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Meta-analysis and systematic review of drone technology in mining and geotechnical engineering

M.Z. Emad*

King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia

**Corresponding author: muhammadzaka.emad@kfupm.edu.sa*

Abstract. Unmanned Aerial Vehicles (UAVs) have revolutionized geotechnical and mining operations by enabling fast, high-resolution, and inexpensive spatial data acquisition, terrain modeling, and monitoring. The current review and meta-analysis integrate observations from over 133 peer-reviewed articles to present a comparison of the accuracy of UAV-based surveying methods, i.e., photogrammetry and LiDAR, and traditional methods such as total stations and terrestrial LiDAR. This study focuses on application of UAVs and drone use in mining and geotechnical engineering in terms of finding stockpile volumes, mining subsidence, mine tailings and dump site, and rock mass identification. UAVs are capable of achieving decent accuracy on a regular basis, as indicated by meta-analysis, if optimized flight parameters, RTK/PPK positioning, and GCPs are utilized. Improved accuracy in UAV LiDAR surveys and balance between visual accuracy and cost-recovery in UAV photogrammetry are feasible. However, error magnitude is dependent on complexity of terrain, flight planning, and meteorology, emphasizing methodical accuracy. Bibliometric analysis indicates exponential publication development per year since 2017 for UAVs, and China once more emerges as the leading contributor with funding, authorship, and research. Keyword and co-authorship network visualization demonstrates increasing adherence to machine learning, 3D reconstruction, and digital twin technologies. SWOT analysis determines UAVs' efficiency of operations, safety benefit, and visual outcome as its major strengths but bottlenecks to data processing, inconsistent accuracy, and difficulties in unfavorable terrain conditions as its weaknesses. Shortages of skills are listed as major weaknesses to extensive deployment. The findings are reinforced by an industry validation survey in which 100% of respondents testified to UAV-improved efficiency and 71% to significant cost savings. There are some concerns regarding the amount of data processing and UAV response in slopes or complex environments. UAVs are transitioning from test equipment to geotechnical equipment of choice, providing real-time actionable information for monitoring, site planning, and hazard analysis. Sensor fusion, artificial intelligence-driven analytics, and normalization of workflow destinies are UAVs to be a major driver of mining digitalization. Future research will focus on underground mapping, automation, and standardization of the regulation to open up the full potential of UAVs across the mining value chain.

Keywords: *drones, UAVs, UAS, photogrammetry, mine waste, volumetrics, accuracy, subsidence, landslide, mapping.*

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1. Introduction

Unmanned Aerial Vehicles (UAVs) are currently an affordable equipment of civilian application, transforming the model of acquiring geoscientific information through high spatial resolution, ease of operation, and enhanced safety [1]. Mineral exploration and geological mapping conventionally rely on time-consuming ground surveys, low-resolution satellite images, and costly airborne geophysics, frequently being incapacitated by logistic limitations and availability [2]. UAV technology directly plugs this observation gap, since low-altitude, generic platforms for miniaturized sensors and rendering remote sensing a focused, precise solution to mineral identification and other geoscientific applications [3]. A highlight of UAVs in mineral prospecting is that they possess the ability to mount hyperspectral and thermal sensors. Spectral signatures are specific for every mineral, these help with identification of minerals on earth. While satellite sensors like ASTER are a favorite for lithological mapping at the regional level, their resolution is often too coarse for deposit-scale investigation in detail [4]. UAV-borne hyperspectral sensors, however, acquire this data at centimeter resolutions, enabling the identification of subtle mineralogical variations and key mineral assemblages (e.g., phyllosilicates, carbonates, iron oxides) that are pathfinders to ore deposits [5]. This facilitates the rapid delineation of alteration zones, reducing the discovery to resource definition timeframe by orders of magnitude.

In addition to direct mineral recognition, UAVs provide a multi-toolset for the modern geoscientist. Coupling high-resolution optical cameras with Structure-from-Motion (SfM) photogrammetry software enables the creation of precise Digital Outcrop Models (DOMs). These 3D models provide essential spatial context to geological interpretation, allowing for the measurement of structural features, bedding attitudes, and fracture intensity with accuracy [6]. Magnetometer and gam-

muhammadzaka.emad@kfupm.edu.sa
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ma-ray spectrometer equipped UAVs are also proving to be useful tools for high-resolution geophysical surveying, mapping anomalies related to subsurface mineralization [6]. The technology adds value across the entire mine lifecycle, from pre-exploration baseline mapping to operational tasks like stockpile volumetrics, pit slope stability monitoring, and post-mining land reclamation assessment.

The advantages of UAVs in a mine site are numerous and primarily hinge on personnel safety, operational efficiency, and data quality [7, 8]. Their ability to access hazardous or logistically challenging areas such as unstable highwalls [9], deep pits, and active blast areas, without endangering human life is a major benefit [10]. They are hence extremely essential for geotechnical applications like landslides and slopes where conventional technologies such as levelling, total stations, and terrestrial laser scanning are time-intensive, labor demanding, and hazardous [11]. UAVs, when equipped with high-end sensors like LiDAR, multispectral, and thermal cameras, provide cheaper, faster, and safer alternatives [12-14] with centimeter-level topographic mapping precision [15], near real-time volume calculations, and remote sensing of dangerous environments [16]. Fast advancement in UAV applications like pit wall stability monitoring, waste dump monitoring, blast fragmentation analysis, and tailings dam monitoring is highlighted in industry reports [7, 17]. Both UAV LiDAR and photogrammetry possess the ability to produce high-resolution Digital Elevation Models (DEMs) and point clouds with greater than 0.1% volumetric accuracy, often outperforming traditional GPS surveys at a cost saving of more than 60% in time and labour [18-21]. This is of specific value in large open-pit mines where routine volumetric monitoring of waste dumps and ore is integral to resource estimation and logistics planning [8, 22]. UAVs also allow real-time monitoring of ground movement and earthworks, with operators able to validate progress to project schedules without the need to interrupt work [23].

The sector is moving toward full autonomy and more integration of data. Drone-in-a-Box (DiaB) technology, under which fully autonomous inspection flights are possible without pilots, is being adopted by industry leaders for routine monitoring of critical infrastructure. UAVs are increasingly being incorporated into more extensive digital platforms that leverage artificial intelligence (AI), machine learning (ML), and IoT-enabled sensor networks [24, 25]. The intersection of UAV hardware, advanced remote sensing algorithms, and autonomous flight platforms is facilitating a new revolution of innovation [26-28]. Deep learning algorithms are being applied routinely to drone imagery for rock fragmentation measurement automation [29, 30], defect detection on conveyor belts [31], and prognostic ground deformation modeling [32]. Moreover, the availability of beyond-visual-line-of-sight (BVLOS) flight and 5G connectivity is facilitating real-time data streaming and centralized control of large-scale mining fleet operations [33-35].

Several detailed reviews capture this range of technology. Vishweshwaran and Sujatha [36] document usage of drones in geotechnical engineering for slope, pavement, and excavation monitoring, complete with methodology guidelines for integrating photogrammetry, SfM, LiDAR, and multispectral imaging. They also note the potential for AI/ML in automating crack detection and rock mass classification. Jackisch [37] has an interest in mineral exploration, demonstrating how drone-borne hyperspectral and magnetic surveys can delineate ore zones at a fraction of the cost of conventional methods, with examples from Greenland and Namibia. Shahmoradi et al. [38] cover applications at abandoned, active, and reclaimed mines, noting the value of collision-tolerant drones like the Elios series for GPS-denied underground mine voids. To these prospects, Andresen and Schultz-Fellenz [39] introduce UAV-facilitated change detection, while Perikleous et al. [40] cover the employment of UAVs in combination with geophysical sensors for subsurface mapping in a review of 59 mining case studies. Hussain et al. [41] and Chen et al. [42] explore the utilization of UAVs in landslide studies, documenting workflows for hazard evaluation. Arif et al. [43] outline the synergistic benefit of integrating InSAR and Global Navigation Satellite System (GNSS) with UAVs in a multi-sensor strategy to the quantification of mining-induced deformation.

To bridge these limitations, this study attempts a structured review of UAV application in mining and geotechnical engineering with particular reference to terrain modeling, stockpile volumetrics, real-time monitoring, and unsafe-site inspection. It is guided by the research question: “How accurate and efficient is terrain modeling and stockpile volumetrics using drones versus traditional surveying methods in various mining environments (open-pit, underground, tailings)?”. Through a multi-method approach adopting the meta-analysis of UAV performance metrics, examining biblio-metric research trends mapping, SWOT analysis, and industry survey, this review seeks to provide an evidence-based synthesis of the current state and future prospects of UAVs in mining. Empirical evidence is used to guide research and make operational guidelines accessible to industry parties interested in optimizing use of UAVs for safety, efficiency, and sustainability. To validate the findings of a preceding meta-analysis and gauge current industry sentiment, a survey was distributed to thirty-three experienced practitioners (with experience of 3 years or more) in the mining and geotechnical fields. The seven responses, as being a specialized segment of the industry, confirm the meta-analysis's hypothesis of pervasiveness on the basis of higher efficiency. The survey also identifies the main issues preventing further integration, with data processing as the most significant technical barrier and sloping terrain as the most limiting environmental constraint.

2. Literature review

2.1. PPK vs RTK

The pursuit of centimeter-level positioning accuracy in Unmanned Aerial Systems (UAS) has made Real-Time Kinematic (RTK) and Post-Processed Kinematic (PPK) GNSS methodologies equally vital. Despite both employing carrier-phase differential corrections for integer ambiguity resolution and achieving high accuracy, their operational paradigms, infrastructure dependence, and robustness are quite disparate, dictating their applicability. The main distinction is the timing of the application of the corrections. RTK is a real-time method. It requires a continuous communication link, typically a radio modem, from a fixed base station to the UAS (rover). This base station, whose location is known, calculates error corrections based on comparing its known location to its location obtained by GNSS. These corrections are transmitted back to the rover in real time, allowing its onboard computer to resolve integer ambiguities immediately and output a corrected, centimeter-level position for direct geotagging of images [44]. The base station could be a user-mounted unit or, more typically, a network of Continuously Operating Reference Stations (CORS). While CORS networks are easy, their availability is dependent on good cellular data coverage at the flight location. The greatest weakness of RTK is that it depends on a continuous communication link; any break can trigger a re-initialization of the ambiguity resolution, leading to periods of degraded accuracy. Conversely, PPK is a post-mission method that decouples the process of correction from flight operation. The base station and the UAS rover both separately record the raw, time-stamped GNSS observation data, i.e., the carrier-phase and pseudo-range measurements. After flight, these data sets are integrated post-processing software to determine the true path of the drone. This approach is understandably more tolerant to faults because it eliminates the risk of in-flight radio link failure and is thus extremely well suited for operation in adversarial environments such as hilly terrain, dense forests, or near infrastructure where the line-of-sight communication is disrupted [45]. The correction origin will typically be a user-defined base station as the timing synchronization for processing with CORS data can be more complex.

The core algorithm for both approaches is the solution for the integer ambiguity in carrier-phase measurements. The Least-Squares Ambiguity Decorrelation Adjustment (LAMBDA) algorithm is the default algorithm for this purpose, where it is widely regarded for its effectiveness and resilience in determining correct integer ambiguities [46]. The global positioning solution is normally accomplished using a Kalman Filter, which combines optimally the GNSS carrier-phase measurements with the Inertial Measurement Unit (IMU) measurements. Sensor fusion is critical since the IMU provides high-rate velocity and attitude measurements that fill short-term gaps in GNSS signal availability and smooth the trajectory. Accuracy of the combined GNSS-IMU system, that is, calibration of the lever arm (physical distance between GNSS antenna and IMU) and sensor biases of the IMU itself, is a primary driver of end accuracy. With advancing sensor technology, cheaper, tactical-grade IMUs are more and more useful for high-accuracy PPK/RTK applications, closing the performance gap to more expensive systems.

2.2. Photogrammetry process

The modern photogrammetric pipeline, driven by SfM algorithms, breaks up a collection of overlapping 2D images into a precise 3D model in the guise of an iteratively performed computationally intensive pipeline. The initial step includes feature detection and matching, where the features are detected by algorithms like SIFT (Scale-Invariant Feature Transform), SURF (Speeded-Up Robust Features), or the computer friendlier ORB (Oriented FAST and Rotated BRIEF), which identify distinctive key points in each image that are scale, rotation, and illumination invariant [47]. By matching those features between a series of images, the program generates a series of tie points, establishing the first correspondence for the entire reconstruction. This sparsely textured point cloud and corresponding image points are fed into the core of SfS/ bundle adjustment and pose estimation. The approach first estimates the exterior orientation (camera location and orientation) of each camera and the 3D coordinates of the tie points simultaneously. This is optimized using bundle adjustment, a top-level optimization that minimizes the reprojection error, the difference between observed 2D feature positions and reprojected 3D points into the images [48]. Bundle adjustment is necessary to achieve a globally consistent and internally accurate model. In the context of rolling-shutter cameras on drones, a rolling-shutter correction needs to be incorporated at this stage. Since every scanline of an image is captured at a varying moment when the drone moves, perspective geometry is distorted. SfM software mimics this phenomenon by calculating the camera path for exposure of a single frame significantly improving accuracy, especially for fast-moving platforms.

Following sparse reconstruction, dense matching algorithms produce a dense point cloud. Semi-Global Matching (SGM) obtains disparity maps inexpensively by maximizing a pixel-wise cost of matching on numerous one-dimensional paths, while more recent approaches like PatchMatch scatter good matches randomly and in parallel, achieving high detail and effectiveness [49]. The dense cloud serves as input to Multi-View Stereo (MVS), which continues to optimize the geometry and generally outputs the final surface mesh or textured model. Along this pipeline, there are two things that are most critical to absolute, especially vertical, accuracy. First, precise camera calibration, measurement of the internal parameters like focal length, principal point, and lens distortion is not possible. Systematic errors due to uncalibrated or poorly calibrated cameras cannot be eliminated at all through bundle adjustment, usually being manifested as a doming or bowing of the model [50]. Second, ground control point (GCP) distribution and quantity are key. GCPs provide reproducible coordinates within a world-wide reference system, positioning the bundle adjustment and eliminating residual errors within the direct georeferencing solution. A uniformly distributed set of GCPs, particularly on the boundaries and at various heights within the study area, is required to control and minimize vertical error propagation. Independent check points are then required to objectively assess the resulting achieved accuracy.

2.3. UAV-LiDAR systems

UAV LiDAR systems integrate a number of sensors, a laser scanner, a GNSS receiver, and an IMU, to directly sense 3D points in space. To reduce the raw data to a coherent, correct point cloud, there is a set of fundamental calibration and alignment procedures to correct for systemic errors that are inherent in the multi-sensor system. Boresight and lever-arm calibration are the simplest calibrations. The lever-arm is the same 3D vector offset between the origin of the IMU and the LiDAR scanner, and the boresight consists of angular misalignments (roll, pitch, yaw) among the body frame of the IMU and the coordinate system of the scanner. Minor inconsistencies in the parameters, particularly in boresight angles, may result in significant positional errors, which manifest as “double walls” or overlapping flight strip misalignments [51]. Calibration is typically achieved by flying over a region with clearly defined planar features (e.g., rooftops of buildings, roads) in multiple directions and adjusting the parameters iteratively until multiple strips' point clouds merge perfectly. Following initial calibration, scan strip adjustment is often a subsequent requirement. This process refines the path and/or boresight angles by minimizing differences between overlapping LiDAR strips. By finding common planar or linear features between strips, a bundle adjustment-type optimization is performed to reduce vertical and horizontal offsets, producing a more consistent data set internally [52].

To register several flights or UAV-LiDAR and ground point cloud scans, point cloud registration algorithms are used. Among the well-known algorithms is the Iterative Closest Point (ICP) algorithm which iteratively computes the optimal rigid transformation (rotation and translation) between two-point clouds in the sense of minimizing the distance between the corresponding points [53]. A more robust alternative is the Normal Distributions Transform (NDT), which models the target point cloud as a set of probability density functions and can achieve better performance with unstructured scenes and partial overlaps [54]. Classic

GNSS/IMU positioning is out of function in GNSS-denied situations such as forests, canyons, or indoors. For these situations, SLAM algorithms fill the gap. LiDAR SLAM relies on the point cloud as a spatial reference. By registering piecewise incoming laser scans to a map of the scene that is incrementally growing, the algorithm simultaneously estimates the 6-degree-of-freedom trajectory of the sensor and builds the 3D model in real-time. This allows one to walk and collect data continuously without using external localization, making it extremely useful in mining, geotechnical, forestry, and infrastructure inspection tasks where GNSS signals do not reach [55]. UAV-LiDAR performance thus lies in an efficient processing pipeline that aligns sensor geometry, data stripping coinciding, and incorporates sophisticated registration or SLAM techniques to achieve metric accuracy for a broad variety of scenes.

2.4. Sensor fusion

The intrinsic limitations of remote sensing and personal navigation sensors become pronounced in challenging terrain, where signal blockage and poor geometries exacerbate error. Sensor fusion is an effective paradigm to overcome these limitations by synergistic integration of the strengths of complementary systems. The integration of GNSS and IMU using advanced filtering algorithms forms the basis of precise direct georeferencing in both LiDAR and photogrammetry, and combining LiDAR and photogrammetric data yields a stronger and more reliable end product. The spirit of GNSS/IMU integration is typically achieved by using an Extended Kalman Filter (EKF) or an Unscented Kalman Filter (UKF). The EKF linearizes the system dynamics and measurement models to propagate the state (position, velocity, attitude) and covariance, whereas the UKF uses deterministic sampling to better handle extreme non-linearities. The GNSS provides absolute position but with low update rate and susceptibility to signal loss. The IMU, by contrast, offers high-rate acceleration and angular rate measurements, which allow for precise dead reckoning between GNSS updates but are subject to unbounded drift due to sensor biases. The Kalman filter combines these data streams most effectively. The IMU propagates the state, and the GNSS measurements update and refine this prediction, estimating and correcting the IMU sensor biases simultaneously [56]. This integration is the primary defense against drift. In complex country side like deep valleys or under forest canopy, where GNSS signals are intermittently shadowed, the tightly coupled IMU is maintaining an accurate short-term track, drastically reducing the positional errors that would otherwise accumulate and manifest as distorted models.

This robust performance is then translated directly to improved elevation precision in bad terrain. A poorly navigated platform will mis-project laser returns or photographs, leading to smearing, “doming” or inability to accurately represent steep slopes and ridges. The combined GNSS/IMU solution provides a robust geometric foundation such that the precise range measurements from the LiDAR or the triangulated points from photogrammetry are properly positioned in space. Additionally, the merging of the end data products, LiDAR and photogrammetry, contributes to accuracy. Photogrammetry loses matches on texturally flat ground (e.g., sand, snow, or high canopy) where feature matching fails, creating voids in the data. LiDAR bridges small gaps in the vegetation and is immune to a lack of texture, providing solid ground points in these areas. LiDAR sacrifices point density and loses fine edges that high-resolution photography preserves. By co-registering the two data sets, systematic errors in LiDAR data can be eliminated using the photogrammetric point cloud, and Digital Terrain Model from LiDAR can be used as an absolute height reference for tying in the photogrammetric bundle adjustment and minimizing vertical error propagation [57]. Such synergy integration creates a better, more robust, and reliable 3D landscape model, directly countering the accuracy trends that single-sensor systems exhibit in challenging environments.

The conversion from measured to true coordinates of drone-based mapping, often reflected in doming or shearing in 3D models, is caused by an intersection of the error sources in the integrated navigation and photogrammetric system. A main contributor is the degradation of the direct georeferencing solution. Errors in onboard GNSS, i.e., multi-path or incorrect resolution of carrier-phase integer ambiguities in RTK/PPK systems, translate directly to the exterior orientation of captured images [45]. Also, in the absence of good ground control, IMU errors, specifically, frame misalignment between GNSS and IMU frames, as well as gyro and accelerometer biases, introduce significant rotational errors. These rotational errors are non-linear and will lead to significant deformations, particularly on the vertical- or z-axis, creating the expected “doming” effect in the output point cloud [58]. The photogrammetric process itself causes additional shifts. Incomplete calibration of the camera, where the residual principal point and focal length errors remain, distort the internal geometry of the image bundle. Combined with insufficient image network geometry, like an insufficient flight plan with too few cross-strips, the bundle adjustment cannot derive the external platform position and orientation reliably from the internal camera parameters. This results in a non-rigid transformation with the system addressing navigation and calibration errors by deforming the 3D scene so that points of objects are transformed from their real positions [50].

2.5. Future of drone technology

The future of drone technology is in a very robust direction of more autonomy, integration, and intelligent data analysis. The future is not in stand-alone platforms, but in coupled systems, flocks of drones flying in coordination, and drones alongside other platforms like satellites, airborne LiDAR, and ground sensors creating multi-scale digital copies of the environment [59]. The principal driver is the necessity to propel edge computing, where data is calculated onboard in real time. This will enable real-time decision-making, such as a drone altering its flight path upon finding an anomaly in the mineralogy or identifying a structural defect, rather than merely collecting data to analyze afterward. Also, miniaturization and reduced cost of advanced sensors, in particular, solid-state LiDAR and hyperspectral cameras, are making high-fidelity remote sensing affordable, taking drones out of basic imaging into the realm of full-size 3D and chemical analysis.

Whether or not sensors or algorithms require more research is not an either/or question, but rather a question of recognizing that they are inter-dependent. When sensor technology advances, the most pressing research needs fall within the domain of algorithms to process, manage, and understand the enormous, disparate data streams generated by these sensors. The current state of the art moves towards generating data bottlenecks, in which terabytes of data are accumulated but remain slow and computationally intensive to analyze. All of the top research priorities are algorithmic. One, there is a pressing requirement for robust onboard SLAM in GPS-degraded environments such as underground tunnels or dense forests, from multi-sensor fusion of cameras, IMUs, and LiDAR. Second, advanced machine learning and artificial intelligence algorithms are required for real-time anomaly detection and feature extraction [60]. These include automatic detection of mineral assemblages in hyperspectral images, infrastructure cracks, or invasive species in agriculture without manual intervention. Third, one needs to study efficient data transmission and compression algorithms to mitigate the bandwidth limitation of real-time streaming of data from the edge [61]. In practice, although upgraded, lighter, and more effective sensors are always welcome, the edge currently is computational. The real potential in drone technology will be delivered not by sensors that collect the data, but by intelligent algorithms that transform this raw data into useful intelligence, autonomously and in near real-time.

2.6. Dense reconstruction in UAV-based mapping

The combination of SfM, dense image matching, LiDAR based Simultaneous Localization and Mapping (SLAM), and GNSS/INS fusion has constituted the core of UAV-based geospatial data collection, offering stable 3D reconstruction and navigation in different operation environments. SfM pipelines with bundle adjustment (BA) support high-accuracy scene modeling via incremental pose estimation and geometric refinement. There have been new advances, such as the graph-indexed Bag-of-Words approach with parallelized Schur complement-based BA (PSCBA) by Liu et al. [62] that improved efficiency while preserving the accuracy. Similarly, feature-matching techniques based on grid-based motion statistics have been demonstrated to be quite useful for suppressing drift in SfM processing [63]. Bergado and Nex [64] transferred UAV images to implement disparity shifting and occlusion masking. This was achieved through stereo networks using unsupervised learning models. Jannati et al. [65] introduce complementary studies seeking computationally efficient alternatives to Semi-Global Matching (SGM) through the introduction of a two-stage disparity estimation process removing image pyramids without sacrificing depth accuracy. In GNSS-denied real-time SLAM, UAV SLAM systems have employed LiDAR-IMU fusion more and more. Wang et al. [60] explained major features such as loop closure and pose graph optimization of outdoor SLAM systems, while Yin et al. [66] employed a two-step iterative calibration strategy to tackle LiDAR-IMU misalignments caused by rotation motion for SLAM robustness. GNSS/INS integration remains at the center of global navigation, but susceptibility to out-ages necessitates multi-sensor augmentation. Elamin et al. [67] demonstrated that tightly integrated GNSS/INS/LiDAR-SLAM systems regain fairly well the navigation performance in GNSS-denied environments, and Abdelaziz and El-Rabbany [68] also gained even better positional stability when incorporating stereo visual SLAM. Although, differing in their sensor dependency and computational topologies, these methods are converging towards hybrid fusion of vision, inertial, and LiDAR observables. SfM is effective with highly structured scenes that have high feature density. LiDAR-SLAM offers texture-poor or dynamic scene robustness, and GNSS/INS offers absolute georeferencing. Dense image matching is shifting from hand-crafted metrics to learning-based pipelines with growing emphasis on domain adaptation, occlusion, and acceleration. Together, these developments point to a common trend for UAV mapping: scalable, real-time, sensor-fused solutions that can provide high-accuracy spatial intelligence in various terrain and operating conditions.

3. Materials and methods

This review adheres to a rigorous, multi-stage methodology that seeks to minimize selection bias, maximize reproducibility, and provide an exhaustive synthesis of innovations in drone technology for mining and geotechnical uses. Unlike conventional narrative reviews that rely on subjective selection of literature and lack open search processes, the current study follows the PRISMA [69] preferred Reporting Items for Systematic Reviews guidelines to ensure methodological transparency, systematic examination of literature, and quantitative synthesis where applicable. The review answers three key research questions:

1). How do drone-based terrain modeling and stockpile volumetrics in terms of accuracy and efficiency compare with conventional surveying methods in other geotechnical and mining environments?

2). What technological (LiDAR vs. photogrammetry) and operational (flight planning, sensor fusion) factors influence UAV performance in real-time mining and geotechnical monitoring?

3.1. Literature search strategy

A systematic search strategy was employed in three major databases including Scopus (last searched on September 10th 2025), Web of Science (last searched on September 10th 2025), Google Scholar (last searched on September 10th 2025) to find peer-reviewed papers from journals, conference proceedings, and industry reports between 2010 and 2025. The search term used Boolean operators and keyword combinations like ("UAV" OR "drone" OR "UAS") AND ("mining" OR "open-pit" OR "Quarries" OR "Coal" OR "Exploration" OR "tailings" OR "Waste") AND ("Landslide" OR "Slope" OR "Deformation" OR "Highway" OR "Sink hole") AND ("Accuracy" OR "Precession"), with broad coverage of the studies.

Additional backward and forward citation tracking was conducted on significant papers to seek out early papers not caught in the initial search. To minimize selection bias, predetermined inclusion/exclusion criteria were applied and only empirical quantification studies (e.g., accuracy tests, efficiency measures) were retained, while purely theoretical or simulation-based studies were excluded except where they suggested novel methodological designs. Non-English publications were also excluded which includes Chinese, French and Russian languages. The PRISMA framework guided the four-stage screening process (Figure 1):

– identification;
– screening;
– eligibility assessment;
– inclusion.

All of the retrieved records ($n = 338$) were initially retrieved. The de-duplicated records were removed by Endnote. Review papers and meta-analysis studies were also excluded, leaving an initial dataset of 162 articles. The author screened title/abstract, resolving disagreements at three points and subsequently combining the remainder. The remaining full-text articles were screened for eligibility, and 94 studies were found eligible for qualitative synthesis and 18 for meta-analysis. A data extraction form with a uniform pattern documented key variables: study year, location, mining type (open-pit, underground, tailings), drone information (sensor type, flight altitude, ground sample data), and comparison metrics (Mean Error, RMSE, Standard Error, Standard Deviation, Minimal Error).

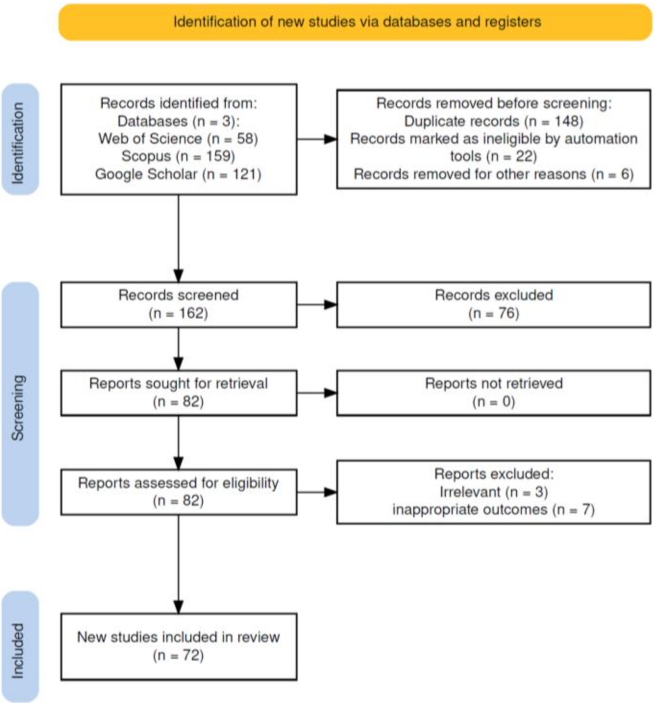

Figure 1. Prisma flowchart

To quantitatively contrast UAV performance with traditional methods (total stations, terrestrial LiDAR), meta-analysis was conducted on those papers reporting subsidence, stockpile volume, accuracy analysis and slope deformation measurement error.

Data was split by sensor type (LiDAR vs. photogrammetry) and mining environment to establish context-dependent differences. The magnitude of efficiency of UAVs in terms of time and cost saving is quantified by calculating effect sizes. Funnel plot, helped with determining subgroup analysis and publication bias. Co-occurring keywords, author collaborations and research trends were shown using Bibliometric maps developed by VOS viewer [70]. Evolving areas of interest were presented by forming clusters. Thematic analysis categorized the studies into technological (sensor technology advances), operational (flight planning concerns) themes, and it noted gaps such as the absence of representation of applications for underground mining.

Strengths-Weaknesses-Opportunities-Threats (SWOT) analysis combined qualitative evidence from existing literature. Strengths included acquiring high-resolution data and avoiding human exposure to hazards, while weaknesses listed battery life limitations and processing of data constraints. Opportunities identified AI-aided predictive modeling and real-time streaming facilitated by 5G, while threats included cybersecurity exposure and fluctuating global regulations. To make findings practically relevant, these were cross-checked with seven mining industry experts through semi-structured interviews, focusing on actual-world implementation issues. Interview findings were utilized as an industry validation for this research.

4. Results and discussion

The results are discussed in five main sections starting with systematic literature review addressing the research questions followed by meta-analysis, Bibliometric analysis, SWOT analysis, and industry survey.

4.1. Systematic review

Accurate measurement is the core of sciences behind mining and geotechnical engineering. For centuries, this relied on the meticulous work of surveyors with theodolites and tripods [71]. There is a revolution in technology currently underway with UAVs, or drones, revolutionizing volumetric analysis and terrain modeling [72-75]. This is founded on unparalleled efficiency and enhanced safety, while providing accuracy that matches the demanding standards of modern industrial uses. The greatest advantage of drone surveying is its efficiency in terms of economy, time and safety [76, 77]. Conventional ground-based methods, using total stations or Differential GPS (DGPS), require crews to physically visit every point of interest. In a large open-pit mine or over very extensive stockpiles, this can take weeks or days of laborious work. In contrast, a drone captures the same area in several hours [78], traveling a pre-programmed grid and automatically capturing thousands of overlapping, high-resolution images [79]. Automation creates digital surface models and 3D models using photogrammetry software [80, 81]. There is a chance of minimal disruption of operations with quicker turnaround times leading to enablement of real-time data monitor [82] at site with much improved mining rate [8] and stockpile volume computations. Mining is a hazardous environment with unstable highwalls, heavy equipment, and unstable stockpiles. Measurement from such environments [83] is far riskier in nature. UAVs are a perfect application for leaching pads, dangerous areas, high and steep slopes or difficult terrain where free access is limited. Drones do not expose men to hazardous conditions on site which greatly improve project safety during mapping and surveying [84]. This ability of drones makes them stand out as they can potentially save human lives at a much lower price compared to ground-based methods. In terms of application in industries requiring high accuracy, the accuracy of data collected from drones has paramount importance [84-86]. While traditional surveying still holds a slight edge in ultra-high-definition point measurement, the difference has narrowed by a significant margin. Modern drone platforms, especially those with RTK or PPK GPS capability and assisted by accurately positioned GCPs, are consistently delivering vertical and horizontal accuracies [87]. This is more than adequate for the majority of mining and geotechnical applications.

For critical operations such as stockpile volume calculations studies have reported drone error rates of between 0 and 3% [11], compared to 1% for conventional methods. Both fall within industry acceptable tolerance of ±3% to make drone-derived data fit for purpose. Industry practitioners and researchers have reported that the accuracy of measurement by drone is influenced by terrain, vegetation, and GCP location [1, 88, 89] but reliability of outputs remains sufficient for operational decision making. Open-pit mines, quarries, slopes, and spoil piles are where drones are best applied, with the ability to image large areas very rapidly being a perfect match for operational needs. They are seeing increased use in geotechnical engineering for slope monitoring, erosion studies, and project monitoring [90, 91]. Notably, drones are typically synergistically coupled with traditional methods [92], providing macro-context with ground-truthed micro-details.

Drone technology application is a quantum leap for the field of geotechnincal and mining engineering. It shatters the traditional trade-off between accuracy and efficiency, with improved safety, accessibility, and rapid data acquisition without compromising accuracy [9, 93, 94]. As sensor technology, LiDAR, and artificial intelligence evolve, the use and usefulness of drones in challenging and complex environments should expand. Drone surveys are also susceptible, to compounding sources of error [95, 96], which is absent in traditional surveying. Incorrect placement of GCPs, poor satellite visibility, or multipath effects can undermine positional accuracy [88]. Inadequate flight planning like an incorrect altitude or insufficient image overlap can reduce model resolution and introduce errors [97]. Severe winds, variable lighting, and difficult terrain (i.e., highly reflective or featureless surfaces) are also environmental conditions that affect data quality. Software processing choices also affect volumetric outputs, and these need to be firmly verified with independent checkpoints [98, 99]. At the core of UAV-based remote sensing is the decision between LiDAR and photogrammetry, each with its own particular strengths. Higher precision is achievable with LiDAR technology with the ability to penetrate vegetation cover [100] and create models. The LiDAR systems provide laser pulses at high speed which offers accurate results and is immune to light conditions, thus suitable for operation in the shade or underground application. Such systems as expensive computationally and otherwise as the payload requirements are huge making them suitable for employment in mega projects. In contrast, photogrammetry builds three-dimensional models by mosaicking overlapping high-resolution images [100] taken from multiple perspectives. Photogrammetry is superb for generating photorealistic site models and is economically viable [101] for use cases such as monitoring haul road surfaces, stockpile inventory volumes, and structural inspections. Some limitations of photogrammetry are its lighting-sensitiveness [102], it cannot penetrate in dense vegetation [100], and it may be less accurate in elevation modeling, particularly in regions of complex terrain [89].

Sensor selection is the starting point, while flight planning is essential for data quality. The main parameters are flying height, speed, image overlap, and direction [103]. Good stereo reconstruction with improved resolution is ensured by sufficient overlapping (80% front and 60% side), reduced ground sample distance (GSD), and lower flying heights. Elevation accuracy is greatly improved for complex terrains by adaptive flight planning [104]. Without such planning, even the most sophisticated sensors can yield suboptimal data. Data fusion is emerging as a frontier in UAV application. The integration of LiDAR point clouds with photogrammetric textures, thermal imaging, or multispectral data enhances visualization and quantitative analysis together [105, 106]. Accelerated data processing can be achieved by using RTK or PPK systems [89] which may eliminate requirement for many GCPs. Now it does not take too much time to assess slope stability or stockpile volume or generate a map thanks to the cloud-based systems and automation. Drones offer an extremely powerful means of volumetric surveying with unmatched speed and safety. Nevertheless, they require rigorous mission planning, flight, and data verification to balance intrinsic inaccuracies. If used correctly, not only do they enhance surveying but also contribute to a safer, more efficient, and data-driven mining industry.

4.2. Meta-analysis

Figure 2 presents a summary of several studies involving UAV photogrammetry and LiDAR for topographic modeling and the reported mean errors. The reported accuracies by results are significantly diverse, ranging from 0.00 m to 0.45 m mean error. Such extreme diversity indicates that achievable accuracy significantly depends upon sensor orientation, flight conditions, terrain characteristics, and data processing techniques.

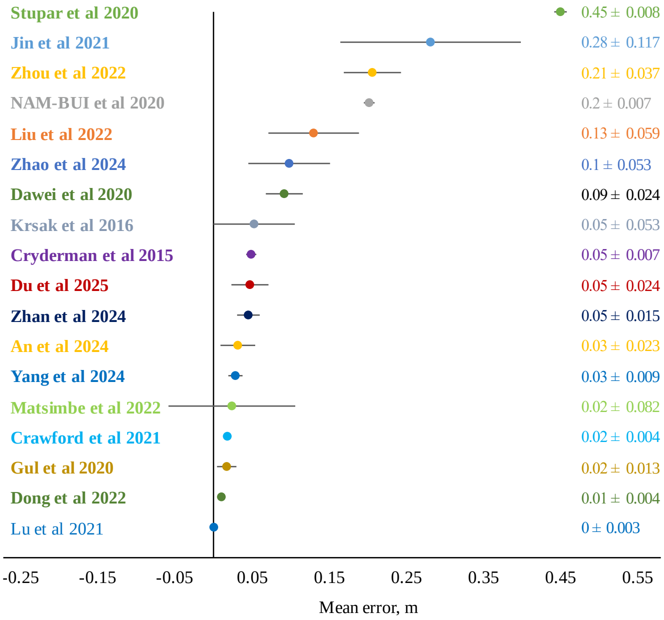

Figure 2. Forest plot showing mean errors as reported in multiple studies available from literature [108-110, 112-126]

An extremely high percentage of research studies achieved high accuracy with mean error below 0.05 m. Strangely enough, Lu et al. [107] reported a mean error value of 0.00 ± 0.003 m, then Dong et al. [108] at 0.01 ± 0.004 m, and Gul et al. [109] at 0.02 ± 0.013 m. This cluster of very close results with tight confidence limits is a demonstration of good methodology. These typically involve the use of high-resolution sensors with RTK/PPK GNSS integration, optimal GCP networks, and advanced SfM algorithms. There is a range in the middle which produced mean errors between 0.05 m and 0.15 m, like Zhao et al. [110] (0.10 ± 0.053 m) and Liu et al. [111] (0.13 ± 0.059 m). A complex terrain and less dense GCP network are likely the cause of obtaining a wider confidence interval. Large scale mapping of geomorphology, classification of land, environmental monitoring can accommodate small errors and low accuracies are sufficient for these applications.

The Figure shows few outliers like Stupar et al. [112] (0.45 ± 0.008 m) and Jin et al. [113] (0.28 ± 0.117 m). These high error levels reflect methodological limitations, perhaps the application of uncorrected consumer drones, poor GCP coverage, or unfavorable environmental conditions during data capture (e.g., high cover density, uniform terrain features, or lighting conditions). Such data can be sufficient for reconnaissance-level mapping but have limited application in quantitative geotechnical studies. A time-wise assessment of the results shows an apparent trend of improvement in accuracy in more recent study articles (2021-2025). This upgrade is likely the result of mass usage of RTK/PPK drones, sophisticated flight planning software, and sophisticated automated processing procedures.

This influence demonstrates UAV surveys can achieve sub-decimeter accuracy under rigorous methodology. The results verify the application of important tasks like volumetric measurements, surface deformation and creation of DEM which require higher precision. Above all, the range of accuracy noted emphasizes that accuracy is not inherent to the platform but rather under systematic survey design. Sensor calibration, image overlap, flight altitude, GCP design, and post-processing approach are essential parameters affecting outcomes. Consequently, rigorous adherence to best practices for data acquisition and processing is necessary for the use of UAVs in mission-critical mining and geotechnical operations.

Figure 3 is a pie chart representing country-level trends of publication of research with focus on the accuracy of UAV and drone technology in geotechnical engineering and mining practices. The figure indicates a highly skewed pattern of publication, which is a representation of the geopolitical imbalance in the output of research and advancement of technology. The chart clearly shows that China is the dominant research country with 55.6% of the overall production. Such dominance is a proof of China's consistent strategic leap in autonomous systems, remote sensing, and digital geotechnical methods. Such dominance justifies China's dominance in rare earth element (REE) value chains, mining digitalization, and UAV manufacturing, emphasizing a national overall direction towards technology independence and innovation in extractive industries. Contrasting Chinese dominance, the following eight nations including Canada, Slovakia, Slovenia, Vietnam, Turkey, USA, Malawi, and China & Mongolia (general category) share 5.6% of global production in research.

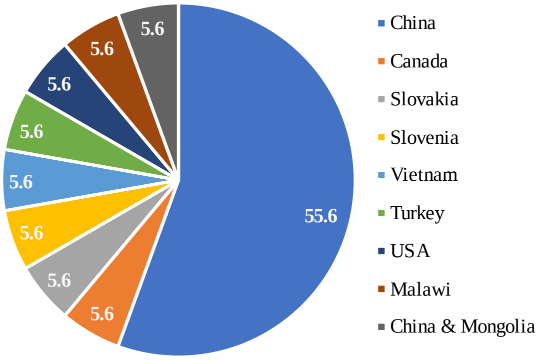

Figure 3. Pie chart showing percentage of country wise publications with China securing top slot

It is a sign of research clusters on nothing but China and others with modest yet increasing attention to precise mapping and volume calculation in mining with the help of UAVs. From the strategic point of view, this graph provides the following critical two observations:

1). Unipolarity by any nation poses risk in global knowledge exchange, standardization, and frontier transfer of technology. This has tremendous significance to mining operations based on the accuracy of UAV for environmental monitoring and regulatory compliance.

2). Having geographically and economically diverse contributors (e.g., Turkey, Vietnam, Malawi) implies untapped potential for North-South and South-South collaborations, particularly in the use of UAV technology to terrain, climatic regimes, and mineralization in their nations.

3). Overrepresentation of top mining economies (e.g., Australia, South Africa, Chile) in this dataset necessitates further bibliometric analysis and may be an indication of language limitation, unpublished industrial knowledge, or dispersed scholarly work not amounting to a recoverable quantity.

Overall, Figure 3 not only indicates variable publication levels but also reflects the need for more diversified and balanced global research setting for UAV geospatial mining applications. Multinational collaboration, sponsorship funding, and open-access publishing can accelerate innovation and render research into UAV precision vulnerable to multinational skills and field-observing contextualization.

Figure 4 shows a funnel plot summarizing the distribution of key application themes explored in UAV-based research within the mining and geotechnical engineering sectors. The data is presented as a percentage share of the total studies reviewed (*N* = 100% base for normalization). The five dominant themes include accuracy analysis, mining subsidence monitoring, dumpsite surveillance, stockpile volumetrics, and rock mass identification. The largest and highest portion of the funnel is “Accuracy analysis” (100%), representing the ubiquitous applicability within the literature examined. This is the fundamental nature of accuracy benchmarking in remote sensing applications, where ground-truth validation, mean error analysis, and comparison against traditional surveying methods (e.g., total stations, RTK-GNSS) are inevitable. High accuracy is the necessary prerequisite to all subsequent work such as volumetric calculation, slope analysis, or feature classification and hence the methodological pillar of UAV-based surveying.

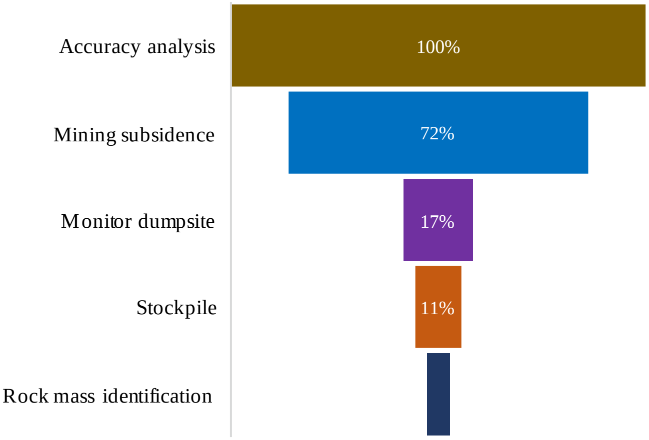

Figure 4. Funnel plot showing distribution of topics studied in the domain

This wide-ranging emphasis (e.g., Zhou et al., [114]; Jin et al., [113]), illustrate that more than 90% of mining drone applications utilize some form of geospatial accuracy validation through GCPs or advanced correction systems like PPK/RTK. The second category, accounting for 72% of research, is “Mining subsidence monitoring”. Such high frequency reflects growing concern over ecological risks from surface deformation due to underground mining, particularly in coal and salt mining districts. UAVs provide regular and high-resolution orthomosaics and DSMs, allowing temporal change detection of millimeter-order ground deformation. Compared to traditional leveling or InSAR, UAVs are more adaptable and can survey larger areas, especially in mountainous or remote terrain. Examples mentioned include subsidence bowl monitoring, fault reactivation zones, and room-and-pillar mining pillar failure, indicating high usage of UAVs for geotechnical risk evaluation.

The “monitor dumpsite” has an increasing focal area but is considered as a secondary factor with 17%. There are greater geo-environmental and geotechnical challenges associated with spoil dumps, tailing storage facilities, and waste rock piles. UAVs increasingly survey slope angles, monitor erosion or storm-driven change, and aid the safe development of landforms. The low figure suggests that this can be a new field of research, possibly because dumped material needs to be discriminated from natural ground in photogrammetry, or visual clutter and surface instability problems. The other top category, “Stockpile monitoring” (11%), is unexpected in light of its crucial role in stock management and logistics. UAV-based photogrammetry estimation of stockpile volume has been demonstrated to be faster, safer, and often less expensive [9] than terrestrial laser scanning or GPS surveying. The low share of this category in the funnel is likely a result of underreporting in peer-reviewed literature since most stockpile surveys are conducted as in-house industrial practice rather than academic research. This indicates a research-to-practice gap, with a possible future standardization and publication of industrial processes. “Rock mass identification” (6%) is at the bottom of the funnel, the least researched amongst UAV applications. Its low occurrence is understandable as the technical potential of UAV photogrammetry and conventional RGB images to extract lithological heterogeneity is low. However, enhancement of sensor fusion, particularly hyperspectral and multispectral imagery, is beginning to push the horizon for remote geological mapping. Initial research has indicated promise in fracture trace mapping, joint orientation analysis, and lithological boundary definition but still remains in its infancy [127]. The low ratio presents a high-potential research frontier, especially with AI-enhanced classification algorithms for spectral and visual UAV-collected data. This funnel chart illustrates a standard “top-heavy” research distribution where anchor topics like accuracy and deformation monitoring are dominating, with less-screened operational and frontier uses lagging behind. The taper from 100% to 6% reveals an advanced-validate-but-nascent-integrate-and-innovate ecosystem of research. This trend replicates technology adoption life cycle, with lead adopters first piloting reliability (accuracy), then in particular applications (subsidence, dumps), followed by blanket application in logistics (stockpiles) and finally into cutting-edge frontiers (rock mass classification).

A multi-dimensional comparison of UAV research applications in geotechnical engineering and mining was conducted with a bubble chart visualization (Figure 5) that integrates three prominent metrics: the amount of data points collected (study volume, x-axis), Root Mean Square Error (RMSE, accuracy, y-axis), and research focus (bubble size). The integrated strategy reveals distinct patterns of research investment and performance for five prominent application areas (Figure 4). The Mining Subsidence Monitoring application has the largest data volume (>250 points) and largest research footprint (largest bubble size), and hence is the most researched application. However, it also has the largest RMSE in all categories (~0.12 m). This combination suggests large-scale use because of regulatory and security requirements in underground mining regions but also indicates significant technical challenges.

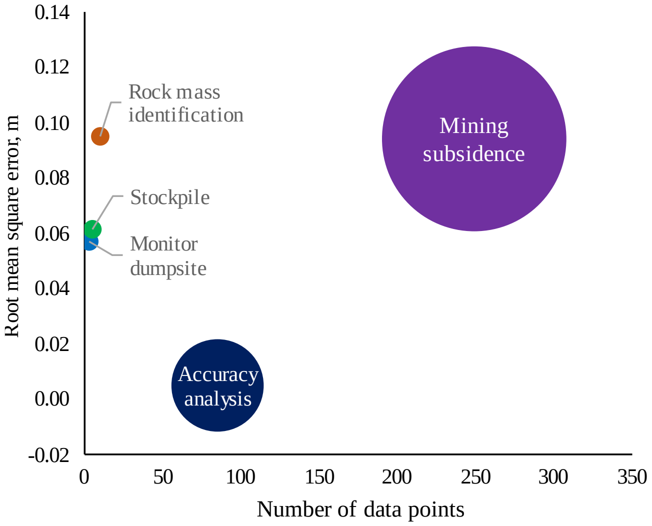

Figure 5. Bubble plot showing multi-parameters including RMSE, number of data points and number of studies on a particular topic

The high error is likely caused by complexity of terrain, ongoing surface deformation, vegetation disturbance, and low-contrast surfaces, all of which interact to make change detection as well as accurate elevation modeling more challenging. These findings emphasize the need for urgent methodological advances, such as multi-sensor data fusion (e.g., fusion of LiDAR and photogrammetry) and better ground control, to achieve higher measurement accuracy in this socially and operationally significant application.

On the other hand, “Accuracy Analysis” research mirrors the highest precision with a very low RMSE of ~0.005 m, in addition to a high volume of data (~90 points). This indicates UAV systems can utilize high precision in controlled situations under validation and benchmarking study conditions, where they are typically applied in rigorous flight planning, high GCPs, and optimized processing parameters. The wide research interest shows the academic community's desire to establish the base-level trustworthiness of UAV-based information. This field is a pivotal building block for the validation of applications in operational environments such as volumetric estimation and deformation monitoring.

The applications of “Stockpile Management” (RMSE ≈ 0.02 m) and “Dumpsite Surveillance” (RMSE ≈ 0.01 m) are both positioned in the high-accuracy, low-data-volume sector of the graph. Their high accuracy confirms that UAVs are very suitable for volumetric measurement and material monitoring in these structured environments. The relatively small bubble sizes guarantee that these applications are perfectly underreported in the literature. This discrepancy most likely results from industrial processes being monitored proprietarily and from a journal bias towards new rather than usual operational monitoring activity. The disagreement confirms a definite trajectory from mere experimentation towards broad-scale uptake, and then a potential wave of innovation again. Greater academic effort is surely an opportunity to develop and standardize automated, high-frequency monitoring pipelines for these high-value commercial applications.

Rock Mass Identification is the smallest bubble, which indicates that it is the least studied application, and it has a moderate RMSE of ~0.06 m (Figure 5). Challenges in lithology conversion here are largely due to the inherent limitations of standard RGB imagery in handling texture-poor or spectrally uniform rock surfaces, exacerbated in numerous instances by challenging lighting conditions. The modest level of error and low research effort constitute a significant opportunity for improvement. Future efforts can attempt to leverage various sensors (e.g., multispectral or thermal cameras) and new machine learning techniques for lithological classification and structural feature extraction. It is a promising area for cross-disciplinary collaboration between remote sensing, computer science, and engineering geology.

Figure 6 shows that UAV photogrammetry was the most researched method (*n* = 9), as it had the highest mean error at 17.11 centimeters. Such inaccuracy is most likely due to its susceptibility to environmental influences (e.g., variation of light, wind blur) and challenging processing of low-texture or vegetated surfaces. The absence of RTK or PPK georeferencing in the majority of photogrammetric processes also contributes to reduced accuracy. The findings show that while low-cost and of general utility, standard photogrammetry requires strict ground control and calibration in order to be sufficient in high-precision uses such as volumetric accounting or small-scale deformation monitoring. The blend of photogrammetry and LiDAR (UAV LiDAR Photogrammetry) delivered a much lower mean value of error at 6.11 cm. The hybrid approach takes advantage of the merits of both technologies:

– LiDAR vegetation penetration;
– height accuracy;
– photogrammetric high-resolution visual texture.

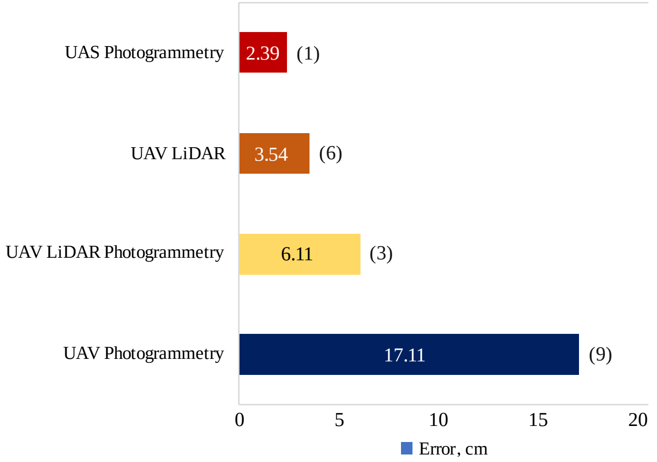

Figure 6. Comparison of error for different methods, showing UAV photogrammetry incurs greater errors

The perceived accuracy gain suggests the benefits of sensor fusion for applications that represent a trade-off between dimensional accuracy and visual information content, i.e., geotechnical change detection and early geological modeling. The lowest mean error of 2.39 cm was obtained by UAS Photogrammetry, typically larger fixed-wing systems in this case.

UAV LiDAR achieved greater accuracy with a mean error of 3.54 cm, based on results of six studies (*n* = 6). This performance demonstrates LiDAR's strong points, both in its independence from ambient illumination and in the generation of distortion of digital terrain models beneath complex topography. The residual error is likely to be dominated by post-processing constraints or calibration problems rather than sensor inaccuracy itself. UAV LiDAR is therefore well-suited to applications demanding high spatial precision, including engineering-grade topographic mapping and slopes stability analysis in detail. UAS Photogrammetry, which in this case typically refers to larger fixed-wing systems, had the lowest average error of 2.39 cm. This result relies on a small sample size of (*n* = 1) and thus lower statistical power. The high accuracy is most likely gained through optimized operating conditions, i.e., RTK-capable positioning, very stable flight, and high-resolution cameras under optimal conditions. While such results indicate potential for high accuracy using photogrammetry, reproduction in a variety of studies is required to confirm results and allow for standards of performance to be generalized. There is evidence for a consistent cost vs ease-of-use vs accuracy trade-off. Photogrammetry remains popular with lower cost and high-resolution visual outputs, yet unpredictable accuracy demands rigorous methodological planning. LiDAR-based methods, being more costly, yield a much improved and uniform level of accuracy. The future focus areas can include sensor fusion to achieve high precision, also optimization studies for UAS platforms will be helped by standard workflows and a vide validation across mining and geotechnical fields and environment.

4.3. Bibliometric & thematic analysis

The pattern of publications over the period from 2010 to 2025 reflects distinct phases of technological and academic progress in the application of UAVs in geotechnical engineering and mining (Figure 7). The disagreement confirms a definite trajectory from mere experimentation towards broad-scale uptake, and then a potential wave of innovation anew.

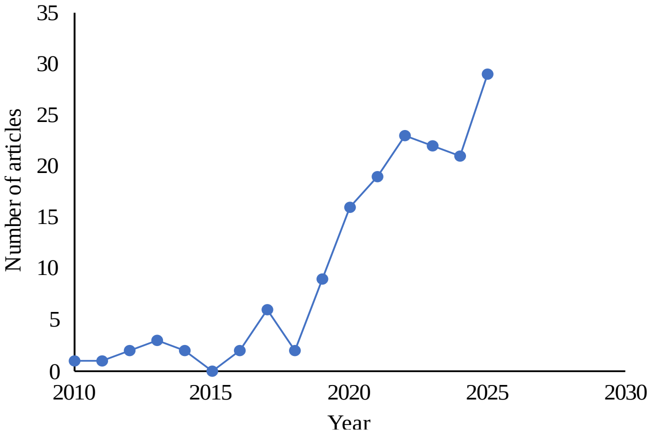

Figure 7. Publication trend over the years showing that the UAV research is increasing tremendously owing to the accessibility of the equipment lately

The first or infancy period of UAV technology is clearly from 0 to 4 annual publications which is considered as a low productivity range. This can be attributed to uncertainties, some developments in technology and commercial immaturity. Research during this period was largely exploratory and consisted of isolated feasibility studies and early case reports. There was a definite point of inflection observed between 2017 and 2019, with annual publication numbers rising from 1 to 9. This growth is coincident with significant developments in UAV affordability, platform stability, and commercial availability of integrated sensors (i.e., photogrammetric, LiDAR, and thermal cameras). The focus of research shifted from fundamental feasibility to applied validation, with studies demonstrating utility in stockpile volumetrics, slope stability monitoring, and high-resolution topographic mapping. Stronger academia-industry partnerships helped with increased pilot deployments. The publications count becomes three times between the year 2019 to 2022. Two factors can be attributed to this growth:

– the maturity of AI-based data processing software for point cloud classification and feature detection;

– COVID-19-induced accelerated uptake of remote monitoring solutions.

The technology is being translated into a valuable geospatial application for industrial and research use. There is a plateau of publication numbers, levelling out at a figure of about 21-23 papers each year, from 2022 to 2024. This would suggest a phase of methodological consolidation and maturity. The research focus would appear to have changed from demonstrating potential for application to improving accuracy, optimizing workflows, and incorporating UAV-derived data into more comprehensive mine planning and management systems, including early digital twin systems.

A record high of 29 publications in the year 2025 (till october) suggests a new era of innovation. This peak is likely the result of innovations in multi-sensor fusion (e.g., hyperspectral LiDAR), novel applications such as underground mine mapping and predictive subsidence modeling, and the integration of UAV data into large-scale digital twin systems. Such a peak would also be driven by increasing regulatory and societal pressure for sustainable mining activities, for which UAVs offer affordable monitoring solutions.

Figure 8 presents the publication pattern of academic papers by their funders, indicating the dominant status of Chinese funding institutions in sponsoring geospatial and UAV studies.

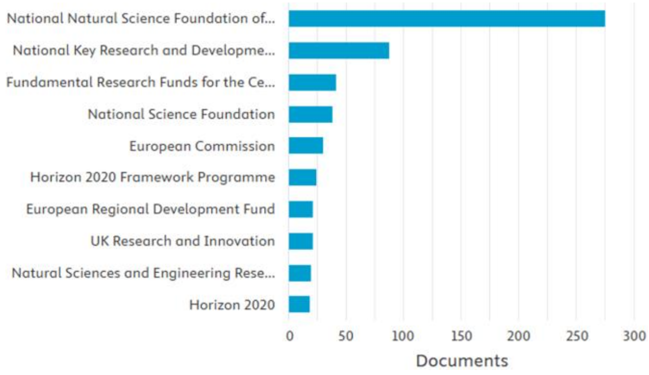

Figure 8. Distribution of scholarly documents by their funding sponsors highlighting the research focus of various organizations and countries

The NNSFC is the dominant one with nearly 300 funded articles, followed by the National Key Research and Development Program of China with about 90 articles. Other Chinese sources, such as the Fundamental Research Funds for the Central Universities, also contribute significantly. On the other hand, the international funders, such as the U.S. National Science Foundation, European Commission, and Horizon 2020 Framework Programme, sponsor relatively fewer documents (between 20 to 50 each). This distribution is proof of China's strategic investment in scientific research in such areas as remote sensing, UAV technology, and geotechnical applications and a reflection of its global leadership position in research output in these fields.

Figure 9 generated using VOSviewer, is a visualization of a co-authorship network of researchers in the field of UAV-based surveying and geotechnical applications. Every node is one author, and the edges between them indicate co-authored papers. The colors indicate different collaboration groups or research teams.

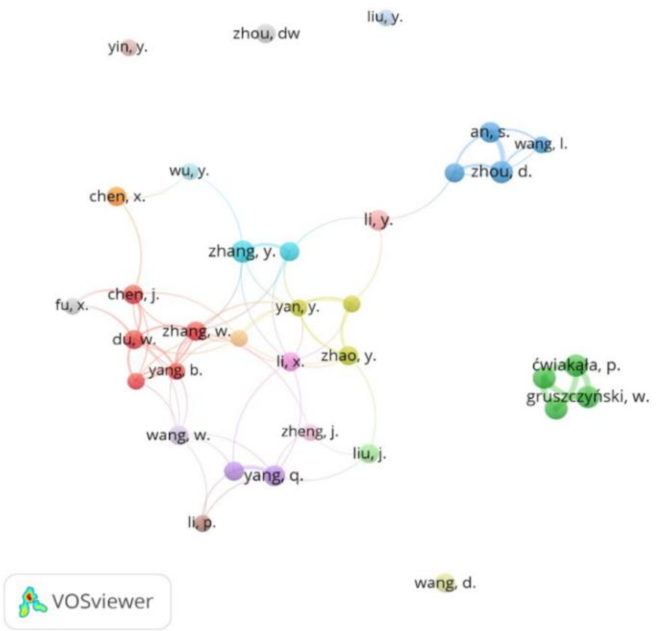

Figure 9. Co-authorship network visualization of researchers working in the domain showing very little collaboration in UAV research

Several highly connected clusters can be seen, which suggests extensive intra-group collaboration most significantly between Chinese researchers (center-left), which possesses the largest network, indicating high output as well as collaborative work. Another green cluster on the right is separate and smaller, representing European authors such as Ćwiakąła, Pawel [128] and Gruszczyński [129], with distribution at regional level. Individual authors such as Yin, [130] and Zhou [114, 131] continue to be isolated at the periphery, reflecting a weak collaborative link in this data set. This visualization is highlighting cross-institutional and cross-country coordination to facilitate innovation in UAV geotechnical research.

Figure 10 illustrates a keyword co-occurrence network visualization developed using VOSviewer, displaying the thematic context of UAV research in the geotechnical and mining sector.

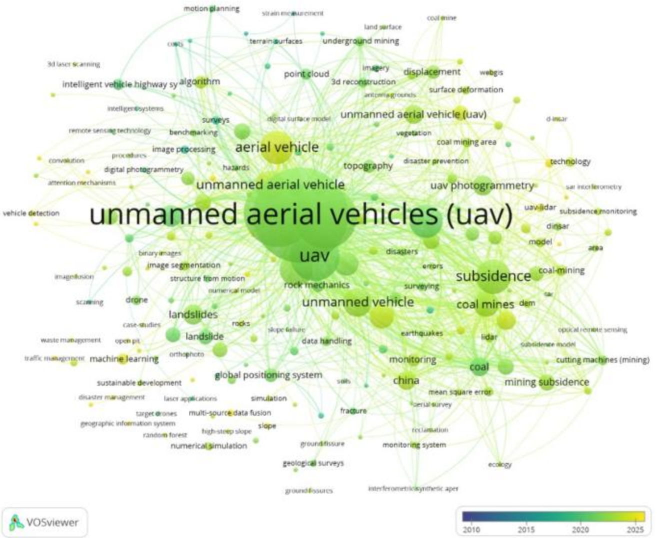

Figure 10. Keyword co-occurrence network visualization showing joint core concepts, topics, and ideas of the researchers in UAV research relevant to geotechnical and mining fields

The size of each node is based on how often the keyword is used in the literature, while the closeness and thickness of the lines connecting them are based on the intensity of keyword co-occurrence.

The central dominance of words “unmanned aerial vehicles (UAV)”, “UAV photogrammetry”, “subsidence”, and “coal mining” indicates that the majority of academic focus is on UAV applications in subsidence monitoring in mining, terrain modeling, and safety inspection. Peripheral clusters reveal closely related subtopics such as “LiDAR”, “monitoring system”, “GPS”, and “machine learning”, indicating new intersections between UAV technology, spatial analysis, and AI-based analytics.

Purple to yellow-green color gradation shows temporal development of research interest, demonstrating that terms like “subsidence monitoring”, “3D reconstruction”, and “laser scanning” have been increasing during the past five years (2020-2025). Overall, this map shows a dynamic multidisciplinary development of UAV-based mining research with huge potential for further innovations in precision surveying and geotechnical monitoring.

4.4. SWOT Analysis of UAV adoption

4.4.1. Strengths

The most widely accepted strength of UAVs is their spectacular reduction in data collection time. Many authors [132, 133] indicated UAVs are “much faster and more efficient”, making weekly or even daily monitoring of sites possible, which is not feasible by conventional means [134].

STRENGTHS
- Overwhelming efficiency gains
- Strong cost-effectiveness
- High adoption for core applications
- Displacement of traditional methods

WEAKNESSES
- Data processing bottleneck
- Accuracy perceptions are mixed
- Personnel and skill gaps

OPPORTUNITIES
- Expansion into new applications
- Technological advancement
- Benchmarking and standardization

THREATS
- Regulatory hurdles
- Challenging terrain limitiations
- Weather dependency
- Complacency and data overload

Figure 11. SWOT analysis highlighting key features

One of the best features of these equipment are they remove human exposure to a dangerous or hazardous areas such as steep slopes [9], fires, waste dumps, accident or harmful radiation sites. The zero harm goal of the industry is clearly targeted through the UAV use in mines and geotechnical sites. The major researches found UAVs to be “much more cost-effective”, driven by reduced labor expenses, reduced site downtime, and the ability to conduct surveys with a small team. UAV photogrammetry not only generates point data but also rich, visually appealing outputs like 3D digital surface models (DSMs), and digital terrain models (DTMs) that are extremely valuable for visualization, planning, and stakeholder management.

4.4.2. Weaknesses

The most commonly cited technical challenge is “data processing and software” [135, 136]. Handling high amounts of data requires significant computational capacity and sophistication [137], thus adding latency between data acquisition and knowledge actionable enough to inform key decisions. This indicates that accuracy is very susceptible to operator experience, equipment quality (e.g., RTK/PPK GPS), and processing technique [89, 138]. The technology creates a “skill gap” which means operators must be skilled in flight planning, data processing, and spatial analysis beyond the task of a traditional surveyor. Mohsan et al. [10] identified “skill gaps or deficiency in trained manpower” as the biggest problem. Another challenge is the limited penetration capabilities of the standard photogrammetry through vegetation [100] to model the bare earth surface. This is considered as a key flaw in exploration or forested regions.

4.4.3. Opportunities

Besides RGB cameras, integration of data from LiDAR (vegetation penetration and accurate height), multispectral/hyperspectral (detection of minerals) and thermal sensors (machine monitoring) [139] can be achieved in developing a more comprehensive digital twin of the site [140]. Machine learning processes can be utilized to process UAV data automatically for specific applications [141, 142], such as automatic crack detection in slopes, stockpile volume measurement, and time-series change detection, reducing the processing bottleneck. Autonomous mapping of underground mines using small and collision-free UAVs is an enormous growth prospect and renders such perilous spaces safer [143]. UAV designs provide the perfect spatial configuration for the development of dynamic digital twins of mines with real-time observation and simulation through sensor network integration.

4.4.4. Threats

This is the most significant external risk. MCTegg [144] described regulations as “Very significant”, mentioning problems with flight permissions and airspace rules. This adds bureaucratic overhead, can decelerate missions, and fluctuates enormously by geography, making operations for firms operating in numerous jurisdictions difficult. The facts clearly indicate two settings where UAVs are least efficient:

1). Steep slopes and highwalls disrupt GPS signals and is usually the very spot that most need to be monitored for safety reasons, and it is a highly dangerous data shortage.

2). Traditional photogrammetry cannot photograph ground cover below the canopy and thus limits its use in woodland exploration or mines.

“Weather conditions” (rain, high winds, fog) are the primary technical problem [145, 146]. Weather conditions that will not ground a traditional survey team will frequently cancel UAV flights, and thus it can lead to delay in acquiring important information. The ease of gathering information will provide surveys being conducted without any particular intent, creating massive amounts of information that are never actually examined or converted into actionable business intelligence, watering down the value proposition.

4.4.5. Industry validation survey results

To cross-check the meta-analysis trends against current industry practice, a customized survey was circulated among practitioners with direct experience in applying UAV technology to mining and geotechnical projects. The survey attempted to quantify the opinions regarding the key areas: application prevalence, adoption level, performance metrics (accuracy, efficiency, cost), and operational challenges. The target sample was 33 practicing engineers, consultants, researchers, and technicians worldwide, selected on the basis of confirmed project experience. Seven full responses were returned, a return rate of 21.2%. Although small in number, the group of returners is specialist and expert, and their contribution represents a qualitative, expert-laid understanding of the practice situation. Collectively, they provide a necessary reality check for the verification of the wider trends in the literature.

The survey confirmed the meta-analysis finding that topographic modeling is the dominant application of UAVs in this industry, as it was cited by 85.7% of the respondents as a significant application. Stockpile volume estimation was second with a rate of 14.3%. With regard to integration with existing workflows, the results exhibit a strong paradigm shift with a combined 85.7% of practitioners confirmed UAVs have 'significantly replaced' (71.4%) or 'fully replaced' (14.3%) traditional surveying methods, whereas a minority (14.3%) regard them as complementary. This reinforces the meta-analysis observation of UAVs having shifted from an emerging tool to a cornerstone operation technology. A strong contrast between perceptions of data accuracy and perceptions of operational efficiency existed. All across the board (100%), the interviewee respondents vows that UAV-based techniques are much faster and require fewer people than traditional surveys. Efficiency has a straightforward effect on perceived savings in cost, with 85.7% of the respondents answering that UAVs are 'fairly more' or 'much more' cost-saving. Perceptions of accuracy were highly polarized and a point of disagreement. Nearly half of the respondents (42.9%) placed UAV-based information as less accurate than traditional survey methods, and the same percentage placed them in bulk as being equivalent (28.6%) or better (28.6%). This gap represents a huge discrepancy between technical accuracy reported in controlled studies of the meta-analysis and its observed place in typical field operations.

The survey also provided insightful comment on the actual-world impediments to UAV uptake, confirming and prioritizing issues which have been identified within the literature. The greatest technical barrier was software and data handling, at 71.4% of the sample. This identifies an obvious bottleneck that exists from data gathering through to handling and interpretation. In addition, respondents provided specific environmental and regulatory constraints. Steep slopes and highwalls (57.1%) and vegetation-laden areas (42.9%) were found to be the most challenging terrain to use UAVs. Finally, regulation systems were also considered a most critical factor where 42.9% and 57.1% of the population considered regulations as a 'very crucial' and 'somewhat crucial' obstacle respectively. The survey results significantly support the meta-analysis inferences of widespread application of UAVs rooted in unparalleled efficiency and cost-effectiveness. More importantly, they provide an able practitioner-based wisdom that refines the literature. They confirm that the largest concerns are now no longer concerned with technology viability per se but with how it is integrated, namely, perceived correctness verification, data procedures, and operation performance under challenging terrains and regulations. The findings redirect future development needs away from hardware design to applications software, standardized practices for correctness verification, and regulatory convergence.

5. Conclusions

This review integrates much more extensively the state-of-the-art in UAV technology application in mining and geotechnical engineering comprehensively, closing knowledge gaps based on an integrated multi-fethod research design that includes meta-analysis, bibliometric mapping, SWOT analysis, and industry confirmation. Clearly, the findings reveal how UAV technology has evolved from an innovative prospecting aid to a critical component of the digital mine and the ways in which data gathering operations have changed. The primary conclusion is that UAVs are able to successfully overcome the age-old trade-off between accuracy, efficiency, and safety. While the traditional survey methods maintain a narrow edge for highest-inaccuracy point measurement, the meta-analysis has shown that modern UAV platforms, particularly when equipped with RTK or PPK technology combined with strict ground control, are able to provide sub-decimeter accuracy. This level of precision, where faults are generally less than 0.05 meters, is highly adequate for the vast majority of industry applications, e.g., stockpile volumetrics, where faults will typically be comfortably within the industry-acceptable range of ±3%. Above all else, this accuracy comes at quick speeds, compressing data gathering time to hours from weeks and minimizing human exposure to hazardous conditions such as collapsing highwalls, active pit walls, and tailings storage facilities.

Bibliometric analysis shows an accelerating discipline with uncontrolled rates of publication after 2017, suggesting a redirection from proof-of-concept experiments towards widespread applications. But it is geographically localized expansion, and China dominates study production, simultaneously potentially undermining diversified knowledge production and providing a potential incentive for even more globalized coordination. Thematic analysis also identifies a research climate with a top-heavy, stable foundation in accuracy verification and subsidence monitoring but diminished exploration of operational applications like automated stockpile management and frontier topicality like AI-based rock mass identification.

SWOT analysis and industry survey both offer a reality check to the extent that technological capability alone is not going to translate into mass success. As much as industry experts on all sides recognize the advantages of UAVs such as speed, safety, affordability, and profusion of data output, there are major hurdles in the path. The most significant problems are not sensor capabilities but operational and manfactors like computing and expertise requirement of processing data, regulatory obstacles to Beyond Visual Line of Sight (BVLOS) flight, and vulnerability to bad weather. The industry survey is consistent in that data processing is viewed as the most serious technical bottleneck, and areas with steep terrain and high vegetation remain problematic environments. Hence, future integration of UAVs is not so much technological hardware but slim automated processing streams, regulatory streamlining, and squaring the skills gap with industry-relevant training programs.

This review supports that UAV technology is a revolutionizing driver of change in geotechnical engineering and mining by paradigm shift to safer, more efficient, and data-centric operations. The technology has lived up to its potential to provide repeat, high-rate geospatial data that form the core of resource estimation, activity planning, and risk mitigation. The way forward is to validate such success by overcoming major gaps and risks outlined above, particularly through investment in automation, building human capital, and policy activism. In this way, the sector can realize the complete potential of UAVs not only to enhance productivity but also drive its operational excellence, safety, and sustainability in the age of digitization.

Author contributions

The sole author was responsible for all aspects of the study and manuscript preparation. The author has read and agreed to the published version of the manuscript.

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Conflicts of interest

Author VL declared that he was Deputy Editor in Chief of the Engineering Journal of Satbayev University at the time of submission. This had no impact on the peer review process and the final decision.

Data availability statement

The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Abbreviations

The following abbreviations are used in this manuscript:

BVLOS	Beyond Visual Line of Sight
DGPS	Differential Global Positioning System
DIB	Drone in Box
DSM	Digital Surface Model
GCP	Ground Control Points
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
LiDAR	Light Detection and Ranging
NNSFC	National Natural Science Foundation of China
PPK	Post-Processed Kinematics
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
RMSE	Root Mean Square Error
RTK	Real Time Kinetics
SfM	Structure from Motion
SGM	Semi Global Matching
SLAM	Simultaneous Localization and Mapping
TLS	Terrestrial Laser Scanner
UAV	Unmanned Aerial Vehicle
UAS	Unmanned Aircraft System
TLS	Terrestrial Laser Scanner

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Тау-кен ісі мен геотехникалық инженерияда ұшқышсыз технологияларды қолдануға арналған мета-талдау және жүйелі шолу

М.З. Емад[*]

Король Фахд атындағы мұнай және пайдалы қазбалар университеті, Дахран, Сауд Арабиясы

**Корреспонденция үшін автор: muhammadzaka.emad@kfupm.edu.sa*

Аңдатпа. Беспилоттық ұшу аппараттары (БПҰА) геотехникалық және тау-кен жұмыстарын орындау тәсілдерін айтарлықтай өзгертті, кеңістіктік деректерді жедел, жоғары дәлдікпен және экономикалық тұрғыдан тиімді алуға, жер бедерін модельдеуге және нысандарды мониторингтеуге мүмкіндік берді. Жүйелі шолу мен мета-талдауда фотограмметрия және LiDAR технологияларын қоса алғанда, БПҰА қолдану арқылы жүргізілетін түсірілім дәлдігін тахеометриялық түсірілім және жерүсті лазерлік сканерлеу сияқты дәстүрлі әдістермен салыстыру мақсатында 133-тен астам рецензияланған жарияланымның нәтижелері жинақталып талданды. Зерттеуде БПҰА-ның тау-кен массасы қоймаларының көлемін анықтауда, жер бетінің шөгуін мониторингтеуде, қалдық қоймалары мен тау жыныстары үйінділерін зерттеуде, сондай-ақ тау жыныстары массивтерін сәйкестендіруде қолданылуы қарастырылды. Мета-талдау нәтижелері ұшу параметрлерін оңтайландыру, RTK/PPK-позициялау технологияларын және жерүсті тірек нүктелерін пайдалану жағдайында БПҰА тұрақты түрде қолайлы дәлдікті қамтамасыз ете алатынын көрсетеді. Беспилоттық LiDAR түсірілім дәлдігін арттыруға мүмкіндік берсе, UAV-фотограмметрия нәтижелер сапасы мен жұмыстар құны арасындағы ұтымды тепе-теңдікті қамтамасыз етеді. Алайда қателік шамасы жер бедерінің күрделілігіне, ұшуды жоспарлауға және метеорологиялық жағдайларға байланысты болады. Библиометриялық талдау 2017 жылдан бастап жарияланымдар санының экспоненциалды өскенін көрсетті, бұл ретте Қытай қаржыландыру, авторлық үлес және зерттеулер саны бойынша жетекші орын алады. Кілт сөздер мен бірлескен авторлық желілерді талдау машиналық оқытуға, үшөлшемді реконструкцияға және цифрлық егіздерге деген қызығушылықтың артып келе жатқанын көрсетеді. SWOT-талдау БПҰА-ның негізгі артықшылықтары ретінде операциялық тиімділікті, қауіпсіздікті арттыруды және нәтижелердің көрнекілігін айқындады. Кемшіліктеріне деректерді өңдеудің үлкен көлемі, дәлдіктің біркелкі болмауы, қолайсыз жер бедері жағдайында пайдалану қиындықтары және білікті мамандардың жеткіліксіздігі жатады. Нәтижелер салалық сауалнама арқылы расталды: респонденттердің 100%-ы жұмыстар тиімділігінің артқанын атап өтсе, 71%-ы шығындардың едәуір төмендегенін көрсетті. БПҰА эксперименттік жабдық санатынан геотехникалық негізгі құралдар санатына өтіп, мониторинг, жұмыстарды жоспарлау және қауіпті факторларды талдау үшін жедел ақпарат ұсынуда. Сенсорларды интеграциялау, жасанды интеллектіні қолдану және жұмыс процестерін стандарттау БПҰА-ны тау-кен өнеркәсібін цифрландырудың негізгі факторларының біріне айналдыруы мүмкін. Болашақ зерттеулер жерасты картографиялауға, автоматтандыруға және нормативтік талаптарды біріздендіруге бағытталуы тиіс.

Негізгі сөздер: *дрондар, ұшқышсыз ұшу аппараттары (ҰҰА), ұшқышсыз авиациялық жүйелер (UAS), фотограмметрия, тау-кен қалдықтары, көлемдік өлшеулер, дәлдік, жер бетінің шөгуі, көшкін, картографиялау.*

Метаанализ и систематический обзор применения беспилотных технологий в горном деле и геотехнической инженерии

М.З. Емад[*]

Университет нефти и полезных ископаемых имени короля Фахда, Дахран, Саудовская Аравия

**Автор для корреспонденции: muhammadzaka.emad@kfupm.edu.sa*

Аннотация. Беспилотные летательные аппараты (БПЛА) существенно изменили подходы к выполнению геотехнических и горных работ, обеспечив быстрое, высокоточное и экономически эффективное получение пространственных данных, моделирование рельефа и мониторинг объектов. В систематическом обзоре и метаанализе обобщены результаты более 133 рецензируемых публикаций для сравнения точности съемки с применением БПЛА, включая фотограмметрию и LiDAR, с традиционными методами, такими как тахеометрическая съемка и наземное лазерное сканирование. Рассмотрено применение БПЛА для определения объемов складов горной массы, мониторинга проседания земной поверхности, исследования хвостохранилищ и породных отвалов, а также идентификации массивов горных пород. Результаты метаанализа показывают, что при оптимизации параметров полета, использовании RTK/PPK-позиционирования и наземных опорных точек БПЛА способны стабильно обеспечивать приемлемую точность. Беспилотный LiDAR позволяет повысить точность съемки, тогда как UAV-фотограмметрия обеспечивает рациональный баланс между качеством результатов и стоимостью работ. Однако величина погрешности зависит от сложности рельефа, планирования полета и метеорологических условий. Библиометрический анализ свидетельствует об экспоненциальном росте числа публикаций с 2017 года, при этом Китай занимает ведущие позиции по финансированию, авторству и количеству исследований. Анализ ключевых слов и сетей соавторства показывает усиление интереса к машинному обучению, трехмерной реконструкции и цифровым двойникам. SWOT-анализ определил операционную эффективность, повышение безопасности и наглядность результатов как основные преимущества БПЛА. К недостаткам относятся значительный объем обработки данных, неоднородность точности, сложности эксплуатации в условиях неблагоприятного рельефа и недостаток квалифицированных специалистов. Результаты подтверждены отраслевым опросом: 100% респондентов отметили повышение эффективности работ, а 71% указали на существенное снижение затрат. БПЛА переходят из категории экспериментального оборудования в категорию основных геотехнических инструментов, обеспечивающих оперативную информацию для мониторинга, планирования работ и анализа опасных факторов. Интеграция сенсоров, применение искусственного интеллекта и стандартизация рабочих процессов могут сделать БПЛА одним из ключевых факторов цифровизации горнодобывающей промышленности. Перспективные исследования должны быть направлены на подземное картографирование, автоматизацию и унификацию нормативных требований.

Ключевые слова: *дроны, беспилотные летательные аппараты (БПЛА), беспилотные авиационные системы (БАС), фотограмметрия, горные отходы, объемные измерения, точность, проседание земной поверхности, оползень, картографирование.*

Publisher’s note