

# Optimizing Autonomous Drone Deployment Strategies to Improve Geological Structural Mapping Accuracy in Complex Mines

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**Abstract:** Accurate geological structural mapping remains a critical requirement for safe, efficient, and economically viable mining operations, particularly in underground and open-pit environments characterized by irregular geometries and hazardous access conditions. Traditional surveying techniques, though reliable, are constrained by line-of-sight limitations, safety risks, and insufficient data density for modelling increasingly complex ore bodies. Autonomous drones provide a transformative alternative, offering continuous, high-resolution data acquisition with minimal human exposure. However, realizing their full potential requires deployment strategies that optimize flight paths, sensor positioning, environmental adaptation, and data-fusion efficiency. This study examines how autonomous drone systems can be strategically deployed to maximize structural-mapping accuracy in complex mines. The analysis begins by reviewing the challenges posed by variable lighting, dust interference, constrained tunnels, GPS-denied zones, and unstable geological surfaces. It then evaluates advanced autonomy modules including SLAM-based navigation, adaptive obstacle avoidance, and multi-sensor calibration to determine how these capabilities influence mapping fidelity. A key emphasis is placed on optimizing flight-trajectory planning using probabilistic models, geospatial uncertainty reduction techniques, and AI-driven waypoint selection tailored to local geological complexity. The study further investigates how multi-modal sensor integration, including LiDAR, hyperspectral imaging, photogrammetry, and magnetometric sensing, enhances the detection of fault planes, discontinuities, joint sets, and micro-fracture networks. Simulation-driven optimization approaches are compared with field-tested deployment patterns to establish best-practice strategies for achieving comprehensive spatial coverage with minimal redundancy. The findings demonstrate that optimized autonomous-drone deployment significantly improves structural-mapping resolution, reduces data-collection time, and enhances operational safety ultimately enabling mining organizations to make faster, more reliable, and data-driven geotechnical decisions.

**Keywords:** Autonomous drones; Geological structural mapping; Mine surveying; SLAM navigation; LiDAR integration; Geospatial optimization

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## 1. INTRODUCTION

### 1.1 Evolution of Geological Mapping Technologies in Mining

Geological mapping has undergone substantial transformation as mining operations expanded into deeper and structurally complex environments [1]. Early mapping practices relied heavily on manual field observation, compass readings, and hand-drawn sketches, which provided foundational geological insights but lacked precision and repeatability in dynamic mine settings [2]. The introduction of geospatial technologies, including total stations, laser scanners, and digital photogrammetry, significantly enhanced spatial accuracy while enabling three-dimensional representation of geological structures [3]. Yet, even these semi-automated tools demanded extensive human presence in hazardous sections of mines, limiting data-collection windows and slowing geological interpretation cycles [4]. As mines became more mechanized and targeted deeper ore bodies, the industry increasingly sought faster, safer, and higher-resolution methods capable of capturing continuously changing subsurface conditions [5]. These technological shifts established the groundwork for the emergence of autonomous aerial systems as an important next step in mine-mapping evolution.

### 1.2 Limitations of Conventional Structural-Mapping Techniques

Conventional structural-mapping approaches, despite their decades of use, present several constraints that hinder accuracy and operational efficiency in modern mining environments [6]. Manual observation is inherently subjective, with interpretations varying based on geologist experience, lighting conditions, and physical accessibility of rock exposures [7]. Laser scanners and photogrammetry improve precision but require tripod setups, stable vantage points, and substantial time during data capture conditions that are often difficult to guarantee in unstable stopes and production areas [8]. Additionally, many traditional tools cannot operate effectively in dust-laden, GPS-denied, or poorly ventilated zones, forcing operators to compromise data completeness or safety [9]. These constraints delay the integration of structural data into mine-planning workflows, lowering the responsiveness of geotechnical decisions and increasing operational risk [10]. By exposing the gaps left by conventional tools, these limitations highlight the need for technologies capable of delivering high-resolution data without requiring prolonged human presence in hazardous zones.

### **1.3 Rise of Autonomous Aerial Systems in Subsurface and Surface Mines**

Autonomous aerial systems have rapidly emerged as an innovative solution to longstanding geological-mapping constraints, offering fast, flexible, and high-resolution data acquisition in both surface and underground mines [5]. Unlike manually operated drones, fully autonomous systems navigate confined, GPS-denied spaces using onboard perception and obstacle-avoidance algorithms, enabling safe mapping where human access is limited [8]. These drones generate dense point clouds, structural orientations, and geological textures in minutes rather than hours [3]. Their ability to repeatedly scan the same areas creates consistent datasets for change-detection analysis, improving geotechnical awareness and operational planning [10].

### **1.4 Research Purpose, Scope, and Contributions**

This article examines how autonomous aerial systems enhance structural-mapping accuracy, reduce underground exposure risks, and improve the responsiveness of geological decision-making [4]. It evaluates system capabilities across navigation, perception, and data-processing workflows, comparing them with conventional structural-mapping practices [1]. The study also outlines operational constraints, integration challenges, and the data-quality considerations necessary for adoption in complex mining environments [7]. By synthesizing technological, geological, and operational perspectives, the article contributes a framework for assessing when and how autonomous drones can replace or complement traditional subsurface-mapping methods [9].

## **2. MINING ENVIRONMENTS AND STRUCTURAL MAPPING REQUIREMENTS**

### **2.1 Geological Complexity in Underground vs Open-Pit Mines**

Geological complexity differs substantially between underground and open-pit mines, shaping both the type and resolution of structural data required for effective mapping [14]. Underground mines typically expose fractured host rock, irregular excavation geometries, and limited wall continuity, making structural interpretation dependent on short-range and high-density observations [9]. These conditions demand precise characterization of folding, discontinuity spacing, and near-face rock conditions that influence both stability and blasting design [7]. Open-pit environments, by contrast, offer broader exposure of lithological boundaries and large-scale fault systems, enabling wider spatial mapping and long-range structural correlation across benches [15]. However, open pits introduce their own challenges: variable lighting, large elevation differences, and extensive dust plumes that distort data capture during drilling and blasting cycles [10]. As pits deepen, slope angles and bench heights create geometric occlusions that require multi-viewpoint imaging to ensure full coverage [12]. The contrast between confined underground drifts and expansive open-pit earthworks demonstrates the

need for adaptive mapping platforms capable of functioning across drastically different geometries, exposure conditions, and rock-mass behaviours [16]. Understanding these complexities informs the operational requirements that autonomous aerial systems must meet.

### **2.2 Structural Features of Interest: Faults, Joints, Bedding Planes, Discontinuities**

Accurate characterization of structural features remains central to geological mapping because these elements directly influence rock-mass integrity, fragmentation behaviour, and long-term mine stability [11]. Faults often control groundwater flow and stress redistribution, requiring high-resolution orientation data to guide ground-support design and slope-monitoring strategies [7]. Joints and joint sets, which frequently dominate rock-mass behaviour in both underground and open-pit contexts, must be mapped for spacing, persistence, roughness, and aperture characteristics that affect excavation performance [13]. Bedding planes in sedimentary environments create anisotropies that strongly govern shear strength and bench-stability outcomes, especially when intersecting fault networks or weathering zones [14]. Smaller discontinuities including fractures, shears, and micro-cracks contribute to localized instability and influence blast-response patterns, making their detection crucial for geotechnical modeling and stope design [15]. Traditional tools often miss subtle orientation changes or discontinuities in obscured areas, reinforcing the value of autonomous systems capable of capturing dense, multi-angle imagery and point-cloud datasets [16]. These structural elements collectively define the minimum geological-data quality required for safe and efficient mining operations.

### **2.3 Environmental Constraints: Dust, Light, Airflow, GPS-Denied Navigation**

Mining environments impose environmental constraints that challenge conventional mapping systems and require advanced autonomy for reliable data acquisition [8]. Underground operations are commonly affected by dust suspensions generated during drilling, mucking, and blasting, which scatter photons and degrade the quality of optical and LiDAR measurements [14]. Low-light or uneven illumination further complicates imaging, particularly in stopes, crosscuts, and declines where shadows and reflective surfaces distort geological textures [10]. Airflow variations from ventilation systems introduce unpredictable drone-stability issues, requiring robust flight-control algorithms capable of compensating for turbulence in narrow drifts [12]. GPS-denied navigation represents another core challenge: underground and deep-pit geometries block satellite signals, eliminating standard positional references used by most commercial drones [9]. As a result, alternative localization approaches such as visual-inertial odometry, simultaneous localization and mapping (SLAM), and onboard obstacle-avoidance sensors are essential to ensure safe navigation and high-precision data capture [15]. These environmental constraints underscore why mining represents one of the most

technically demanding settings for aerial mapping technologies [16].

#### **2.4 Safety, Accessibility, and Data-Density Requirements**

Safety considerations in mining environments require mapping technologies that minimize human exposure to hazardous zones while still producing geotechnically actionable data [13]. Conventional mapping often forces geologists into unstable stopes, loose-rock areas, or steep pit walls where rockfalls and ventilation failures pose significant risks [7]. Autonomous systems mitigate this by enabling remote acquisition of dense, near-face structural data without requiring personnel to enter dangerous locations [14]. Accessibility limitations such as narrow drifts, collapsed zones, or high benches further reinforce the need for compact aerial platforms capable of maneuvering in restricted geometries [12]. High data density is critical for structural modelling, requiring drones to capture fine discontinuities, bedding variations, and rock-mass textures with minimal shadowing or occlusion [10]. Meeting these density requirements supports more accurate geotechnical simulations, slope analyses, and excavation planning [15]. These combined safety and data-quality imperatives define the operational performance standards for autonomous systems in modern mines [16].

### **3. AUTONOMOUS DRONE TECHNOLOGIES FOR GEOSTRUCTURAL MAPPING**

#### **3.1 Drone Navigation Systems: LiDAR SLAM, Visual SLAM, Inertial Navigation**

Reliable navigation is the foundation of autonomous drone performance in mining environments, where GPS signals are frequently absent and geometric constraints are extreme [17]. LiDAR-based simultaneous localization and mapping (SLAM) is widely regarded as one of the most robust solutions because it constructs real-time 3D maps using dense point clouds, enabling drones to navigate through tunnels, stopes, and shaft intersections with high positional accuracy [20]. LiDAR SLAM is resilient in low-light and dusty conditions, making it particularly suited for deep underground operations where optical systems struggle [15]. Visual SLAM, by contrast, uses camera imagery to estimate motion and map surroundings; although cost-effective and computationally lighter than LiDAR, it is more vulnerable to occlusions, uneven illumination, and particulate interference [14]. Modern drones often combine LiDAR and visual SLAM into hybrid systems to compensate for each approach's limitations, improving both redundancy and environmental adaptability [21]. Inertial navigation systems (INS) complement SLAM pipelines by providing rapid motion estimates using accelerometers and gyroscopes, allowing the drone to maintain stability during sudden lighting changes, dust bursts, or high-velocity airflow from mine ventilation [19]. While INS alone suffers from drift over time, fusing INS with LiDAR or visual SLAM significantly reduces cumulative

error, ensuring consistent localization throughout multi-minute autonomous flights [22]. Together, these navigation technologies form an integrated autonomy stack capable of supporting precise geological-mapping operations in complex mining environments [16].

#### **3.2 Sensor Payloads for Geological Mapping**

##### **3.2.1 LiDAR Scanners**

LiDAR scanners generate dense three-dimensional point clouds essential for structural-geology applications, capturing faults, joints, foliation surfaces, and discontinuities with high spatial fidelity [18]. Their ability to function under low-light conditions and penetrate dust better than optical sensors makes them ideal for underground mines where environmental constraints are severe [21]. Short-range LiDAR units provide millimetre-level resolution required for near-face mapping, while long-range units enable bench-scale coverage in open pits [14]. The real-time performance of LiDAR improves drone stability by feeding SLAM algorithms with continuous depth information, reducing localization drift and avoiding collision events [17]. These characteristics make LiDAR one of the most versatile and reliable sensors for autonomous subsurface mapping [20].

##### **3.2.2 Photogrammetry and HDR Imaging**

Photogrammetry uses overlapping images to reconstruct textured 3D models, offering rich geological detail for structural interpretation, lithology discrimination, and rock-mass classification [16]. High Dynamic Range (HDR) imaging extends this capability by capturing visual data across extreme lighting contrasts a critical advantage in underground drifts where illumination is sparse or inconsistent [18]. Although photogrammetry is sensitive to dust and requires adequate lighting, it provides colour-accurate imagery that LiDAR cannot replicate, allowing geologists to classify alteration zones, mineral patterns, and subtle bedding features [22]. The low cost and high resolution of photogrammetry make it an effective complementary sensor in autonomous systems [15].

##### **3.2.3 Hyperspectral and Multispectral Sensors**

Hyperspectral and multispectral sensors capture reflectance signatures across numerous wavelengths, enabling identification of minerals, alteration halos, and moisture conditions that are not observable through RGB imagery alone [19]. These sensors enhance ore-body modelling by detecting spectral variations linked to mineral composition, oxidation levels, or hydrothermal alteration [21]. In open-pit mines, hyperspectral data supports slope-stability assessment by highlighting weathered or weak zones, while in underground environments it helps identify lithological transitions obscured by poor lighting [14]. Although computationally intensive, spectral data offers transformative value when fused with LiDAR or photogrammetric models, producing detailed geological layers aligned with structural data [20].

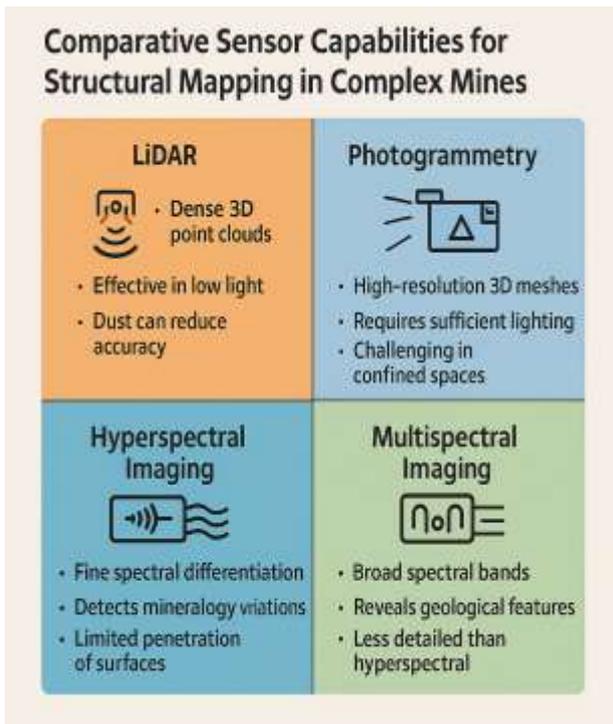


Figure 1: Comparative Sensor Capabilities for Structural Mapping in Complex Mines.

### 3.3 Real-Time Environmental Adaptation: Obstacle Avoidance, Drift Stabilization

Autonomous drones must adapt in real time to sudden environmental changes, making obstacle-avoidance and drift-stabilization capabilities essential for safe and effective geological mapping [22]. Obstacle-avoidance systems rely on fused LiDAR, stereo vision, and ultrawideband ranging to detect rock walls, equipment, ventilation ducts, and mesh screens that crowd underground corridors [16]. These systems compute avoidance maneuvers within milliseconds, ensuring uninterrupted mapping even in tight stopes or unsupported areas [18]. Drift stabilization compensates for turbulent airflow produced by fans or blasting operations, using INS-SLAM fusion to adjust flight controls rapidly when the drone encounters pressure fluctuations [20]. Combined, these adaptation mechanisms protect both the drone and the integrity of the data being captured, ensuring reliable mapping under harsh mining conditions [14].

## 4. OPTIMIZATION MODELS FOR DRONE DEPLOYMENT IN COMPLEX MINES

### 4.1 Flight-Path Optimization Algorithms (Probabilistic, Deterministic, Hybrid)

Flight-path optimization is central to maximizing mapping efficiency, safety, and data fidelity in complex mining environments where confined geometries and unstable conditions restrict maneuverability [23]. Probabilistic algorithms, such as Rapidly-Exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM), are widely applied due to

their ability to explore uncertain spaces and generate feasible collision-free trajectories under dynamic environmental constraints [20]. These models evaluate multiple potential paths, selecting those with the lowest estimated risk and most efficient coverage, making them particularly effective in stopes and narrow drifts where unexpected obstructions are common [27]. Deterministic algorithms, including A\* and Dijkstra-based path planners, generate highly predictable and repeatable trajectories suitable for pre-mapped open-pit benches or underground haulageways with stable geometry [25]. Although deterministic planners provide reliable paths, they lack the flexibility needed for rapidly changing conditions. Hybrid optimization models integrate the strengths of both approaches, combining deterministic exploration with probabilistic sampling to produce robust, adaptive flight paths that react to evolving dust, ventilation airflow, and illumination changes [29]. Many hybrid systems use real-time sensor feedback especially LiDAR-SLAM fusion to iteratively adjust trajectories as the drone encounters new obstacles or geological features of interest [21]. This layered approach solves practical challenges in underground mapping by tailoring trajectory-generation methods to environmental variability, sensor ranges, and mission objectives [30]. Ultimately, flight-path optimization ensures safe operation, maximizes structural feature capture, and enhances geotechnical interpretation accuracy in demanding mining conditions [22].

### 4.2 Spatial-Coverage Models: Overlap Ratios, Path Redundancy Minimization

Spatial-coverage optimization ensures that structural and geological datasets maintain sufficient density for precise feature extraction while eliminating unnecessary overlap that increases flight duration and battery depletion [28]. Coverage models determine the optimal camera or LiDAR sweep patterns, calculating overlap ratios required for reliable photogrammetric reconstruction or SLAM-based map consistency [24]. In underground environments, confined geometries demand higher overlap (often exceeding 70%) to compensate for occlusions and uneven illumination, while open-pit benches can operate effectively at lower ratios due to wider exposure and greater sensor standoff distances [26]. Redundancy-minimization algorithms identify zones already captured at adequate resolution and redirect drones toward unmapped areas, improving mission efficiency [23]. Some models use grid-based partitioning, where the mine geometry is divided into small sectors that the drone must cover, while others employ continuous-surface optimization that adapts coverage density based on expected structural complexity [21]. In more advanced workflows, adaptive-coverage systems dynamically change flight altitude, angle, or sensor frame rate based on SLAM-inferred geometric roughness or feature density [29]. These tools reduce computational overhead and processing time while ensuring geological and geotechnical data remain accurate and complete [30].

**Table 1: Comparison of Flight-Path Optimization Models and Their Computational Requirements**

Model Type	Example Algorithms	Core Strengths	Limitations in Mining Environments	Computational Requirements	Best-Fit Use Cases
<b>Deterministic Models</b>	A*, Dijkstra, Graph-Search Planners	<ul style="list-style-type: none"> <li>Highly predictable</li> <li>Repeatable paths</li> <li>Good for structured environments</li> </ul>	<ul style="list-style-type: none"> <li>Poor adaptability to dust, airflow, or unexpected obstacles</li> <li>Dependent on pre-mapped geometry</li> </ul>	<b>Low–Moderate</b> CPU-friendly; runs on embedded computers	<ul style="list-style-type: none"> <li>Stable haulageways</li> <li>Benchmarking in open pits</li> </ul>
<b>Probabilistic Models</b>	RRT, RRT*, PRM	<ul style="list-style-type: none"> <li>Strong exploration in unknown spaces</li> <li>Good for irregular and evolving geometries</li> </ul>	<ul style="list-style-type: none"> <li>Can produce suboptimal paths</li> <li>Sensitive to noise in SLAM inputs</li> </ul>	<b>Moderate–High</b> Requires repeated sampling and tree expansion	<ul style="list-style-type: none"> <li>Irregular drifts</li> <li>Blind corners</li> <li>Dust-affected underground tunnels</li> </ul>
<b>Hybrid Models</b>	A* + RRT*, PRM-guided D*	<ul style="list-style-type: none"> <li>Balanced performance</li> <li>Adaptive yet structured</li> <li>Highly robust to dynamics</li> </ul>	<ul style="list-style-type: none"> <li>Higher complexity</li> <li>Requires tight sensor-planner integration</li> </ul>	<b>High</b> Needs CPU + occasional GPU acceleration for SLAM integration	<ul style="list-style-type: none"> <li>Deep underground mapping</li> <li>Hazardous stopes</li> <li>Mixed-geometry flight zones</li> </ul>

Model Type	Example Algorithms	Core Strengths	Limitations in Mining Environments	Computational Requirements	Best-Fit Use Cases
		<ul style="list-style-type: none"> <li>Smooth trajectories</li> <li>Strong for high-precision standoff control</li> </ul>	<ul style="list-style-type: none"> <li>Requires accurate gradients</li> <li>Struggles in cluttered or unmapped areas</li> </ul>		
<b>Continuous Optimization Models</b>	Gradient-based, Nonlinear Optimization, CHOMP-style planners	<ul style="list-style-type: none"> <li>Smooth trajectories</li> <li>Strong for high-precision standoff control</li> </ul>	<ul style="list-style-type: none"> <li>Requires accurate gradients</li> <li>Struggles in cluttered or unmapped areas</li> </ul>	<b>High–Very High</b> Often GPU-accelerated	<ul style="list-style-type: none"> <li>Close-range structural scans</li> <li>Precision mapping in tight drifts</li> </ul>
<b>Evolutionary/Metaheuristic Models</b>	Genetic Algorithms, PSO, Ant Colony Optimization	<ul style="list-style-type: none"> <li>Effective for multi-objective missions</li> <li>Handle noisy and complex landscapes</li> </ul>	<ul style="list-style-type: none"> <li>Slow convergence</li> <li>High compute load not ideal onboard</li> </ul>	<b>Very High</b> Better suited for off-board optimization	<ul style="list-style-type: none"> <li>Large stopes</li> <li>Multi-drone coordination planning</li> </ul>

**4.3 Uncertainty Reduction Models for Geological Feature Detection**

Uncertainty-reduction models enhance the reliability of autonomous mapping by quantifying and minimizing ambiguities in geological-feature detection [25]. Bayesian frameworks are frequently employed to estimate the probability that a surface discontinuity, bedding plane, or joint orientation has been correctly identified based on sensor fidelity, angle of incidence, and environmental noise [20]. Gaussian-process regression further supports uncertainty estimation by predicting where structural measurements require densification to achieve geotechnical reliability thresholds [28]. These models instruct the drone to revisit specific zones, adjust flight altitude, or capture additional sensor modalities to clarify ambiguous areas [22]. In poorly lit or dust-intense environments, uncertainty-reduction algorithms guide drones toward alternative viewing angles or

slower flight speeds to improve data clarity and compensate for degraded visual signals [27]. When combined with LiDAR-SLAM mapping, these probabilistic approaches significantly improve the accuracy of orientation statistics, structural-domain classifications, and geotechnical hazard assessments [30]. By reducing uncertainty, these systems deliver safer and more actionable geological datasets.

#### 4.4 Multi-Drone Coordination in Confined Mine Geometries

Coordinating multiple autonomous drones in underground or deep-pit environments requires sophisticated communication, collision-avoidance, and task-allocation models that distribute mapping responsibilities efficiently [24]. Multi-drone systems use decentralized swarm algorithms or leader-follower frameworks to maintain safe spacing despite unpredictable airflow, dust, and geometric constraints [29]. Communication is often based on short-range radio or ultrawideband channels, compensating for signal attenuation caused by rock masses and machinery [30]. Task-allocation algorithms divide the mine into spatial segments or structural-feature targets, ensuring that drones avoid duplication while maximizing collective coverage [23]. Coordinated fleets enable faster mapping of large stopes, multi-level drifts, or expansive open-pit benches, reducing downtime and accelerating decision-making for production and geotechnical teams [28]. Multi-drone collaboration ultimately increases data density, reduces operation time, and enhances safety by minimizing human presence in hazardous zones [21].

### 5. DEPLOYMENT STRATEGIES IN UNDERGROUND AND OPEN-PIT MINES

#### 5.1 Tunnel-Mapping Strategies in GPS-Denied Environments

Tunnel mapping requires flight strategies that compensate for the complete absence of GPS signals, irregular geometries, and abrupt environmental transitions common in underground mines [29]. To maintain localization, drones rely on LiDAR-SLAM or visual-inertial odometry, generating real-time maps that allow autonomous positioning even when particulate concentration or shadowing disrupts camera input [28]. Flight paths must be designed to maximize wall visibility by maintaining consistent lateral standoff distances, avoiding steep approach angles that reduce structural clarity [30]. In narrow drifts or crosscuts, path planners typically use “serpentine” or “lateral-oscillation” patterns to ensure complete coverage of both walls while allowing the SLAM engine to maintain robust loop closures [33]. Because dust and airflow can produce micro-stability disturbances, drones often employ low-velocity profiles and high-frequency pose-estimation updates to prevent drift accumulation and collision [31]. Additionally, tunnel intersections require adaptive path switching, where the drone identifies branching corridors and prioritizes mapping order based on obstacle density and sensor confidence [27]. These strategies collectively enable

high-density structural data capture while minimizing safety risks and ensuring continuity of SLAM accuracy throughout confined underground networks [35].

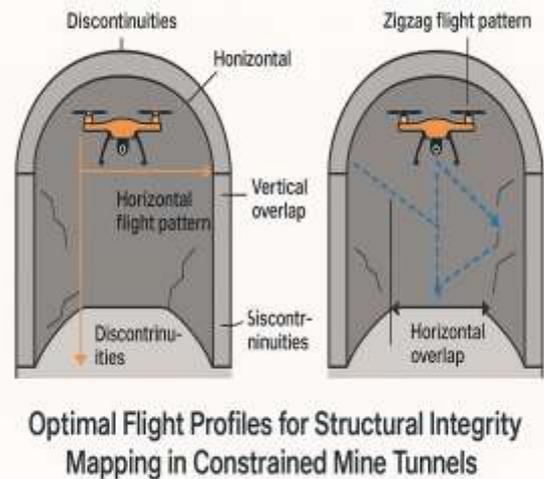


Figure 2: Optimal Flight Profiles for Structural Integrity Mapping in Constrained Mine Tunnels.

#### 5.2 Autonomous Surface-Mine Scanning under Variable Topography

Surface-mine scanning presents a different set of challenges, primarily driven by elevation variability, open exposure, and dynamic topographic changes caused by blasting or excavation cycles [32]. Autonomous drones must adjust altitude continuously in response to slope angles, bench height differences, and large voids created by pit-wall recession [27]. LiDAR-based terrain-following algorithms are often employed to maintain optimal sensor-to-surface distances, preserving data density across uneven ground [35]. Wind turbulence significantly higher in open pits requires predictive stabilization models that anticipate gust directions using inertial-sensor feedback [30]. Multi-viewpoint imaging is essential in deep pits because shadows and occlusions develop as sun position shifts; autonomous systems compensate by adjusting approach angles and capturing supplementary passes to fill spatial gaps [28]. In addition, geological heterogeneity in open pits demands wider flight footprints but lower overlap ratios than underground environments, allowing efficient mapping without compromising structural clarity [33]. These adaptations enable drones to produce consistent, high-resolution geotechnical datasets across rapidly evolving surface-mine landscapes [29].

#### 5.3 Hybrid Vertical and Horizontal Flight Profiles for Structural Detail Capture

Hybrid flight profiles combine vertical and horizontal survey paths to optimize structural-data resolution across complex mine geometries [31]. Horizontal passes capture large-scale wall continuity and lithological layering, while vertical sweeps provide close-range orientation data for faults, joints,

and discontinuities that may be obscured when viewed laterally [34]. This approach is particularly beneficial in stopes, ore passes, and steep pit walls where single-direction imaging fails to resolve dipping or intersecting structural sets [27]. Sensor fusion plays a central role: LiDAR depth maps consolidated with photogrammetric textures allow geological interpreters to extract orientation clusters and classify structural domains with greater confidence [35]. Hybrid profiling also enhances SLAM continuity, as vertical views introduce additional feature points that stabilize mapping in areas with limited lateral texture or high wall uniformity [30]. The adaptability of vertical-to-horizontal transitions allows drones to manage occlusions created by protruding rock faces or equipment, ensuring continuous structural visibility [28]. These hybrid profiles significantly improve the accuracy of geotechnical modelling while reducing the need for repeated manual inspections [32].

#### **5.4 Safety Protocols: Drone-to-Wall Standoff Control and Collision Management**

Safety protocols in autonomous drone deployments emphasize precise drone-to-wall standoff distances and real-time collision-avoidance behaviour [33]. Maintaining consistent standoff is essential for data fidelity too close and sensors saturate, too far and structural detail becomes insufficient for geological interpretation [27]. Adaptive standoff control uses fused SLAM-INS estimates to adjust lateral distance dynamically, particularly in narrow drifts where wall roughness and rockfall debris create unpredictable contours [29]. Collision-management algorithms integrate LiDAR scanning, stereo-vision depth cues, and ultrawideband ranging to detect protrusions, hanging mesh, overbreak zones, and ventilation hardware [30]. When obstacles are encountered, drones initiate emergency sidestep maneuvers or hover routines until safe paths are recalculated [35]. These safety features not only protect equipment but also ensure uninterrupted structural-data collection by preventing abrupt mission terminations caused by loss of stability or unexpected contact with the environment [28].

## **6. DATA PROCESSING, FUSION, AND GEOLOGICAL INTERPRETATION**

### **6.1 Processing LiDAR Point Clouds for Structural Mapping**

Processing LiDAR point clouds begins with noise filtering, voxel down-sampling, and registration to ensure spatial consistency across multiple passes [31]. Underground datasets often contain dust-induced artifacts or motion-distortion noise caused by rapid drone maneuvers; therefore, statistical outlier filters are typically applied to remove spurious points without degrading structural fidelity [29]. Once cleaned, point clouds are aligned using iterative closest point (ICP) algorithms that refine pose estimates generated during SLAM navigation, enabling accurate reconstruction of wall geometries and rock-mass surfaces [34]. Feature-extraction workflows then compute surface normals, curvature fields, and roughness metrics to identify discontinuities and structural domains

relevant to geotechnical interpretation [30]. High-resolution LiDAR datasets also allow for segmentation of planes, faults, and joint sets through clustering methods that group points with similar orientation signatures [33]. These processed point clouds form the geometric backbone of autonomous structural-mapping systems, providing the accuracy and density required for advanced modelling and hazard assessment [35].

### **6.2 Photogrammetry Mesh Reconstruction and Georeferencing**

Photogrammetry processing begins with automated feature matching across overlapping images, followed by bundle adjustment to estimate camera positions and orientations [29]. These steps produce a sparse point cloud that is subsequently densified and converted into a textured 3D mesh, revealing geological surfaces with colour detail not available from LiDAR alone [32]. Underground illumination inconsistencies require HDR-balanced preprocessing to stabilize brightness gradients and improve feature matching [35]. For surface mines, georeferencing typically uses ground-control targets or LiDAR-derived anchor points to align photogrammetric meshes with mine-coordinate systems [31]. The resulting textured models support lithological classification, rock-mass characterization, and training datasets for AI-based geological interpretation [30].

### **6.3 Multi-Sensor Fusion for Enhanced Fault and Discontinuity Detection**

Multi-sensor fusion integrates LiDAR geometry with photogrammetric texture and, where available, spectral signatures to produce geologically enriched structural maps [33]. Fusion begins by aligning LiDAR point clouds with image-based meshes through shared keypoints or ICP-refined correspondences, ensuring both datasets occupy a unified spatial coordinate system [29]. Photogrammetric textures improve the interpretability of LiDAR surfaces by highlighting colour changes, mineralization zones, or weathering patterns that may coincide with structural discontinuities [31]. Hyperspectral or multispectral data further enhance detection by linking reflectance anomalies to lithological variations or alteration halos often associated with fault zones [34]. Fused datasets enable more reliable extraction of joint orientations, persistence, and clustering patterns, particularly in areas where LiDAR geometry alone struggles such as uniform rock walls or low-texture regions [30]. This integration significantly improves structural-mapping accuracy and reduces ambiguity in geotechnical decision-making [35].

**Table 2: Sensor-Fusion Techniques and Their Impact on Structural-Mapping Accuracy**

Sensor-Fusion Technique	Input Data Sources	Fusion Method	Advantages for Structural Mapping	Limitations / Challenges	Impact on Overall Mapping Accuracy
<b>LiDAR + Photogrammetry Fusion</b>	LiDAR point clouds + RGB/HDR imagery	Point-level or surface-level registration using ICP and feature matching	<ul style="list-style-type: none"> <li>Adds colour/texture to geometric surfaces</li> <li>Enhances detection of bedding, mineralization, weathering zones</li> <li>Improves visual interpretability</li> </ul>	<ul style="list-style-type: none"> <li>Sensitive to lighting variations</li> <li>Requires precise camera-LiDAR calibration</li> </ul>	<b>High</b> — up to significant improvements in feature visibility and discontinuity detection
<b>LiDAR + Inertial Navigation (SLAM-INS Fusion)</b>	LiDAR depth returns + IMU accelerometers/gyroscopes	Extended Kalman Filter (EKF) or tightly coupled SLAM	<ul style="list-style-type: none"> <li>Reduces drift in GPS-denied mines</li> <li>Enables stable navigation in dust, vibration, and airflow disturbances</li> </ul>	<ul style="list-style-type: none"> <li>Computationally intensive</li> <li>Drift may occur if LiDAR features are sparse</li> </ul>	<b>Very High</b> — major gains in geometric stability and pose accuracy
<b>Photogrammetry + IMU Fusion</b>	RGB/HDR frames + inertial-motion data	Visual-inertial odometry (VIO)	<ul style="list-style-type: none"> <li>Improves camera pose estimation when visual texture is inconsistent</li> </ul>	<ul style="list-style-type: none"> <li>Sensitive to dust and low light</li> <li>Higher noise under rapid</li> </ul>	<b>Moderate–High</b> — improves mesh alignment and

Sensor-Fusion Technique	Input Data Sources	Fusion Method	Advantages for Structural Mapping	Limitations / Challenges	Impact on Overall Mapping Accuracy
			<ul style="list-style-type: none"> <li>Enables smoother mesh reconstruction</li> </ul>	<ul style="list-style-type: none"> <li>motion</li> </ul>	<ul style="list-style-type: none"> <li>feature continuity</li> </ul>
<b>LiDAR + Multispectral/Hyperspectral Fusion</b>	LiDAR geometry + spectral reflectance signatures	Co-registration in shared spatial reference	<ul style="list-style-type: none"> <li>Identifies mineralogical alterations linked to faults</li> <li>Enhances lithology classification</li> <li>Detects moisture/oxidation zones</li> </ul>	<ul style="list-style-type: none"> <li>Very heavy data processing</li> <li>Requires stable lighting for spectral imaging</li> </ul>	<b>High</b> — significant gains for geochemical + structural interpretation
<b>LiDAR + Radar/Depth Sensors</b>	LiDAR + radar backscatter or ToF depth	Multi-depth fusion using voxel integration	<ul style="list-style-type: none"> <li>Penetrates dust better than optics</li> <li>Supports mapping of occluded or shadowed geometries</li> </ul>	<ul style="list-style-type: none"> <li>Limited resolution of radar vs LiDAR</li> <li>Needs careful noise filtration</li> </ul>	<b>Moderate</b> — boosts completeness in low-visibility zones
<b>Triple Fusion: LiDAR + RGB + IMU</b>	LiDAR + camera + inertial sensors	Tightly coupled SLAM pipeline	<ul style="list-style-type: none"> <li>Produces the most stable, dense, and visually interpretable</li> </ul>	<ul style="list-style-type: none"> <li>High computational load</li> <li>Requires careful onboard</li> </ul>	<b>Very High</b> — best balance of accuracy, compl

Sensor-Fusion Technique	Input Data Sources	Fusion Method	Advantages for Structural Mapping	Limitations / Challenges	Impact on Overall Mapping Accuracy
		nes	ble models • Maintain s mapping reliability across harsh conditions	resource management	eteness, and robustness

#### 6.4 Automated Feature Extraction Using AI-Based Geological Modelling

AI-driven feature-extraction models automate the identification of faults, fractures, bedding planes, and rock-mass domains using geometric and visual cues from fused datasets [32]. Convolutional neural networks (CNNs) trained on photogrammetric textures detect colour or texture boundaries corresponding to geological contacts, while point-cloud neural architectures such as PointNet analyze LiDAR geometry to classify discontinuity planes [29]. Hybrid models combine both modalities, improving detection in noisy or visually obscure environments [34]. Automated extraction reduces subjectivity inherent in manual geological mapping and accelerates the generation of structural models used for slope-stability assessment, rock-mass rating, and excavation planning [31]. These AI systems continuously improve through incremental retraining using validated field datasets, ensuring higher precision with each deployment cycle [35].

### 7. PERFORMANCE EVALUATION AND ACCURACY METRICS

#### 7.1 Metrics: RMSE, Spatial Resolution, Surface Completeness

Performance evaluation of autonomous drone-based structural mapping relies heavily on quantitative metrics that assess geometric accuracy, data density, and overall completeness of the reconstructed surfaces [36]. Root Mean Square Error (RMSE) remains the most common accuracy indicator, comparing reconstructed points against reference measurements to identify deviations caused by sensor noise, SLAM drift, or environmental interference [34]. In underground settings, RMSE analysis is especially important because uneven lighting and dust can degrade visual or LiDAR inputs, making precise accuracy quantification essential for reliability [39]. Spatial resolution, defined as the smallest structural feature that can be consistently detected,

provides insight into how effectively joint traces, bedding surfaces, or minor discontinuities are represented across varying standoff distances [33]. Surface completeness measures the percentage of exposed geology captured without occlusion, a critical metric in mines where overbreak, equipment shadows, and geometric restrictions frequently limit sensor line-of-sight [38]. Together, these metrics offer a robust framework for evaluating whether autonomous acquisitions meet the thresholds required for geotechnical modelling, stability analysis, and mine-planning integration [40].

#### 7.2 Benchmarking Against Manual and Terrestrial Laser Scanning

Benchmarking autonomous drone-based mapping against manual structural surveys and terrestrial laser scanning (TLS) helps validate the accuracy and operational value of aerial systems [37]. Manual mapping offers geological interpretation insight but suffers from spatial subjectivity and limited reach in hazardous slopes or steep benches [35]. TLS provides highly accurate geometric data but requires physical setup, stable ground positions, and substantial time for multi-station acquisitions constraints that limit its use in dynamic production zones [33]. Drone-based LiDAR and photogrammetric mapping often achieve comparable or superior completeness due to multi-angle coverage and access to otherwise inaccessible faces [39]. Comparative studies frequently show that autonomous mapping achieves RMSE values within acceptable geotechnical tolerances while reducing personnel exposure and operational downtime [36].

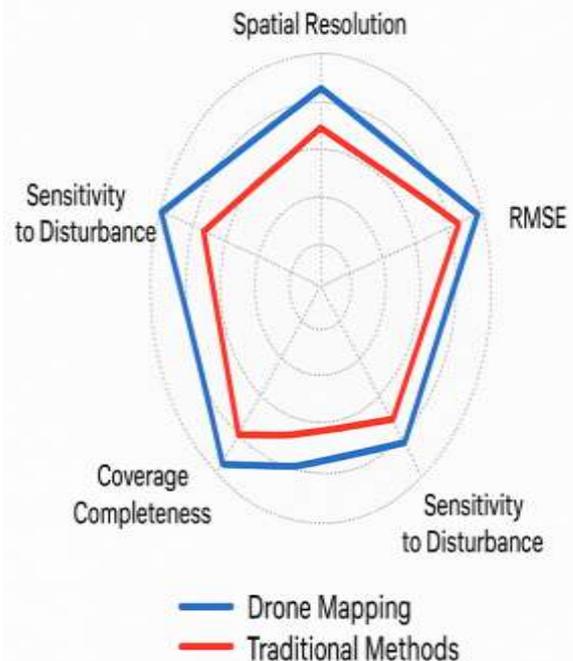


Figure 3: Accuracy and Completeness Comparison—Drone Mapping vs Traditional Methods.

### 7.3 Sensitivity to Environmental Disturbances

Environmental disturbances significantly influence mapping performance, making sensitivity analysis essential for validating drone-derived datasets [34]. Dust concentration can attenuate LiDAR returns and obscure photogrammetric features, increasing positional noise and reducing structural clarity [38]. Airflow variability caused by mine ventilation introduces micro-instabilities that affect SLAM performance and increase INS drift, particularly during long flights in narrow headings [40]. Low-light environments create challenges for visual-SLAM systems, often requiring HDR preprocessing or alternative illumination strategies to maintain feature detection [33]. Temperature gradients and moisture variations may also influence sensor calibration, especially in deeper underground zones where thermal stratification is common [37]. Sensitivity evaluations provide insight into the reliability of acquired datasets under real operating conditions, enabling adaptive mission planning, sensor-mode switching, or redundancy strategies to mitigate adverse effects [36].

## 8. IMPLEMENTATION CONSIDERATIONS AND OPERATIONAL GUIDELINES

### 8.1 Workforce Training and Autonomous-Operations Readiness

Effective deployment of autonomous geological-mapping drones requires a workforce trained not only in drone operation but also in interpreting SLAM outputs, point-cloud data, and fused geological models [37]. Traditional mine-survey and geology teams often possess strong field skills but may lack exposure to autonomous-navigation diagnostics, LiDAR-quality assessment, and real-time mission monitoring [33]. Structured training programs must therefore address sensor calibration, SLAM-failure detection, battery-cycle management, and safety-override logic to ensure reliable field operation [39]. Additionally, workforce readiness involves developing new technical roles such as drone-mission controllers, data-processing engineers, and digital-geology analysts to support increasing automation levels [35]. Collaborative training frameworks that integrate OEM instruction with in-mine simulations significantly improve operational confidence, enabling teams to adapt autonomous workflows to variable geological and environmental conditions [40].

### 8.2 Integration with Mine-Planning Software and Digital Twins

For autonomous mapping to deliver full value, datasets must integrate seamlessly with mine-planning platforms and digital-twin environments that support geotechnical modelling, blast design, and long-term monitoring [36]. LiDAR point clouds and photogrammetric meshes must be exported into formats compatible with geological-modelling suites, ensuring that structural orientations, discontinuity clusters, and volumetric shapes are directly usable in planning workflows [33]. Digital-twin integration allows time-stamped

drone scans to be layered into continuous 4D geological representations, improving the ability to track deformation trends, overbreak progression, or stope-closure behaviour [38]. This interoperability also enhances predictive-maintenance models for equipment and infrastructure by linking structural changes to operational metrics [40]. High-resolution autonomous-mapping data therefore strengthens short-term tactical decisions and long-term strategic planning across complex mining systems [35].

### 8.3 Cost, Scheduling, and Maintenance Considerations

Operationalizing autonomous drones requires careful evaluation of lifecycle costs, maintenance cycles, and scheduling impacts [34]. While initial acquisition and training costs may exceed those of manual mapping, reduced personnel exposure, faster data-collection cycles, and lower resurvey frequencies typically yield significant operational savings [37]. Scheduling drones during shift changes or low-traffic periods minimizes interference with production while ensuring continuous geological updates [39]. Maintenance protocols covering sensor cleaning, propeller checks, calibration routines, and firmware updates are essential to preserve data quality and system reliability in harsh mining conditions [33]. These considerations collectively determine long-term cost-effectiveness and operational sustainability [40].

## 9. STRATEGIC, SAFETY, AND INDUSTRY IMPLICATIONS

### 9.1 Impact on Mine Safety and Worker Exposure Reduction

Autonomous mapping significantly enhances mine safety by removing geologists and surveyors from hazardous areas such as unstable stopes, high benches, and poorly ventilated drifts [35]. Drone-based LiDAR and visual inspections reduce physical exposure to rockfall zones, overbreak sections, and unsupported backs where traditional methods historically required close-range observation [38]. By enabling remote data capture, drones minimize time spent in high-risk zones and support more frequent safety assessments, improving hazard detection and geotechnical oversight [40]. These operational safety gains contribute directly to lower incident rates and stronger compliance with mine-safety protocols [36].

### 9.2 Contribution to Faster and More Accurate Mine-Planning Cycles

Autonomous mapping accelerates mine-planning cycles by generating high-resolution structural datasets in minutes rather than hours, reducing delays associated with manual surveys or multi-station terrestrial scanning [39]. Rapid availability of point clouds and photogrammetric imagery improves geological-model refresh rates, enabling planners to integrate updated discontinuity data, stope-boundary conditions, and bench-wall geometries into design workflows [37]. Enhanced structural accuracy supports optimized blast design, improved

dilution control, and more reliable slope-stability analysis [35]. These efficiencies shorten decision-making timelines and increase operational responsiveness, strengthening the alignment between production schedules and geotechnical requirements [40].

### 9.3 Long-Term Economic Benefits from Optimized Drone Deployment

Long-term economic benefits arise from reduced resurvey costs, fewer production delays, and minimized equipment downtime enabled by continuous autonomous monitoring [36]. Higher data completeness lowers the likelihood of unexpected geological conditions disrupting development or extraction, improving cost forecasting and operational stability [38]. Drone deployment also reduces labour-intensive mapping hours, freeing skilled personnel for higher-value analytical tasks [35]. Over time, integrated autonomous workflows create compounding efficiency gains across planning, safety, and production cycles, delivering substantial return on investment for mines that adopt drone-based structural mapping at scale [40].

## 10. CONCLUSION

### 10.1 Summary of Key Insights

This article has demonstrated how autonomous aerial systems are reshaping geological and structural mapping across underground and surface mining environments. By integrating advanced navigation frameworks, LiDAR-SLAM, photogrammetry, multi-sensor fusion, and AI-driven feature extraction, drones now deliver high-resolution datasets with greater safety, speed, and accuracy than traditional methods. Optimization algorithms, hybrid flight profiles, and real-time adaptation capabilities ensure reliable performance even in harsh, GPS-denied conditions. The combined impact enhances mine-planning precision, reduces worker exposure, and supports continuous operational awareness. Collectively, these innovations mark a significant shift toward data-driven, automated geotechnical decision-making in modern mining operations.

### 10.2 Implications for Future Autonomous Geomapping Technologies

Future advancements will focus on deeper autonomy, including fully self-coordinating multi-drone fleets, semantic geological understanding, and predictive navigation that anticipates environmental hazards before they occur. Integration with real-time digital twins will enable continuous 4D geological monitoring, while onboard edge-AI processing will reduce dependence on ground-based computation. Expanded use of hyperspectral sensors, radar-based imaging, and adaptive illumination will extend mapping reliability across increasingly complex geological settings. Ultimately, autonomous geomapping technologies will evolve beyond data capture toward proactive geotechnical intelligence supporting safer operations, optimized extraction strategies, and more resilient mine-planning ecosystems.

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