurian to Early Devonian periods, which influenced the region's geological framework (Gee et al., 2017; Stephens, 2020; Waldron et al., 2022).

Specifically for Hitra Island, the Caledonian orogeny led to significant deformation, metamorphism, and magmatism. The island is underlain by the Smøla-Hitra Batholith, a large granitic intrusion that formed as a result of magmatic activities associated with the orogeny (Gautneb and Roberts, 1989). The batholith's emplacement is directly linked to the subduction and collision processes (Gee et al., 2013). The granitic rocks on Hitra are well-exposed and belong to the Smøla-Hitra Batholith, which is associated with the Caledonian orogeny (Gee et al., 2017). It includes a range of plutonic rocks from gabbro to granite, indicating a complex magmatic evolution through successive intrusions—from initial gabbro and hornblende diorite to later granite and granodiorite phases—marking the end of a subduction cycle (Debon and Le Fort, 1983; Gautneb and Roberts, 1989). The Møre-Trøndelag Fault Complex (MTFC, Fig. 1A, B) is still moderately active today, offshore to the south of the Møre Basin (Watts Lee M. et al., 2023). Hitra and its neighboring islands, like Frøya, are situated in the transition zone between the stable continental crust of Norway and the more dynamic offshore regions of the passive margin (e.g., Bøe et al., 2005; Gee et al., 2013). They effectively represent the landward limit of the

mid-Norwegian passive margin. The passive margin here is characterized by the thinning of continental crust and the onset of oceanic crust formation associated with the opening of the Norwegian Sea and North Atlantic Ocean. The current structural setting of Hitra Island is heavily influenced by both inherited structures from earlier orogenic events and more recent tectonic processes associated with passive margin development (e.g., Tartaglia et al., 2022). The reactivation of pre-existing faults, particularly those associated with the MTFC, plays a crucial role in the present-day deformation observed on the island.

The ENE-WSW faults of the MTFC are generally steeply dipping toward the north/northwest and represent the inland boundaries of the offshore Froan Basin (Gabrielsen et al., 1999; Nasuti et al., 2010). The fault zone's tectonic evolution has been marked by significant shifts in kinematic patterns, transitioning from dextral transpression at the onset of the Devonian period to sinistral transtension kinetics persisting until the early Permian, with a shift to purely sinistral strike-slip by the Jurassic. Although there are hypotheses suggesting reactivation during the Permo-Triassic, the current evidence remains insufficient to fully substantiate these theories (Grønlie et al., 1990).

6.3.1 Batholith Composition

The Hitra-Smola batholith intrudes into earlier geological formations, including low-grade metamorphic sedimentary and bimodal metavolcanic rocks of the Arenig-Llanvirn period, as well as high-grade, extensively deformed gneisses of likely Proterozoic age (Gautneb and Roberts, 1989). The oldest identified rocks within the batholith are gabbro, monzodiorite, and hornblende diorite, succeeded by tonalite, granodiorite, and granite, manifesting in both plutonic forms and as dykes and veins (Gautneb and Roberts, 1989). The evolution of this batholith, characterized by high-K

calc-alkaline compositions, points to its formation in a mature magmatic arc setting, possibly marking the end of a subduction cycle (Debon and Le Fort, 1983; Gautneb and Roberts, 1989). The petrochemical analysis reveals major trace element variations, with preliminary isotopic dating indicating an age range from c. 450 Ma to c. 428 Ma, suggesting a significant Ordovician to Early Silurian tectonomagmatic cycle prior to the continent-continent collision initiating the Scandian orogeny.

6.4 Data and Methodology

This section outlines the processes of image acquisition, orthophoto generation, fracture interpretation across different scales, and the steps taken to ensure accuracy and consistency during the fracture tracing process. The data that was used for making geological interpretations were: 1) drone imagery collected in the field, with a resolution of 2cm/px, and 2) pre-existing regional orthoimagery, with a resolution of 0.165m/px. It is acknowledged that imagery resolution can significantly affect the number, size, and continuity of interpreted fractures (e.g., Bonnet et al., 2001; Xie et al., 2008). Here, we combine aerial images (0.165 m/px) and drone images (0.02 m/px) to capture large-scale structural patterns and finer, outcrop-scale features, respectively. However, because the datasets differ substantially in resolution and spatial extent, direct comparisons between them must be made with caution. In particular, small fractures below the detection limit of coarse imagery, or subtle offsets in high-resolution data, may not be replicated at a broader scale. Therefore, the analyses presented below should be interpreted in light of this inherent scale dependency.

6.4.1 Data Acquisition

Drone imagery used for this study was captured using a DJI Phantom 4® drone, which is equipped with a 1/2.3" CMOS sensor at 12.4 MP. The original images were

processed into two sets of orthophotos, forming a mosaic of 1,301 photos, with a final resolution of 0.02 meters per pixel (Figure 6.1C, D). The drone operated at altitudes ranging between 25 and 35 meters. The camera settings during sampling included an exposure time of 1/500s, an ISO speed of 100, and a focal length of 9mm.

6.4.2 Remote Sensing and Datasets

To enhance the analysis of fractures on Hitra Island, a combination of aerial and drone-based orthoimagery was utilized. The regional orthoimagery dataset used in this study comes from a 2015 aerial survey covering the islands of Hitra and Frøya, with a specific resolution of 0.165 meters per pixel for the Hitra dataset. This dataset allows for the interpretation of regional-scale and local-scale features ranging from as short as 1.3 meters to as long as 14 kilometers. Complementing this dataset, drone-based orthoimagery provided a higher resolution of 0.02 meters per pixel, used for interpreting outcrop-scale features ranging from 0.07 m to 65 m in length. During the acquisition, the target photo overlap was 70% (e.g., Bilmes et al. 2019). The data were processed into an orthomosaic using WebODM, an open-source tool for generating maps, point clouds, terrain, and 3D models from aerial images. Within WebODM, the Akaze feature-type algorithm was used along with default neighbor matching settings, employing the Flann matcher type. The resulting resolution of the orthophotos was 2 cm.

6.4.3 Fracture Interpretation

Fractures were interpreted at three scales throughout this study: at the regional scale, aerial orthoimagery covering approximately 131 km² with a resolution of 0.165 meters per pixel was used, interpreting fractures ranging from 34 meters to 14 kilometers in length. At the local scale, within a 4.4 km² area, the same imagery, with the same resolution, but at a closer zoom allowed us to interpret fractures from 1.35

meters to over 3,240 meters. For the outcrop scale, high-resolution drone-based orthoimagery covering 0.017 km² with a resolution of 0.02 meters per pixel enabled the identification of fractures from 0.07 meters to 65 meters in length. As part of the manual fracture interpretation, a series of criteria were adopted, including minimum length in pixels, allowed angles for intersecting features across vegetated areas, and maximum separation for merging traces (see Table 6.1). The interpretation also took into consideration the handling of narrow vegetated areas, detailing the tracing process, zoom levels, and minimum vertices required per feature. Adopting these criteria aimed to ensure accuracy, consistency, and reproducibility of the fracture interpretation process across the three scales of interest while minimizing bias.

Criteria	Aerial Imagery	Drone Image
Line tracing	Center of the feature	
Min Length [px]	8	4
Angle for int. features across veg. areas	180±2°	
Max separation for merging	n/a	20cm
Max narrow vegetated areas	0.5m. Beyond that, trace along the closest and clearest edge from the start of the fracture	
Tracing process	Center between edges	
Zoom	1:55,000/1:7,000	1:120
Minimum vertices per feature	3	3

Table 6.1 Criteria followed for manual fracture tracing across all scales.

Features were manually traced and their attributes (i.e., length, orientation, offsets) were calculated in QGIS. All network-related analyses were performed with the NetworkGT plugin (Nyberg et al., 2018). NetworkGT is a QGIS plugin designed for the analysis of fracture networks, providing tools to evaluate connectivity, topology, density, intensity, orientation, sets, and geometrical attributes of fracture networks. Traces were interpreted at the center between the edges of each fracture to accurately represent their orientation and scale. Tracing fractures through areas with vegetation proved challenging. However, the visibility of traces even in vegetated sections allowed for consistent mapping, thus capturing the full extent of the fracture systems. Moreover, we also performed a younging table analysis to quantify the relative timing between fractures, following the methodology outlined by Potts & Reddy (2000). This approach allows for the systematic assessment of cross-cutting relationships, where fractures that truncate others are interpreted as younger, while fractures that are truncated are considered older (Potts and Reddy, 2000). Additionally, uncertain or ambiguous relationships were classified separately to account for cases where relative timing could not be confidently determined. The strength of this analysis lies in its structured approach to establishing the sequence of fracture formation, providing an objective and systematic approach for the interpretation of fracture relationships.

In this study, fractures extending into on-shore water bodies were traced based on visible alignment and on the principle that, once a fracture initiates, it tends to persist across different terrains (e.g., Fagerland 1990; Wilson et al. 2006). Specifically, when a fracture identifiable on land approaches a water body and a similarly oriented fracture resumes on the opposite shoreline, it was inferred that the fracture extends and forms a continuous geological feature. It is important to note that this

methodology relies on the interpretation of surface indications and geological continuity rather than direct subsurface data.

In this study, fault planes were inferred based on selected kinematic indicators, which were identified by observing evidence of lateral offset in fracture traces. These includes features that appear bent, broken up, and displaced. Visual indications such as changes in alignment, orientation, and terminations of fractures were used to infer the movement sense and displacement along the fractures. Relative age relationships were also carried out throughout the study, and were established based on cross-cutting relationships between fractures. This approach involves analyzing how fractures interact, cross, and terminate against each other. By observing these interactions, it could be inferred which fractures were older or younger relative to each other. Throughout this study, some features appeared to be duplicates between regional- and local-scale interpretations. While, in principle, it might be possible to digitally eliminate duplicates, the uncertain nature of working at different resolutions makes it difficult to confirm whether they truly represent the same fracture or reflect legitimate differences (e.g., coalescence at one scale versus separation at another). In addition, their overall number was negligible and did not significantly affect the analysis. Consequently, we opted to retain these features rather than risk removing fractures whose actual continuity or segmentation cannot be definitively established from remote imagery alone.

6.5 Results and Observations

This section presents the results of our analysis. Throughout, the terms 'regional-scale features,' 'local-scale features,' and 'outcrop-scale features' will be used to describe features ranging from 34 m to 14 km, 1.35 m to 3,240 m, and 0.07 m to 65 m, respectively. Because each scale of imagery offers a distinct resolution and

coverage, the fracture networks described in sections 6.5.1–6.5.4 are not intended for direct, like-for-like comparisons. Instead, they illustrate how broad patterns can be captured regionally, while finer details, such as small fractures, offsets, or closely spaced nodes, emerge more clearly in higher-resolution data. This approach stresses the scale dependence of fracture mapping and requires caution when contrasting quantitative metrics, such as fracture density, from one scale to another.

6.5.1 Regional Scale Structural Analysis

6.5.1.1 Fracture Population and Orientation

Highlighted in Figure 6.2A, our analysis identified 320 features ranging from 34 meters to 14 kilometers in length, identified at a fixed zoom level of 1:55,000.

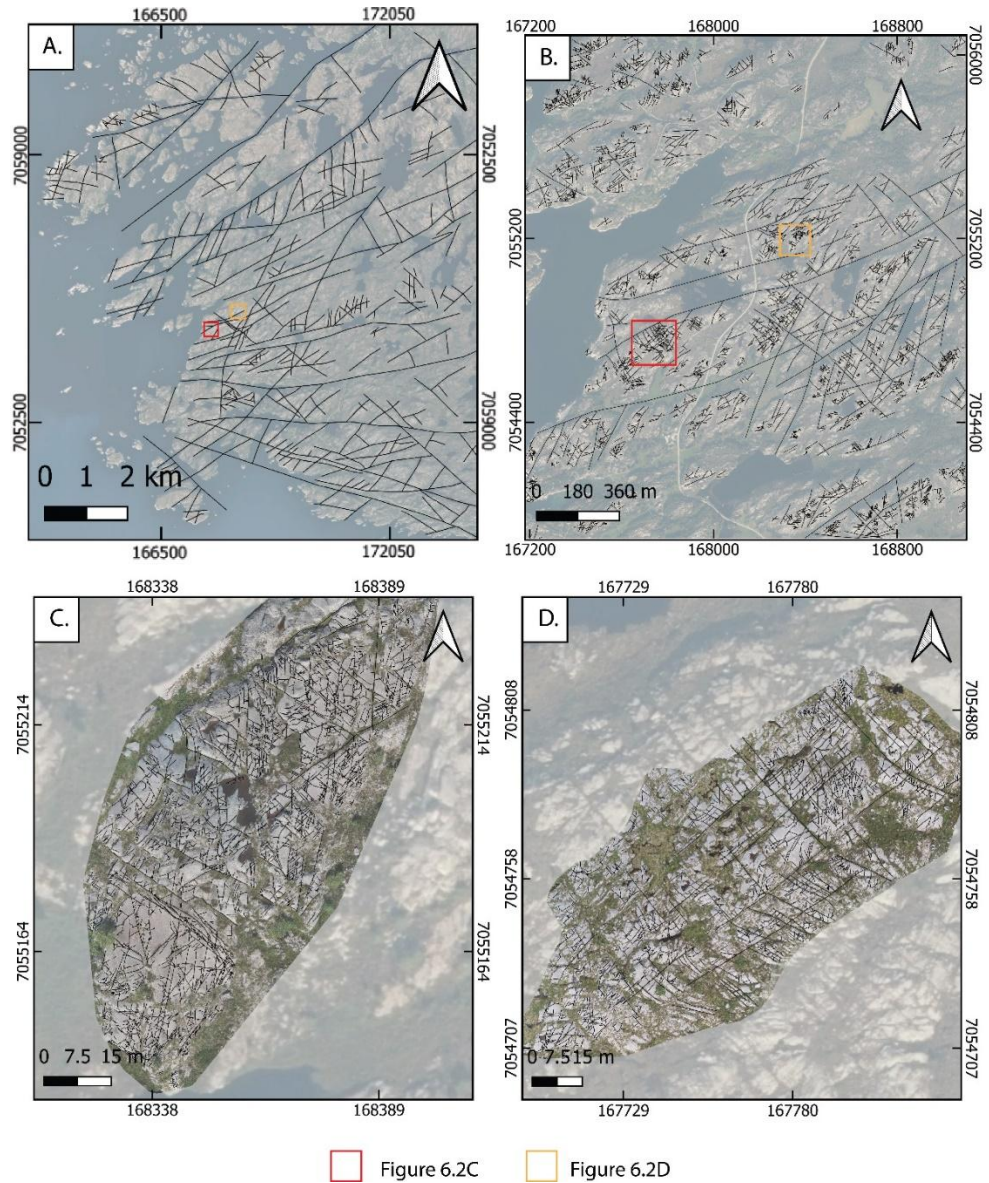


Figure 6.2 Maps showing fracture patterns traced in the western region of Hitra Island at different scales and interpretations using RGB images. (A) Overview map at 1:55,000 scale showing general fracture orientations. (B–D) Detailed zoom-ins of selected areas, highlighting differences in fracture orientations and densities.

Figure 6.3A presents a fracture intensity map at a 1:55,000 scale and covers a large region in the western part of Hitra Island.

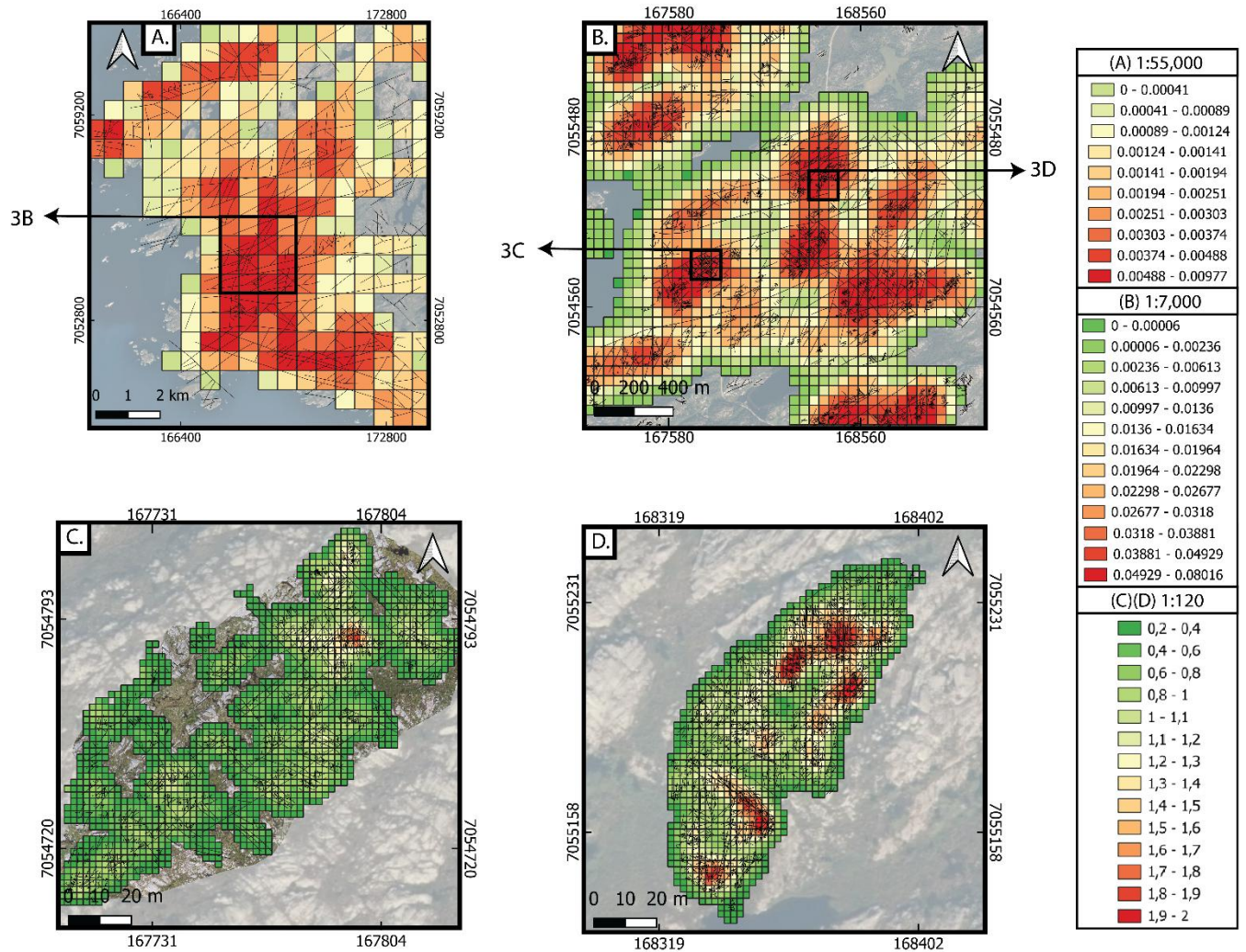


Figure 6.3 Fracture intensity maps (m/m^2) for all areas of investigation, showing how fracture intensity varies across different scales. 3A. intensity for regional-scale features. Intensity is highest in the southwestern part of the island; 3B. Intensity for local-scale features, showing clusters of high fracture intensity, juxtaposed with patches of lower intensity, attributed to vegetated areas; 3C. Intensity for outcrop-scale features (West outcrop), which are generally quite low across the exposure; 3D Intensity for outcrop-scale features (East outcrop), showing patches of high and moderate fracture intensity.

Figure 6.3 shows the varying levels of fracture intensity by using different color scales, with red and orange representing higher fracture intensities and green and yellow

indicating lower intensities. The highest intensity regions are concentrated in the central and southwestern parts of the mapped area, where calculated intensity ranges between 0.00488 and 0.00977 m/m², which is the highest intensity amongst the areas of interest.

The rose diagrams in Figure 6.4 show the presence of three main sets: ENE-WSW, NE-SW, and NW-SE and prominent N/S trend.

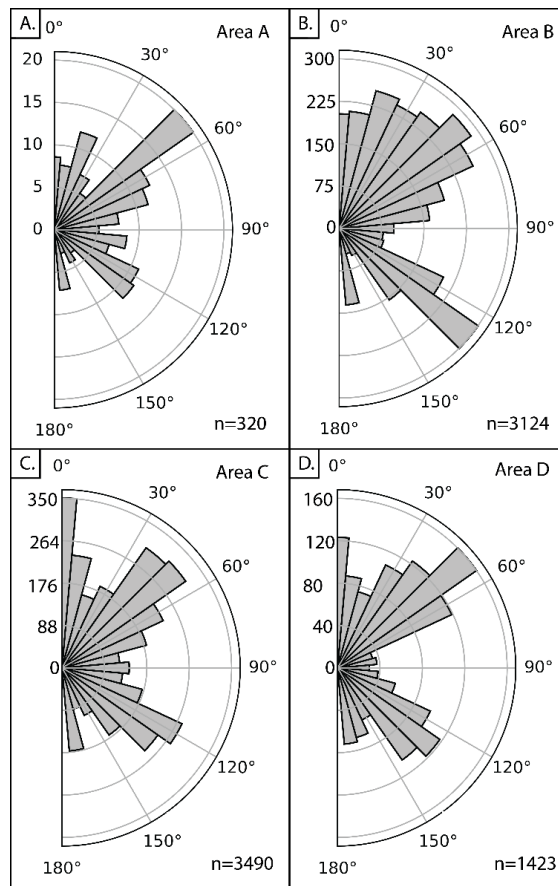


Figure 6.4 Four rose diagrams showing fracture orientation distributions at different scales: (A) 320 fractures ranging from 34 m to 14 km, showing orientations ENE-WSW and NE-SW; (B) 3,124 fractures ranging from 1.35 m to over 3,000 m, confirming similar orientations; (C) and (D) 3,490 and 1,423 fractures respectively, with lengths ranging from 0.07 m to ~65 m, highlighting dominant fracture sets.

The three trends were grouped up into two separate sets, based on cross-cutting relationships. Figure 6.5 shows how fracture orientation changes spatially for regional-scale features ranging from 34 m to 14 km.

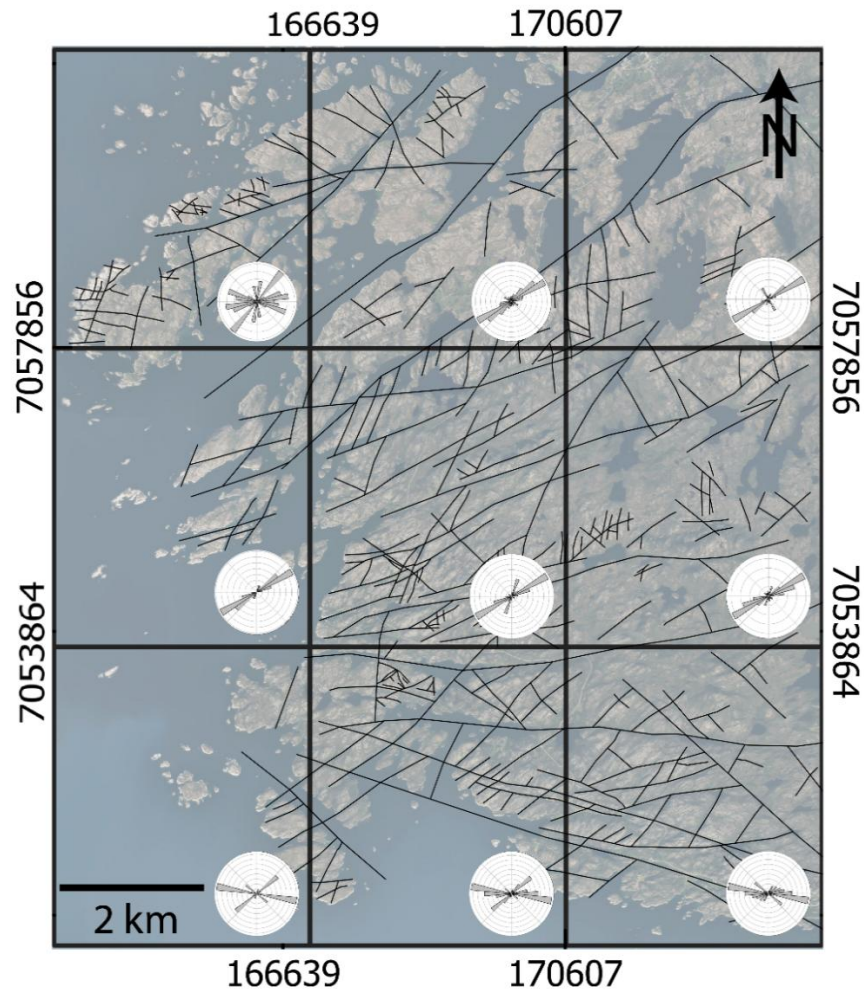


Figure 6.5 Length-weighted spatial variability of fracture orientation. The shift toward ENE-WSW is clearly visible.

In Figure 6.4, despite slight changes in the main trends observable in each section, the NE-SW trend remains dominant across the area of interest, without providing any specific insights on how the orientation of cross-regional features changes toward the south. However, in Figure 6.5, where the rose diagrams are weighted by length, it is possible to see how the orientation of the major cross-regional features gradually

shifts from NNE in the north of the area of interest to WNW/NW in the south, near the MTFC/Hitra-Snåsa fault.

6.5.2 Local Scale Structural Analysis – from 1.35 meters to over 3,240 meters

6.5.2.1 Fracture Population and Orientation

In the southwestern part of Hitra Island (Figure 6.2B), mapping at a 1:7,000 scale revealed a highly fractured rock formation. A total of 3,124 geological features were identified, with lengths spanning from about 1.35 m to over 3,000 m. Features ranging from 34 m to 14 km (Figure 6.2A) have three dominant trends, ENE-WSW, NE-SW, and NW-SE. In terms of fracture geometry, similarly to regional-scale features, the intersection angle between fractures averages 63 degrees. Features at this scale are also very linear, which again is reflected in a factor of linearity of 0.99. The calculated fracture density for fractures interpreted at local scale was 0.024 fractures/m². Finally, the average spacing between fractures is one order of magnitude smaller compared to the spacing of regional-scale features, with it being approximately 74 meters.

Figure 6.3B shows a fracture intensity map for local-scale features. This map reveals a highly heterogeneous fracture intensity distribution compared to regional-scale features, with numerous hotspots of high fracture intensity (shown in orange (0.02298 m/m² and red 0.080165 m/m²) juxtaposed with areas of lower intensity (shown in green and yellow 0.0006 m/m² to 0.02298 m/m²). However the exposure is generally highly fractured and the highest intensity values, reaching up to 0.08016 m/m², are concentrated in many clusters, indicating multiple localized zones of intense fracturing. The rose diagram in Figure 6.4B shows how fracture sets were divided. As previously mentioned, three main fracture trends were identified across the area of interest: ENE-WSW, NE-SW, and NW-SE. However, the three trends were grouped into two separate sets, based on cross-cutting relationships.

6.5.3 Outcrop Scale Structural Analysis – from 0.07 meters to 65 meters

6.5.3.1 Fracture Population and Orientation

Two areas with high-resolution orthoimagery (Figure 6.2C, D), approximately 750 meters apart, covering areas of 0.006 km² and 0.011 km² respectively were interpreted. At this scale, a total of 4914 features were interpreted across both areas in Figure 6.2C, D, with lengths ranging from 0.07 m to 65 m. Orientation analysis identified two primary sets for features with this length, which are consistent with trends observed for regional- and local-scale features (Figure 6.2A, B). In Set A fractures are primarily oriented NW-SE, with a peak frequency between 120° to 145°, as shown in Figure 6.4C, D. In Set B, fractures are oriented ENE-WSW, and the most frequent occurrence is between 0° to 55° in both outcrops, as shown in Figure 6.4C, D.

At outcrop scale, the average intersection angle ranged between 66 and 67 degrees in the two outcrops that were investigated. In terms of linearity, fractures in both outcrops have a linearity factor of 0.99. In terms of spacing, at outcrop scale it was measured at 1.47 m. The calculated fracture density for outcrop scale was 0.441 fractures/m².

Figure 6.3C and D show fracture intensity maps for the outcrop-scale features identified at locations in Figure 6.2C and D. The fracture intensity in these maps ranges from 0.2 to 2 fractures per square meter, with red and orange areas indicating zones of very high fracture density (from 1.4 m/m² to 2 m/m²). In Figure 6.3C, high-intensity zones are concentrated in the central north and southern-central east parts, suggesting multiple focal points of high fracture intensity. In Figure 6.3D, the high-intensity regions are concentrated in the northeastern part of the exposure, whilst generally fracture intensity ranges between 0.2m/m² to 1.3 m/m² across the

exposure. The maps in Figure 6.3A, B, C, and D show how fracture intensity and density vary with scale, and how significant the increases in observed fracture intensity are as we zoom in and the scale of investigation changes.

6.5.4 Cross-Cutting Relationships Across Scales

Changes in fracture orientation across the island are evident in Figure 6.5: starting with a NE/SW direction at the northern end, shifting to ESE/WSW midway, and transitioning to WNW/ESE near the MTFC/Hitra-Snåsa fault at the southern end.

These initial fractures are overprinted by a series of younger NE-SW/ENE-WSW oriented fractures. The presence of these latter fractures, indicative of a subsequent tectonic phase and observed to often displace the earlier NW-SE oriented fractures, suggests that the area has experienced progressively evolving stress conditions, impacting the existing fracture networks. On a regional scale, fracture tracing revealed a detailed sequence of deformation events. The sequence begins with the NW-SE and NNW-SSE oriented fractures, which form the oldest set of fractures (Set A). This fracture set is cut by the older NE-SW oriented fractures, forming Set B. The fractures associated with ENE-WSW directions are also part of Set B and are the youngest amongst all the mapped fractures. These fractures predate those in Set A but also intersect and offset NE-SW oriented fractures (Figure 6.8C), indicating their relative youth and suggesting a continued influence of tectonic activity. The spatial distribution, orientation, and crosscutting relationships of these sets suggest a temporal succession where the NW-SE/NNW-SSE orientations formed first, setting the stage for the later NE-SW and ENE-WSW fracture systems.

At outcrop-scale, the relative chronology analysis revealed a sequence similar to patterns observed at larger scales. Fractures were grouped into two main sets, A and B, based on their orientation, overprinting, and inferred age relationships. Set A,

featuring the oldest NW-SE trending fractures, laid the initial structural framework. The younger fractures, oriented ENE-WSW and classified as part of Set B, postdate those in Set A, indicating they are the most recent. This continuation of stress fields and tectonic processes points to a dynamic geological history, with the latest chapter marked by the MTFC's influence. The ENE-WSW fractures formed during the Triassic under an extensional regime.

6.5.5 Topology

Topology at each scale is summarized in Figure 6.6.

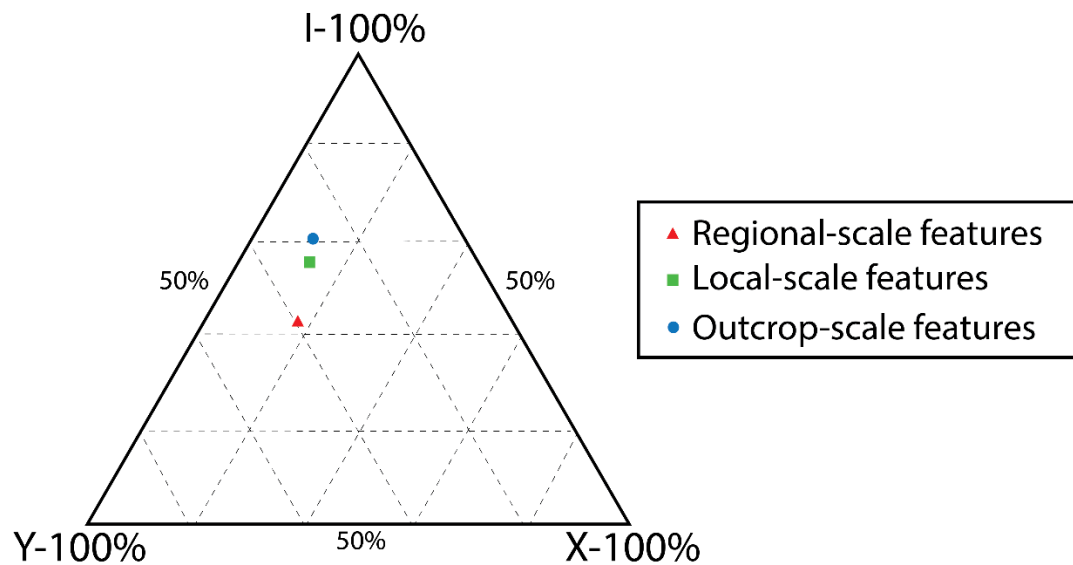


Figure 6.6 The triangular plot shows the distribution of I, Y, and X nodes for regional-, local- and outcrop-scale features. For outcrop-scale features I nodes dominate due to fractures terminating without intersections, often attributed to exposure or resolution limits. For local scale, I nodes decrease, and Y nodes increase to ~32%. For regional scale features, I nodes further decrease, Y nodes become most prevalent, and X nodes increase slightly, indicating improved traceability and interaction of fractures at larger scales.

The plot shows that for outcrop-scale features, I nodes are the most common. However, this prevalence of I nodes can be attributed to fractures where one tip

(either beginning or end) is not traceable due to limitations such as the edge of the exposure or termination in grass or other cover. Additionally, while using a 2 cm pixel resolution enabled to capture many detailed fractures and their relative connections, its resolution may not always be sufficient to detect connections between these fractures and the broader network. This could mean that the connections are present but fall below the resolution limit, resulting in an apparent increase in I nodes. A noteworthy consideration for outcrop-scale I nodes is whether the fracture truly terminates or is merely truncated by the outcrop boundary or resolution limits. Forstner and Laubach (2022) introduce the concept of contingent nodes (C-nodes) to describe locations where apparent fracture terminations may, in fact, connect via microfractures or narrow openings below the scale of observation. In such cases, an I node on the trace map could actually be a concealed Y node or an uninterrupted fracture if viewed at a higher resolution or through microscopic petrographic analysis. Consequently, some I nodes in our outcrop-scale dataset may be artifacts of boundary censoring rather than genuine geological terminations. Confirming whether these nodes represent true fracture endpoints or unresolved connections would require field checks, higher-resolution imaging, or more detailed petrographic work.

At local scale, I nodes decrease in frequency, and X nodes become less common while the relative percentage of Y nodes becomes more frequent compared to local scale. In fact, for regional-scale features, a percentage of Y nodes of ~32% was observed, whilst for outcrop-scale features a percentage of Y nodes of ~27% was calculated. For regional-scale features, I nodes are in a lower percentage compared to the previous cases, suggesting a higher level of fracture interaction and better traceability of fractures due to the larger scale. This implies that at this scale, it is easier to trace fractures as they are large enough that resolution is no longer a limiting factor. Y

nodes are more prevalent, indicating a complex and interconnected network. Although still the least common, X nodes are more present than at smaller scales. Overall, the networks across all scales are well interconnected.

6.5.6 Kinematic Evidence

The three dashed red lines in Figure 6.7, oriented ENE/WSW, outline two distinct zones in the center-west, and south-west areas of the island.

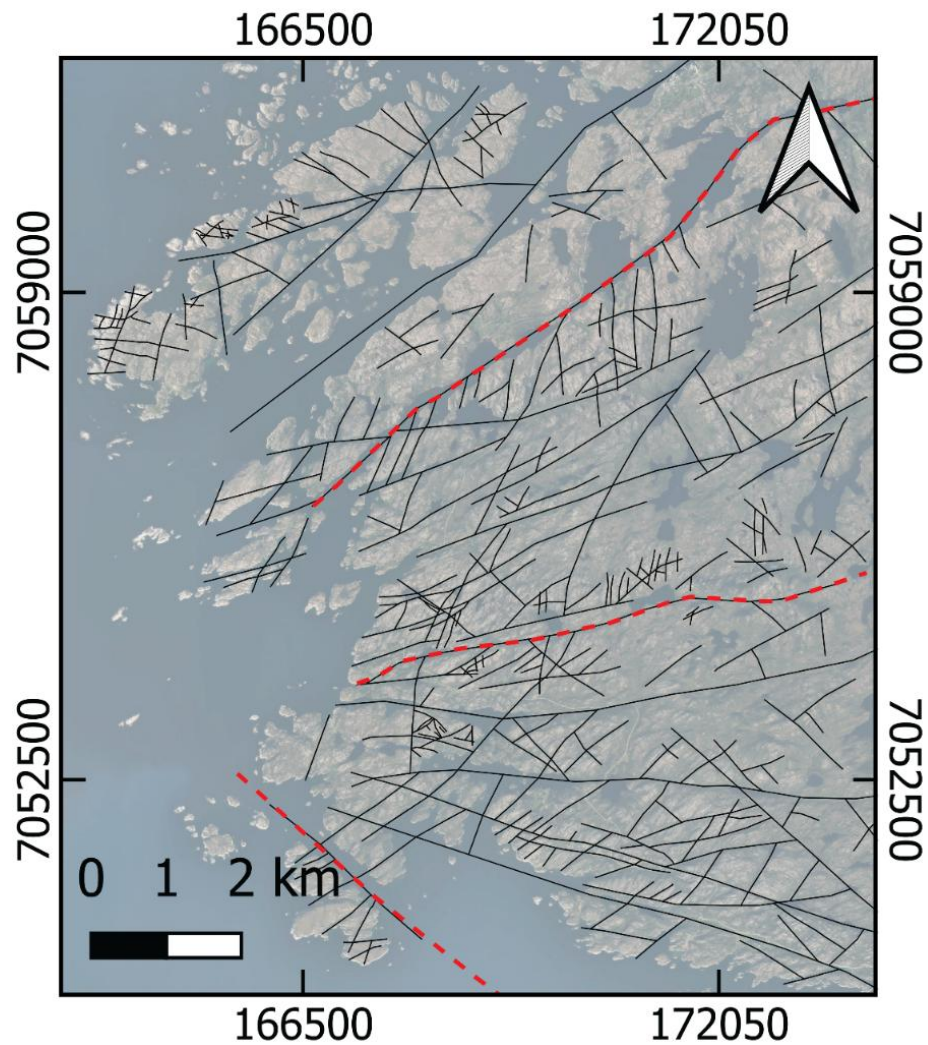


Figure 6.7 Shear zone that is hypothesized to affect the area between the three dashed red lines. The dashed red lines mark a distinct ENE/WSW-oriented shear zone where fractures are consistently NE/SW, indicating dextral movement. The gradual change in fracture

orientation from NE/SW to ESE/WWN toward the MTFC suggests stress field rotation and adaptation to sinistral movement. The ESE/WWN orientations near the MTFC show the effect of the fault zone's sinistral movement on the region.

Within these zones, fractures are consistently oriented NE/SW suggesting the existence of a shear zone that may have accommodated sinistral (left-lateral) movement. This fracture pattern is consistent with what is typically observed within shear zones, where fractures form at an angle to the principal shear direction. Within the central shear zone, long cross-regional fractures/faults are oriented NE (approximately 60 degrees), while smaller features are oriented NNE (approximately 20 degrees). In the southern shear zone, large cross-regional fractures are oriented ESE (approximately 100 degrees), and smaller features are oriented around 40 degrees.

Some evidence of movement is also visible for local-scale features (Figure 6.8A, B, C).

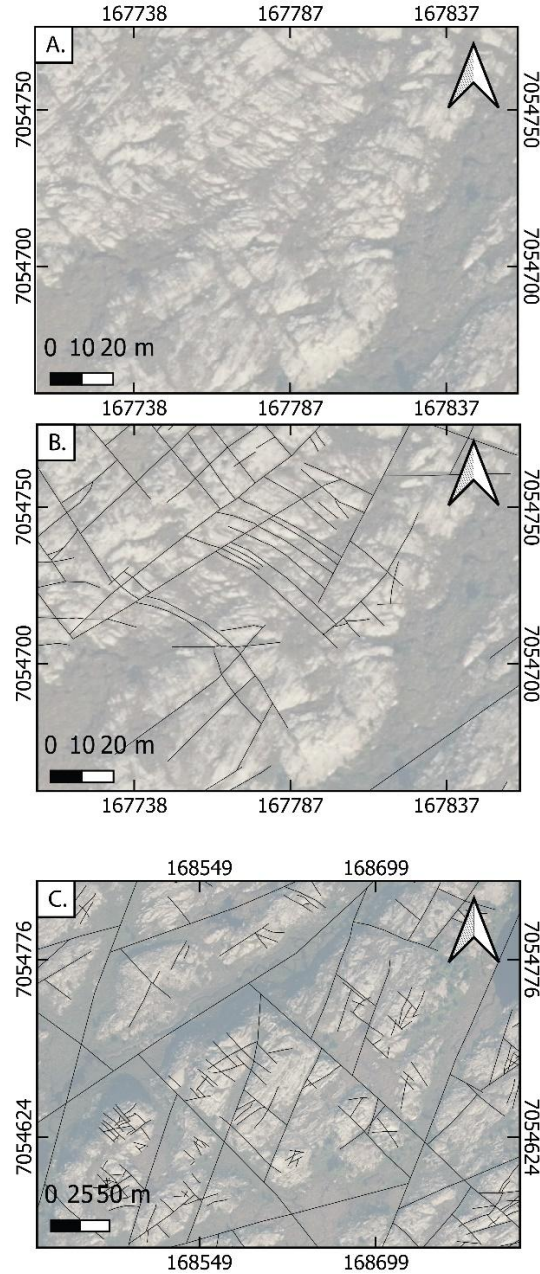


Figure 6.8 (A) Low-resolution aerial imagery of the area with no fractures traced. (B) The same area with interpreted fractures and inferred fault planes (based on visible offsets and alignments), suggesting eastward displacement consistent with local left-lateral shear movements in later stages of the MTF. (C) A view just east of areas A and B, where additional signs of fracture displacement are observed.

Figure 6.8A appears to show features that might be interpreted as displaced westward, as shown in Figure 6.8B. Similarly, Figure 6.8C suggests the possibility of sinistral offsets along ENE/WSW-oriented features, which could indicate a left-lateral shear regime consistent with early stages of the MTFC.

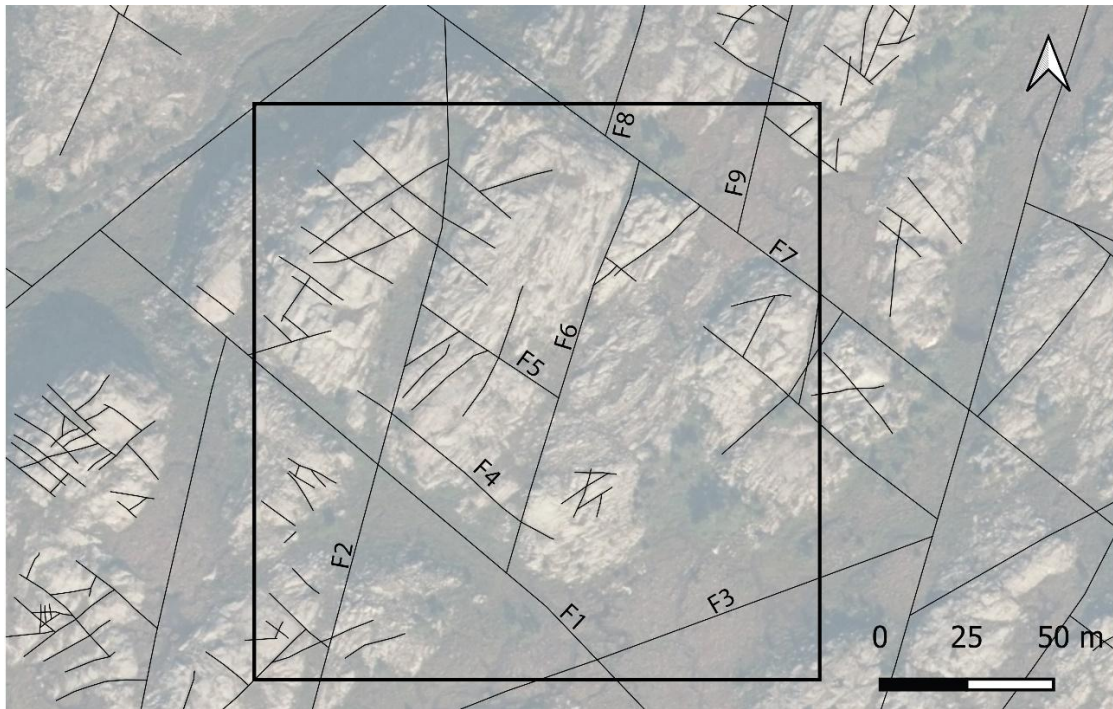


Figure 6.9 Fractures selected for relative-age analysis to determine the chronological sequence of fracture formation.

\\	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1		o	o	θ	θ	+	θ	θ	θ
F2	o		θ	o	+	θ	θ	θ	θ
F3	o	θ		θ	θ	θ	θ	θ	θ
F4	θ	o	θ		θ	o	θ	θ	θ
F5	θ	-	θ	θ		+	θ	θ	θ
F6	-	θ	θ	o	-		-	θ	θ
F7	θ	θ	θ	θ	θ	+		+	+
F8	θ	θ	θ	θ	θ	θ	-		o
F9	θ	θ	θ	θ	θ	θ	-	o	

Table 6.2 Younging table summarizing relative age relationships among fracture sets. "+" indicates a younger fracture, "-" an older one, "o" an unconfirmed relationship, and "Ø" no observed relationship.

However, these interpretations based solely on aerial imagery are inherently speculative. Aerial imagery, while useful for broad observations, does not provide the necessary detail to confirm the sense of displacement or the precise kinematic indicators. Accurate determination of such features requires corroborative field data, which are not available in this study. Consequently, while the imagery may hint at certain geological processes, any conclusions drawn must be regarded with caution.

6.5.7 Fracture Length Distribution

The cumulative distribution of fracture lengths in Figure 6.10 was initially modeled using a power-law fit, yielding an R-squared value of 0.995. While this high R-squared might suggest scale-invariant or fractal behavior, it is important to note that least-squares methods can be misleading for heavy-tailed data (Clauset et al., 2009). Consequently, we interpret the apparent power-law behavior cautiously, recognizing that alternative distributions could also offer plausible fits. In line with previous studies (e.g., Bonnet et al., 2001), the observed data appear broadly consistent with fractal-like trends.

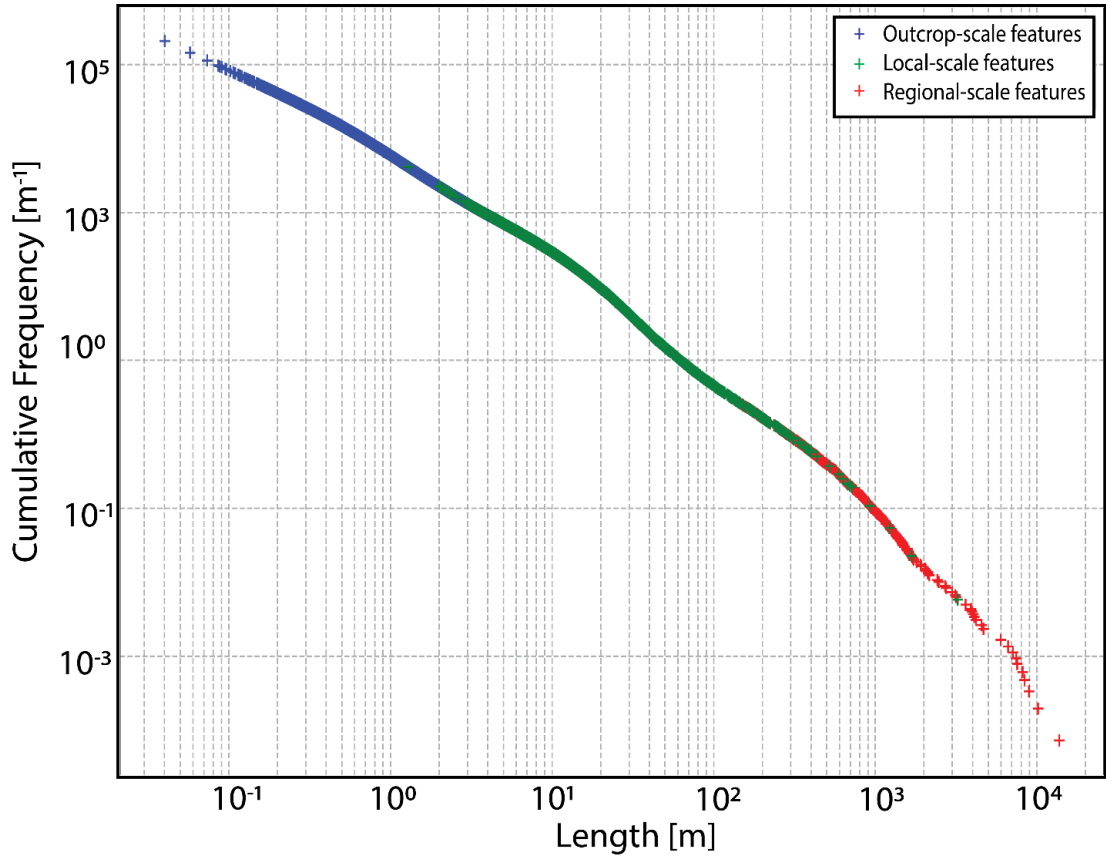


Figure 6.10 Cumulative distributions of length for the three resolutions of interest.

The cumulative distribution of fracture lengths in Figure 6.10 was modeled using a power-law fit, with an R-squared value of 0.995. This suggests that the fracture network shows consistent scale-invariant or fractal behavior across all scales of observation. The power-law exponent of -1.10 for the combined data set, along with the exponents of -1.72, -1.32, and -1.10 for regional, local, and outcrop-scale features respectively, implies that shorter fractures are more frequent, consistent with a self-similar distribution. Although our fracture length data appear to follow a power-law trend, we acknowledge that the least-squares approach can overestimate the robustness of such fits (Clauset et al., 2009). Consequently, while the data suggest self-similar fracturing processes, implying some degree of scale invariance, more rigorous analyses (e.g., maximum likelihood estimation) would be necessary to

definitively characterize the distribution. Nonetheless, these observations do indicate that the same tectonic influences may operate across multiple scales, consistent with the notion that structural inheritance can lead to fractal-like or heavy-tailed fracture patterns (Bonnet et al., 2001).

This brittleness is reflected in the abundance of small fractures observed at outcrop-scale, indicating rapid brittle failure rather than ductile flow. The consistent power-law exponents across different scales further suggest that the regional stress conditions lead to similar fracture scaling behaviors in these rock types.

6.6 Discussion and Conclusions

The findings of this study emphasize the complex nature of fracture networks in the granitic rocks of west Hitra Island, shaped by multiple stages of deformation. The consistent fracture orientations across scales align with the Møre-Trøndelag Fault Complex (MTFC), indicating a strong influence of structural inheritance. The power-law distribution of fracture lengths suggests self-similar processes operating across different scales, while variations in fracture connectivity and intensity reveal how scale impacts the visibility and interpretation of these features. While this multiscale approach provides valuable insights into the structural evolution of Hitra's granites, it is essential to acknowledge that each dataset has inherent resolution constraints. Higher-resolution imagery revealed more numerous and shorter fractures, which coarser regional datasets may underrepresent. Therefore, the quantitative differences noted (e.g., density, intensity) between scales likely reflect both genuine geological variation and the resolution limits of the images. Similar resolution effects have been documented in other studies (e.g., Bonnet et al., 2001), highlighting the need for careful interpretation of multi-scale fracture data.

6.6.1 Brittle Deformation Patterns

The fracture networks characterized at multiple scales allowed us to identify the main trends of the brittle structural features observed at the three different scales of interest. Moreover, movement indicators identified at the three scales helped put the deformational patterns observed into the broader geological context.

6.6.1.1 Tectonic Framework and Fracture Chronology of the Mid-Norwegian Margin

The NE-SW/ENE-WSW and NW-SE striking features observed in our study across various scales align closely with the orientation of the Møre-Trøndelag fault complex, especially near the Hitra-Snåsa fault in the channel to the south of Hitra Island. As indicated in Figure 6.2, NE-SW/ENE-WSW features are almost parallel to the MTFC fault zone. It was previously pointed out that the ENE-WSW trend not only cut through all detected trends but also offset them, which is particularly evident for fractures identified at outcrop scale (Figure 6.8A, B, and C). This points toward the area being subjected to significant stresses.

As for the NE-SW striking features, they can be observed across the entire mid-Norwegian passive margin (e.g., Gabrielsen et al. 1999; Peron-Pinvidic and Osmundsen 2020; Redfield and Osmundsen 2009; Wilson et al. 2006), and represent some of the oldest fractures within the region (Redfield and Osmundsen, 2009; Tartaglia et al., 2022). Kinematic points toward the fact that these fractures have been displaced by sinistral regimes (Figure 6.8C). This is consistent with findings by Seranne (1992), who reported that the area experienced sinistral stress regimes from the early Devonian to the early Carboniferous period (410 Ma – 360 Ma). However, it is important to acknowledge the inherent uncertainties in such interpretations. The identification of sinistral displacement is based on indirect evidence and assumptions derived from the fracture patterns observed in aerial imagery, which although might

be accurate, is not correctly backed up by definitive evidence. Without direct observations gathered from field data or corroborative data such as detailed petrographic analysis or in-situ stress measurements, these interpretations remain tentative. Additionally, the resolution and quality of the imagery can significantly influence the accuracy of the fracture characterization, potentially leading to misinterpretations of the underlying stress regimes. Therefore, while the suggested kinematic alignment with historical geological events appears plausible, further research incorporating a broader range of data sources is necessary to substantiate these findings and clarify the extent of these uncertainties. The orientation and kinematic observed along the NE-SW faults suggest they formed under a transtensional stress regime, which is characterized by simultaneous horizontal extension and shear. Although the transpressional stress regimes associated with the closure of the Iapetus Ocean preceded this phase (Seranne, 1992), a series of transtensional regimes throughout history has since overprinted much of the earlier geology, contributing to the complex tectonic fabric observed today.

With regards to the NW-SE features, those are the oldest features that pervaded the area of interest. Fractures with this trend formed in the very late stages of the Devonian, and have been attributed to a North-South shortening related to a short transpressional regime (Tartaglia et al., 2022). In other areas of the mid-Norwegian passive margin, evidence of compressional stress fields has been observed by previous authors in the Sunnfjord region and some areas in Hitra and Frøya, and have been associated with N-S shortening related to a contractional/transpressional event in the Late Devonian–early Carboniferous, referred to as the “Solundian phase” (Braathen, 1999; Osmundsen and Andersen, 2001).

6.6.1.2 Effect of Structural Inheritance and Stress Regimes on Fracture Development

At outcrop scale, the observed increase in isolated nodes could have multiple explanations. One possibility is that the distribution of stresses and the mode of failure play a significant role. Variations in stress distribution can cause differences in how fractures propagate, with some fractures terminating early and forming isolated nodes due to localized stress concentrations or changes in stress regime. Additionally, localized lithological variability or pre-existing microstructures like small faults could influence the rock's ability to propagate fractures fully. These features may lead to increased fracture initiation without significant propagation if the local stress conditions favor tensile failure over shear failure, or vice versa (Zhang et al. 2022). However, another critical factor to consider is the effect of resolution on our interpretation. For regional- and local-scale features there is a non-negligible risk of over-interpreting the connectivity of fracture nodes. The characterization of fracture intersections can be subjective, particularly when it is near or below the resolution limit of the imagery used. This issue is further compounded in cases where large features are obscured by vegetation or other cover, which can hide actual connections, leading to the false identification of isolated nodes. Such scenarios demonstrate that even with high-resolution data, physical obstructions can skew our perception of fracture connectivity. This needs a cautious approach to interpreting apparent discontinuities in fracture networks and underscores the importance of considering environmental and technical limitations alongside geological data when analyzing fracture patterns across different scales.

Our findings indicate that the fracture patterns observed are significantly influenced by structural inheritance (Samsu et al., 2020), where pre-existing geological features within the Smøla-Hitra Batholith have directed the formation of new fractures. These structures, formed during earlier tectonic events such as the Caledonian orogeny

(approximately 490 to 390 million years ago), create zones of weakness that dictate the orientation and propagation paths of new fractures under current stress conditions. The Møre-Trøndelag Fault Complex (MTFC), which initiated during the Early Devonian period around 409 million years ago, overlaps with the latter part of the Caledonian orogeny, further influencing fracture development. This interplay between inherited structures and present-day tectonic forces can be seen in the gradual shift in fracture orientations from NE/SW to ENE/WSW to EW and finally to ESE/WNW as we move southwards, which underscores the continuing influence of older, reactivated fault systems. By mapping these fracture orientations across different scales and integrating them with the known tectonic history, we gain a comprehensive view of how past geological processes shape present-day rock deformation patterns. The concept of structural inheritance is thus crucial for understanding the full complexity of fracture development in granitic rocks, highlighting the need to consider both ancient and recent geological events in geological analyses and models.

Furthermore, the effects of exposure limitations (Sanderson and Nixon 2018), such as edges of the study area obscured by vegetation, may also contribute to the observed increase in isolated nodes. If fracture terminations occur near the boundary of the study area or beyond the imagery resolution, it can result in an overrepresentation of isolated nodes. The consistent trends identified in power-law plots across scales in our observations (Figure 6.10) indicate self-similarity across scales, regardless of the scale at which the observations were made. This principle, also central to the findings of Lavoine et al. (2023), suggests that consistent tectonic stresses, such as those from regional compression, extension, and shear forces, govern the fracturing process across different scales, leading to self-similar fracturing patterns.

Interpreting the topology plot (Figure 6.6) alongside the rose (Figure 6.5) and power-law plots (Figure 6.10) offers a comprehensive understanding of the fracturing processes and their implications in the region. The predominance of Y nodes for regional-scale features suggests that fractures were frequently terminating upon meeting other fractures rather than crossing or extending past them. This can be a direct result of the variation in fracture orientation. In networks with multiple fracture orientations, especially those that are perpendicular to each other, the likelihood of abutting intersections (Y nodes) increases. This is because fractures with different orientations are more likely to meet and terminate at each other, forming Y nodes (e.g., Peacock, Sanderson, and Magán 2023). In contrast, in networks with fractures primarily oriented in a single direction, intersections are less frequent, and fractures are more likely to continue through, potentially forming X nodes.

The formation of Y nodes, as opposed to through-going X nodes, could also be influenced by stress release around propagating fractures. When fractures propagate, the differential stress fields created can cause areas of rock to experience tensile or shear failure. This stress release can influence whether fractures terminate at existing structures (forming Y nodes) or intersect and cross through them (forming X nodes). Thus, the topology of the fracture network is not only a result of the orientation but also a function of the stress conditions present during fracture propagation, reflecting the dynamic interplay between tectonic forces and the mechanical properties of the rock (e.g., Branellec et al. 2015; Lei and Wang 2016).

The orientation of regional-scale features correlates with the predominant stress orientation σ_1 (NW-SE), which reflects the regional stress regimes linked to the tectonic activities associated with the Møre-Trøndelag Fault Complex, such as sinistral ductile shearing during the Devonian, sinistral transtensional reactivation during the Permo-Carboniferous, and normal to oblique slip faulting during the Jurassic to early

Cretaceous associated with the opening of the North Atlantic (Braathen, 1999; Redfield and Osmundsen, 2009). The Smøla-Hitra Batholith, which is approximately 450 to 528 MY old (Mid Ordovician to Early Silurian age), experienced different stages of tectonic activity during the Devonian period, around 400 million years ago, associated with the MTFC. This tectonic history suggests that the fracture patterns observed in the granitic rocks of Hitra Island are a result of the stress fields and mechanical interactions imposed by the MTFC during its active periods. Understanding these fracture patterns and their scaling relationships is crucial for inferring the stress history and mechanical properties of the granitic rocks.

6.6.2 Regional Considerations

The fracturing of granite, the key focus of this study, ties into the geological context shaped by the Møre-Trøndelag Fault Complex (MTFC) and its associated stress regimes. The regional tectonic processes, including periods of compression, transpression, and extension, have influenced the deformation patterns observed in the granitic rocks of Hitra.

Granites, due to their composition, crystalline structure, and the fact that they are usually massive bodies (Collins, 1994), react distinctly and usually in a brittle manner to stress (Benjamin Ntieche et al., 2020). This brittle behavior was observed in the fracture networks characterized across all scales subject of this investigation in the west of Hitra Island, where fractures reflect the orientation of the principal stresses in the region. Regional-scale features predominantly display ENE-WNW orientations, shifting to EW and WNW-ESE toward the south (Figure 6.5A, B), near the Møre-Trøndelag Fault Complex (MTFC), which indicates evolving stress conditions across the geological history.

Fracture mapping and relative age relationships of fractures reveal a complex, multistage brittle evolution of the Hitrean granite. Local-scale features are oriented with the ENE-WSW trend observed in the MTFC, suggesting a dextral shear zone influence. Outcrop-scale features show similar fracture networks, with primary fractures oriented ENE-WSW and NW-SE, indicating self-similar fracturing processes across scales.

The analysis of fracture patterns across scales revealed very complex, interacting fracture networks with different orientations and connectivity that are representative of the multiphase brittle evolution hypothesized for the mid-Norwegian passive margin (Gabrielsen et al., 1999; Seranne, 1992; Tartaglia et al., 2022; Wilson et al., 2006). At regional scale, the earliest fractures formed in NW-SE/SSE orientations, establishing the primary set of the region. They were dated back to the Silurian and Ordovician periods, and formed under compressional stress during the Caledonian orogeny (Tartaglia et al., 2022). During the Silurian and Ordovician periods (approx. 485-443 Ma and 443-419 Ma), the region was under compressional stress with a NW-SE σ_1 (Tartaglia et al. 2022), which corresponded to the Caledonian orogeny period. This resulted in NW-SE trending fractures. It was interpreted that features oriented ENE-WSW are the youngest set, and formed during the Triassic (about 251 to 201 Ma) (Tartaglia et al., 2022). During this period, the MTFC was characterized by an extensional regime with σ_1 oriented ENE-WSW (Tartaglia et al. 2022). Within shear zones that were identified, long cross-regional fractures/faults are oriented NE (approximately 60 degrees), while smaller features are oriented NNE (approximately 20 degrees) in the central shear zone. In the southern part, large cross-regional fractures are oriented ESE (approximately 100 degrees), and smaller features are oriented around 40 degrees. These fractures, oriented approximately between 25 to

45 degrees to σ_1 , suggest the existence of a shear zone (e.g., Cosgrove, 2007) that may have accommodated dextral (right-lateral) movement.

Moreover, results point toward the fact that the granites of Hitra have undergone multiple deformation phases. The brittle deformation observed, characterized by ENE-WSW and NW-SE fractures, aligns with the orientation of stresses of the Møre-Trøndelag Fault Complex (MTFC).

The study leveraged multiscale investigations to map the fracture networks pervading Hitra Island across the scales of interest. While multiscale imagery can provide comprehensive geological investigations, validation of such interpretations fundamentally relies on corroborative field-based analyses. Despite advancements in remote sensing technologies, fieldwork remains indispensable for grounding interpretations in empirical geological data. This stresses that, although multiscale remote sensing is a powerful tool for geological characterization over extensive areas, it cannot fully replace the level of detail and accuracy gained from direct geological field studies. Therefore, integrating multiscale remote sensing with rigorous fieldwork is essential to ensure the reliability and accuracy of geological analyses.

6.7 Conclusions

Using aerial and drone imagery, fracture patterns in the granites of west Hitra Island were analyzed at regional, local, and outcrop scales. This analysis allowed us to partially reconstruct its deformation history.

The fracture networks observed across all scales showed a variety of orientations and extensive brittle structures. It was found that NE-SW/ENE-WSW and NW-SE striking features align with the Møre-Trøndelag Fault Complex (MTFC). This was consistent with the major stress fields experienced by the area during geological history and is closely aligned with the MTFC's kinematics.

Relative-age investigations revealed that NW-SE features date back to the Silurian and Ordovician periods (485-419 Ma) under compressional stress during the Caledonian orogeny, while the ENE-WSW features formed during the Triassic (251 to 201 Ma) under an extensional regime.

Power-law-like fracture length distributions across multiple scales can indicate self-similar or fractal fracturing processes, suggesting that the same fundamental mechanical or tectonic drivers operate over a broad range of scales (Bonnet et al., 2001). Essentially, if fracture lengths follow an approximately scale-invariant pattern, it implies that the fracturing mechanism, such as repeated stress accumulation and release, remains consistent whether fractures are centimeters or kilometers in size. This consistency aligns with the concept of structural inheritance, whereby pre-existing weaknesses in the rock (formed during earlier tectonic events) influence new fracture growth. Thus, the self-similar fracturing observed here may reflect not only uniform tectonic stresses across scales, but also the persistent reactivation or propagation along inherited structures, creating fracture patterns that display fractal characteristics.

One of the most important takeaway points from this study is the strengths of employing multiscale remote sensing techniques to explore geological structures. By analyzing data across three different scales, we improved the robustness of our interpretations and gained a more comprehensive understanding of the fracture dynamics over a broad spatial context. Each scale contributed to our understanding of geology for the area of west Hitra: larger scales provided a comprehensive overview of the large-scale geological setting, while finer scales offered detailed insights into local variations and fine features that might otherwise be overlooked. However, while remote sensing can be valuable for identifying potential kinematic indicators such as offsets and alignments that suggest geological movements, it has

inherent limitations in confirming the direction and nature of such movements. Accurate kinematic analysis necessitates corroborative field data to validate and interpret the signs observed through remote sensing. Remote sensing can suggest hypotheses about geological processes, but without ground truthing, these remain hypotheses. Field investigations remain a crucial part of geological investigations, necessary for verifying initial remote-based observations and providing the definitive interpretations needed to understand the tectonic forces shaping the landscape.

Chapter 7 Discussion and Conclusions

This chapter summarizes the findings from the previous research chapters, and discusses implications, uncertainties, and points toward the direction for future research.

7.1 Summary of Findings

This research explored the reliability, reproducibility, and limitations of both automated and manual fracture extraction methods using high-resolution imagery. Through three focused studies, the effects of factors such as image resolution, contrast, surface width of fractures, and exposure continuity on the accurate characterization of geological fracture networks were investigated. The key findings from each chapter are summarized below:

- Chapter 4: Investigated the reproducibility and reliability of automated approaches using decimeter-resolution data. The chapter provided the first quantitative measure of reproducibility and reliability for these approaches. It quantified reproducibility by comparing length distributions of different results from various ensembles and determined reliability by comparing length distributions between the two different automated approaches used throughout Chapter 4.
- Chapter 5: Investigated the impact of image resolution on fracture network characterization across multiple scales. It quantified not-resolved information by comparing fracture properties—such as length, intensity, and connectivity—across datasets with different resolutions. It also established that reliable fracture tracing requires a minimum surface width of 2 pixels and

a length of 4 pixels. The findings demonstrated that resolution significantly impacts network topology, with higher resolutions capturing more complex connections. It highlighted the limitations of low-resolution data in detecting fine details and the necessity of multiscale approaches to ensure comprehensive and accurate geological interpretations. Finally, it concluded that integrating multiple resolutions is crucial for robust fracture network analysis.

- Chapter 6: Investigated the granitic fracture patterns in west Hitra Island, Norway, spanning from 0.07 meters to 14 kilometers in length at regional, local, and outcrop scales using aerial and drone imagery. Mapping revealed a variety of fracture orientations and extensive brittle structures, reflecting the island's complex tectonic history near the Møre-Trøndelag Fault Complex (MTFC). Although some fractures align with known regional tectonic trends, the present evidence does not conclusively demonstrate that pre-existing structural features have predominantly guided the development of new fractures. The observed patterns are suggestive of potential structural inheritance; however, additional field studies and high-resolution analyses are required to substantiate this hypothesis. Likewise, although the length distributions suggested possible fractal-like behavior, further analysis is required to determine whether these observations indicate truly self-similar processes governed by consistent tectonic stresses. Lastly, this study emphasized that while imagery can reveal potential kinematic indicators in fractures, it cannot reliably characterize those kinematics without corroborative field data, thereby highlighting the limitations of remote sensing for interpreting geological movements.

Although the three chapters had different focuses, the common thread among them was how contrast, resolution, surface width of fractures, and exposure continuity play a key part in the robust and reliable characterization of a site of interest. First and foremost, the reliability and reproducibility of automated approaches are strongly influenced by the contrast levels in an image, along with the level of continuity. Unlike automated approaches that primarily identify fractures by tracing linear pixel alignments based on intensity values, human experts employ their training, experience, and geological knowledge to distinguish and interpret fractures, integrating a deeper understanding of the contextual geological setting. The limitations of both automated and manual fracture tracing methods highlight the need for a more integrated approach in geological analyses. Contrast-based automated methods struggle with high-contrast features and often misinterpret vegetated areas as fractures due to their reliance on pixel intensity, leading to tracing many non-geological features (Chapter 4). Manual methods, while more accurate, are time-consuming and subject to human bias, particularly when dealing with features that are near the resolution limit or obscured by vegetation (Chapters 5 and 6). Observations indicate that features need to be at least two pixels wide to be confidently traced, which affects both automated and manual approaches. This requirement emphasizes the importance of high-resolution imagery for accurate fracture characterization. However, higher resolution also introduces challenges, such as increased data volume and the potential for overinterpreting minor features. Chapter 6 presented a multiscale geological characterization, demonstrating that integrating various scales of observation can mitigate some of the limitations. The successful characterization of deformational patterns at regional, local, and outcrop

scales suggests that combining data from different resolutions enhances the reliability and reproducibility of geological interpretations.

7.2 Considerations in Fracture Interpretations

Multiscale investigations offer substantial advantages for geological analyses by allowing a more comprehensive characterization of fracture networks across different scales. This approach combines detailed local observations from high-resolution imagery, with broader regional contexts afforded by lower resolutions imagery, covering much larger areas. Multiscale investigations allow for the identification of both fine-scale fracture details that are below detection limit in low-resolution datasets, and larger structural formations that are censored in localized high-resolution datasets. This facilitates more accurate and reliable geological interpretations. The ability to study geological features at multiple scales is particularly beneficial in capturing complex interactions within fracture networks and ensuring that both macroscopic trends and mesoscopic details contribute to the overall understanding of the study area. Represented in Table 7.1, a recommended workflow for automated contrast-based fracture extraction is outlined to guide researchers and practitioners through key steps, going from initial dataset assessment and image pre-processing to parameter tuning, post-processing, and final validation. This workflow distills the findings from Chapters 4 and 5 into a structured approach designed to enhance reliability and reproducibility in fracture network interpretations.

Step	Action / Technique	Rationale	Key Considerations
1. Assess Dataset Properties	- Identify resolution, pixel size, exposure continuity, vegetation cover - Convert imagery to grayscale if required	Ensures you understand image constraints (e.g., rock vs. vegetation contrast) and whether the dataset is suitable	- Check if fracture width is at least 2 pixels - High vegetation or discontinuous rock mass may require extra pre-processing (e.g., cropping) - If using grayscale, confirm that contrast is sufficient to distinguish fractures
2. Preprocess Image	- Crop or mask out dense vegetation or water bodies if possible - Apply filters (e.g., Gaussian blur) to reduce random noise	Improves contrast-based extraction by removing irrelevant features and reducing spurious edges	- Decide carefully which areas to remove vs. keep - Over-aggressive masking risks losing real fractures- Keep a copy of the original data for reference
3. Select Initial Parameters	- Set contrast thresholds (min/max intensity) - Define morphological filters (e.g., skeletonization options) - Choose filter sizes or thresholds	Provides a starting point for identifying edges or lineaments based on pixel intensity	- Ensure parameter values reflect your data's range of brightness - Start with broad thresholds to avoid losing features prematurely

			- Document each parameter setting for reproducibility
4. Iterative Tuning	- Run extraction once, examine results - Adjust contrast thresholds or filters incrementally - Repeat until most true fractures appear and noise is minimized	Fine-tunes extraction to your specific dataset, balancing false positives vs. missed fractures	- Track each parameter set used- Evaluate how changes in thresholds affect trace continuity and noise - Look at different parts of the image (vegetation, shadows, bright areas) to confirm consistency
5. Postprocessing & QC	- Remove obvious non-geological lineaments (e.g., roads, shadows, vegetation edges) - Merge or split fractures where the software over/under-segmented	Cleans up artifacts introduced by the automated process, improving geological consistency	- Use a structured approach (e.g., criteria for removing or merging lines) to avoid reintroducing bias - Retain a log of manual edits for reproducibility
6. Validate Against Subset	- Compare extracted features to partial manual interpretation or field data in a known subset area - Check length, orientation, connectivity	Verifies that the automated approach reflects reality reasonably well	- If large discrepancies exist, revisit thresholds or QC - Consider geologist's expert input for ambiguous features
7. Final Extraction	- Repeat automated extraction with chosen	Ensures consistency across entire dataset,	- Maintain consistent parameters for entire

	parameters on the full dataset- Export fracture lines to GIS for further analysis	uses best-tuned parameters	area- Store outputs with metadata (parameter settings, date, software version)
8. Network Analysis	- Use tools like NetworkGT or other GIS plugins to calculate length, density, topology- Interpret results with caution, noting limitations	Provides quantitative fracture attributes for geological interpretation	- Remember that results depend on earlier parameter choices - Acknowledge resolution, continuity, or lighting artifacts that may skew interpretations

Table 7.1 Proposed workflow for automated contrast-based fracture extraction, summarizing key steps and considerations to enhance reliability and reproducibility of fracture network interpretations.

7.2.1 Reliability and Reproducibility of Automated and Manual Approaches

One of the limitations observed across the three chapters was the inherent challenge of maximizing reproducibility and reliability. As discussed in Chapter 2, manual approaches are starting to be suboptimal in terms of how quickly information can be extracted from imagery (Prabhakaran et al., 2019), and one of the reasons why automated approaches are emerging in the literature is their time efficiency. However, there is an entire piece that is missing from current literature, which is the reproducibility and reliability of the results they produce. Investigations into contrast-based automated fracture detection from decimeter-resolution aerial imagery has successfully proven that, in their current state, automated approaches definitely produce more reproducible results than manual methods. With automated

approaches the same results can be replicated any number of times, provided that the input image remains unchanged. However, these results are not necessarily reliable, as they often fail to accurately reflect the true geological features. Another key finding is that the user must reflect upon the properties of the image such as levels of contrast and continuity, and even after this, further adjustments to extraction parameters are essential. This process requires multiple iterations to ensure that the automated methods yield satisfactory results. In cases of discontinuous exposures, especially when rock mass continuity is below 50%, additional steps are necessary to prepare the dataset for automated extraction. If using the image as is for fracture extraction, subsequent manual removal of features mistakenly traced within vegetated areas becomes essential. This approach requires extra care and rigorously defined criteria for fracture removal, as it could reintroduce bias. Alternatively, image pre-processing can be employed to crop out vegetated areas, thereby focusing the analysis solely on the rock mass. Automated extraction methods still produce results that are more reproducible compared to manual approaches, where results are hardly reproducible even if the dataset is re-interpreted by the same expert (Andrews et al., 2019; Mabee et al., 1994). However, the investigations into contrast-based automated fracture detection revealed their general unreliability. Additionally, depending on the degree of exposure continuity, human bias might be reintroduced into the equation as manual interpretations rely heavily on the geologist's judgment and experience. This is the reason why there is a need to standardize interpretation guidelines. However, automated methods can still misinterpret discontinuous features, leading to inaccurate or skewed results. Subsequent manual removal of such features can introduce bias, as can clipping out vegetated areas between exposures.

The reproducibility of automated fracture extraction methods was demonstrated in Chapter 4, where fractures were automatically extracted from different geological settings. Despite the different lithologies across the test cases, quantitative network analyses confirmed the consistency of trends for topology, length, intensity, and density across the different test cases.

The challenge of making analyses more reproducible was addressed in all chapters. In Chapters 5 and 6, fracture characterization was carried out solely manually, hence the focus was on clearly defining criteria to make manual analyses easier for others to replicate. However, as also pointed out by Andrews et al. 2019, regardless of how consistently these criteria will be applied throughout the manual fracture tracing process, it will be almost impossible to reproduce results exactly. In general, despite their time efficiency and higher reproducibility, automated methods can struggle with misinterpretations, whereas manual interpretations, although more reliable in challenging settings, are time-consuming and prone to user bias. To visualize these trade-offs, Figure 7.1 presents a spider plot comparing key metrics – time, reliability, reproducibility, and bias – across the approaches discussed.

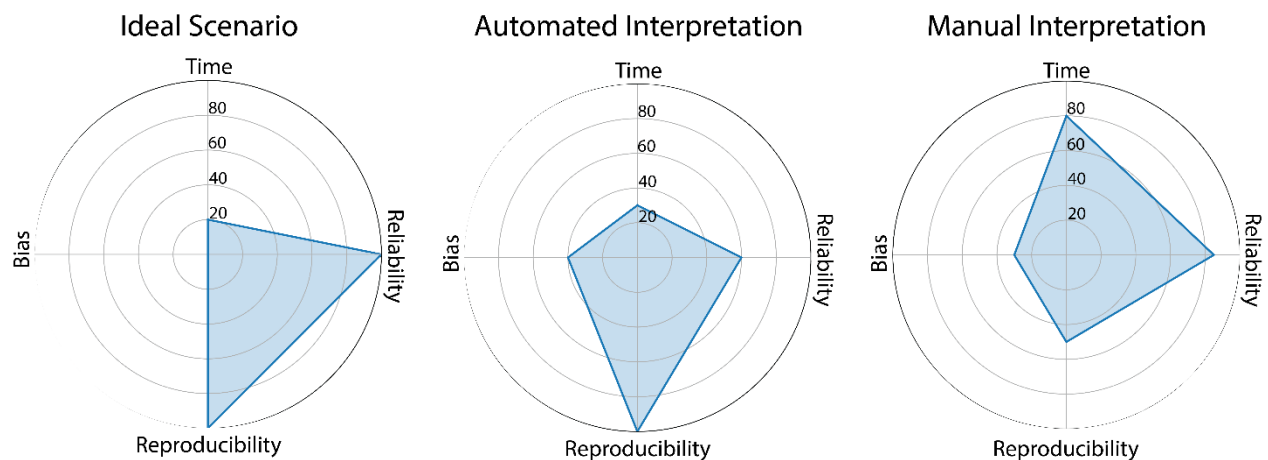


Figure 7.1 Qualitative radar (spider) plot comparing manual fracture extraction vs. two automated approaches. Each axis ranges from 0% (lowest) to 100% (highest). The plot

highlights how automated approaches rank highly in reproducibility but require careful parameter tuning to achieve high reliability. Manual approaches score lower in reproducibility yet can be quite reliable, especially when guided by expert insight.

7.2.2 Impact of Exposure Extent and Continuity on Fracture Interpretations

Another limitation encountered throughout our analyses across the chapters was exposure continuity. In Chapter 4, it was demonstrated that exposure continuity is the property that most significantly contributes to non-geological interpretations in automated approaches. One of the reasons why automated approaches are also emerging as alternatives to manual methods is the fact that supposedly they are proposed to curb, or outright remove bias introduced by manual approaches (Lv et al., 2022), where features could be inadvertently omitted or deliberately ignored (Bond et al., 2007; Scheiber et al., 2015). Understanding the dataset properties, parameters that must be used for extracting features, and eventual clipping of vegetated areas out of the picture are all expert-based, very subjective, and time-consuming tasks. It was observed that outcrops with a lower rock mass continuity had the highest proportion of non-robust features. Non-deep-learning automated approaches, in their current state, trace linear patterns of pixels that fall within a certain pixel intensity (or contrast). Using grayscale imagery, the contrast of vegetated areas is very similar to the contrast of fractures, which would lead to erroneous interpretations. Analyses outlined in Chapter 4 demonstrated that the reliability of results was generally quite low, with the worst cases for discontinuous exposures. This was evident from the discrepancies observed in the length distributions when features were extracted from the same dataset using the two automated extraction methods used for this thesis. By varying parameters such as contrast thresholds, it was found that the number and characteristics of the extracted features changed

significantly. This sensitivity to parameter selection highlights a critical limitation of current non-deep-learning automated approaches: they lack robustness against parameter variability, which can lead to inconsistent and unreliable results. Therefore, without standardized guidelines or adaptive algorithms that can optimize parameters in response to dataset characteristics, these automated methods may introduce as much bias as they aim to eliminate, as it will be up to the expert to decide what feature was traced reliably and what feature is non-geological. It was also found that current contrast-based approaches are limited by the fact that they are tracing solely pixel intensity and not linearity. This resulted in many features being incorrectly segmented if pixel intensities deviated slightly from the set thresholds. Additionally, the unreliability of current contrast-based approaches is also proven by the significant number of features that were traced by the two approaches taken into consideration, which varied by almost 6.5 times using the exact same starting image. Moreover, the questionable reliability of the results led to avoiding the use of automated approaches in the subsequent two research chapters. Instead, the focus was on establishing clear guidelines for manually tracing features. This approach aimed to enhance the reproducibility of manual methods, aiming to achieve levels of reproducibility closer to those of automated fracture extraction methods.

Exposure continuity poses a problem for manual approaches too, although for slightly different reasons. While contrast-based automated approaches trace features in vegetation because they are not able to distinguish between vegetation and rock mass, manual approaches rely on the expert's judgment, where the expert would not trace features in vegetation unless there is clear geological evidence or continuity that suggests the presence of underlying structural features. In Chapters 5 and 6, multiple datasets of Hitra with different resolutions were used. Generally, the exposure from Hitra tends to be relatively discontinuous, with frequent interruptions

in the rock mass due to vegetation. For manual approaches, vegetation is problematic because it interrupts fractures, potentially introducing bias into interpretations (Figure 7.2).

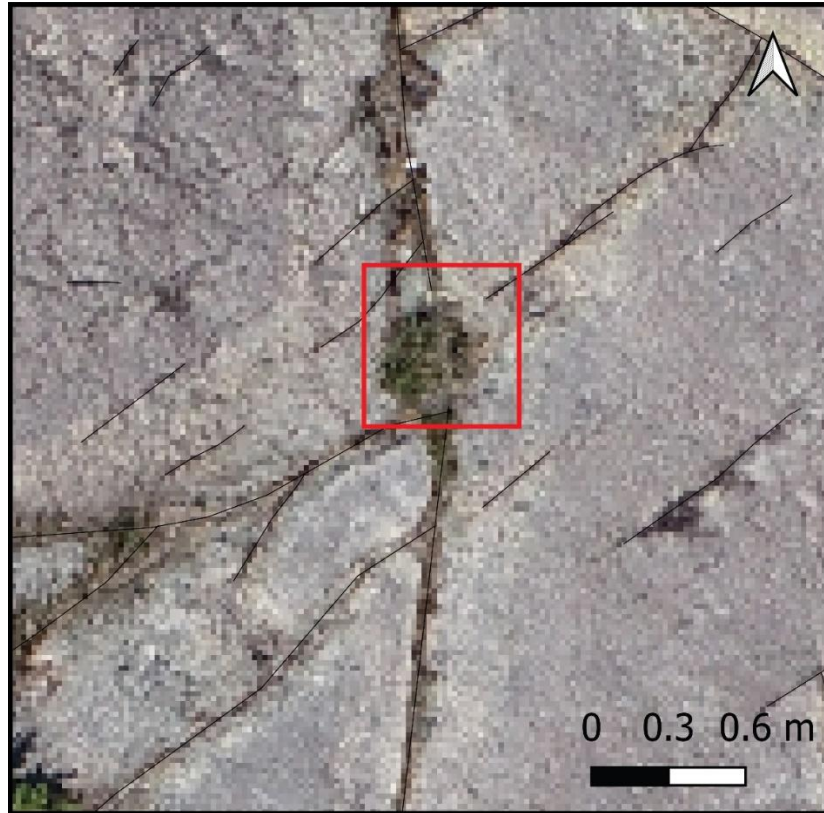


Figure 7.2 Example of feature being interrupted by a vegetated patch, which brings uncertainty and bias to the interpretation

To mitigate this bias, specific guidelines were developed in chapters 5 and 6 to assist users in fracture tracing when encountering uncertainties due to vegetation interruptions. These guidelines provide clear instructions on how to proceed in situations where fractures are interrupted by vegetation but can be reasonably inferred to continue, as well as how to handle significant interruptions caused by vegetation. These tables are designed to make the fracture tracing process more reproducible, accounting for the inherent variability in human geological interpretation (e.g., Andrews et al., 2019).

Exposure extent, as well as image extent, has an impact on the reliability and reproducibility of geological analyses. When the exposed rock mass is limited to a small area, especially when surrounded by dense vegetation, the challenges in analysis are considerable. Similarly, the extent of the image coverage can affect the comprehensiveness of the analysis, as insufficient image coverage may omit geological features from interpretations, leading to incomplete analyses. Small, isolated exposures often lack the context necessary for comprehensive interpretations, leading to an increased likelihood of non-geological or biased interpretations in both manual and automated approaches. In such cases, the limited extent of the exposure can make it difficult to distinguish between genuine geological features and artifacts caused by the surrounding vegetation. This can lead to non-geological interpretations, especially with automated approaches, further reducing the reliability of the results.

7.2.3 Impact of Resolution on Fracture Interpretations

Another key limitation that impacted all the analyses in each research chapter was surface width. From findings in Chapter 4, it was clear that the visual appearance of features, particularly the separation between the two edges in imagery, played a key role during the fracture tracing process. Perhaps the greatest limitation of all image-based approaches is determining the extent to which the dataset's resolution and quality allow for the extraction of useful and reliable geological data. Effectively, when an expert is tracing fractures, they are tracing pixels arranged in a linear manner. Across the three chapters, it was understood that the degree of reliability of the tracing process is strongly bound to three properties: surface width, length, and resolution. Three conditions related to each of these properties were formulated: 1) Surface Width: The surface width must be at least two pixels to ensure accurate and

reliable tracing of a feature; 2) Length: The length must be at least 4 pixels to make a reliable measurement because dots or lines only two pixels long do not necessarily represent geologically significant features. This is particularly relevant in automated fracture tracing, where such short segments below detection limit may introduce non-reliable components in the interpretation. They often represent minor irregularities in the rock mass rather than true geological features, which is what occurred extensively in this study. Therefore, a minimum length of 4 pixels ensures that the traced features are more likely to be reliable; 3) Resolution: The user must clearly define the scope of their investigations before starting any kind of remote-sensing investigation. It is essential for researchers to choose a dataset with a resolution that matches their specific investigative needs. For instance, if sub-centimeter details are crucial for understanding fracture topology, a dataset with only 20 cm resolution would be insufficient. All these conditions must be satisfied in order to have accurate, reliable, and meaningful geological feature extractions, and, if anything below that length is traced, then it will be considered strongly biased, inaccurate, and unreliable.

Chapter 5 was specifically meant to analyze the specifics of how resolution affects fracture characterization and to quantify the amount of information lost at different resolutions. In the chapter it was found that high-resolution imagery offered unparalleled detail, and revealed complex and detailed connections within fracture networks; however, high resolution did not have the extent necessary to capture the broader geological context. For instance, length measurements are impacted by a truncation effect where the full extent of fractures is not captured, resulting in skewed statistics. Similarly, topology might be overrepresented because the granular imagery complicates discerning connections when operating close to detection limit (Figure 7.3A, B, C), which could in turn impact reliability.

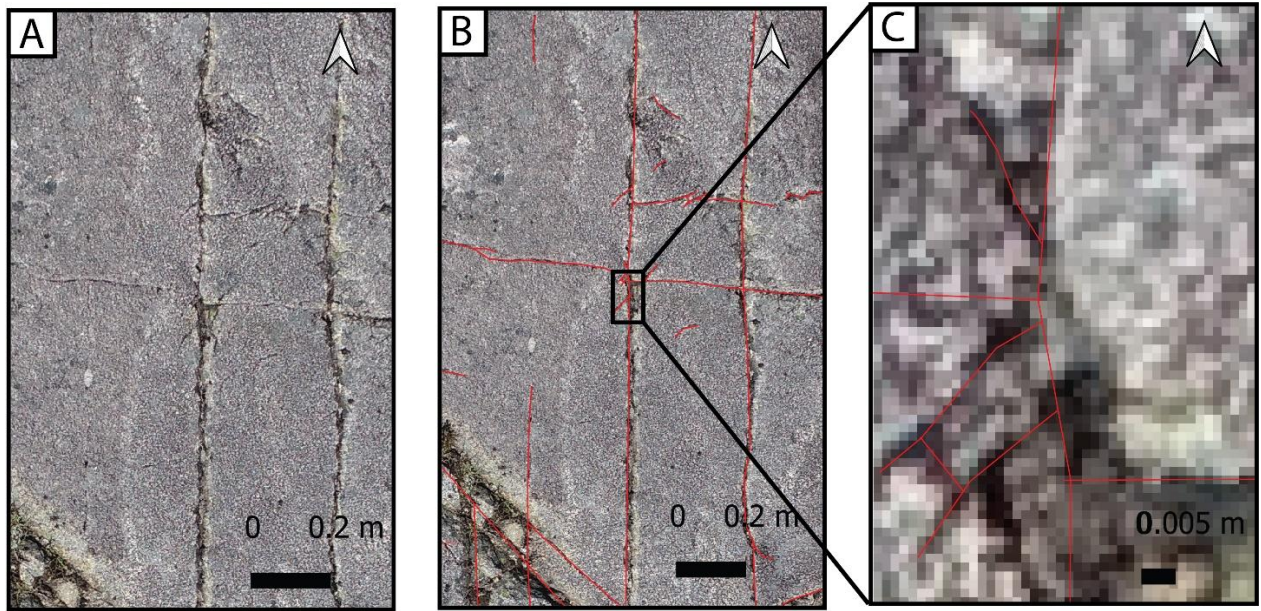


Figure 7.3 A. Fractures seen at high-resolution; B. Fractures traced manually; C. Granularity of high-resolution imagery posing problems for correct identification of fracture connections.

Medium-resolution imagery provides a balanced overview of the area of interest and is ideal for comprehensive geological analyses that need a good degree of fine-scale accuracy. In contrast, while low-resolution imagery is good for identifying broader geological trends, it often misses crucial details like topological connections or fine-scale fractures, which can compromise its reliability for localized studies. High-resolution data excels in capturing the finest details of fracture networks but can be hard to use when working close to detection limit. Having quantified the minimum standards for obtaining a reliable and accurate characterization of fracture networks, the final piece of this research focused on characterizing the geology of an area of roughly 40 km². The main objective of Chapter 6 was characterizing fracture networks across three scales using only imagery, for understanding deformation patterns in granitic rocks. It aimed to demonstrate the key role of multi-scale approaches for interpreting fault and fracture networks, emphasizing the importance of scale in

geological analysis. Although accurate geological characterization was achieved using low-, medium- and high-resolution imagery, it needed to be supplemented by field data, specifically measurements of fracture length and surface width. While imagery can provide a whole range of indispensable information about fault and fracture networks like length, orientation, topology, and intensity, field data still remain crucial for verifying and substantiating image-based interpretations. This study, similarly to others (e.g., Gabrielsen and Olesen, 2024; Tartaglia et al., 2022), used imagery in conjunction with field data (e.g., Bertrand et al., 2015). It is important to note that low-resolution imagery alone is insufficient for comprehensive site characterization. Such imagery must be integrated with field data, including geological observations at exposures or higher-resolution imagery, to address the deficiencies of low-resolution data. This integrative approach ensures a more robust and reliable geological interpretation. The reliability of geological analyses is fundamentally tied to the resolution of the imagery used because resolution dictates whether key features – like fracture width and continuity – are adequately captured. In Chapter 4, using decimeter-resolution imagery, we observed how automated methods frequently misinterpreted vegetation and shadows as fractures, significantly impacting the reliability of extracted networks. These errors were amplified when rock mass continuity was low, revealing that suboptimal resolution can obscure or distort fracture attributes. Chapter 5 then systematically tested multiple resolutions (from 0.2 cm/px to 21 cm/px) and showed that higher resolution datasets capture a greater number of shorter fractures, leading to more connected networks and fewer ambiguities in length measurements. Specifically, we found that fractures needed to be at least two pixels wide (surface width) and four pixels long for consistent interpretations. Lower-resolution datasets often merged or omitted these finer-scale fractures, reducing the reliability of the resulting fracture network metrics such as

intensity, connectivity, and topology. Finally, in Chapter 6, a multiscale analysis (0.07 m to 14 km features) demonstrated how coarse imagery could capture the broad tectonic framework but missed crucial short fractures and intersections critical for understanding local-scale deformation. Meanwhile, high-resolution (2 cm/px) drone imagery provided greater certainty in identifying smaller fractures – improving the overall reliability of the interpreted networks.

Taken together, these findings show that as resolution improves, users can delineate a larger spectrum of fractures with higher confidence, thereby enhancing the reliability and reproducibility of both automated and manual interpretations. Conversely, coarse or marginal resolution can mask smaller fractures, merge closely spaced features, and lead to divergent, less reliable network characterizations.

7.3 Implications of Findings

The findings from this thesis offer valuable insights for researchers involved in interpreting fractures and geology from imagery. As discussed in Chapter 2, while interpreting geological features from imagery is now a widespread practice, the lack of standardized criteria for ensuring reliability and reproducibility is a significant gap in the field. This thesis addresses that gap by highlighting the critical need for well-defined guidelines, particularly when using automated or semi-automated fracture extraction methods.

In Chapter 4, it was demonstrated that while automated methods are increasingly popular due to the vast amount of imagery available, they are often unreliable and require considerable effort to fine-tune, particularly in determining appropriate contrast thresholds. This reveals a critical challenge: while automation can accelerate data processing, as stated before, it can also introduce non-geological features during the tracing process, which could impact subsequent analytical decisions and project

outcomes. Therefore, while automated approaches enhance some aspects of the fracture extraction process, like reproducibility, their outputs also need rigorous validation to ensure the integrity and usefulness of the interpretations they generate. This is crucial for researchers considering automated approaches, as it underscores the necessity of a deep understanding of image characteristics and the establishment of a standardized benchmark for assessing reliability. Such a benchmark would facilitate consistent comparisons across studies and provide a definitive measure of the reliability of fracture interpretations in various contexts. Incorporating this as part of a broader QA/QC protocol ensures that interpretations are both accurate and reliable.

Chapter 5 emphasizes the importance of addressing resolution limitations in geological datasets. By understanding what is needed from a dataset, and recognizing the impact that resolution may have for targeted geological analyses, researchers can improve the quality of geological interpretations. The chapter advocates for multiscale investigations to mitigate resolution-related issues and suggests incorporating additional data to fill information gaps. It outlines a clear workflow, which provides criteria for different resolution levels, such as guidelines for line tracing, handling vegetated areas, and appropriate zoom levels. Following these guidelines will significantly improve the reliability and reproducibility of manual tracing, addressing a key limitation in geological analysis. This will consequently lead to more robust and consistent geological interpretations across datasets with different resolutions.

Finally, Chapter 6 applies these principles to a real-world geological investigation, demonstrating their practical effectiveness. By validating the results against existing literature, this chapter provides a clear example of how the methods developed in this thesis can enhance the accuracy and reliability of geological studies. The key

implication is that, when relying solely on a low-resolution dataset, there is a high risk of overlooking essential geological details necessary for a reliable analysis. For instance, in Chapter 5, we showed that fractures below a certain surface width remain undetected in low-resolution imagery, whereas higher-resolution data reveal these finer fractures and their intersections. Had we relied exclusively on the low-resolution dataset, we would have missed multiple short yet geologically significant fractures, thus underestimating the true fracture intensity and connectivity (Chapter 5, Figure 5.4, Figure 5.5 and Figure 5.6). Similarly, in Chapter 6, low-resolution imagery could capture major structural trends but masked the presence of shorter fractures (<1 meter in length) and subtle intersection angles that were crucial for identifying secondary sets. By comparing local-scale and outcrop-scale datasets at higher resolutions, we discovered cross-cutting relationships and minor shear offsets that would have gone undetected with coarse data alone. Therefore, while remote sensing is indispensable for broad geological assessments, combining multiple resolutions – or at least validating low-resolution findings with field checks – ensures that key fracture details are not lost and that interpretations remain robust.

In conclusion, the insights and methodologies presented in this thesis have significant implications for industry applications. The ability to achieve reliable fracture analyses from imagery alone offers a cost-effective and efficient tool for industries such as mining, energy exploration, and civil engineering. Importantly, these methods also facilitate the interpretation of outcrops as analogs for subsurface structures, which is critical for understanding subsurface fracture networks in contexts like reservoir management or tunneling operations. Additionally, the interpretation of fracture sets has direct relevance to engineering applications, where understanding fracture orientation, spacing, and connectivity is crucial for stability assessments and infrastructure (i.e., tunneling) design. By adopting the rigorous workflows and criteria

outlined in this research, industry professionals can enhance the reliability and reproducibility of their geological interpretations, leading to more informed, case-specific decision-making for structural stability analysis, and resource extraction.

7.4 Future Research

This project carried out a thorough investigation of all the image properties that must be understood by researchers in order to pursue an accurate geological investigation that maximizes reproducibility and reliability of results. However, there are still some uncertainties that need to be investigated.

First of all, the investigations carried out in this thesis were limited to 2D datasets, leaving 2.5D and 3D datasets out of the scope of the study. Although a range of automated and semi-automated methods have emerged from the literature, the extent to which these methods extract reliable and reproducible results has not yet been investigated. These methods are capable of tracing features automatically or semi-automatically and, when applied to georeferenced 3D data such as DTMs, DSMs, and 3D models, they can extract additional valuable information like plane dips and their corresponding dip directions. A promising future direction involves developing a “blended” or dynamic approach that integrates multiple resolutions in an automated workflow. Rather than isolating each scale to a separate analysis, algorithms could shift between coarse and fine imagery based on the level of detail required at different locations. For instance, a high-resolution dataset might be automatically invoked when coarse imagery identifies regions of potentially complex fracturing, such as areas with dense fracture clusters or abrupt changes in fracture orientation. Conversely, the low-resolution coverage would be used to maintain efficient processing across large extents, ensuring global trends are captured without excessive computational demands. This blended technique would dynamically fuse

outputs from each scale, leveraging the strengths of both fine and coarse resolution imagery to create a unified fracture network map. Such a system would have significant advantages in time-critical or large-scale geological projects, since it could automatically refocus on higher-resolution imagery only where needed, preserving computational resources while still capturing essential small-scale details critical for reliable fracture interpretation. Moreover, future research could focus on developing workflows that utilize this 3D information to determine the dip and dip direction of fracture planes. This data would then serve as a basis for generalizing the model to predict fracture lineaments with matching orientations across different datasets. By using 3D planes and information extracted from georeferenced 3D data, it is possible to constrain the construction of more accurate 3D models. This can serve as a foundation for developing Discrete Fracture Network (DFN) models. The reliability and accuracy of the model can be evaluated by comparing it with another DFN model constructed using both virtual data and actual field measurements. Such a comparison is crucial for validating the effectiveness of cost-effective geological investigations and determining whether they can produce results comparable and reliable to those achieved using traditional, more expensive field campaigns. Specifically, by comparing two DFN models, one built from 3D geometries extracted from virtual outcrops and the other derived from conventional 2D models or field measurements, the strengths and limitations of using virtual analogs in geological modeling can be assessed. Successfully demonstrating this would imply the transformative potential of cost-effective methods, proving they can match the quality of results traditionally obtained from extensive and costly fieldwork. Finally, one last critical point is the quantification of information loss due to the use of grayscale imagery as input for automated approaches. The reduction to a single channel, as opposed to the full RGB (Red, Green, Blue) spectrum, results in a

significant loss of information. Currently, contrast-based methods such as shearlet transforms, CNNs, ImageJ Segmentation, and similar techniques do not utilize full RGB images for automated extraction, as processing all three-color channels simultaneously presents considerable challenges. However, this limitation presents a promising avenue for future research. By developing contrast-based methods that effectively harness the full potential of RGB imagery, it is possible to achieve more accurate and reliable automated analyses. Moreover, with the advent of artificial intelligence, it could be possible to train AI to discern between vegetation and fractures, allowing the AI to distinguish between areas of rock mass and areas of vegetation/shadows. This would also enable RGB images to be used effectively for training purposes, instead of using grayscale images for training, which would be much more inaccurate because everything is represented in one color intensity scale.

References

- Abelin, H., Birgersson, L., Moreno, L., Widén, H., Ågren, T., Neretnieks, I., 1991. A large-scale flow and tracer experiment in granite: 2. Results and interpretation. *Water Resources Research* 27, 3119–3135.
- Agosta, F., Alessandrini, M., Antonellini, M., Tondi, E., Giorgioni, M., 2010. From fractures to flow: A field-based quantitative analysis of an outcropping carbonate reservoir. *Tectonophysics* 490, 197–213.
<https://doi.org/10.1016/j.tecto.2010.05.005>
- Al-Azzawi, A., 2018. *Light and optics: principles and practices*. CRC Press.
- Alvarez, L.L., Guimarães, L.J. do N., Gomes, I.F., Beserra, L., Pereira, L.C., Miranda, T.S., Maciel, B., Barbosa, J.A., 2021. Impact of fracture topology on the fluid flow behavior of naturally fractured reservoirs. *Energies* 14, 5488.
- Anderson, O.J., Lucas, S.G., 1992. The Middle Jurassic Summerville Formation, northern New Mexico. *New Mexico Geology* 14, 79–92.
- Andrews, B.J., Roberts, J.J., Shipton, Z.K., Bigi, S., Tartarello, M.C., Johnson, G., 2019. How do we see fractures? Quantifying subjective bias in fracture data collection. *Solid Earth* 10, 487–516. <https://doi.org/10.5194/se-10-487-2019>
- Baars, D., Doelling, H., 1987. Moab salt-intruded anticline, east-central Utah. *Geological Society of America Centennial Field Guide—Rocky Mountain Section* 275–280.
- Bäckblom, G., Martin, C.D., 1999. Recent experiments in hard rocks to study the excavation response: Implications for the performance of a nuclear waste geological repository. *Tunnelling and Underground Space Technology* 14, 377–394. [https://doi.org/10.1016/s0886-7798\(99\)00053-x](https://doi.org/10.1016/s0886-7798(99)00053-x)

- Bai, Q., Tu, S., 2019. A General Review on Longwall Mining-Induced Fractures in Near-Face Regions. *Geofluids* 2019, 3089292.
<https://doi.org/10.1155/2019/3089292>
- Balabanian, F., Sant'Ana da Silva, E., Pedrini, H., 2017. Image Thresholding Improved by Global Optimization Methods. *Applied Artificial Intelligence* 31, 197–208.
<https://doi.org/10.1080/08839514.2017.1300050>
- Ballantyne, C.K., 2021. Upland Landscapes and Landforms of the Southern Uplands, in: Ballantyne, C.K., Gordon, J.E. (Eds.), *Landscapes and Landforms of Scotland*. Springer International Publishing, Cham, pp. 453–465.
https://doi.org/10.1007/978-3-030-71246-4_27
- Baltsavias, E.P., 1996. Digital ortho-images—a powerful tool for the extraction of spatial-and geo-information. *ISPRS Journal of Photogrammetry and Remote sensing* 51, 63–77.
- Barton, C.A., Zoback, M.D., Moos, D., 1995. Fluid flow along potentially active faults in crystalline rock. *Geology* 23, 683–686. [https://doi.org/10.1130/0091-7613\(1995\)023<0683:FFAPAF>2.3.CO;2](https://doi.org/10.1130/0091-7613(1995)023<0683:FFAPAF>2.3.CO;2)
- Bateman, P.C., 1992. Plutonism in the central part of the Sierra Nevada Batholith, California (Report No. 1483), Professional Paper.
<https://doi.org/10.3133/pp1483>
- Bateman, P.C., Clark, L.D., Huber, N.K., Moore, J.G., Rinehart, C.D., 1963. The Sierra Nevada batholith: a synthesis of recent work across the central part (No. 2330–7102).
- Bateman, P.C., Eaton, J.P., 1967. Sierra Nevada Batholith. *Science* 158, 1407–1417.
<https://doi.org/10.1126/science.158.3807.1407>
- Bemis, S.P., Micklethwaite, S., Turner, D., James, M.R., Akciz, S., Thiele, S.T., Bangash, H.A., 2014. Ground-based and UAV-Based photogrammetry: A multi-scale,

- high-resolution mapping tool for structural geology and paleoseismology. *Journal of Structural Geology* 69, 163–178.
<https://doi.org/10.1016/j.jsg.2014.10.007>
- Benjamin Ntieche, Pauline Wokwenmendang Nguet, Zakari Nchouwet, Mahomed Aziz Mounjouhou, Daouda Mfepat, 2020. Deformation Features and Structures in Some Igneous and Metamorphic Rocks: A Case Study of Central African Fold Belt in Cameroon, in: Miloš René, Gemma Aiello, Gaafar El Bahariya (Eds.), *Geochemistry*. IntechOpen, Rijeka, p. Ch. 4.
<https://doi.org/10.5772/intechopen.93201>
- Berkowitz, B., 2002. Characterizing flow and transport in fractured geological media: A review. *Advances in Water Resources* 25, 861–884.
[https://doi.org/10.1016/s0309-1708\(02\)00042-8](https://doi.org/10.1016/s0309-1708(02)00042-8)
- Bertrand, L., Géraud, Y., Diraison, M., 2021. Petrophysical properties in faulted basement rocks: Insights from outcropping analogues on the West European Rift shoulders. *Geothermics* 95, 102144.
<https://doi.org/10.1016/j.geothermics.2021.102144>
- Bertrand, L., Géraud, Y., Le Garzic, E., Place, J., Diraison, M., Walter, B., Haffen, S., 2015a. A multiscale analysis of a fracture pattern in granite: A case study of the Tamariu granite, Catalunya, Spain. *Journal of Structural Geology* 78, 52–66. <https://doi.org/10.1016/j.jsg.2015.05.013>
- Bistacchi, A., Balsamo, F., Storti, F., Mozafari, M., Swennen, R., Solum, J., Tueckmantel, C., Taberner, C., 2015. Photogrammetric digital outcrop reconstruction, visualization with textured surfaces, and three-dimensional structural analysis and modeling: Innovative methodologies applied to fault-related dolomitization (Vajont Limestone, Southern Alps, Italy). *Geosphere* 11, 2031–2048. <https://doi.org/10.1130/GES01005.1>

- Biswas, U., Mukhopadhyay, M., Mandal, N., 2023. Fractal analysis of anisotropic shear-fracture roughness from rocks and analogue laboratory models: A new approach for heterogeneous-slip characterization. *International Journal of Rock Mechanics and Mining Sciences* 169, 105432.
<https://doi.org/10.1016/j.ijrmms.2023.105432>
- Bøe, R., Mørk, M.B., Roberts, D., VIGRAN, J., 2005. Possible Mesozoic sediments in fault and brecciation zones in Frøyfjorden, Mid Norway. *Norges geologiske undersøkelse Bulletin* 443, 29–35.
- Bonato, J., Wohnrath Tognoli, F.M., Costa Nogueira, F.C., de Miranda, T.S., Inocencio, L.C., 2022. The use of network topology to assess connectivity of deformation bands in sandstone: A quantitative approach based on digital outcrop models. *Journal of Structural Geology* 161, 104682.
<https://doi.org/10.1016/j.jsg.2022.104682>
- Bond, C.E., Gibbs, A.D., Shipton, Z.K., Jones, S., 2007. What do you think this is?: “Conceptual uncertainty” In geoscience interpretation. *GSA Today* 17, 4–10.
<https://doi.org/10.1130/GSAT01711A.1>
- Bonnet, E., Bour, O., Odling, N.E., Davy, P., Main, I., Cowie, P., Berkowitz, B., 2001. Scaling of fracture systems in geological media. *Reviews of Geophysics* 39, 347–383. <https://doi.org/10.1029/1999rg000074>
- Booyesen, R., Booyesen, R., Gloaguen, R., Lorenz, S., Zimmermann, R., Nex, P.A.M., 2019. *Geological Remote Sensing*. Elsevier. <https://doi.org/10.1016/B978-0-12-409548-9.12127-X>
- Booyesen, R., Lorenz, S., Jackisch, R., Gloaguen, R., Madriz, Y., 2021. How Can Drones Contribute to Mineral Exploration?, in: *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*. Presented at the 2021 IEEE

- International Geoscience and Remote Sensing Symposium IGARSS, pp. 1867–1870. <https://doi.org/10.1109/IGARSS47720.2021.9554041>
- Bossennec, C., Seib, L., Frey, M., van der Vaart, J., Sass, I., 2022. Structural Architecture and Permeability Patterns of Crystalline Reservoir Rocks in the Northern Upper Rhine Graben: Insights from Surface Analogues of the Odenwald. *Energies* 15, 1310–1310. <https://doi.org/10.3390/en15041310>
- Bowman M. B. J., Smyth Helen R., 2016. Reducing uncertainty and risk through field-based studies. Geological Society, London, Special Publications 436, 1–8. <https://doi.org/10.1144/SP436.13>
- Braathén, A., 1999. Kinematics of post-Caledonian polyphase brittle faulting in the Sunnfjord region, western Norway. *Tectonophysics* 302, 99–121. [https://doi.org/10.1016/S0040-1951\(98\)00281-9](https://doi.org/10.1016/S0040-1951(98)00281-9)
- Branellec, M., Callot, J.-P., Nivière, B., Ringenbach, J.-C., 2015. The fracture network, a proxy for mesoscale deformation: Constraints on layer parallel shortening history from the Malargüe fold and thrust belt, Argentina. *Tectonics* 34, 623–647.
- Bratton, T., Canh, D.V., Van Que, N., Duc, N.V., Gillespie, P., Hunt, D., Li, B., Marcinew, R., Ray, S., Montaron, B., 2006. The nature of naturally fractured reservoirs. *Oilfield Review* 18, 4–23.
- Briggs, A.H., Weinstein, M.C., Fenwick, E.A.L., Karnon, J., Sculpher, M.J., Paltiel, A.D., 2012. Model Parameter Estimation and Uncertainty: A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force-6. *Value in Health* 15, 835–842. <https://doi.org/10.1016/j.jval.2012.04.014>
- Brovelli, M.A., Cannata, M., Longoni, U.M., 2004. LIDAR data filtering and DTM interpolation within GRASS. *Transactions in GIS* 8, 155–174.

- Burrough, P.A., McDonnell, R.A., Lloyd, C.D., 2015. Principles of geographical information systems. Oxford University Press, USA.
- Canny, J., 1986. A Computational Approach to Edge Detection. IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI-8, 679–698.
<https://doi.org/10.1109/TPAMI.1986.4767851>
- Cao, M., Sharma, M.M., 2023. Effect of fracture geometry, topology and connectivity on energy recovery from enhanced geothermal systems. Energy 282, 128368.
<https://doi.org/10.1016/j.energy.2023.128368>
- Carrivick, J.L., Smith, M.W., Quincey, D.J., Carver, S.J., 2013. Developments in budget remote sensing for the geosciences. Geology Today 29, 138–143.
- Casini, G., Hunt, D., Monsen, E., Bounaim, A., 2016. Fracture characterization and modeling from virtual outcrops. AAPG Bulletin 100, 41–61.
- Castaing, C., Halawani, M.A., Gervais, F., Chilès, J.P., Genter, A., Bourguine, B., Ouillon, G., Brosse, J.M., Martin, P., Genna, A., Janjou, D., 1996. Scaling relationships in intraplate fracture systems related to Red Sea rifting. Tectonophysics 261, 291–314. [https://doi.org/10.1016/0040-1951\(95\)00177-8](https://doi.org/10.1016/0040-1951(95)00177-8)
- Chabani, A.T., 2021. Multiscale Characterization of Fracture Patterns: A Case Study of the Noble Hills Range (Death Valley, CA, USA), Application to Geothermal Reservoirs. Geosciences Journal 11, 1–28.
- Chen, J., Zhou, M., Huang, H., Zhang, D., Peng, Z., 2021. Automated extraction and evaluation of fracture trace maps from rock tunnel face images via deep learning. International Journal of Rock Mechanics and Mining Sciences 142, 104745. <https://doi.org/10.1016/j.ijrmms.2021.104745>
- Chitsaz, H., Amjady, N., Zareipour, H., 2016. Wind Power Forecast Using Wavelet Neural Network Trained by Improved Clonal Selection Algorithm.

- Christensen, M.N., 1966. Late Cenozoic crustal movements in the Sierra Nevada of California. *Geological Society of America Bulletin* 77, 163–182.
- Cihlar, J., Latifovic, R., Beaubien, J., Guindon, B., Palmer, M., 2003. Thematic mapper (TM) based accuracy assessment of a land cover product for Canada derived from SPOT VEGETATION (VGT) data. *Canadian Journal of Remote Sensing* 29, 154–170. <https://doi.org/10.5589/m02-091>
- Clark, R.N., 2020. Spectroscopy of rocks and minerals, and principles of spectroscopy.
- Clauset, A., Shalizi, C.R., Newman, M.E.J., 2009. Power-Law Distributions in Empirical Data. *SIAM Rev.* 51, 661–703. <https://doi.org/10.1137/070710111>
- Coleman, D.S., Glazner, A.F., 1997. The Sierra Crest magmatic event: Rapid formation of juvenile crust during the Late Cretaceous in California. *International Geology Review* 39, 768–787.
- Collins, L.G., 1994. The Origin of Granite and Continental Masses in an Expanding Earth, in: Barone, M., Selleri, F. (Eds.), *Frontiers of Fundamental Physics*. Springer US, Boston, MA, pp. 309–314. https://doi.org/10.1007/978-1-4615-2560-8_35
- Cosgrove, J., 2007. The use of shear zones and related structures as kinematic indicators: A review. *Geological Society, London, Special Publications* 272, 59–74. <https://doi.org/10.1144/GSL.SP.2007.272.01.05>
- Debon, F., Le Fort, P., 1983. A chemical–mineralogical classification of common plutonic rocks and associations. *Earth and Environmental Science Transactions of the Royal Society of Edinburgh* 73, 135–149.
- Ding, L., Goshtasby, A., 2001. On the Canny edge detector. *Pattern Recognition* 34, 721–725. [https://doi.org/10.1016/S0031-3203\(00\)00023-6](https://doi.org/10.1016/S0031-3203(00)00023-6)

- Doelling, H.H., 1985. Geology of Arches National Park (Utah). Utah Geological & Mineral Survey.
- Drury, S.A., 1987. Image interpretation in geology.
- Dutler, N., Nejati, M., Valley, B., Amann, F., Molinari, G., 2018. On the link between fracture toughness, tensile strength, and fracture process zone in anisotropic rocks. *Engineering Fracture Mechanics* 201, 56–79.
<https://doi.org/10.1016/j.engfracmech.2018.08.017>
- EDINA, 2024. Geology Digimap.
- Esri, 2024. Raster To Polyline (Conversion).
- Esteva, A., Kuprel, B., Novoa, R.A., Ko, J., Swetter, S.M., Blau, H.M., Thrun, S., 2017. Dermatologist-level classification of skin cancer with deep neural networks. *nature* 542, 115–118.
- Fagerland, N., 1990. Mid-Norway shelf-hydrocarbon habitat in relation to tectonic elements. *Norsk geologisk tidsskrift* 70, 65–79.
- Faiq Adenan, M., Fathi, E., Carr, T.R., Panetta, B., 2024. Advancing subsurface analysis: Integrating computer vision and deep learning for the near real-time interpretation of borehole image logs in the Illinois Basin-Decatur Project. *Interpretation* 12, SB19–SB27.
- Faleide, T.S., Braathen, A., Lecomte, I., Mulrooney, M.J., Midtkandal, I., Bugge, A.J., Planke, S., 2021. Impacts of seismic resolution on fault interpretation: Insights from seismic modelling. *Tectonophysics* 816, 229008.
<https://doi.org/10.1016/j.tecto.2021.229008>
- Feng, G., Wang, X., Kang, Y., Luo, S., Hu, Y., 2019. Effects of Temperature on the Relationship between Mode-I Fracture Toughness and Tensile Strength of Rock. *Applied Sciences* 9. <https://doi.org/10.3390/app9071326>

- Gabrielsen, R.H., Braathen, A., 2014. Models of fracture lineaments — Joint swarms, fracture corridors and faults in crystalline rocks, and their genetic relations. *Tectonophysics* 628, 26–44. <https://doi.org/10.1016/j.tecto.2014.04.022>
- Gabrielsen, R.H., Odinsen, T., Grunnaleite, I., 1999. Structuring of the Northern Viking Graben and the Møre Basin; the influence of basement structural grain, and the particular role of the Møre-Trøndelag Fault Complex. *Marine and Petroleum Geology* 16, 443–465. [https://doi.org/10.1016/S0264-8172\(99\)00006-9](https://doi.org/10.1016/S0264-8172(99)00006-9)
- Gabrielsen, R.H., Olesen, O., 2024. The Concept of Lineaments in Geological Structural Analysis; Principles and Methods: A Review Based on Examples from Norway. *Geomatics* 4, 189–212. <https://doi.org/10.3390/geomatics4020011>
- Gard, L.M., 1976. Geology of the north end of the Salt Valley anticline, Grand County, Utah (No. 2331–1258). US Geological Survey,.
- Gardiner, C.I., Reynolds, S.H., 1932. The Loch Doon “Granite” Area, Galloway. *Quarterly Journal of the Geological Society* 88, 1-NP. <https://doi.org/10.1144/gsl.jgs.1932.088.01-04.03>
- Gautneb, H., Roberts, D., 1989. Geology and petrochemistry of the Smola-Hitra Batholith, Central Norway. *Norges geofogiske undersekefse* 1–24.
- Gavazzi, B., Frey, M., lipinn9plw, Alashari, D.M., Gorginyan, Y.A., Solodusha, S.V., da Silva, J.D.C., Tyagi, S., Cecchini, L.M., 2023. A new tool to automatise the characterisation of fracture networks from 3D point cloud data. <https://doi.org/10.5194/egusphere-2023-1316>
- Gee, D.G., Andréasson, P.-G., Li, Y., Krill, A., 2017. Baltoscandian margin, Sveconorwegian crust lost by subduction during Caledonian collisional orogeny. *GFF* 139, 36–51. <https://doi.org/10.1080/11035897.2016.1200667>

- Gee, D.G., Janák, M., Majka, J., Robinson, P., van Roermund, H., 2013. Subduction along and within the Baltoscandian margin during closing of the Iapetus Ocean and Baltica-Laurentia collision. *Lithosphere* 5, 169–178.
- Geoinformatics, 2024. Top 10 Types of Aerial Surveying Equipment & Their Uses. Geoinformatics.
- Ghamgosar, M., Doğan, N., 2015. A NUMERICAL STUDY ON OSCILLATING DISC CUTTING (ODC) TECHNOLOGY FOR HARD ROCK CUTTING A NUMERICAL STUDY ON OSCILLATING DISC CUTTING (ODC) TECHNOLOGY FOR HARD ROCK CUTTING. <https://doi.org/10.13140/RG.2.1.3285.5202>
- Ghasemi, S., Khamsehchiyan, M., Taheri, A., Nikudel, M.R., Zalooli, A., 2020. Crack Evolution in Damage Stress Thresholds in Different Minerals of Granite Rock. *Rock Mechanics and Rock Engineering* 53, 1163–1178. <https://doi.org/10.1007/s00603-019-01964-9>
- Gillespie, P.A., Howard, C.B., Walsh, J.J., Watterson, J., 1993. Measurement and characterisation of spatial distributions of fractures. *Tectonophysics* 226, 113–141. [https://doi.org/10.1016/0040-1951\(93\)90114-Y](https://doi.org/10.1016/0040-1951(93)90114-Y)
- Gilluly, J., Reeside Jr., J.B., 1928. Sedimentary rocks of the San Rafael Swell and some adjacent areas in eastern Utah (Report No. 150D), Professional Paper. <https://doi.org/10.3133/pp150D>
- Giordan, D., Hayakawa, Y., Nex, F., Remondino, F., Tarolli, P., 2017. Review article: The use of remotely piloted aircraft systems (RPAS) for natural hazards monitoring and management. *Natural Hazards and Earth System Sciences Discussions* 1–26. <https://doi.org/10.5194/nhess-2017-339>
- Goldstein, D.H., 2017. Polarized light. CRC press.

- Gomez, C., Purdie, H., 2016. UAV- based Photogrammetry and Geocomputing for Hazards and Disaster Risk Monitoring – A Review. *Geoenvironmental Disasters* 3, 23. <https://doi.org/10.1186/s40677-016-0060-y>
- Grønlie, A., Harder, V., Roberts, D., 1990. Preliminary fission-track ages of fluorite mineralisation along fracture zones, inner Trondheimsfjord, Central Norway. *Norsk geologisk tidsskrift* 70, 173–178.
- Gudmundsson, A., 2011. Rock fractures in geological processes. Cambridge University Press.
- Guerriero, V., Iannace, A., Mazzoli, S., Parente, M., Vitale, S., Giorgioni, M., 2010. Quantifying uncertainties in multi-scale studies of fractured reservoir analogues: Implemented statistical analysis of scan line data from carbonate rocks. *Journal of Structural Geology* 32, 1271–1278.
- Guo, J., Wu, L., Zhang, M., Liu, S., Sun, X., 2018. Towards automatic discontinuity trace extraction from rock mass point cloud without triangulation. *International Journal of Rock Mechanics and Mining Sciences* 112, 226–237. <https://doi.org/10.1016/j.ijrmms.2018.10.023>
- Gupta, R.P., 2017. Remote sensing geology. Springer.
- Guth, P.L., Van Niekerk, A., Grohmann, C.H., Muller, J.-P., Hawker, L., Florinsky, I.V., Gesch, D., Reuter, H.I., Herrera-Cruz, V., Riazanoff, S., López-Vázquez, C., Carabajal, C.C., Albinet, C., Strobl, P., 2021. Digital Elevation Models: Terminology and Definitions. *Remote Sensing* 13, 3581. <https://doi.org/10.3390/rs13183581>
- Hansman, R.J., Ring, U., 2019. Workflow: From photo-based 3-D reconstruction of remotely piloted aircraft images to a 3-D geological model. *Geosphere* 15, 1393–1408.
- Harder, E., 1910. IRON ORES NEAR DAYTON, NEVADA. *Bulletin* 430, 240.

- Hashim, M., Ahmad, S., Johari, M.A.M., Pour, A.B., 2013. Automatic lineament extraction in a heavily vegetated region using Landsat Enhanced Thematic Mapper (ETM+) imagery. *Advances in Space Research* 51, 874–890.
<https://doi.org/10.1016/j.asr.2012.10.004>
- Heggernes, H., Rotevatn, A., Demurtas, M., Nixon, C.W., Fossen, H., 2023. Spatial variability in topology, connectivity and permeability of deformation band networks: Insights from the Jurassic Entrada Sandstone, Utah. *Journal of Structural Geology* 176, 104951. <https://doi.org/10.1016/j.jsg.2023.104951>
- Hilley, G., Blisniuk, P., Strecker, M., 2005. Mechanics and erosion of basement-cored uplift provinces. *Journal of Geophysical Research: Solid Earth* 110.
- Hines, R., Paterson, S.R., Memeti, V., Chambers, J.A., 2018. Nested Incremental Growth of Zoned Upper Crustal Plutons in the Southern Uplands Terrane, UK: Fractionating, Mixing, and Contaminated Magma Fingers. *Journal of Petrology* 59, 483–516. <https://doi.org/10.1093/petrology/egy034>
- Hoek, E., Bieniawski, Z.T., 1965. Brittle fracture propagation in rock under compression. *International Journal of Fracture Mechanics* 1.
<https://doi.org/10.1007/bf00186851>
- Hoek, E., Bray, J.D., 1981. *Rock slope engineering*. CRC press.
- Howell, J.A., Martinius, A.W., Good, T.R., 2014. The application of outcrop analogues in geological modelling: a review, present status and future outlook. *Geological Society, London, Special Publications* 387, 1–25.
- Howell, L., Brown, C.S., Egan, S.S., 2021. Deep geothermal energy in northern England: Insights from 3D finite difference temperature modelling. *Computers & Geosciences* 147, 104661.
<https://doi.org/10.1016/j.cageo.2020.104661>

- Hunt Jr, E.R., Hively, W.D., Fujikawa, S.J., Linden, D.S., Daughtry, C.S., McCarty, G.W., 2010. Acquisition of NIR-green-blue digital photographs from unmanned aircraft for crop monitoring. *Remote Sensing* 2, 290–305.
- Hynek, S., Comas, X., Brantley, S.L., 2017. The Effect of Fractures on Weathering of Igneous and Volcaniclastic Sedimentary Rocks in the Puerto Rican Tropical Rain Forest. *Procedia Earth and Planetary Science* 17, 972–975.
<https://doi.org/10.1016/j.proeps.2017.01.001>
- Iding, M., Ringrose, P., 2010. Evaluating the impact of fractures on the performance of the In Salah CO₂ storage site. *International Journal of Greenhouse Gas Control* 4, 242–248. <https://doi.org/10.1016/j.ijggc.2009.10.016>
- ImageJ, 2024a. Process [WWW Document]. URL <https://imagej.net/ij/docs/guide/146-29.html>
- ImageJ, 2024b. AnalyzeSkeleton [WWW Document]. URL <https://imagej.net/imagej-wiki-static/AnalyzeSkeleton>
- ImageJ, 2023. Analyze Particles [WWW Document]. URL <https://imagej.nih.gov/ij/docs/menus/analyze.html#:~:text=The%20formula%20for%20circularity%20is,outlines%20of%20the%20measured%20particles.>
- IntelliSpatial, 2024. Manned Aerial Surveys [WWW Document]. URL <https://intellispatial.io/services/reality-capture/manned-aerial-surveys/> (accessed 8.17.24).
- Ireland, M., Algarabel, G., Steventon, M., Munafo, M., 2022. How reproducible is geophysical research? A review of the availability of code, software and data in journals.
- J., N.A., M., S.S., 2016. Linking outcrop analogue with flow simulation to reduce uncertainty in sub-surface carbon capture and storage: an example from the

- Sherwood Sandstone Group of the Wessex Basin, UK. Geological Society, London, Special Publications 436, 231–246. <https://doi.org/10.1144/SP436.2>
- Jannin, P., Krupinski, E., Warfield, S.K., 2006. Validation in medical image processing. *IEEE Transactions on Medical Imaging* 25, 1405–9.
- Jayasuriya, S., 2021. Image sensors, in: *Computer Vision: A Reference Guide*. Springer, pp. 639–643.
- Jenkins, F.A., White, H.E., 1976. *Fundamentals of Optics*, 4th ed. McGraw-Hill, New York, USA.
- Ji, Y., Song, S., Zhang, W., Li, Y., Xue, J., Chen, J., 2025. Automatic identification of rock fractures based on deep learning. *Engineering Geology* 345, 107874.
- Jinghong, W., Caineng, Z., Jiuqiang, J., Rukai, Z., 2011. Characteristics and controlling factors of fractures in igneous rock reservoirs. *Petroleum Exploration and Development* 38, 708–715. [https://doi.org/10.1016/S1876-3804\(12\)60005-6](https://doi.org/10.1016/S1876-3804(12)60005-6)
- Kanoun, B., Cherif, M.A., Manighetti, I., Tarabalka, Y., Zerubia, J., 2022. An enhanced deep learning approach for tectonic fault and fracture extraction in very high resolution optical images. Presented at the ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, pp. 3403–3407.
- Kardasz, P., Doskocz, J., Hejduk, M., Wiejkut, P., Zarzycki, H., 2016. Drones and possibilities of their using. *J. Civ. Environ. Eng* 6, 1–7.
- Kerschner, M., 2001. Seamline detection in colour orthoimage mosaicking by use of twin snakes. *ISPRS journal of photogrammetry and remote sensing* 56, 53–64.
- Kharrat, R., Ott, H., 2023. A Comprehensive Review of Fracture Characterization and Its Impact on Oil Production in Naturally Fractured Reservoirs. *Energies* 16. <https://doi.org/10.3390/en16083437>

- Klee, J., Trullenque, G., Ledésert, B., Potel, S., Hébert, R., Chabani, A., Genter, A., 2020. Petrographic analyzes of fractured granites used as an analogue of the soultz-sous-forêts geothermal reservoir: Noble Hills, CA, USA. Presented at the Proceedings of the World Geothermal Congress.
- Konnen, G., 1985. Polarized light in nature. CUP Archive.
- Kovesi, P., 1999. Image features from phase congruency. *Videre: Journal of computer vision research* 1, 1–26.
- Krotkov, E., 1988. Focusing. *International Journal of Computer Vision* 1, 223–237.
- Kutyniok, G., Labate, D., 2012. Introduction to Shearlets, in: *Shearlets: Multiscale Analysis for Multivariate Data*. pp. 1–38. https://doi.org/10.1007/978-0-8176-8316-0_1
- Kwon, Y., Casebolt, J.B., 2006. Effects of light refraction on the accuracy of camera calibration and reconstruction in underwater motion analysis. *Sports biomechanics* 5, 315–340.
- Kwon, Y.-H., 1999. Object plane deformation due to refraction in two-dimensional underwater motion analysis. *Journal of applied biomechanics* 15, 396–403.
- Labate, D.; L., 2005. Sparse multidimensional representation using shearlets. *Wavelets Optics and Photonics XI*.
- Lattman, L.H., Parizek, R.R., 1964. Relationship between fracture traces and the occurrence of ground water in carbonate rocks. *Journal of Hydrology* 2, 73–91. [https://doi.org/10.1016/0022-1694\(64\)90019-8](https://doi.org/10.1016/0022-1694(64)90019-8)
- Lauritsen, T., Slagstad, T., Olesen, O., Ofstad, F., Dumais, M.-A., Brønner, M., 2019. Proposal for a new national radon hazard map-Trøndelag test area-COOP Project.

- Lei, J., Fan, Y., 2024. Rock CT Image Fracture Segmentation Based on Convolutional Neural Networks. *Rock Mechanics and Rock Engineering* 57, 5883–5898.
<https://doi.org/10.1007/s00603-024-03824-7>
- Lei, Q., Wang, X., 2016. Tectonic interpretation of the connectivity of a multiscale fracture system in limestone. *Geophysical Research Letters* 43, 1551–1558.
- Lepillier, B., Bruna, P.-O., Bruhn, D., Bastesen, E., Daniilidis, A., Garcia, Ó., Torabi, A., Wheeler, W., 2020. From outcrop scanlines to discrete fracture networks, an integrative workflow. *Journal of Structural Geology* 133, 103992.
<https://doi.org/10.1016/j.jsg.2020.103992>
- Leta, F.R., Clua, E., Biondi, M., Pacheco, T., do Socorro de Souza, M., 2013. An Automatic Process to Identify Features on Boreholes Data by Image Processing Techniques, in: Öchsner, A., Altenbach, H. (Eds.), *Experimental and Numerical Investigation of Advanced Materials and Structures*. Springer International Publishing, Cham, pp. 249–262. https://doi.org/10.1007/978-3-319-00506-5_18
- Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.A.A., Ciompi, F., Ghafoorian, M., Van Der Laak, J.A., Van Ginneken, B., Sánchez, C.I., 2017. A survey on deep learning in medical image analysis. *Medical image analysis* 42, 60–88.
- Liu, S., Lan, H., Martin, C.D., 2022. Progressive Transition from Extension Fracture to Shear Fracture of Altered Granite During Uniaxial Tensile Tests. *Rock Mechanics and Rock Engineering* 55, 5355–5375.
<https://doi.org/10.1007/s00603-022-02897-6>
- Liu, Y., Li, S., Zhang, H., 2020. Multibaseline Interferometric Phase Denoising Based On Kurtosis In the NSST Domain. *Sensors* 20, 551.
<https://doi.org/10.3390/s20020551>

- Lockner, D.A., Byerlee, J.D., Kuksenko, V., Ponomarev, A., Sidorin, A., 1991. Quasi-static fault growth and shear fracture energy in granite 350, 39–42.
<https://doi.org/10.1038/350039a0>
- Lv, D., Cheng, Y., Xiao, H., Hai, G., 2022. A Framework for Fracture Extraction Under Glaciological Property-Based Constraints: Scientific Application on the Filchner–Ronne Ice Shelf of Antarctica. *Earth and Space Science* 9, e2022EA002293.
- Ma, G., Wei, Q., Sui, H., Qin, Q., 2013. Method for large-area satellite image quality enhancement with local aerial images based on non-target multi-point calibration. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 6, 2174–2183.
- Mabee, S.B., Hardcastle, K.C., Wise, D.U., 1994. A method of collecting and analyzing lineaments for regional-scale fractured-bedrock aquifer studies. *Groundwater* 32, 884–894.
- Madjid, M., Vandeginste, V., Hampson, G., Jordan, C.J., Booth, A., 2018. Drones in carbonate geology: Opportunities and challenges, and application in diagenetic dolomite geobody mapping. *Marine and Petroleum Geology* 91. <https://doi.org/10.1016/j.marpetgeo.2018.02.002>
- Maerz, N.H., Franklin, J.A., Bennett, C.P., 1990. Joint roughness measurement using shadow profilometry. *International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts* 27, 329–343.
[https://doi.org/10.1016/0148-9062\(90\)92708-M](https://doi.org/10.1016/0148-9062(90)92708-M)
- Manfreda, S., McCabe, M.F., Miller, P.E., Lucas, R., Pajuelo Madrigal, V., Mallinis, G., Ben Dor, E., Helman, D., Estes, L., Ciraolo, G., 2018. On the use of unmanned aerial systems for environmental monitoring. *Remote sensing* 10, 641.

- Maréchal, J.C., Dewandel, B., Subrahmanyam, K., 2004. Use of hydraulic tests at different scales to characterize fracture network properties in the weathered-fractured layer of a hard rock aquifer. *Water Resources Research* 40. <https://doi.org/10.1029/2004WR003137>
- Mark, D.F., Rice, C.M., Hole, M., Condon, D., 2020. Multi-chronometer dating of the Souter Head complex: rapid exhumation terminates the Grampian Event of the Caledonian Orogeny. *Earth and Environmental Science Transactions of the Royal Society of Edinburgh* 111, 95–108. <https://doi.org/10.1017/S1755691020000043>
- Massaro, L., Forte, G., De Falco, M., Rauseo, F., Santo, A., 2024. Rockfall source identification and trajectory analysis from UAV-based data in volcano-tectonic areas: a case study from Ischia Island, Southern Italy. *Bulletin of Engineering Geology and the Environment* 83, 75. <https://doi.org/10.1007/s10064-024-03569-1>
- Matson, G.C., 1905. Peridotite Dikes near Ithaca, NY. *The Journal of Geology* 13, 264–275.
- Mauldon, M., Dunne, W.M., Rohrbaugh, M.B., 2001. Circular scanlines and circular windows: new tools for characterizing the geometry of fracture traces. *Journal of Structural Geology* 23, 247–258. [https://doi.org/10.1016/s0191-8141\(00\)00094-8](https://doi.org/10.1016/s0191-8141(00)00094-8)
- McBeck, J.A., Zhu, W., Renard, F., 2020. The competition between fracture nucleation, propagation and coalescence in the crystalline continental upper crust. *Solid Earth Discussions* 2020, 1–24.
- Merembayev, T., Amanbek, Y., 2022. Natural Fracture Network Model Using Machine Learning Approach. https://doi.org/10.1007/978-3-031-37114-1_26

- Mindat.org [WWW Document], 2024. . Liafjellet, Hitra, Trøndelag, Norway. URL <https://www.mindat.org/feature-9139802.html> (accessed 6.13.24).
- Miranda, M., Dezayes, C., Giordano, N., Inès, K., Raymond, J., Carvalho, J., 2018. Fracture Network Characterization as Input for Geothermal Energy Research: Preliminary Data from Kuujuaq, Northern Québec, Canada.
- Mlsna, P.A., Rodríguez, J.J., 2009. Chapter 19 - Gradient and Laplacian Edge Detection, in: Bovik, A. (Ed.), The Essential Guide to Image Processing. Academic Press, Boston, pp. 495–524. <https://doi.org/10.1016/B978-0-12-374457-9.00019-6>
- Molnar, P., Anderson, R.S., Anderson, S.P., 2007. Tectonics, fracturing of rock, and erosion. *Journal of Geophysical Research* 112. <https://doi.org/10.1029/2005jf000433>
- Murphy, J.C., Schafer, L.A., Mize, S., 2023. Differing field methods and site conditions lead to varying bias in suspended sediment concentrations in the Lower Mississippi and Atchafalaya Rivers. *Environmental Monitoring and Assessment* 195. <https://doi.org/10.1007/s10661-023-11836-z>
- Mwaniki, M.W., Matthias, M.S., Schellmann, G., 2015. Application of remote sensing technologies to map the structural geology of central Region of Kenya. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 8, 1855–1867.
- Narr, W., Suppe, J., 1991. Joint spacing in sedimentary rocks. *Journal of Structural Geology* 13, 1037–1048. [https://doi.org/10.1016/0191-8141\(91\)90055-N](https://doi.org/10.1016/0191-8141(91)90055-N)
- Nasseri, M.H.B., Tatone, B.S.A., Grasselli, G., Young, R.P., 2009. Fracture Toughness and Fracture Roughness Interrelationship in Thermally treated Westerly Granite, in: *Rock Physics and Natural Hazards*. Birkhäuser Basel, pp. 801–822.

- Nasuti, A., Pascal, C., Ebbing, J., Biedermann, A., 2010. A detailed geophysical and geological study of Møre-Trøndelag Fault Complex (MTFC), Mid Norway.
- National Park Service, 2021. Interim Digital Geologic-GIS Map of Arches National Park and Vicinity, Utah (NPS, GRD, GRI, ARCH, ARCH digital map) adapted from Utah Geological Survey Maps by (collectively) Doelling, Ross, Kuehne, Yonkee, Hand, Morgan and Mulvey (1994, 1997, 2000, 2002, 2013 and 2014).
- National Research Council, 1996. Rock Fractures and Fluid Flow: Contemporary Understanding and Applications. The National Academies Press, Washington, DC.
- Nédélec, A., Bouchez, J.-L., 2015. 87Emplacement and shape of granite plutons, in: Nédélec, A., Bouchez, J.-L., Bowden, P. (Eds.), *Granites: Petrology, Structure, Geological Setting, and Metallogeny*. Oxford University Press, p. 0.
<https://doi.org/10.1093/acprof:oso/9780198705611.003.0006>
- Nelson, R.A., 1985. Geologic analysis of naturally fractured reservoirs. Gulf Professional Publishing.
- Nex, F., Remondino, F., 2014. UAV for 3D mapping applications: a review. *Applied Geomatics* 6, 1–15. <https://doi.org/10.1007/s12518-013-0120-x>
- Nhat-Duc, H., Nguyen, Q.-L., Tran, V.-D., 2018. Automatic recognition of asphalt pavement cracks using metaheuristic optimized edge detection algorithms and convolution neural network. *Automation in Construction* 94, 203–213.
<https://doi.org/10.1016/j.autcon.2018.07.008>
- Nishita, T., Sirai, T., Tadamura, K., Nakamae, E., 1993. Display of the earth taking into account atmospheric scattering. Presented at the Proceedings of the 20th annual conference on Computer graphics and interactive techniques, pp. 175–182.

- Nordgulen, Ø., Sundvoll, B., Solli, A., 1995. Caledonian granitoids in the Frøya-Froan area, central Norway.
- Norwegian Geological Survey (NGU), 2024. National Bedrock Database.
- Nyberg, B., Nixon, C.W., Sanderson, D.J., 2018. NetworkGT: A GIS tool for geometric and topological analysis of two-dimensional fracture networks. *Geosphere* 14, 1618–1634. <https://doi.org/10.1130/ges01595.1>
- Nyquist, J.E., 1996. Applications of low-cost radio-controlled airplanes to environmental restoration at Oak Ridge National Laboratory. United States.
- O'Connor, J., Smith, M.J., James, M.R., 2017. Cameras and settings for aerial surveys in the geosciences: Optimising image data. *Progress in Physical Geography: Earth and Environment* 41, 325–344. <https://doi.org/10.1177/0309133317703092>
- Odling, N.E., Roden, J.E., 1997. Contaminant transport in fractured rocks with significant matrix permeability, using natural fracture geometries. *Journal of Contaminant Hydrology* 27, 263–283. [https://doi.org/10.1016/S0169-7722\(96\)00096-4](https://doi.org/10.1016/S0169-7722(96)00096-4)
- Olkiewicz, O., 1979. Geology and fracture system at Stripa.
- Olson, J.E., Hennings, P.H., Laubach, S.E., 1998. Integrating Wellbore Data and Geomechanical Modeling for Effective Characterization of Naturally Fractured Reservoirs. Presented at the SPE/ISRM Rock Mechanics in Petroleum Engineering, p. SPE-47352-MS. <https://doi.org/10.2118/47352-MS>
- OpenCV, 2024. Feature Matching.
- Osmundsen, P.T., Andersen, T.B., 2001. The middle Devonian basins of western Norway: sedimentary response to large-scale transtensional tectonics? *Tectonophysics* 332, 51–68. [https://doi.org/10.1016/S0040-1951\(00\)00249-3](https://doi.org/10.1016/S0040-1951(00)00249-3)
- O'Sullivan, R.B., 1981. New Mexico Geological Society. <https://doi.org/10.3133/oc113>

- Ozturk, H., Saricam, I.T., 2017. Core Segmentation and Fracture Path Detection Using Shadows. *Journal of Image and Graphics* 6, 69–73.
<https://doi.org/10.18178/JOIG.6.1.69-73>
- Palamakumbura, R., Krabbendam, M., Whitbread, K., Arnhardt, C., 2020. Data acquisition by digitizing 2-D fracture networks and topographic lineaments in geographic information systems: further development and applications. *Solid Earth* 11, 1731–1746.
- Peacock, D., Sanderson, D., Bastesen, E., Rotevatn, A., Storstein, T., 2019. Causes of bias and uncertainty in fracture network analysis. *Norwegian Journal of Geology* 99. <https://doi.org/10.17850/njg99-1-06>
- Peacock, D., Sanderson, D., Magán, M., 2023. Superposed fracture networks. *Geological Magazine* 160, 1817–1831.
- Peacock, D.C.P., Sanderson, D.J., Rotevatn, A., 2018. Relationships between fractures. *Journal of Structural Geology* 106, 41–53.
<https://doi.org/10.1016/j.jsg.2017.11.010>
- Peron-Pinvidic, G., Osmundsen, P.T., 2020. From orogeny to rifting: insights from the Norwegian ‘reactivation phase.’ *Scientific Reports* 10, 14860.
- Physics LibreTexts, 2024. 2.7: The Camera.
- Piper, J., 2007. Palaeomagnetism of the Loch Doon Granite Complex, Southern Uplands of Scotland: the Late Caledonian palaeomagnetic record and an Early Devonian episode of true polar wander. *Tectonophysics* 432, 133–157.
- Potts, G.J., Reddy, S.M., 2000. Application of younging tables to the construction of relative deformation histories—1: Fracture systems. *Journal of Structural Geology* 22, 1473–1490. [https://doi.org/10.1016/S0191-8141\(00\)00044-4](https://doi.org/10.1016/S0191-8141(00)00044-4)

- Prabhakaran, R., Bruna, P.-O., Bertotti, G., Smeulders, D., 2019. An automated fracture trace detection technique using the complex shearlet transform. *Solid Earth* 10, 2137–2166. <https://doi.org/10.5194/se-10-2137-2019>
- Prabhakaran, R., Urai, J.L., Bertotti, G., Weismüller, C., Smeulders, D.M.J., 2021a. Large-scale natural fracture network patterns: Insights from automated mapping in the Lilstock (Bristol Channel) limestone outcrops. *Journal of Structural Geology* 150, 104405. <https://doi.org/10.1016/j.jsg.2021.104405>
- Pruess, K., Narasimhan, T., 1982. On fluid reserves and the production of superheated steam from fractured, vapor-dominated geothermal reservoirs. *Journal of Geophysical Research: Solid Earth* 87, 9329–9339.
- Redfield, T.F., Osmundsen, P.T., 2009. The Tjellefonna fault system of Western Norway: Linking late-Caledonian extension, post-Caledonian normal faulting, and Tertiary rock column uplift with the landslide-generated tsunami event of 1756. *Tectonophysics* 474, 106–123. <https://doi.org/10.1016/j.tecto.2009.02.006>
- Reeves, D.M., Parashar, R., Zhang, Y., Rahman, R., 2012. Hydrogeologic characterization of fractured rock masses intended for disposal of radioactive waste. INTECH Open Access Publisher.
- Rizzo, R.E., Healy, D., Farrell, N.J., Heap, M.J., 2017. Riding the right wavelet: Quantifying scale transitions in fractured rocks. *Geophysical Research Letters* 44, 11–808.
- Rizzo, R.E., Inskip, N.F., Fazeli, H., Betlem, P., Bisdom, K., Kampman, N., Snippe, J., Senger, K., Doster, F., Busch, A., 2024. Modelling geological CO₂ leakage: Integrating fracture permeability and fault zone outcrop analysis. *International Journal of Greenhouse Gas Control* 133, 104105. <https://doi.org/10.1016/j.ijggc.2024.104105>

- Rohbaugh, M.B.J.; D., 2002. Estimating fracture trace intensity, density, and mean length using circular scan lines and windows. *The American Association of Petroleum Geologists* 86, 2089–2104.
- Rosenfeld, A., 1976. *Digital picture processing*. Academic press.
- Rost, E., Hecker, C., Schodlok, M.C., Van der Meer, F.D., 2018. Rock sample surface preparation influences thermal infrared spectra. *Minerals* 8, 475.
- Rountree, C.L., Kalia, R.K., Lidorikis, E., Nakano, A., Van Brutzel, L., Vashishta, P., 2002. Atomistic aspects of crack propagation in brittle materials: Multimillion atom molecular dynamics simulations. *Annual Review of Materials Research* 32, 377–400.
- Rowlands, D.A., 2020. *Physics of Digital Photography (Second Edition)*. IOP Publishing. <https://doi.org/10.1088/978-0-7503-2558-5>
- Sabins, F.F., 1999. Remote sensing for mineral exploration. *Ore Geology Reviews* 14, 157–183. [https://doi.org/10.1016/S0169-1368\(99\)00007-4](https://doi.org/10.1016/S0169-1368(99)00007-4)
- Saibi, H., Bersi, M., Mia, M.B., Saadi, N.M., Bloushi, K.M.S.A., Avakian, R.W., 2018. Applications of Remote Sensing in Geoscience, in: *Recent Advances and Applications in Remote Sensing*. InTech.
- Samsu, A., Cruden, A.R., Micklethwaite, S., Grose, L., Vollgger, S.A., 2020. Scale matters: the influence of structural inheritance on fracture patterns. *Journal of Structural Geology* 130, 103896.
- Sanderson, D.J., 2016. Field-based structural studies as analogues to sub-surface reservoirs. *Geological Society, London, Special Publications* 436, 207–217.
- Sanderson, D.J., Nixon, C.W., 2015. The use of topology in fracture network characterization. *Journal of Structural Geology* 72, 55–66. <https://doi.org/10.1016/j.jsg.2015.01.005>

- Sarkar, S., Toksoz, M.N., Burns, D.R., 2004. Fluid flow modeling in fractures. Massachusetts Institute of Technology. Earth Resources Laboratory.
- Scaioni, M., Barazzetti, L., Brumana, R., Cuca, B., Fassi, F., Prandi, F., 2009. RC-Heli and Structure & Motion Techniques for the 3-D Reconstruction of a Milan Dome Spire. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 1–8.
- Scheiber, T., Fredin, O., Viola, G., Jarna, A., Gasser, D., Łapińska-Viola, R., 2015. Manual extraction of bedrock lineaments from high-resolution LiDAR data: methodological bias and human perception. *GFF* 137, 362–372.
<https://doi.org/10.1080/11035897.2015.1085434>
- Schöberl, M., Föbel, S., Bloss, H., Kaup, A., 2009. Modeling of image shutters and motion blur in analog and digital camera systems. Presented at the 2009 16th IEEE International Conference on Image Processing (ICIP), IEEE, pp. 3457–3460.
- Schofield, N., Newton, R., Thackrey, S., Watson, D., Jolley, D., Morley, C., 2021. Linking surface and subsurface volcanic stratigraphy in the Turkana Depression of the East African Rift system. *Journal of the Geological Society* 178, jgs2020-110.
- Schopf, J.M., 1960. Field description and sampling of coal beds. US Govt. Print. Off.,.
- Schultz, R.A. (Ed.), 2019. Introduction to Geologic Structural Discontinuities, in: *Geologic Fracture Mechanics*. Cambridge University Press, Cambridge, pp. 1–26. <https://doi.org/10.1017/9781316996737.001>
- Seetharam, S.C., Perko, J., Jacques, D., Mallants, D., 2014. Influence of fracture networks on radionuclide transport from solidified waste forms. *Nuclear Engineering and Design* 270, 162–175.
<https://doi.org/10.1016/j.nucengdes.2013.12.048>

- Seranne, M., 1992. Late Paleozoic kinematics of the Møre-Trøndelag Fault Zone and adjacent areas, central Norway. *Norsk Geologisk Tidsskrift* 72, 141–158.
- Shakhatreh, H., Sawalmeh, A.H., Al-Fuqaha, A., Dou, Z., Almaita, E., I. Khalil, N. S. Othman, A. Khreishah, M. Guizani, 2019. Unmanned Aerial Vehicles (UAVs): A Survey on Civil Applications and Key Research Challenges. *IEEE Access* 7, 48572–48634. <https://doi.org/10.1109/ACCESS.2019.2909530>
- Shapiro, L.G., 1992. Computer and robot vision. Addison-Wesley.
- Sibson, R.H., 1996. Structural permeability of fluid-driven fault-fracture meshes. *Journal of Structural Geology* 18, 1031–1042. [https://doi.org/10.1016/0191-8141\(96\)00032-6](https://doi.org/10.1016/0191-8141(96)00032-6)
- Siler, D.L., Hinz, N.H., Faulds, J.E., 2018. Stress concentrations at structural discontinuities in active fault zones in the western United States: Implications for permeability and fluid flow in geothermal fields. *GSA Bulletin* 130, 1273–1288. <https://doi.org/10.1130/B31729.1>
- Simon, G., Vakulya, G., Rátosi, M., 2022. The way to modern shutter speed measurement methods: A historical overview. *Sensors* 22, 1871.
- Singh, D.K., Hoskere, V., 2023. Post Disaster Damage Assessment Using Ultra-High-Resolution Aerial Imagery with Semi-Supervised Transformers. *Sensors* 23, 8235.
- Siratovich, P.A., von Aulock, F.W., Lavallée, Y., Cole, J.W., Kennedy, B.M., Villeneuve, M.C., 2015. Thermoelastic properties of the Rotokawa Andesite: A geothermal reservoir constraint. *Journal of Volcanology and Geothermal Research* 301, 1–13. <https://doi.org/10.1016/j.jvolgeores.2015.05.003>
- Stephens, Michael B., 2020. Upper and uppermost thrust sheets in the Caledonide orogen, Sweden: outboard oceanic and exotic continental terranes, in: Stephens, M. B., Bergman Weihed, J. (Eds.), *Sweden: Lithotectonic Framework*,

- Tectonic Evolution and Mineral Resources. Geological Society of London, p. 0.
<https://doi.org/10.1144/M50-2019-12>
- Steventon, M.J., Jackson, C.A.-L., Hall, M., Ireland, M.T., Munafo, M., Roberts, K.J.,
2022. Reproducibility in Subsurface Geoscience. *Earth Science, Systems and Society* 2.
- Stock, B., Frampton, A., 2023. Fracture aperture generation using surface scan measurements of natural rock samples. ESS Open Archive.
- Tartaglia, G., Ceccato, A., Scheiber, T., van der Lelij, R., Schönenberger, J., Viola, G.,
2022. Time-constrained multiphase brittle tectonic evolution of the onshore mid-Norwegian passive margin. *GSA Bulletin* 135, 621–642.
<https://doi.org/10.1130/B36312.1>
- Tedersoo, L., Küngas, R., Oras, E., Köster, K., Eenmaa, H., Leijen, Ä., Pedaste, M., Raju, M., Astapova, A., Lukner, H., Kogermann, K., Sepp, T., 2021. Data sharing practices and data availability upon request differ across scientific disciplines. *Scientific Data* 8, 192. <https://doi.org/10.1038/s41597-021-00981-0>
- Thiele, S.T., Grose, L., Samsu, A., Micklethwaite, S., Vollgger, S.A., Cruden, A.R., 2017. Rapid, semi-automatic fracture and contact mapping for point clouds, images and geophysical data. *Solid Earth* 8, 1241–1253. <https://doi.org/10.5194/se-8-1241-2017>
- Tindle, A.G., Pearce, J.A., 1981. Petrogenetic modelling of in situ fractional crystallization in the zoned Loch Doon pluton, Scotland. *Contributions to Mineralogy and Petrology* 78, 196–207. <https://doi.org/10.1007/BF00373781>
- Titus, S.J., Clark, R., Tikoff, B., 2005. Geologic and geophysical investigation of two fine-grained granites, Sierra Nevada Batholith, California: Evidence for structural controls on emplacement and volcanism. *Geological Society of America Bulletin* 117, 1256–1271.

- Torre, V., Poggio, T., 1983. Differential operators for edge detection.
- Toth, C., Józków, G., 2016. Remote sensing platforms and sensors: A survey. *ISPRS Journal of Photogrammetry and Remote Sensing* 115, 22–36.
- Trollvik, J.A., 2014. Produktark: Digitale Ortofoto.
- Tsai, C.-H., Lin, Y.-C., 2017. An accelerated image matching technique for UAV orthoimage registration. *ISPRS Journal of Photogrammetry and Remote Sensing* 128, 130–145.
- Turner, A.K., 2006. Challenges and trends for geological modelling and visualisation. *Bulletin of Engineering Geology and the Environment* 65, 109–127.
<https://doi.org/10.1007/s10064-005-0015-0>
- Twiss, R.J., Moores, E.M., 2007. Fractures and Joints, in: J. Carey Publishing Service (Ed.), *Structural Geology*. W.H. Freeman and Company, New York.
- Unruh, J.R., 1991. The uplift of the Sierra Nevada and implications for late Cenozoic epeirogeny in the western Cordillera. *Geological Society of America Bulletin* 103, 1395–1404.
- Uotinen, L., Janiszewski, M., Baghbanan, A., Caballero Hernandez, E., Oraskari, J., Munukka, H., Szydlowska, M., Rinne, M., 2020. Photogrammetry for recording rock surface geometry and fracture characterization.
- U.S. Geological Survey, 2024. Digital Geologic-GIS Map of Yosemite National Park and Vicinity, California.
- Vandergraaf, T.T., Drew, D.J., Archambault, D., Ticknor, K.V., 1997. Transport of radionuclides in natural fractures: some aspects of laboratory migration experiments. *Journal of Contaminant Hydrology* 26, 83–95.
[https://doi.org/10.1016/S0169-7722\(96\)00060-5](https://doi.org/10.1016/S0169-7722(96)00060-5)
- Vasuki, Y., Holden, E.-J., Kovesi, P., Micklethwaite, S., 2014. Semi-automatic mapping of geological Structures using UAV-based photogrammetric data: An image

- analysis approach. *Computers & Geosciences* 69, 22–32.
<https://doi.org/10.1016/j.cageo.2014.04.012>
- Waldron, J., Snyder, M., 2020. Geological Structures: A practical introduction.
- Waldron, J.W.F., McCausland, P.J.A., Barr, S.M., Schofield, D.I., Reusch, D., Wu, L., 2022. Terrane history of the Iapetus Ocean as preserved in the northern Appalachians and western Caledonides. *Earth-Science Reviews* 233, 104163.
<https://doi.org/10.1016/j.earscirev.2022.104163>
- Walter, C., Faraj, F., Fotopoulos, G., Braun, A., 2022. Augmenting geological field mapping with real-time, 3-D digital outcrop scanning and modeling. *Geosphere* 18, 762–779.
- Wang, H., 2019. Hydraulic fracture propagation in naturally fractured reservoirs: Complex fracture or fracture networks. *Journal of Natural Gas Science and Engineering* 68, 102911. <https://doi.org/10.1016/j.jngse.2019.102911>
- Watkins, H., Bond, C.E., Healy, D., Butler, R.W.H., 2015. Appraisal of fracture sampling methods and a new workflow to characterise heterogeneous fracture networks at outcrop. *Journal of Structural Geology* 72, 67–82.
<https://doi.org/10.1016/j.jsg.2015.02.001>
- Watts Lee M., Holdsworth Robert E., Roberts David, Sleight Janine M., Walker Richard J., 2023. Structural evolution of the reactivated Møre–Trøndelag Fault Complex, Fosen Peninsula, Norway. *Journal of the Geological Society* 180, jgs2022-139. <https://doi.org/10.1144/jgs2022-139>
- Weismüller, C., Prabhakaran, R., Passchier, M., Urai, J.L., Bertotti, G., Reicherter, K., 2020. Mapping the fracture network in the Lilstock pavement, Bristol Channel, UK: manual versus automatic. *Solid Earth* 11, 1773–1802.
<https://doi.org/10.5194/se-11-1773-2020>

- Williams, R., Brasington, J., Vericat, D., Hicks, D., 2014. Hyperscale terrain modelling of braided rivers: fusing mobile terrestrial laser scanning and optical bathymetric mapping. *Earth Surface Processes and Landforms* 39, 167–183.
- Wilson, R.W., McCaffrey, K.J.W., Holdsworth, R.E., Imber, J., Jones, R.R., Welbon, A.I.F., Roberts, D., 2006. Complex fault patterns, transtension and structural segmentation of the Lofoten Ridge, Norwegian margin: Using digital mapping to link onshore and offshore geology. *Tectonics* 25.
<https://doi.org/10.1029/2005TC001895>
- Xie, Y., Sha, Z., Yu, M., 2008. Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology* 1, 9–23. <https://doi.org/10.1093/jpe/rtm005>
- Yuguchi, T., Izumino, Y., Sasao, E., 2021. Genesis and development processes of fractures in granite: Petrographic indicators of hydrothermal alteration. *Plos one* 16, e0251198.
- Zeng, Q., Deng, F., Zhang, Y., Shao, Y., Ye, Y., Wang, W., Hu, Y., 2020. Automatic Extraction of Fractures in Digital Geological Outcrop of Carbonate Rocks and Its Application, in: Lin, J. (Ed.), *Proceedings of the International Field Exploration and Development Conference 2019*. Springer Nature Singapore, Singapore, pp. 2297–2309.
- Zhang, J., Xu, Shilin, Zhao, Y., Sun, J., Xu, Shibiao, Zhang, X., 2023. Aerial orthoimage generation for UAV remote sensing. *Information Fusion* 89, 91–120.
- Zhang, W., Wu, T., Li, Z., Li, Y., Qiu, A., Shi, Y., 2021. Automatic Detection of Fractures Based on Optimal Path Search in Well Logging Images. *Journal of Sensors* 2021, 1–10. <https://doi.org/10.1155/2021/5577084>
- Zhou, C.-B., Chen, Y.-F., Hu, R., Yang, Z., 2023. Groundwater flow through fractured rocks and seepage control in geotechnical engineering: Theories and

practices. *Journal of Rock Mechanics and Geotechnical Engineering* 15, 1–36.
<https://doi.org/10.1016/j.jrmge.2022.10.001>

Zimik, H.V., Thiele, S.T., Khanna, P.K., 2023. Outcrop analogue constraints on subsurface reservoir properties of the Puga geothermal field, NW Himalaya. Research Square. <https://doi.org/10.21203/rs.3.rs-2812131/v1>

Ziou, D., Tabbone, S., 1993. A multi-scale edge detector. *Pattern Recognition* 26, 1305–1314. [https://doi.org/10.1016/0031-3203\(93\)90137-L](https://doi.org/10.1016/0031-3203(93)90137-L)