

RESEARCH ARTICLE

Integrated Ground–Air–Space Exploration Technology of Jingpo Lake Lava Tubes

Teng Hu^{1,2,3}, Haiting Yang^{1,2,3}, Zhizhong Kang^{1,2,3*}, Xiaojun Liu⁴, Changjun Wu⁵, Haohao Wu⁴, Haifeng Zhao⁶, Xue Wan⁶, Yuyan Zhao⁷, Wenzhe Fa⁸, Matteo Massironi⁹, Shengbo Ye⁴, Riccardo Pozzobon⁹, Honglei Yang¹, Linsheng Chen⁴, Yan Li¹, Sai Cheng⁶, Yuanzhi Qu⁵, Qiao Yang^{1,2,3}, and Jinhao Cai^{1,2,3}

¹School of Land Science and Technology, China University of Geosciences Beijing, Beijing 100083, China. ²Hebei Key Laboratory of Aerospace Information and Intelligentized Surveying and Mapping, China University of Geosciences Beijing, Beijing 100083, China. ³International Research Cooperation Sub-center for Lunar and Planetary Exploration, Joint Research Center for Deep Space Exploration, Ministry of Education, Beijing 100083, China. ⁴Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China. ⁵Heilongjiang Second Surveying and Mapping Engineering Institute, Harbin, Heilongjiang 150025, China. ⁶Technology and Engineering Center for Space Utilization, Chinese Academy of Sciences, Beijing 100094, China. ⁷International Research Center for Planetary Sciences, College of Earth Sciences, Chengdu University of Technology, Chengdu 610059, China. ⁸Institute of Remote Sensing and Geographic Information Systems, School of Earth and Space Sciences, Peking University, Beijing 100871, China. ⁹Department of Geosciences, University of Padova, Padua 35131, Italy.

*Address correspondence to: zzkang@cugb.edu.cn

Lava tubes play an important role in base construction and understanding planetary geological development on extraterrestrial bodies. However, our understanding of lava tube morphology on Earth as a reference for extraterrestrial bodies remains limited. Existing research mainly focuses on their formation mechanisms and uses a single approach to study their morphology. To fill this gap, we conducted a multi-platform investigation of a lava tube near Jingpo Lake, Heilongjiang Province, China, employing space-, air-, and ground-based techniques. The method presented in this paper can assist in the comprehensive exploration of lunar lava tubes in the future. First, data covering this large lava tube area were collected using synthetic aperture radar (SAR), due to its all-weather capability, from which distribution information on lava tube skylights was retrieved. Furthermore, close-range point cloud data of the lava tube skylight areas were collected from drones equipped with the DJI Zenmuse L1 LiDAR sensor, which allows for high-resolution data acquisition and the creation of detailed models, providing local high-precision point clouds. Additionally, Light Detection and Ranging (LiDAR) was used for detailed point cloud collection inside the lava tubes, and through the registration of high-precision point clouds of the skylights both inside and outside the tube, comprehensive point cloud data of the entire lava tube were obtained. Hyperspectral LiDAR was also used to collect data of the tube walls under dark conditions, addressing the issue of consistency matching between hyperspectral imaging and laser far-field spots, enabling integrated spatial–spectral data acquisition. Finally, ground-penetrating radar was also employed for subsurface structural analysis, benefiting from its high penetration capabilities to acquire more detailed information on the underground morphology of the lava tubes. Our experiments demonstrate that this multi-sensor approach provides comprehensive information on terrain, lava tube orientation, cave distribution, and the internal environment of the lava tube system.

Introduction

Lava tubes, which form as underground conduits during volcanic activity, illustrate the unique processes of volcanic activity and geological evolution. As a distinct geological feature, lava tubes can transport lava flows over distances of several tens of

kilometers. Such formations have been identified not only on Earth but also on extraterrestrial bodies where volcanic activity is or was highly probable [1]. Recent research has identified evidence of lava tubes on both Mars and the Moon [2], which are now recognized as prime locations for future habitats on those celestial bodies [3].

Citation: Hu T, Yang H, Kang Z, Liu X, Wu C, Wu H, Zhao H, Wan X, Zhao Y, Fa W, et al. Integrated Ground–Air–Space Exploration Technology of Jingpo Lake Lava Tubes. *Space Sci. Technol.* 2026;6:Article 0438. <https://doi.org/10.34133/space.0438>

Submitted 13 June 2025

Revised 25 November 2025

Accepted 28 November 2025

Published 27 March 2026

Copyright © 2026 Teng Hu et al. Exclusive licensee Beijing Institute of Technology Press. No claim to original U.S. Government Works. Distributed under a Creative Commons Attribution License (CC BY 4.0).

Lava tubes on the Moon and Mars are considered ideal locations for future bases [4], providing natural shielding from cosmic radiation and thermally stable conditions [5]. The unique geological features of the Jingpo Lake lava tube make it a prime terrestrial analogue for simulating these extraterrestrial environments. In line with China's advancing lunar exploration program, the Jingpo Lake lava tube has been selected as the core site for the "Simulated Lunar Underground Space" teaching and practice base. Field tests at Jingpo Lake allow researchers to develop and validate robotic technologies for lunar lava tube exploration. These robots must be capable of autonomous navigation and multifunctional operations in complex environments, and the Jingpo Lake lava tube provides a realistic testing ground for this purpose.

On Mars, deep skylights discovered on lava flows exhibit striking similarities to features seen on Earth. On the Moon, underground cavities have been inferred from several skylights in the Maria plains and confirmed with gravimeters and radar detectors. Because of the lack of atmospheric protection on the Moon, lunar exploration research faces challenges such as extreme temperature fluctuations, cosmic radiation, and threats from lunar dust and meteoroids affecting both equipment and astronauts [1]. Moreover, numerous volcanic landforms resembling lava tubes have been found in basaltic regions on the Moon and Mars [6]. In the context of future space exploration, lunar base construction has become an essential aspect, with NASA and the European Space Agency conducting extensive studies and preliminary planning. Notably, lunar lava tube caves are increasingly recognized as prime locations for future habitats [7], as these vast tubular spaces could provide ideal environments for establishing stable and protective bases on extraterrestrial rocky planets [8].

To enhance our understanding of lunar lava tubes and support future lunar base construction, comprehensive terrestrial analogs are essential. Lava tube formation is complex, influenced by factors such as terrain and magma viscosity. The length of a lava tube is mainly determined by the eruption duration, lava accumulation rate, and the thermal efficiency and stability of the tube system [9]. The formation process encompasses 4 main stages: natural growth, arched roof formation due to lava spattering, merging of floating lava slabs, and the remaining lava spreading along cracks. Analysis of the internal morphology of lava tubes provides insights into the geological activities during their formation. Furthermore, systematic investigation of terrestrial lava tubes, serving as accessible natural laboratories, in conjunction with comparative planetology, provides critical reference data and practical experience for future exploration of extraterrestrial lava tubes [10].

Previous studies of lava tubes have often relied on singular or limited methods, resulting in significant limitations in technology, resolution, and data coverage that hinder a comprehensive understanding of their internal morphology. Traditional exploration equipment is often insufficient; for instance, conventional lunar rovers and exploration robots are primarily designed for surface operations and are thus ill-suited for the complex subterranean environment inside lava tubes. These environments can contain narrow passages, rugged terrain, and sharp rocks, placing significant demands on a robot's maneuverability and durability. Furthermore, there are limitations with laboratory simulations. Early studies often relied on small-scale laboratory experiments to simulate lava tube environments, but these experiments cannot fully replicate the complexity, scale,

and diversity of real lava tubes, thereby limiting the applicability of the findings. Separately, ground-penetrating radar (GPR) can exhibit high resistivity anomalies in heterogeneous volcanic environments, which can cause the perceived location and morphology of lava tubes to be magnified, artificially shallowed, or laterally shifted. The deployment concept of unmanned aerial GPR has been proposed for surveying caves on Mars. Studies such as FlyRadar have defined specific objectives for future unmanned aerial GPR surveys of Mars [11]. For small or densely packed lava tubes, GPR struggles to distinguish between a single tube and multiple tubes or interstitial areas. Similarly, while orbital remote sensing technology can identify surface features, it cannot penetrate deep enough to map the internal structure of lava tubes, limiting a comprehensive understanding of their morphology. Finally, direct in situ data collection faces its own set of severe challenges. The low light, rough terrain, and potential hazards (such as rockfalls) inside lava tubes make direct access and data collection extremely difficult, often limiting studies to surface observations or exploration of limited areas. The persistent low light or complete darkness, combined with sharp rocks, poses challenges to the optical systems and physical durability of detection equipment. Traditional light sources are often ineffective on the dark, rough surface of lava tubes, increasing the difficulty of data collection. Moreover, the shielding effect of rocks inside lava tubes can severely disrupt communications with surface equipment, limiting the ability to transmit data in real time and operate remotely.

State of the art in lava tube detection

Morphology of lava tubes

Lava tubes are formed during volcanic activity when an eruption generates a significant lava flow. As the lava spreads, erosion-carved channels may overflow, resulting in the accumulation of lava along the sides of these channels. Over time, the accumulation of lava layers results in their thickening and elevation, accompanied by a gradual narrowing at the top until the structures reach a point of closure, forming a solid, shell-like structure around the flowing lava, thereby creating a lava tube. Upon cessation of volcanic activity, the lava flow stops, leaving behind the hollow tubes that are observed today, often with remnants of the lava flow visible along the sides. The formation of lava tubes is primarily influenced by the size of the lava flow during the eruption [12]. Lava flows of a larger magnitude are more likely to produce these structures. As the lava flows, thermal diffusion occurs, causing the lava to cool gradually and form a solid outer shell, or pipe case. Once the shell has reached a sufficient thickness, it is capable of supporting its own weight and the pressure exerted by the flowing lava. The thickness of the pipe case is directly correlated with the cooling rate of the lava. A higher thermal diffusion coefficient results in greater heat loss over time, leading to the formation of a thicker shell. Conversely, a higher lava viscosity reduces the thermal diffusion coefficient, influencing the formation process [13].

Inside a lava tube, the inner walls can exhibit remarkable smoothness, a consequence of the rapid cooling and solidification of the lava as it flows. During this process, the lava flows rapidly, minimizing contact time with the surrounding air or ground. This prevents the escape of gases, which in turn leads to the formation of these smooth walls. It is typical for sections with smoother walls to be thinner and narrower. Conversely, rough inner walls form when the lava flow slows down. The extended contact time with the air or ground allows for the

escape of gases, creating a bubble-like structure or vesicular texture. A reduction in flow rate also results in the lava spending a greater proportion of its time within a given area of the tube. This can lead to localized corrosion and the formation of irregular lava masses. Lava stalactites, similar to those observed in limestone caves, may form at the top of the lava tube. Once a solid rock layer has formed at the top of the tube, the remaining hot gases or vapors still present inside (e.g., derived from the cooling lava) may transport minerals and other dissolved materials from the lava. These materials can then deposit on, or react with water or carbon dioxide on, the inner surface of the rock layer, resulting in dissolution and the precipitation of new minerals. The precipitated minerals, such as sulfates, sulfides, or calcium sulfate, can create small stalactites that exhibit a range of shapes depending on the internal environment of the tube and the composition of the dissolved materials. The interior of lava tubes typically exhibits a constant temperature and humidity due to the absence of air circulation. While skylights or collapsed structures may be present, they often have a negligible impact on the overall internal environment, especially in deeper sections. This lack of air circulation can result in lower oxygen levels, creating a unique setting for studying life in anoxic conditions, and offering insights for future lunar base construction. Younger lava tubes may even contain water flows or pools, as observed in Raufarhólshellir in Iceland and Kazumura Cave in Hawaii [12].

Lava tube skylights are typically characterized as nearly circular or elliptical vertical holes with steep or overhanging walls. This characteristic is a key distinction from typical impact craters, which possess shallow depth-to-diameter ratios and are surrounded by significant ejecta accumulations. Skylights, in contrast, typically have much higher depth-to-diameter ratios and lack observable ejecta blankets around their margins, indicating they are not impact-formed. For example, the Marius Hills Hole (MHH) on the Moon is approximately 65 m in diameter but extends 80 to 88 m deep, exhibiting a ratio much higher than that of typical impact craters. Skylights may also be surrounded by traces of lava flows or be associated with sinuous rilles, features that suggest they formed from the partial collapse of an underlying lava tube.

The size of a skylight varies depending on its geological environment and the local planetary gravity. On Earth, skylights are typically smaller in diameter; for example, lava tubes in Hawaiian volcanoes often have diameters ranging from a few meters to tens of meters. On the Moon, however, due to its lower gravity (approximately one-sixth that of Earth), skylights can grow significantly larger. Data from the Lunar Reconnaissance Orbiter (LRO) has led to the identification of over 200 potential skylights, with diameters ranging from approximately 5 to 900 m. While MHH is exceptionally deep, another skylight in the Marius Mons region is estimated to be 65 m in diameter and approximately 36 m deep. Skylights on Mars may also reach hundreds of meters in diameter, although precise measurements of their dimensions are currently limited by the resolution of available exploration technology and incomplete data coverage.

Lava tubes exhibit complex and diverse structures, which can be categorized according to their formation and features. These include transverse, longitudinal, and composite tubes. Such tubes may manifest as single caves, interconnected cave systems, or branched formations. Over time, a single lava tube can undergo multiple volcanic activities, leading to the accumulation of multiple flow layers as successive lava flows scour

and expand the tube. Inside a lava tube, rope-like structures are often visible on the walls and floor. These formations are the result of the characteristics of the lava flows that created the tube, particularly their varying viscosities and velocities. These same flow dynamics can also cause trapezoidal wall structures to form within the tube.

Lava tube skylights represent another distinctive geological feature. The formation of these structures can be broadly classified into 2 categories. The first category of skylight formation is internal. This occurs when the top of the lava tube, being relatively thin, collapses due to erosion or corrosion. In some cases, even thicker lava tube roofs can form skylights as a result of internal collapse, which is influenced by the nature of the lava flow and its volatile content. The second category is exogenous, whereby tectonic activity and earthquakes can cause external structural changes to lava tubes, leading to collapse and skylight formation. Human activities can also induce such changes. Similar chain-collapse skylight structures have been observed on the Moon and are being identified in the Jingpo Lake lava tubes [14].

Detection methods

The purpose of lava tube exploration is to determine the location, shape, size, depth, and potential geological stability or hazards of the lava tubes, for further research and monitoring. Exploration technologies include geological exploration, geophysical exploration (such as seismic exploration and electrical resistivity exploration), satellite remote sensing, and surface geomorphological analysis. Currently, many technologies are used to detect lava tubes. GPR is a commonly used technology to detect the top and bottom structures of underground lava tubes. Light Detection and Ranging (LiDAR) is used to collect information inside an accessible tube, and analysis of magnetic anomalies, sometimes combined with LiDAR data, is also used for detection and characterization.

GPR is a mainstream detection method for lava tubes, with different megahertz (MHz) frequencies applied for detection in various terrains and depths. Some researchers have used multi-frequency radar sounders [15] for lava tube detection. High-frequency radar sounders have been used to more accurately detect small and shallow lava tubes. Techniques like phase inversion, Doppler analysis, and clutter simulation are used to further enhance the reliability of detecting lava tubes by exploiting the phase inversion feature on the echoes from the roof of the lava tube. A 30-MHz GPR antenna was employed for the exploration of the Mirror Lake World Geopark [16]. That study focused only on tangential measurements of the lava tube's orientation, without systematically measuring the trend or path of the lava tube. A single-frequency GPR dataset was used for the same tangent, without comparisons using different frequencies along it. There were certain flaws in collecting key information about the lava tube, and the analysis was based solely on single-frequency GPR data, resulting in a limited data scope. In the TubeX task [17], research on the Lava Tube Network (Lava Beds National Monument) located on the northern side of Mount Medicine Lake in the Cascade Mountains employed a 100-MHz radar to measure the top and bottom of the lava tube. However, the detection of the lava tube's width was somewhat distorted due to the resolution limits of the antenna. The data errors caused by the single antenna resolution require correction using additional data sources. Therefore, there is a need for data calibration using multi-source data. An analog study of lava tube

detection in the Shishan volcanic group was conducted in Haikou, Hainan, using a 400-MHz GPR [1]. This study used genetic algorithms for radar data inversion to obtain the dielectric constant of the tube wall and compared the results with depth-based and sample measurement methods to verify the reliability of the inversion algorithm. These experiments demonstrated that GPR can effectively measure the internal spatial information of underground lava tubes.

LiDAR technology, as a non-contact measurement method, provides high precision and high-density point cloud information. Automatic cave exploration robots have been applied to enter the lava tube and autonomously detect the 3-dimensional (3D) geometric information and material composition of the lava tube [18]. One study used active remote sensing LiDAR as the primary detection payload to overcome the low-light or no-light conditions inside the lava tube and achieve precise 3D mapping of the cave interior. Using LiDAR-collected point cloud data for modeling is a common method. A lightweight mobile measurement system has been applied to conduct 3D detection of extraterrestrial lava tubes, achieving efficient and detailed map construction and 3D morphological representation [19]. The study also verified this method through Earth lava tube detection and used LiDAR scanning to efficiently capture point clouds inside lava tubes. Using intelligent point cloud processing methods, they achieved the 3D intelligent reconstruction of lava tubes and performed morphological analysis. A lava tube 3D modeling method integrating airborne LiDAR, close-range photogrammetry, and GeoSLAM handheld laser scanner point cloud data has also been proposed [20]. Their method used a multi-layer modeling approach and a skeleton plus detail modeling method to build mesh models of the inner surface of the lava tube. Finally, they constructed solids between different layers of the model to simulate the solid rock mass between different internal surfaces or flow levels and performed measurements. Because LiDAR can collect information on the structural width and height inside the lava tube, many studies have used the collected point cloud data to analyze its structure. The field surveys of lava tubes in the Shishan volcanic group area in Haikou have used LiDAR technology to efficiently and accurately capture the morphological structure of the lava tubes and conduct quantitative analysis [21]. They proposed a grid-based skylight detection method and used a data augmentation and multi-scale feature learning network-based crack detection method to detect and study the internal structure and morphology of lava tubes. Ground-based laser scanning technology has also been combined with field observations, and geochemical analysis of past lava to reconstruct the 3D geometric structure of lava tube systems, ancient surface channels, and the volcanic series of their carved paths. That study indicated that a volcanic detrital layer from the late Quaternary Strombolian activity played a key role in the development of a specific lava tube, spanning almost the entire length of its path and defining the paleogeography.

In addition to mainstream lava tube detection methods, other geophysical approaches include the analysis of micro-seismic data and gravitational gradient data. Using gravitational gradient data from the GRAIL (Gravity Recovery and Interior Laboratory) mission [22], researchers analyzed the Marius Hills region on the Moon and discovered north-south anomalies, which could indicate the potential presence of lava tubes (Fig. 1). The use of magnetic anomalies for lava tube detection has also been explored; in one study, magnetic data were combined with 3D

LiDAR data to perform a magnetic reconstruction of the lava tubes. However, that particular study focused solely on the tangential direction of the lava tube's orientation when measuring and analyzing its magnetic characteristics.

Up to now, research on the Moon has focused primarily on its surface. Consequently, there is a paucity of data and relevant techniques to support the exploration of the interior of lunar lava tubes. While research on Earth's lava tubes mainly focuses on their interiors (once accessed), the methods for initially detecting undiscovered tubes from the surface or orbit, crucial for the Moon, are less developed or directly transferable, presenting a significant challenge in meeting the current demand for lunar lava tube detection. In addition, the exploration of lava tube distribution areas has paid less attention to the stratigraphic distribution between the tubes and the surface, as well as to collapse areas that are difficult to penetrate. The prolonged absence of light in lava tubes renders conventional methods of obtaining morphology and spectral data from the internal surface challenging. This in turn results in a paucity of data for comprehensive physical characterization of the internal surface of lava tubes. A lack of comprehensive data, as well as the absence of a unified database for large- and small-scale analysis, has hindered investigation into the influence of topographic factors on the growth of lava tubes.

To fill these gaps, we conducted a comprehensive survey of lava tubes in Jingpo Lake using an integrated ground-air-space measurement approach. The main innovations include the following: combining multi-source point cloud data to construct a realistic 3D model of the lava tube with an error of less than 0.1 m, accurately reflecting its internal structure; pioneering the use of hyperspectral LiDAR to collect data on the inner wall of the lava tube in a lightless environment, achieving greater clarity in discerning the inner wall; exploring the potential for lava tube monitoring using GPR by cross-checking the point cloud cross-sections from surface detection and Geo-SLAM data collected inside the cave; conducting surface, tube, and airborne measurements for the first time to collect comprehensive data on the lava tube distribution area, providing a practical basis for more accurate and diverse numerical simulations; and carrying out large-scale skylight detection to achieve systematic multi-scale measurements of the lava tube distribution area.

This study employs 3 main types of detection instruments: surface, aerial, and internal, each designed to collect different types of data, such as topographic data, cross-sectional data, and internal tube data. Spaceborne synthetic aperture radar (SAR) imagery plays a crucial role in the research by providing

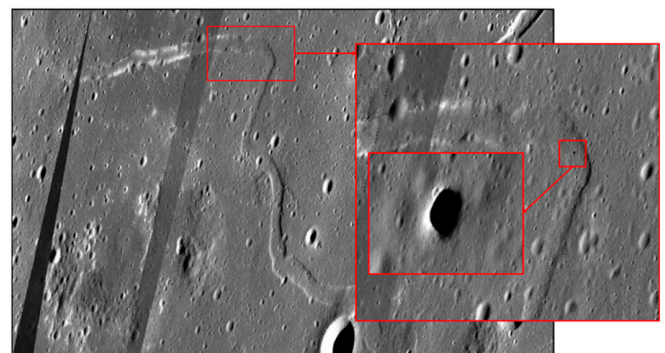


Fig. 1. Lava tube skylight in the Marius Hills with views progressing from the entire lunar rille to the entrance and the skylight.

detailed geometric, radiometric, and phase information, making it a key technology for all-weather, round-the-clock Earth observation.

Owing to the considerable height of the skylight sidewalls, traditional ground surveying methods are challenging for acquiring cross-sectional data of lava tube skylights. Technological advancements have enabled the creation of 3D models through oblique photography. By utilizing unmanned aerial vehicle (UAV)-based close-range photogrammetry, we can efficiently capture the cross-sections of skylights.

GPR effectively reflects radar pulses from voids in the ceiling and floor of lava tubes, allowing for the investigation of underground lava tube segments, voids, and stratigraphic distribution.

The complex internal structure and low light conditions within lava tubes pose challenges for conventional data collection methods. To address this, we use the Geo-SLAM system for high-precision reconstruction, coupled with hyperspectral LiDAR to provide spectral information and supplement structural classification data. By merging data collected from both the Geo-SLAM and UAV systems [23], we create an accurate 3D model. These 3D models have been widely applied across various industries, including data integration, building preservation [24], and mining activities [25].

Study area and data acquisition

Overview of the study area

The Jingpo Lake Global Geopark is situated in the southwestern region of Ning'an City, Heilongjiang Province, approximately 50 km from the city center as shown in Fig. 2. The park encompasses a variety of geological features, including Zhangguangcai Ridge, Laoye Ridge, and the region's underground lava tubes of Changbai Mountain. Over 600 million years ago, the Jingpo Valley began to form, laying the foundation for the region's geological framework. However, the area's present-day landscape was primarily shaped by volcanic eruptions in the Jingpo Lake volcanic field, controlled by the northeast-trending Dunhua-Mishan fault. Around 5,500 to 5,200 years ago, major eruptions released extensive lava flows, covering approximately 500 km² with tholeiitic basalt, alkali basalt, and basanite. These eruptions subsequently blocked the upper reaches of the Mudan River, forming Jingpo Lake, China's largest volcanic lava-dammed lake, with an area of 95 km² and a water volume of 1.63 billion m³. Concurrently, the lava tubes, a hallmark of the Jingpo Lake Global Geopark, were formed as the outer edges of lava flows cooled and solidified into a hard crust, while the molten lava within continued to flow and eventually drained away, leaving hollow channels. These tubes, both large and small, reflect the dynamic volcanic processes of the Holocene, with additional eruptions occurring at approximately 3550 BCE, 1540 BCE, and 520 BCE, which further enriched the region's volcanic landscape. The interplay of fault-controlled volcanism and river damming, together with its diverse volcanic rocks and mantle xenoliths, underscores the geological marked of the Jingpo Lake region, establishing it as a critical site for studying Earth's volcanic history.

The area is characterized by multiple volcanic systems, with rocks from different periods, including those from the early Pleistocene, mid-Pleistocene, and Holocene basalts. The Jingpo Lake area is divided into 2 districts: the Eastern District and the Western District [10]. The Holocene volcanoes in the park encompass a total of 12 craters. Ten of these craters are located in the Western District, while the Eastern District contains the

remaining 2 craters. These 2 craters are associated with 5 volcanic eruption centers, including notable sites such as "Wudaogou" and "Toad Pond".

This study examines the transitional area where lava tubes were formed approximately 5,200 to 5,500 years ago. The landscape in this region is predominantly hilly. The park features 3 main landscape types: virgin forests within crater areas, volcanic eruption sites, and landscapes characterized by parallel lava tubes in the Jingpo Lake area. In the Jingpo Lake region, there are 2 primary categories of lava tubes. The first category consists of larger lava tube channels. During volcanic eruptions, the outer edge of a lava flow cools first, forming a protective shell. As the internal lava drains away, it leaves behind a large channel. To date, 5 such larger lava tube channels have been identified. The second category of lava tube channel is smaller in scale. Because of the presence of pressure gradients, gas within the lava flow may contribute to the formation or shaping of smaller tubes, often aligned with the direction of the lava flow. These smaller channels are typically distributed around the larger lava tubes, resembling branches extending from the main channels.

Integrated data collection

We use a variety of methods to survey and characterize lava tubes, including extracting SAR images of the experimental area through the Haisi-1 satellite; extracting ground point clouds and close-range point clouds of lava tube skylights through drone photogrammetry; extracting information about the subsurface structure, including the depth to the top of the lava tube and overlying rock layers, through GPR instruments; classifying the material composition or rock types of the lava tube wall through hyperspectral LiDAR instruments; and scanning the entire lava tube with a handheld laser scanner. As shown in Fig. 3, lava tubes are surveyed in an integrated manner through a variety of methods.

Satellite-based SAR data acquisition and processing

The C-band HISEA-1 satellite-borne SAR was selected for data acquisition with a resolution of 1 m × 5 m in clustering mode. Subsequently, the data were processed using the SARscape software [26].

Satellite SAR emits single-frequency electromagnetic waves that scatter differently based on various ground surfaces. This phenomenon, known as coherent superposition, generates speckle noise. Speckle noise is prevalent in monovision SAR data products from HISEA-1. To improve the quality of the SAR images, multi-view processing was conducted on the oversampled SAR data. By averaging multiple views derived from the data, typically degrading spatial resolution by a factor related to N (the number of looks), a reduction in speckle noise was achieved. This process resulted in an increase in the signal-to-noise ratio by $N/2$ times and the effective suppression of speckle noise.

Subsequently, filtering techniques were employed to further reduce speckle noise in the radar intensity image. Post-imaging noise reduction typically involves spatial-domain and frequency-domain filtering. Spatial-domain filtering, which employs statistical methods and local statistical information, was utilized to remove speckle noise. For the HISEA-1 data, we applied the Refined Lee Filter to achieve a balance between noise suppression and image detail retention [27]. The final processed image is shown below in Fig. 4. Visually, the refined SAR image exhibited significantly reduced speckle noise, with clearer delineation of

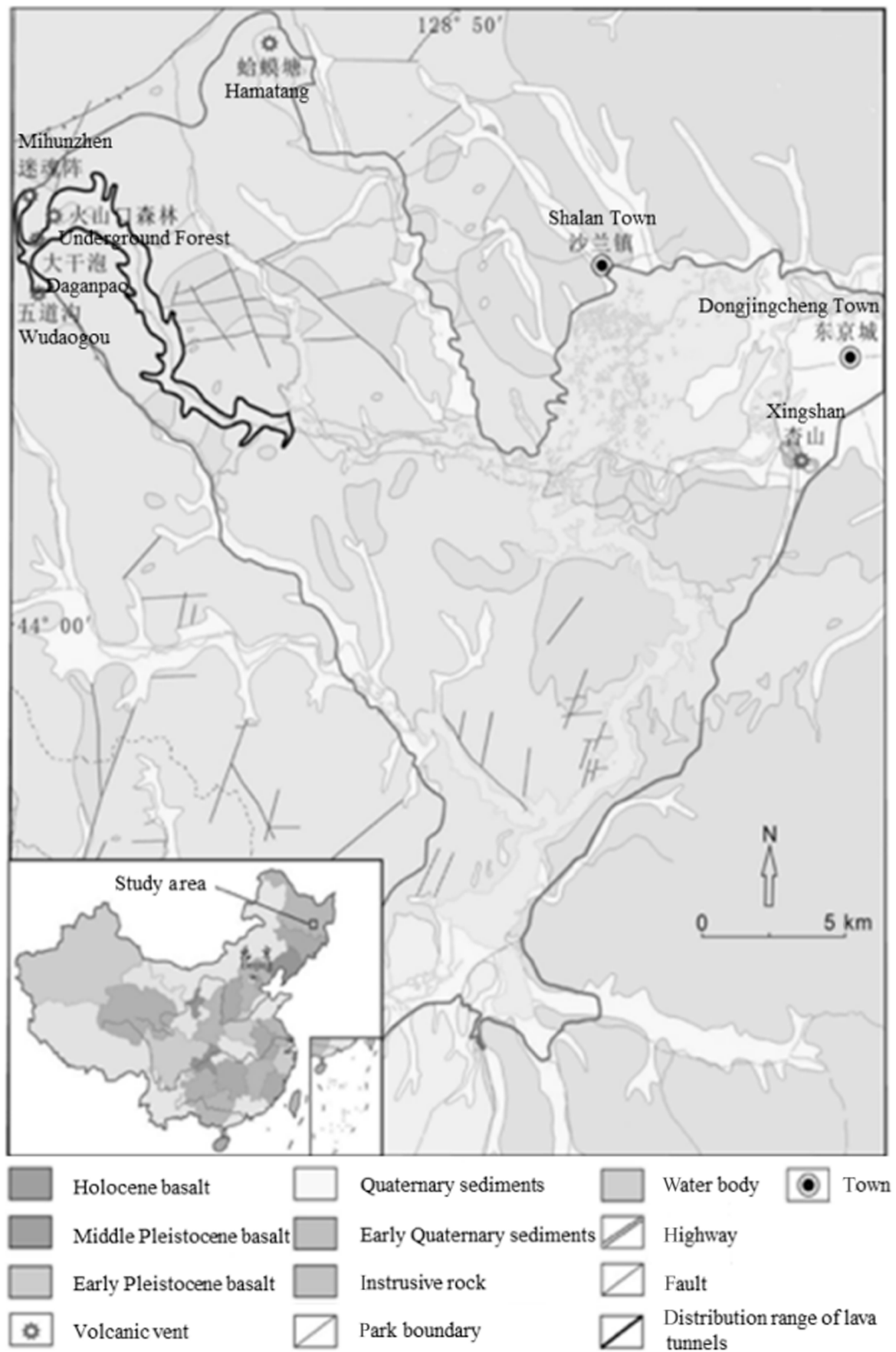


Fig. 2. Location of volcanic vents in the Jingpo Lake Holocene volcano [59].

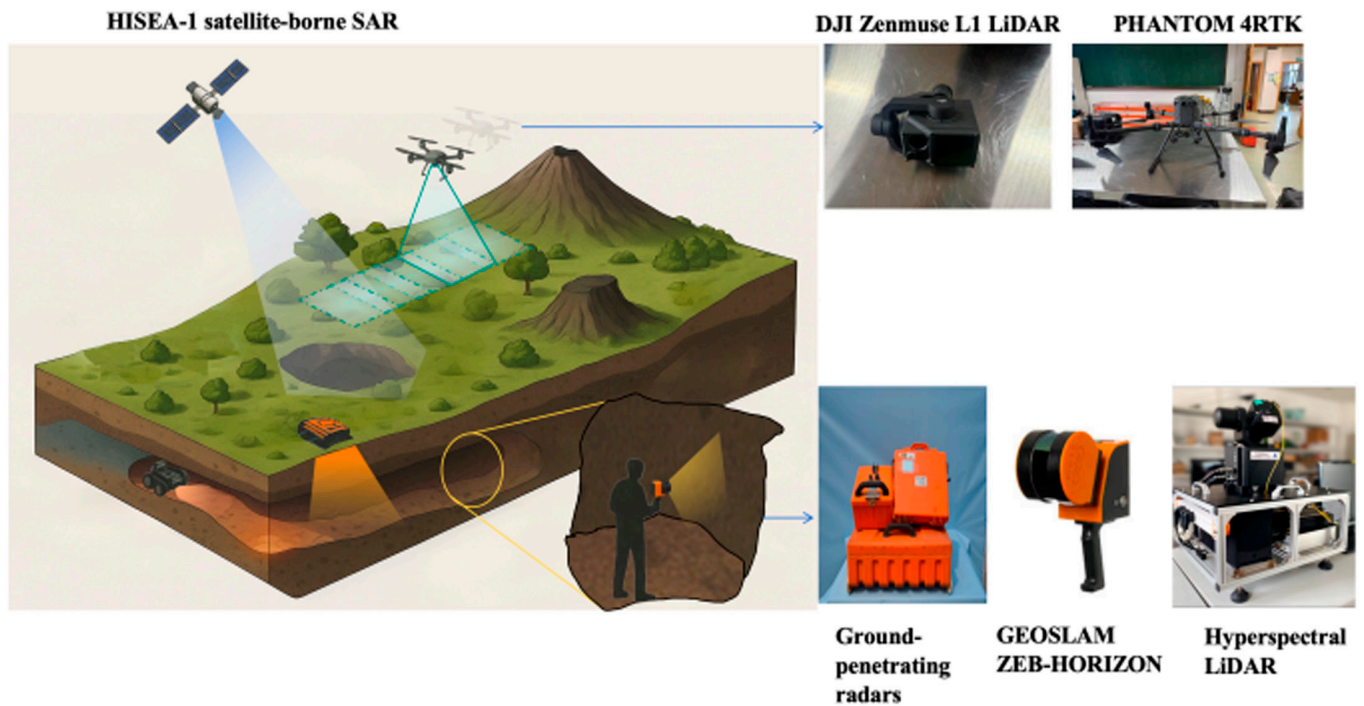


Fig. 3. Integrated detection schematic diagram.

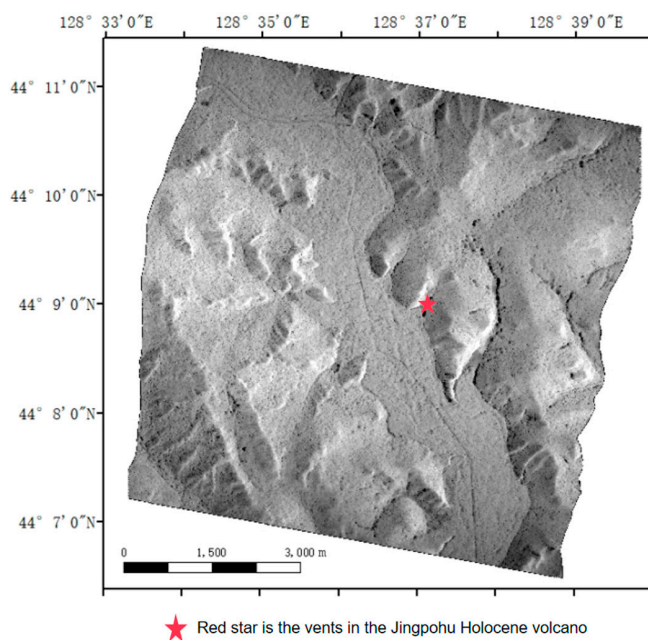


Fig. 4. Location of volcanic vents in the Jingpo Lake Holocene volcano.

linear and circular morphological features, assisting in distinguishing them from other landforms, which are critical for identifying skylight pits associated with subsurface lava tubes. In particular, shadow and layover effects, which are commonly observed in SAR imagery over uneven terrain, became more interpretable after noise suppression, facilitating the recognition of abrupt terrain depressions and structural discontinuities indicative of collapsed ceilings or open conduits. Overall, the improved SAR image quality directly contributes to the interpretability and reliability of morphological analysis.

UAV image acquisition and processing

This study used the PHANTOM 4RTK drone to collect high-resolution photogrammetric data by flying close to the skylight's side walls. The drone camera parameters are shown in Table 1. This approach complements the limitation of the HISEA-1 SAR, which can primarily detect the presence of lava tube skylights from above but cannot resolve the interior walls of the skylight, and addresses the issue that handheld laser scanners are unable to efficiently capture dense point cloud data from higher skylight walls. This study primarily utilized close-range photogrammetry to collect data of the exposed surfaces within and around lava tube skylights. Close-range photogrammetry employs an UAV to capture imagery of the target surface at a sub-centimeter or millimeter level, thereby enabling high-precision reconstruction through aerial triangulation [28]. By focusing on the "face" of the object and employing close-range aerial photography, this method yields high-resolution 3D geometric information at the millimeter level [29].

The flexibility of the DJI Phantom 4 RTK drone is crucial for this task, as it is capable of adapting its flight path to adhere closely to the surface contours and of adjusting the shooting angle dynamically. The DJI Phantom 4 RTK is a high-precision multi-rotor drone, equipped with a GPS/GLONASS dual-mode positioning system and a D-RTK differential positioning system. The device features a 1/2.3-inch 12-megapixel CMOS sensor, which supports high-precision aerial photography and mapping [30].

Given the presence of vegetation in the vicinity of the lava tube skylight, the data collection was conducted in 2 stages: First, the UAV gathered preliminary terrain data to inform flight planning. For skylights with wall heights or depths estimated between 30 and 50 m, flight routes were planned using 3D terrain data, and automatic close-range flights were employed to capture images. For skylights situated closer to the surface (e.g., with depths/wall heights of 5 to 20 m), where complex terrain

Table 1. DJI PHANTOM 4 RTK drone camera parameters

Parameter	Numerical value
Pixel	Effective pixels, 20 million
Image sensor	1 inch CMOS
Lens	FOV 84° 8.8 mm/24 mm (35 mm equivalent focal length)
	Aperture f/2.8-f/11
IOS scopes	100–3,200 (auto) 100–12,800 (manual)
Maximum resolution	5,472 × 3,078 (16:9) 4,864 × 3,648 (4:3) 5,472 × 3,648 (3:2)
Shutter speed	Mechanical shutter 8-1/2,000 S Electronic shutter 8-1/8,000 S
Close-range photogrammetry and resolution	15–20 m and 3–5 mm

and dense vegetation pose challenges, manual flights were employed to ensure high-resolution image acquisition while maintaining flight safety.

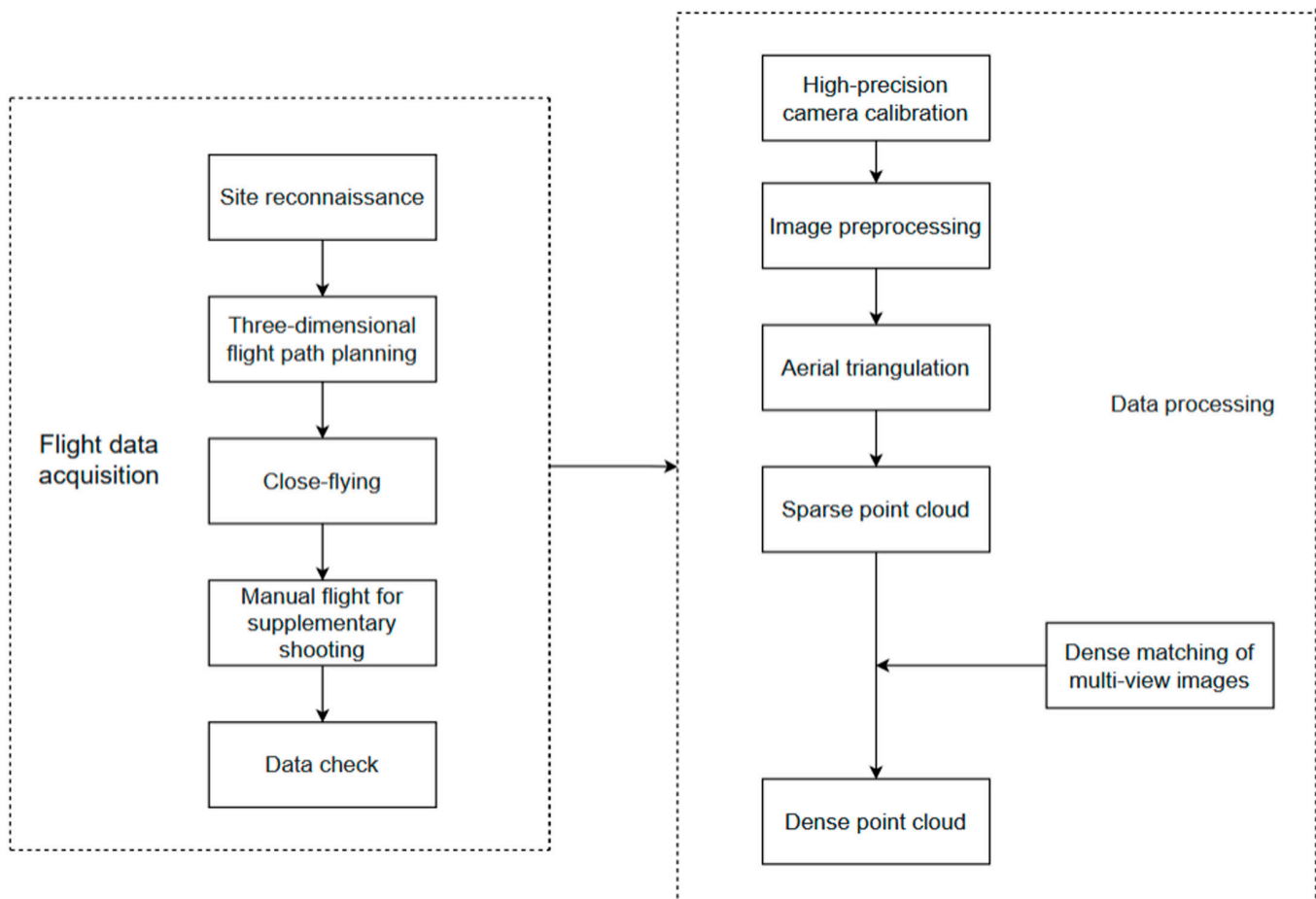
The images captured from both flight modes were then combined to create a detailed and dense point cloud. The overall technical process is illustrated in Fig. 5.

After data acquisition, processing was carried out using Metashape software. The process begins with the aerial triangulation of the images, which involves detecting feature points and matching corresponding points across images. Subsequently, the camera's exterior orientation elements were calculated from these matched points, resulting in the creation of a sparse point cloud.

Next, a depth map was generated, and a dense 3D point cloud was constructed based on the depth map along with the camera's internal and external orientation elements. The dense point cloud was then classified and filtered to enhance the quality of the data. Finally, the processed point cloud was integrated with the previously mentioned handheld laser scanner (Geo-SLAM) data to produce a comprehensive dataset.

GPR acquisition and processing

Portable geological radars emit high-frequency, broadband electromagnetic pulses into the subsurface. As these waves traverse the underground medium, they encounter fluctuations in electrical properties at targets such as voids and

**Fig. 5.** Technology roadmap for drone data acquisition.

interfaces. When encountering such variations, the waves are reflected back to the surface and captured by the receiving antenna. By analyzing the received radar signals, including the waveform, intensity, and 2-way travel time, it is possible to determine the spatial location, structure, electrical characteristics, and geometry of the underground targets [31]. This non-contact method allows for the detection of hidden structures without disrupting their physical integrity, thereby providing a visual representation of the detected objects. To address the specific characteristics of lava tubes, which are typically large and elongated, a tailored measurement program has been implemented. Measurement lines were strategically placed perpendicular to the lava tube's orientation, with a distance of 10 m between each line and individual line lengths of 40 to 50 m. Antennas with center frequencies of 50, 100, 200, and 400 MHz were used to scan along the aforementioned lines to investigate the lava tubes [32]. The parameters of the ground-penetrating radar equipment are shown in Table 2.

After data collection, the radar data undergo thorough internal processing via specialized software. The process begins with the establishment of a zero line, which serves to determine the baseline time position of the profile. The pre-processing stage involves adjusting the zero value with a decay time set to one for gradual adjustment. Background noise was then reduced through careful denoising. This involves a fine-tuning of the start and end channels used for background reference to eliminate extraneous noise. Optimal Gaussian window filtering was applied for one-dimensional filtering, with the objective of suppressing interference signals outside the effective signal band, thereby improving signal clarity and the signal-to-noise ratio.

Bandpass filtering was applied based on the frequency ranges of each antenna. The 50-MHz antenna data were filtered to pass signals from 20 to 100 MHz; the 100-MHz antenna data were filtered to pass signals from 50 to 300 MHz; and the 200- and 400-MHz antennas' data were processed to remove signals at their respective frequencies. Signal gain processing amplifies weaker signals from deeper subsurface areas, enhancing their visibility and ensuring accurate detection of lava tube features [33].

LiDAR data acquisition and processing

Meanwhile, this study employed a DJI M300 Pro equipped with a DJI Zenmuse L1 LiDAR to measure the surface and obtain detailed point cloud data of the terrain. The specific instrument parameters used are listed in Table 3. This approach complements the limitation of the HISEA-1 SAR satellite, which cannot provide high-resolution 3D point cloud data of the surface with comparable precision, and provides surface data (e.g., a digital elevation model [DEM]) for GPR, supporting subsequent GPR analysis.

First, the close-range photogrammetric data were processed. In this study, the image data obtained through close-range photogrammetry were converted into point cloud data using the Metashape software. The point clouds from the 3 main data sources (photogrammetry, airborne LiDAR, and GeoSLAM) were then merged based on common points. The Cloth Simulation Filter [34] algorithm was employed to extract ground points from the relevant surface point clouds and remove interference from surface vegetation, such as trees [35].

Given the dense vegetation surrounding the lava tube, we utilized the DJI Warp M300 RTK equipped with the Zenmuse L1 LiDAR sensor, to obtain topographic data and DEMs within the specific area. The data acquisition process involved a series

Table 2. Ground-penetrating radar parameters

Parameter	Numerical value	Numerical value	Numerical value
Antenna center frequency/MHz	50	100	200 400
Output pulse amplitude/V	≥200	≥400	≥800
Dynamic range/dB	≥180	≥168	≥96

Table 3. DJI Zenmuse L1 LiDAR parameters

Parameter	Numerical value
Measuring range	450 m @ 80%, 0 klx 190 m @ 10%, 100 klx
Point cloud data rate	Single echo: 240,000 points/s Multi-echo: 480,000 points/s
System accuracy (RMS)	Flat surface: 10 cm @ 50 m Elevation: 5 cm @ 50 m
Ranging accuracy (RMS)	3 cm @ 100 m
Maximum number of echoes supported	3
FOV	Repetitive scan: 70.4° × 4.5° Non-repetitive scan: 70.4° × 77.2°
Close distance and resolution	15–20 m and 3–4 mm

of steps, including field surveys, route design, operational flights, and data verification. After passing the data check, the collected data were processed using DJI Intelligent Imaging software to obtain point cloud data in a common format.

Following data export, the point cloud data from the airborne LiDAR and Geo-SLAM systems were subjected to pre-processing to eliminate stray points. Owing to the high density of the Geo-SLAM point cloud, it was cropped according to the actual size of the study area, with the aim of reducing the hardware load. The airborne LiDAR data were also cropped to match the experimental region [36].

Since the airborne LiDAR data already contained coordinate information, it was employed as a reference for registering the point cloud data obtained from close-range photogrammetry with the Geo-SLAM data. Initial registration was conducted through the use of feature point matching or ICP algorithms, followed by potentially resampling the close-range photogrammetric data into a point cloud of a similar density, thus facilitating the subsequent registration process.

Following the initial coarse registration, precise adjustments were conducted. Because of the limited overlap between the point clouds, the conventional automatic fine registration methods proved ineffective. Therefore, manual fine-tuning was

employed on multiple occasions to refine the point cloud data and enhance the registration outcomes. For the nearby lava tube skylight surface within 5 to 20 m, due to the complex terrain and many trees near the lava tube, manual flight was adopted to obtain high-resolution images for flight safety.

Next, the adjusted point cloud data were merged with the point cloud data from the airborne LiDAR. After completing the registration process, 3 sets of distinctive corresponding points were selected from each of the 3 point clouds (airborne LiDAR, photogrammetry, and GeoSLAM) and the mean distance between them was calculated to determine the final registration accuracy.

After completing the multi-scale data collection of the lava tube distribution area, this study employed the GeoSLAM ZEB-HORIZON mobile handheld scanner to obtain data within the lava tube. The key parameters of the instrument are listed in Table 4. This approach complements the limitation of the drone-based close-range point cloud, which cannot fly inside the lava tube or capture the overall point cloud data of the interior. Additionally, the GeoSLAM ZEB-HORIZON data can be correlated with GPR results for precise spatial matching of detected features.

Hyperspectral LiDAR data acquisition and processing

In order to obtain spectral information in an environment devoid of light within the lava tube, this study employed the principal prototype developed by the Key Laboratory of Quantitative Remote Sensing Technology of the Institute of Space and Space, Chinese Academy of Sciences. This prototype utilizes an acousto-optical tunable filter (AOTF) to achieve autonomous tunable band spectrum collection. The working parameters of this prototype are listed in Table 5.

Considering that the lunar lava tubes in the future will also be in the dark, the hyperspectral LiDAR data collection work is carried out to simulate the environment of future lunar lava tube exploration. To address the challenge of acquiring both scene topography and material composition in the absence of light within a lava tube, a combined approach utilizing hyperspectral and LiDAR imaging technologies was employed. This approach addresses the issue of consistency between hyperspectral imaging and laser far-field spots by employing a single device for detection. (The far-field laser spot is the stable intensity distribution of laser light after propagating over extremely long distances. It marks the transition of the beam from the complex “near-field” to the “far-field”, where its behavior is determined by its intrinsic properties. At this point, the spot’s shape, size, and divergence remain constant. Analyzing the far-field spot is crucial because it directly reflects the laser beam quality.) This ensures that both spatial and spectral data were acquired simultaneously at the same location, thereby allowing

for the integrated collection of spatial–spectral information at the target site [37].

Given the complexity of the illumination conditions in the measurement area—such as water coverage, which generates specular reflections of the transmitted hyperspectral LiDAR signals, and the small, confined configuration of the measurement area that presents a challenge to echo reception—specific procedures are followed for the acquisition of hyperspectral LiDAR data. These procedures include field surveying, data acquisition design, operational commencement, and data verification [38].

Since each instrument has its own limitations, we use a combination of complementary instruments to compensate for their respective shortcomings. SAR satellites have low resolution and cannot provide detailed surface or internal structure information, which can lead to the inaccurate positioning of skylights. Therefore, drones are used to provide high-resolution surface and skylight interior models, compensating for the lack of details provided by SAR. However, drones are limited by operational constraints such as lighting conditions and line of sight, and they cannot detect subsurface structures. Handheld GeoSLAM and hyperspectral LiDAR are suitable for internal exploration. In contrast, GPR provides subsurface information. While handheld GeoSLAM cannot operate in low-light conditions, hyperspectral LiDAR is used to collect high-fidelity point cloud data and perform rock classification in dark conditions. The interpretation of complex geological structures from GPR can be inaccurate, as its resolution is limited by material heterogeneity. Therefore, surface and internal data from hyperspectral LiDAR can assist in verifying GPR results and improving their accuracy.

This multi-sensor fusion ensures a comprehensive understanding of the lava tube. SAR identifies potential skylight locations, UAV LiDAR refines surface features, handheld GeoSLAM and hyperspectral LiDAR reveal internal structures and materials, and GPR supplements subsurface data to construct a complete lava tube model. By cross-validating data from different sensors, multi-sensor fusion significantly reduces errors from individual sensors. SAR can misidentify skylight details due to resolution limitations, but the high-resolution point cloud

Table 4. SLAM scanner parameters

Parameter	Value/Specification
Maximum measuring range/m	100
Scanning angle/(°)	270 × 360
Relative accuracy/cm	1.5–3

Table 5. Principal prototype parameters of hyperspectral LiDAR

Key items	Technical indicators
Technical system	AOTF spectroscopy, single detector time-sharing spectrum collection
Spectral coverage/nm	500–1,000
Number of bands	Adjustable, set as needed
Bandwidth/nm	Better than 20
Working distance/m	Not less than 20
Scan mode	Station type: horizontal + pitch
Scan range	100° horizontal, 50° tilt
Spatial resolution	1° (35 cm @ 20 m), 0.5° (17.5 cm @ 20 m)
Ranging accuracy/cm	1–3
Collection efficiency	Full waveform sampling efficiency: about 1/s

data from UAV LiDAR correct these errors. GPR's subsurface detection results are cross-verified with LiDAR's surface data, improving overall data reliability. Lava tubes are characterized by low illumination and rugged terrain, making them difficult for a single sensor to fully characterize. SAR can survey large areas in all weather conditions, LiDAR can generate high-precision models in low-light environments, and GPR can penetrate rock layers to obtain subsurface information. This adaptability makes multi-sensor fusion an ideal tool for studying complex geological environments. Multi-sensor fusion not only provides detailed geological data regarding the formation mechanism and stability of lava tubes but also supports practical applications. For instance, as potential human habitats or resource storage sites, information about the internal structure and materials of lava tubes is crucial for the design of future lunar bases. Multi-sensor fusion can provide detailed information about the geological structure, composition, and resource distribution of extraterrestrial lava tubes. Hyperspectral LiDAR can analyze rock composition, and GPR can detect underground cavities. These data are crucial for assessing the potential of lava tubes as human habitats or resource bases. The study of terrestrial analogues, such as the lava tubes at Jingpo Lake, provides a valuable opportunity to test and optimize these technologies before extraterrestrial deployment.

While multi-sensor fusion holds great potential for extraterrestrial exploration, its practical application still faces challenges. In extraterrestrial environments, power supplies may be limited, and operating multiple sensors requires optimized energy management. Communication latency between Earth and the Moon or Mars can impact real-time data transmission and processing, necessitating the development of autonomous data fusion algorithms. Extreme conditions in extraterrestrial environments, such as extreme temperatures or radiation, can damage sensors, necessitating the development of more robust equipment.

Methods

Based on the integrated space, air, ground, and in-tube detection technologies, we analyzed the surface structure of the lava tube region, the skylight structure, the lava tube's internal structure, and the composition of the tube wall materials (Fig. 6).

Since skylights exhibit prominent morphological features in radar imagery (Fig. 7), satellite-based SAR was used for large-scale detection and skylight localization within the lava tube region. Satellite SAR provides extensive coverage, allowing rapid acquisition of large-scale surface data. It operates in all weather conditions, unaffected by lighting or atmospheric changes, ensuring consistent and reliable data acquisition.

To complement satellite SAR, UAV-based high-resolution LiDAR data collection was employed for surface and skylight inner wall surveys. The surface and skylight wall information helps us study the formation mechanism of lava tube skylights. UAVs provide high-resolution imagery and detailed surface DEMs, as well as high-precision, colored point cloud data of skylight inner walls. This approach compensates for the limitations of satellite SAR in acquiring high-resolution surface and skylight inner wall models.

Additionally, handheld LiDAR scanners and hyperspectral LiDAR were utilized to obtain high-density, high-precision 3D point cloud models of the lava tube's internal structure. Hyperspectral LiDAR was employed to analyze the material

composition of the tube walls under low-light conditions. Through unsupervised classification, different material components were distinguished effectively.

Finally, multi-frequency GPR was used to investigate the subsurface structure of the lava tube. GPR's strong penetration capability and unique echo characteristics for varying material compositions and morphologies make it highly effective for extracting tube wall structures and characterizing the dielectric properties of materials at the top of the lava tube and within the surrounding subsurface.

Skylight structure analysis

The acquisition of spaceborne SAR data marks the starting point of the entire workflow. The "Haisi-1" satellite, operating in the C-band (approximately 5.4 GHz), employs spotlight mode to collect Single Look Complex (SLC) data, which includes both amplitude and phase information, providing high-resolution raw data for subsequent processing. Spotlight mode enhances azimuthal resolution by focusing the radar beam, making it ideal for detecting surface features such as lava tube skylights [39]. During acquisition, the satellite transmits electromagnetic waves and receives echoes from the target, with the echo signals encapsulating the backscatter information of the terrain. The imaging geometry relies on slant range calculations, which represent the distance between the satellite and the target [40]. Data quality is influenced by factors such as orbital parameters, incidence angle, and terrain characteristics, requiring a high signal-to-noise ratio to ensure reliability [41]. The relevant formula is presented as Eq. (1):

$$s(t) = A \cdot \exp(j\phi) \cdot \exp(j2\pi f_c t) \quad (1)$$

In the formula, $s(t)$ represents the echo signal; A denotes amplitude; ϕ signifies phase; A indicates the angular carrier frequency; and t represents time.

The data import and preprocessing are performed using SARscape (an ENVI module), with the aim of converting SLC data into an analyzable format while correcting for system errors. The import process involves parsing header files to extract orbital parameters, imaging mode, and other relevant information, followed by antenna pattern correction, range compression, and azimuth compression to produce a standardized SLC image. Radiometric calibration transforms pixel intensity values into the backscatter coefficient, facilitating terrain characteristic analysis. This calibration accounts for incidence angle and a correction factor to ensure data consistency. This step lays the foundation for subsequent multi-looking and feature extraction; improper handling may result in amplified noise or geometric distortion [42]. The relevant formula is presented as Eq. (2):

$$\sigma^0 = |S|^2 \cdot K \cdot \sin \theta \quad (2)$$

In this context, σ^0 represents the backscattering coefficient, S denotes the SLC complex signal (where $|S|^2$ is the intensity), K is the correction factor, and α indicates the incidence angle.

Multi-look processing enhances the signal-to-noise ratio by averaging in both the range and azimuth directions, which initially suppresses speckle noise but reduces spatial resolution. Speckle noise is an inherent multiplicative noise in SAR images that affects target recognition. Multi-look processing mitigates noise fluctuations through pixel averaging. We establish the ground range

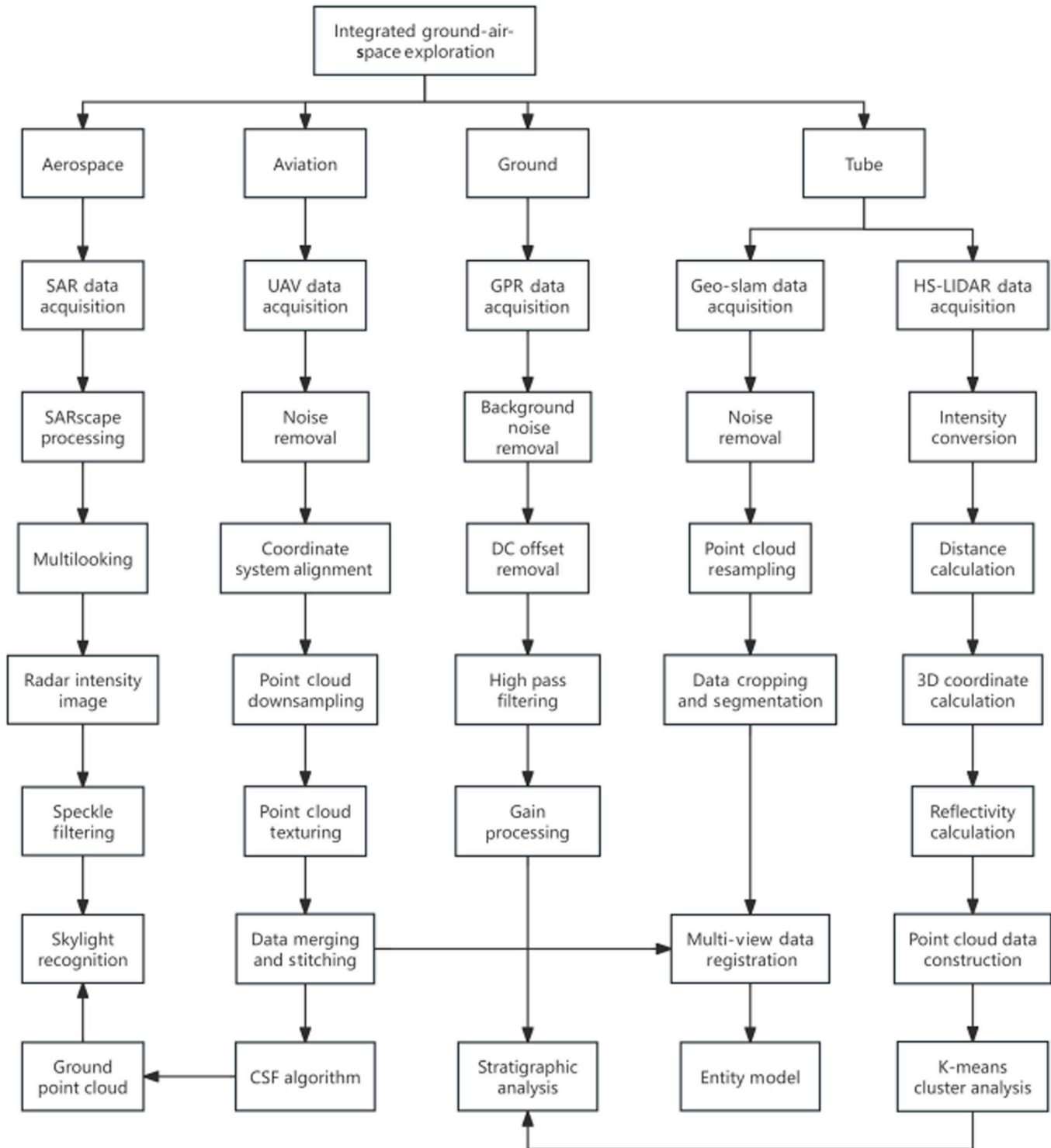


Fig. 6. Integrated data preprocessing process.

resolution using the relationship between slant range resolution and incidence angle, as defined by the following Eq. (3):

$$\Delta R_g = \frac{\Delta R_s}{\sin \alpha} \quad (3)$$

Here, ΔR_g represents the ground range resolution, ΔR_s denotes the slant range resolution, and α indicates the incidence angle.

Subsequently, enhanced filtering is performed using an improved version of the refined Lee filter, which has demonstrated excellent performance in handling speckle noise in SAR images [43]. This approach is particularly suited for extracting skylights in lava tubes, as it effectively preserves edge details and texture features. The method optimizes the traditional Lee filter by introducing adaptive weights and local statistical characteristics. Speckle noise in SAR images is inherently multiplicative,

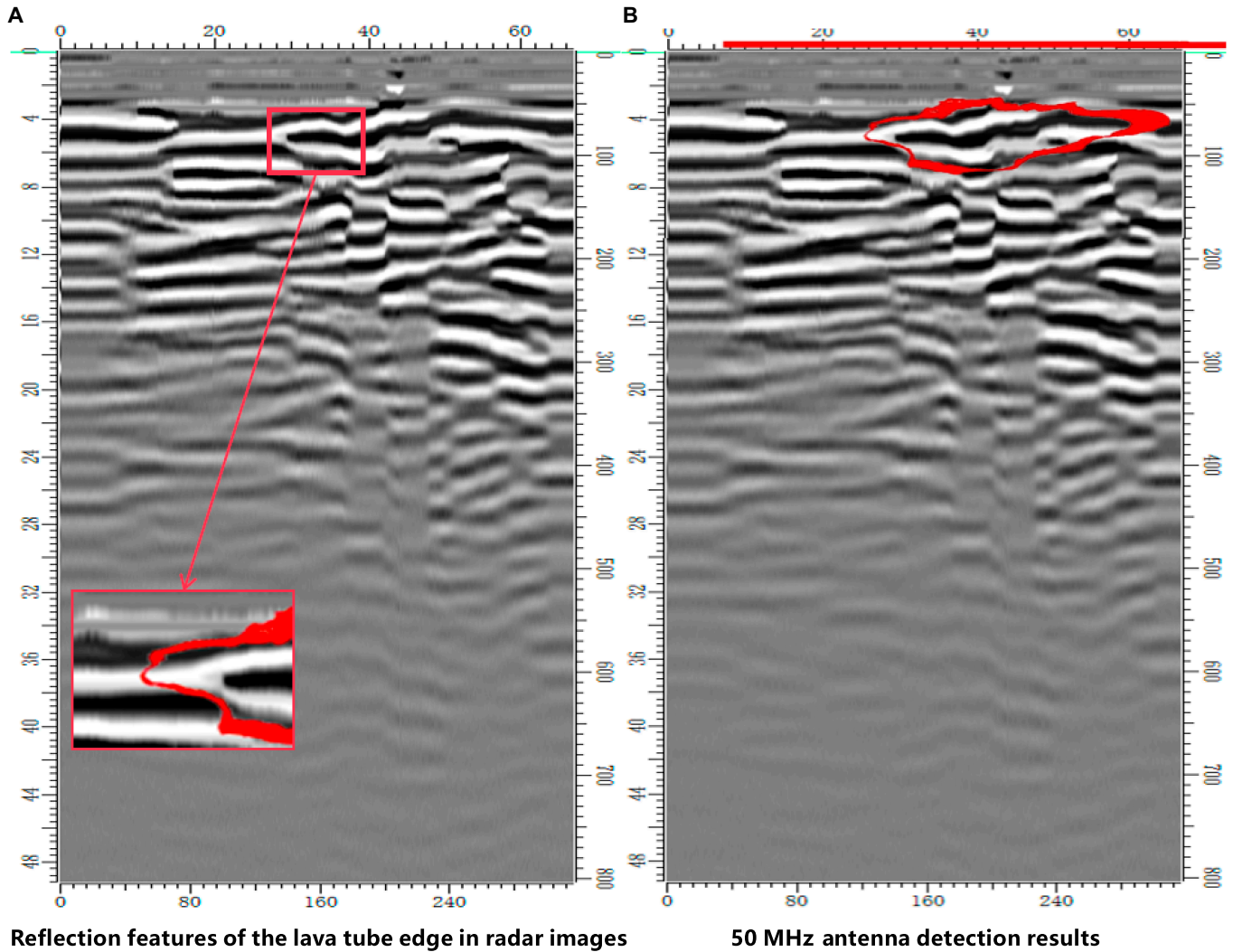


Fig. 7. Radar cavity detection results at the bottom of lava tubes. The bottom X-axis represents the number of channels, the top X-axis denotes distance (unit: meters), the left Y-axis indicates depth distance (unit: meters), and the right Y-axis stands for time (unit: nanoseconds). (A) Reflection features of the lava tube edge in radar images. (B) Fifty megahertz antenna detection results.

and enhanced filtering dynamically adjusts the filtering intensity by analyzing the local window's mean, variance, and noise variance [25]. For skylights in lava tubes, which are characterized by distinct edges and low backscatter, enhanced filtering smooths noise while retaining subtle variations in skylight boundaries and internal textures, improving the accuracy of subsequent feature extraction. The processing begins by calculating local statistics (such as mean and variance) and then determines the filter weight based on pixel homogeneity, evaluated through the comparison between C_u and C_{max} . In homogeneous regions, strong smoothing is applied, while in non-homogeneous regions (like edges), the filtering effect is reduced, balancing noise suppression with detail preservation. A weighting factor $W(x, y)$ is introduced in the calculation, reflecting the local characteristics of each pixel, making the enhanced filter significantly more adaptive than fixed-window methods. Moreover, by controlling the noise variance σ_v^2 and the maximum coefficient C_{max} , the method avoids excessive smoothing, ensuring that the geometric shape and low-intensity features of the lava tube skylights are preserved. In practical applications, the

window size (typically 5×5 or 7×7) should be adjusted based on image resolution and target scale, with parameters optimized to match the characteristics of the target features. The output of the enhanced filtering is a high-quality SAR intensity image, providing reliable input for subsequent texture analysis and classification. The corresponding Eq. (4) is shown below:

$$I'(x, y) = R(x, y) = \begin{cases} I(x, y) = a, & (x, y) \leq C_u \\ [a + (b - a)W(x, y)], & C_u \leq C_u(x, y) \leq C_{max} \\ I_c(x, y) = b, & C_u(x, y) \geq C_{max} \end{cases} \quad (4)$$

Here, $I'(x, y)$ represents the filtered output intensity value, $R(x, y)$ is the estimated true reflectance, and $I(x, y)$ denotes the original SAR intensity value. $I_c(x, y)$ indicates the mean intensity within the local window, while $W(x, y)$ is the weighting factor calculated based on local statistical characteristics. $C_u(x, y)$ is the local coefficient calculated as the ratio of the local standard deviation to the local mean. C_u serves as the threshold

for homogeneous regions, and $C_{\max}$ is the maximum threshold for the local coefficient.

For image output and visualization, the filtered SAR intensity image is exported in formats such as Geo-TIFF and undergoes geocoding to align with geographic coordinates. The geocoding process is based on orbital parameters and a DEM to correct terrain and projection distortions. Visualization adjustments include grayscale or pseudo-color mapping to highlight the low backscatter and texture features of skylights. High-quality images form the foundation for subsequent analysis, ensuring that resolution and contrast meet the required standards.

Based on the findings of previous studies and analyses, the lava tube has been modeled as a quasi-cylindrical underground structure. In this model, the bottom of the tube is represented by the internal ground surface, while the top is depicted as the vault. As the lava flow within the tube gradually empties, the vault often collapses, forming a skylight. Skylights serve as key indicators of these underground structures, which are otherwise not visible at the surface. Additionally, they provide potential access points from the surface to the underground tubes.

The study area is located on the western side of the Dunhua-Mishan fault zone, within a volcanic region oriented along the NNE axis. The area is characterized by the presence of rolling hills and a highly complex topography and geomorphology. To mitigate the geometric and radiometric distortions caused by the large, complex faults that affect SAR data interpretation, we initially employed high-precision optical images obtained through the use of DJI Phantom 4 RTK close-range photogrammetry. The images provided detailed topographic information through 3D reconstruction. Subsequently, threshold judgments based on DEM derivatives or optical image characteristics were employed to identify regions exhibiting indications of collapsed caves, thereby facilitating the extraction of skylight features from the SAR data.

The use of SAR technology enables the detection and extraction of the skylight structure by utilizing the distinctive contrasts in the intensity of scattered echoes. When radar waves interact with the skylight, they produce echoes that differ significantly from those of the surrounding environment, which is visible in the radar image as a difference in brightness or intensity levels. The backscatter intensity is influenced by multiple factors, including surface morphology and the dielectric constant of surface materials. The backscatter intensity of radar images is influenced by surface features, including height, shape, and slope. Skylights, often accompanied by collapse slopes, can result in the formation of dark areas or shadows within radar images when the slope faces away from the radar sensor or is steeper than the radar grazing angle.

Additionally, the dielectric constant of the geological body affects the intensity of the radar echo. An increase in water content increases the material's permittivity, which in turn leads to a higher backward scattering coefficient and a brighter appearance in the radar image. A comparison of the optical and radar images of the Lava Tube IV example reveals that, while the area is heavily vegetated, the skylight-exposed lava tube floor displays a residual lava flow cover that is distinctly different from the surface.

Surface structure analysis

The lava tube was divided into several distinct zones for detailed analysis, including the skylight collapse zone, the floor inside the lava tubes, the skylight sidewalls, the vault of the lava tubes, and

the top section and sides of the collapse zone. The point cloud data for the skylight collapse zone and the lava tube's interior floor were primarily sourced from data collected through a skylight opening, looking downwards, and from within the accessible parts of the tube, thereby revealing the removal of the bottom cover in some areas. The integration of these data with the cave floor surfaces enabled the reconstruction of the original orientation of the lava tube, highlighting key features such as rock steps at the tube's base. The point cloud data for the skylight sidewalls were captured between the spliced surface and the tube point cloud. The data illustrate the characteristics of a cliff wall and provide a cross-sectional view of the lava tube's top, offering insights into its stratigraphy over time. The lava tube vaults, including the baked layers and the curved tops of lava stalactites, represent the original surface of the lava tube's innermost part. This detailed segmentation facilitates our understanding of the lava tube's formation and evolution [10].

In the final presentation of the model, we enhanced its visual impact and authenticity through careful rendering and material selection. By utilizing available image data and focusing on specific features of the model, colors and materials that ensure both high recognizability and accuracy were selected.

The process began with a pre-modeling phase that employed a multi-layered modeling technique. This method provided a solid foundation for the application of materials, allowing for a precise and realistic representation of the model. The integration of this approach ensured that the model not only was visually realistic but also effectively communicated key information [44].

In selecting and applying materials, we prioritized details such as faults, gaps in the rock formations, and aesthetics to ensure the model was both visually appealing and realistic. Each component of the model received a material that highlighted its unique characteristics, enhancing its overall form and structure. Consistent materials were used throughout the model to maintain a cohesive visual style.

These steps culminated in a model imbued with high-quality material information, significantly enhancing its visual clarity and realism. This improved presentation not only boosted the model's accuracy and recognizability but also established a strong foundation for future research and analysis.

Internal structure analysis

GPR operating at 4 frequencies—50, 100, 200, and 400 MHz—can achieve multi-scale exploration of lava tubes, from deep to shallow depths. The main differences between these 4 types lie in wavelength, resolution, and penetration depth. The 50-MHz radar has the longest wavelength (approximately 2 to 3 m), allowing penetration depths of tens or even hundreds of meters, making it suitable for detecting the overall morphology and top and bottom interfaces of lava tubes. The 100-MHz radar offers both reasonable resolution and deep penetration, enabling the identification of meter-scale structures. The 200-MHz radar, with a wavelength of approximately 0.5 to 0.7 m, can resolve sub-meter-scale bedding and filling variations. The 400-MHz radar, with the shortest wavelength (approximately 0.25 to 0.4 m), offers high resolution, enabling the identification of rock formation details as shallow as a few centimeters to tens of centimeters, but its penetration depth is limited to a few meters.

Despite their different frequencies, these 4 types of GPR operate on the same principle: they transmit and receive reflected electromagnetic waves to reveal electrical differences in the subsurface medium, thereby identifying structures such as strata boundaries,

cavities, and fractures. They are all affected by the underground dielectric constant, moisture, and conductivity, and signal attenuation is inversely proportional to resolution. The combined use of multiple frequencies complements their strengths: low frequencies reflect macroscopic structures, while high frequencies reveal fine features. Through time-depth conversion and data fusion, a continuous profile from the surface to the depths can be formed, enabling the systematic identification and interpretation of lava tube structures, rock sequences, and collapse characteristics.

In the preprocessing of GPR data, we primarily carried out the following steps [45]. Background removal was performed to eliminate fixed interference or static components in the radar data, thereby highlighting the dynamic, target-related signals. The formula is shown in Eq. (5), where $S(t)$ represents the original signal, and $\langle S(t) \rangle$ denotes the average value of the background signal calculated over a specific period [46]:

$$S'(t) = S(t) - \langle S(t) \rangle \quad (5)$$

Radar systems may sometimes capture noise from the static environment or fixed echoes generated by the system itself. These background signals can obscure the target echoes. By calculating the average signal intensity at each location over time (for static background elements), the background can be treated as a static value and subtracted from the radar data, thereby reducing interference with target detection.

Direct current (DC) component removal aims to eliminate the DC offset in the radar signal caused by hardware or environmental factors, making the processed signal more balanced and symmetrical. The formula is shown in Eq. (6), where $\frac{1}{N} \sum_{n=1}^N S(n)$ represents the average value (DC component) of the signal:

$$S'(t) = S(t) - \frac{1}{N} \sum_{n=1}^N S(n) \quad (6)$$

The DC component typically refers to the zero-frequency component of a signal, which is essentially the signal's average value or low-frequency content. By setting the signal's average value to zero, these DC components can be removed, effectively reducing low-frequency interference caused by radar system hardware or environmental conditions, thereby enhancing the high-frequency target echoes [47]. High-pass filtering is then used to remove low-frequency noise and background interference from radar data, preserving the high-frequency portion of the signal, such as target echo signals. In the following equations, $S(f)$ represents the signal in the frequency domain, obtained through Fourier transform, while $H(f)$ is the frequency response function of the high-pass filter, with f_c denoting the cutoff frequency of the filter [48], as Eqs. (7) and (8):

$$S'(f) = H(f) \cdot S(f) \quad (7)$$

$$H(f) = \begin{cases} 0, & \text{if } f < f_c \\ 1, & \text{if } f \geq f_c \end{cases} \quad (8)$$

A high-pass filter allows signals above a specified frequency to pass while attenuating signals below that frequency. In radar echoes, low-frequency noise (such as environmental noise or background echoes) is often present. By eliminating these low-frequency components, the high-pass filter enhances the target-related high-frequency signals.

Gain processing is used to amplify the overall strength of radar echo signals, making weak target signals detectable and increasing the signal's contrast and dynamic range [49]. The formula is shown in Eq. (9), where $G(t)$ is the gain factor, typically a function of distance or time, used to compensate for signal attenuation over varying distances [50]. The gain factor $G(t)$ can be designed based on specific applications, and a common form is an increasing function of time to compensate for propagation attenuation: $G(t) = G_0 + \alpha t$, where G_0 is the initial gain, and α is the coefficient representing the rate of gain variation over time [51]:

$$S'(t) = G(t) \cdot S(t) \quad (9)$$

The results of the data processing of the GPR data are presented in Fig. 7.

Analysis of rock stratigraphy [52]: By examining the variations in the intensity of reflected radar signals, it is possible to infer the stratigraphy of the rock formations. The reflection coefficients and electromagnetic wave propagation characteristics of different rock types are unique, resulting in varying signal intensities for different stratigraphic layers.

Soil and rock layers typically exhibit distinct reflection characteristics in GPR data as shown in Fig. 8. For example, clay layers often produce stronger echo signals, while some types of intact bedrock typically yield weaker echoes unless fractured or water-saturated. By analyzing these intensity changes, it is possible to identify the distribution and sequence of rock strata.

By observing the changes in the reflectivity of the radar data, the locations of selected sections for detailed stratigraphic interpretation were determined. The routing of the GPR is shown in Fig. 9. This method can accurately delineate different rock layers based on their reflectivity.

The interpreted stratigraphic profile results are presented in Fig. 10.

Lava tube cavity analysis [53]: The analysis of lava tube cavities reveals that the interface between different materials typically produces robust reflection signals. These reflections often exhibit distinct wavelet characteristics and arrival patterns, commonly appearing as regular or irregular hyperbolic waveforms.

The signals display a pronounced triple-phase vibration, indicating complex interactions at the interface. Additionally, the lower portion of the cavity often exhibits robust interface signals as well. The time difference between these 2 sets of signals is significant, highlighting the existence of a clear separation between the various layers or materials present within the lava tube cavity.

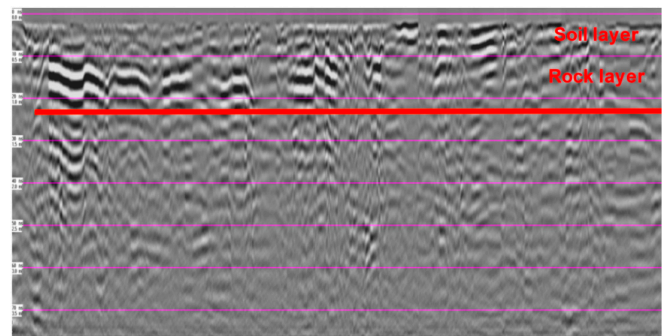


Fig. 8. Radar image segmentation results; the first layer is the soil layer, and the rest are rock layers.

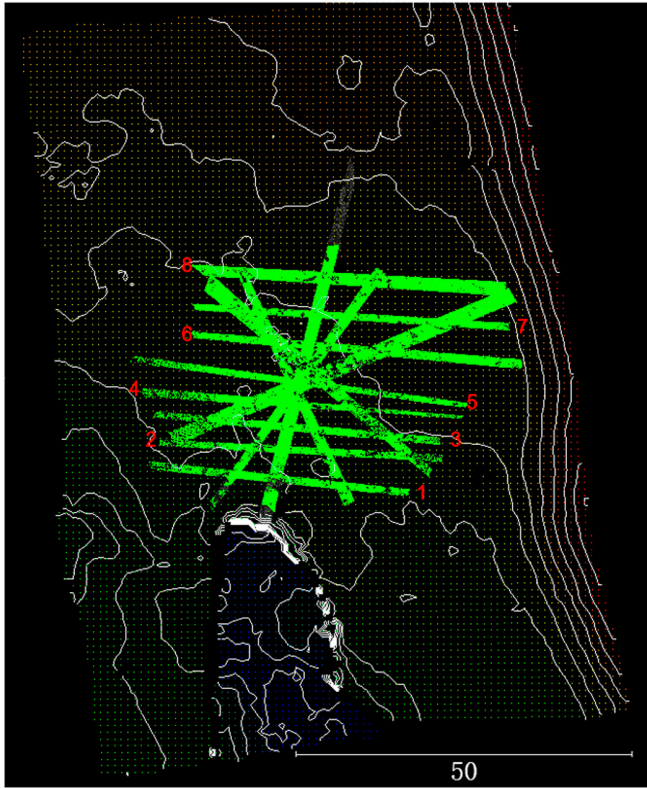


Fig. 9. Ground-penetrating radar wiring design for the study area.

After delineating the rock formation sequence from the GPR data, we employed a precise radar-to-point-cloud spatial registration method to fuse the GPR imagery with the point cloud profiles, constructing a joint profile model that aligns the radar profiles with the real-world spatial structure. Furthermore, we utilized high-resolution UAV-acquired point cloud data from the skylight region of the lava tube. By applying aircraft-type region clustering and surface segmentation techniques to these data, we were able to automatically delineate the rock formations within the skylight region. The delineation results revealed distinct stratification at the top of the skylight area. The delineated rock formations within the skylight region were then incorporated into the fused GPR-point cloud model to calibrate and verify the top reflectors in multiple radar profiles.

The composition analysis of the tube wall materials

We employed the HSL (Hyperspectral LiDAR) system to classify the rock materials of the lava tube walls under lightless conditions using hyperspectral techniques. The HSL system consists of several key modules, including a laser emission module, a laser echo signal reception module, a scanning control module, and an integrated control software system. These modules work in coordination to ensure efficient system operation. The system operates as follows: a supercontinuum laser source emits a laser beam directed into a filter, which selects a specific wavelength based on instructions from the integrated control computer. The scanning control module then directs this monochromatic laser beam toward the target and receives the corresponding echo signal. A data acquisition card, triggered by the light source signal and controlled by the integrated control software, captures and records the detector's echo signal, completing laser detection at

a single wavelength. At a single point, the integrated control software adjusts the filter, allowing the system to emit lasers of different wavelengths at different moments and collect the corresponding target echoes. Once data collection for all wavelengths is complete, the scanning control module directs the laser to the next point, repeating the above process [54]. The raw intensity values collected by the acquisition card are converted into target backscatter intensity voltage values, following the conversion relationship shown in Eq. (10):

$$P_r = \left(\frac{\text{Digital}_{\text{level}}}{2^{15}} \right) \cdot \left(\frac{\text{Digital}_{\text{analog}}}{2} \right) \quad (10)$$

In this context, $\text{Digital}_{\text{level}}$ represents the actual intensity value measured by the acquisition card, P_r denotes the converted backscatter intensity, and $\text{Digital}_{\text{analog}}$ is the analog voltage input of the acquisition card, which is set to 1 V in this system.

The ranging principle of the HSL system is similar to that of conventional single-wavelength LiDAR. It primarily calculates the distance between the LiDAR and the target by measuring the time interval between the laser emission signal and the received echo signal. The calculation of the distance between the LiDAR and the target is expressed in Eq. (11):

$$R = \frac{1}{2} c \Delta t \quad (11)$$

Here, Δt represents the round-trip travel time of the laser pulse, while c denotes the speed of light.

To achieve target scanning, the HSL system's emission module relies on a 2-dimensional turntable in the scanning module, enabling rotation in both azimuth and elevation directions. This rotational capability allows the laser beam to perform comprehensive scanning of the target, thereby acquiring its 3D information. The azimuth angle (α) is defined as the angle in the XY-plane measured from a reference direction (e.g., the X-axis), with a positive value for clockwise rotation, while the elevation angle (β) is defined as the angle from the XY-plane to the laser beam. The laser beam projection is determined by its position on the plane defined by the X- and Y-axes. The emission center of the HSL system is defined as the origin, denoted as (X_0, Y_0, Z_0) , and any scanned point is labeled as (X, Y, Z) . The spatial coordinates of the scanned point in the Cartesian coordinate system are calculated using the following Eq. (12):

$$\begin{cases} X = X_0 + R \cdot \cos \beta \cdot \sin \alpha \\ Y = X_0 + R \cdot \cos \beta \cdot \cos \alpha \\ Z = Z_0 + R \cdot \sin \beta \end{cases} \quad (12)$$

When scanning a target using the HSL system, the reflectance information of the target is calculated by determining the ratio of the target's backscatter intensity to that of a standard diffuse reflection panel at the same distance [55]. This calculation is expressed by the following Eq. (13):

$$\rho_{\text{obj}}(\lambda) = \frac{f_{\text{APD}_{\text{obj}}}(\lambda)}{f_{\text{APD}_{\text{ref}}}(\lambda)} \rho_{\text{ref}}(\lambda) \quad (13)$$

Here, $f_{\text{APD}_{\text{ref}}}(\lambda)$ represents the backscatter intensity of the standard diffuse reflection panel, $f_{\text{APD}_{\text{obj}}}(\lambda)$ is the backscatter

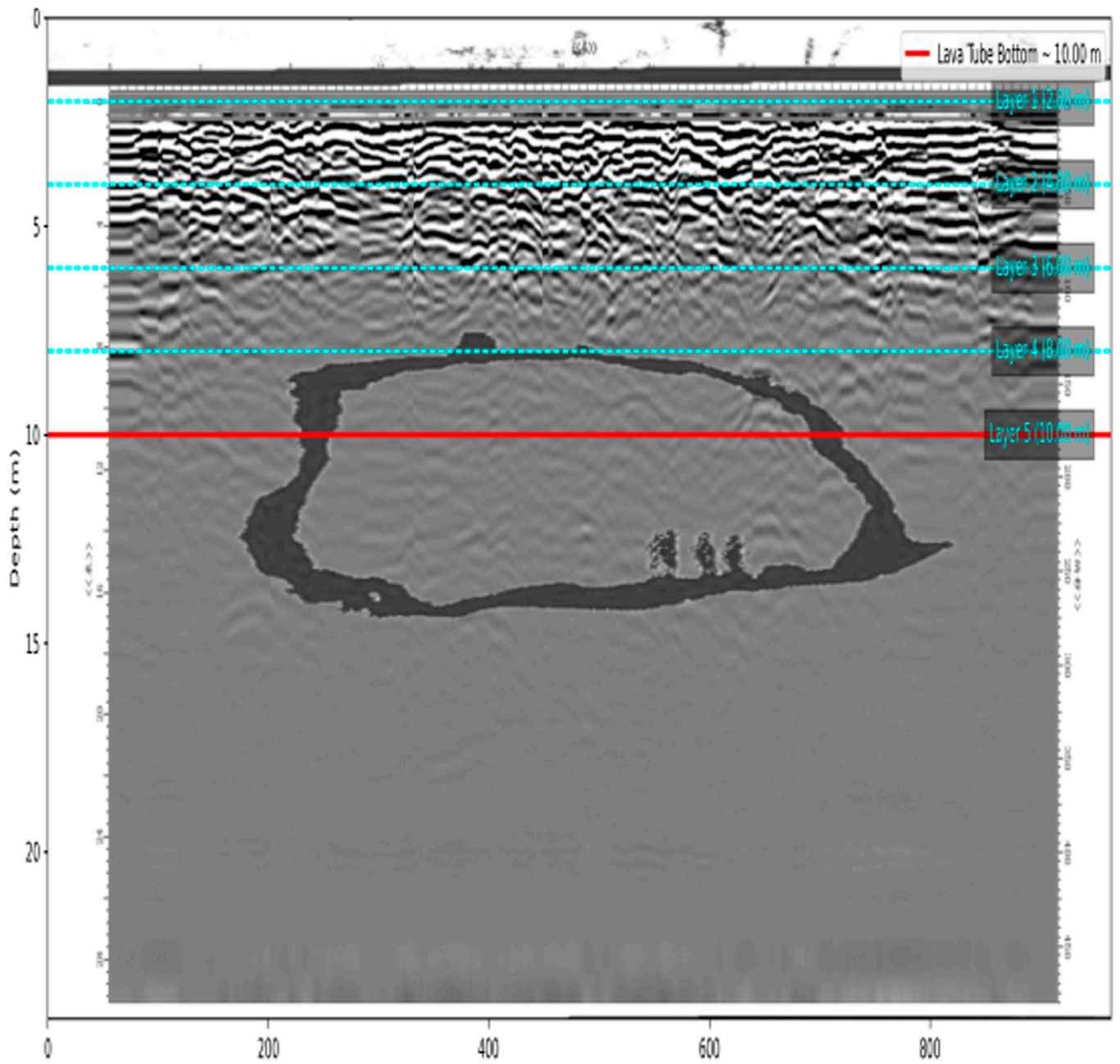


Fig. 10. Segmentation results of 400 MHz antenna with 4 m depth of detection.

intensity of the target, $\rho_{\text{ref}}(\lambda)$ is the reflectance of the standard reflection panel, and $\rho_{\text{obj}}(\lambda)$ is the reflectance of the target.

Based on the above principle, the acquired signal data are converted into point cloud data. After preprocessing these point cloud data, we perform clustering using the K-means clustering method [56]. Initially, K random cluster centers (centroids) are selected, denoted as $\mu_1, \mu_2, \dots, \mu_k$ where each μ_i is a feature vector of the same dimension as the data points. Subsequently, for each data point x_i , which corresponds to a spectral feature vector of a point in the hyperspectral point cloud, the Euclidean distance to each centroid μ_j is calculated in Eq. (14):

$$\text{Distance} = \|x_i - \mu_i\|_2 = \sqrt{\sum_{d=1}^D (x_{i,d} - \mu_{j,d})^2} \quad (14)$$

Here, D represents the number of feature dimensions, which can be either the number of spectral bands or the reduced dimensionality. Each data point is assigned to the cluster of the nearest centroid, following the calculated Euclidean distance Eq. (15):

$$C_i = \underset{j}{\text{argmin}} \|x_i - \mu_j\|_2 \quad (15)$$

For each cluster j , the mean of all points within that cluster is calculated to serve as the new centroid, following the equation:

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i \quad (16)$$

Here, C_j represents the set of all data points in cluster j , and $|C_j|$ is the total number of points in that cluster. The process of assigning points to clusters and updating centroids is repeated until the centroids no longer change or the maximum number of iterations is reached, marking the end of the clustering process.

After completing the outlined procedures, hyperspectral LiDAR echoes were successfully acquired within the lava tube, despite the challenging conditions of low luminosity and limited visibility. By decomposing the echo data, calculating ranging distances, and performing preprocessing, a hyperspectral laser point cloud was generated. Subsequently, spectral features were utilized to classify and sort the point cloud, enabling the differentiation of material components based on their echo characteristics at varying wavelengths.

This approach facilitated the accurate delineation of substance layering within the lava tube, even in the absence of light. An integrated 3D model of the lava tube's internal walls was constructed, encompassing detailed segmentation of the structural and material components. This comprehensive model provides valuable insights into the composition and organization of materials inside the lava tube. From the spectral data, we can see that there are differences in the reflectance characteristics of different substances. Further research is needed to determine the similarities and differences between different substances. Experiments using geochemical methods can be used to determine the material composition. At present, only the differences in material composition have been proven, and the different reflectance characteristics are classified using the K-means algorithm in Fig. 11.

Compared to traditional remote sensing technologies, such as hyperspectral multi-angle remote sensing and the fusion of LiDAR point clouds with hyperspectral images, the use of hyperspectral LiDAR represents a significant advancement [57]. This approach overcomes the limitations of conventional methods by enabling the simultaneous acquisition of spatial and spectral data for feature targets. This technology integrates spatially and spectrally resolved imaging, thereby offering all-day, multi/hyper-spectral (within its operational range), high-precision, and high-resolution capabilities.

Hyperspectral LiDAR overcomes the problem of spectrometers being unable to collect data in the absence of light by combining spectral and distance information. This enables it to simultaneously detect differences in material composition within lava tubes and details of the wall structure inside lava tubes. Consequently, it offers a robust solution for 3D structural modeling and material analysis of lava caves. Additionally, this technology provides innovative approaches to 3D modeling and material composition analysis, which could prove beneficial for future lunar exploration and the construction of human habitats on the moon.

Results

Topographic analysis results of large-scale lava tube distribution and skylight extraction

This analysis shows that skylights exhibit significant differences between radar and optical images. In radar images, skylights have distinct morphological features, making them easy to extract and identify. In the charts referenced below (e.g., Figs. 12 and 13), light red color highlights the extent of the lava tube

on the image, and dark red dots indicate the location of skylights within the highlighted lava tube area. Skylights are typically circular to elliptical in shape, as shown in Fig. 12A).

Within the same area, they develop in chains or beads along the direction of lava tube growth on radar images, as illustrated in Fig. 12B. Shadows may accompany the edges of skylight pits, as illustrated in Fig. 12C below.

By combining the aforementioned features, we extracted the skylights of lava tube No. 3 in the Jingpo Lake region, and the results are presented in Fig. 13.

As illustrated in Fig. 13, satellite-based SAR technology demonstrates the capacity to capture both subtle surface features and changes, as well as to penetrate vegetation, thereby enabling accurate identification of lava tube skylights and inferring the presence of underlying caves. This capability is significant for the exploration and verification of lava tubes, providing a valuable tool for further investigation.

Lava tubes above and below ground

The lava tube was divided into several distinct zones for detailed analysis, including the skylight collapse zone, the floor inside the lava tubes, the skylight sidewalls, the vault of the lava tubes, and the top section and sides of the collapse zone. The point cloud data for the skylight collapse zone and the lava tube's interior floor were primarily sourced from data collected by scanning through the skylight opening down to the floor and of the collapse pile at the bottom of the skylight, thereby revealing the removal of the bottom cover. The integration of these data with the cave floor surfaces enabled the reconstruction of the original orientation of the lava tube, highlighting key features such as rock steps at the tube's base. The point cloud data for the skylight sidewalls were captured by merging data from surface-based scans/photogrammetry of the skylight opening with data from internal scans (e.g., GeoSLAM) extending toward the skylight. The data illustrate the characteristics of a cliff wall and provide a cross-sectional view of the lava tube's top, offering insights into its stratigraphy over time. The lava tube vaults (ideally, a lava tube forms a circular pipe, but in reality, it is deformed by various factors such as gravity, and the top part of the pipe still has an arched top, which we call the lava tube vault), including the baked layers and the curved tops of lava stalactites, represent the original surface of the lava tube's innermost part. This detailed segmentation facilitated our understanding of the lava tube's formation and evolution.

The top section of the internal collapse zone within the lava tube exhibits significant damage due to the internal collapse. This collapse has exposed the top fault and altered the original vault, resulting in a section that is square in shape and distinctly different from the original lava tube vault. This section required separate identification to accurately distinguish it from the intact vault.

Although the top of the lava tube has collapsed, as shown in Fig. 14A, the flanks of the internal collapse zone still retain some of the original structure, as shown in Fig. 14B. After separating the top portion, the remaining flanks of the collapse zone need to be identified and analyzed separately.

This detailed segmentation thus enabled a deeper examination of the lava tube's diverse components, thereby facilitating a more nuanced understanding of its formation and evolutionary processes. The resulting data not only enhanced our knowledge but also provided a robust basis for constructing models and conducting simulation analyses.

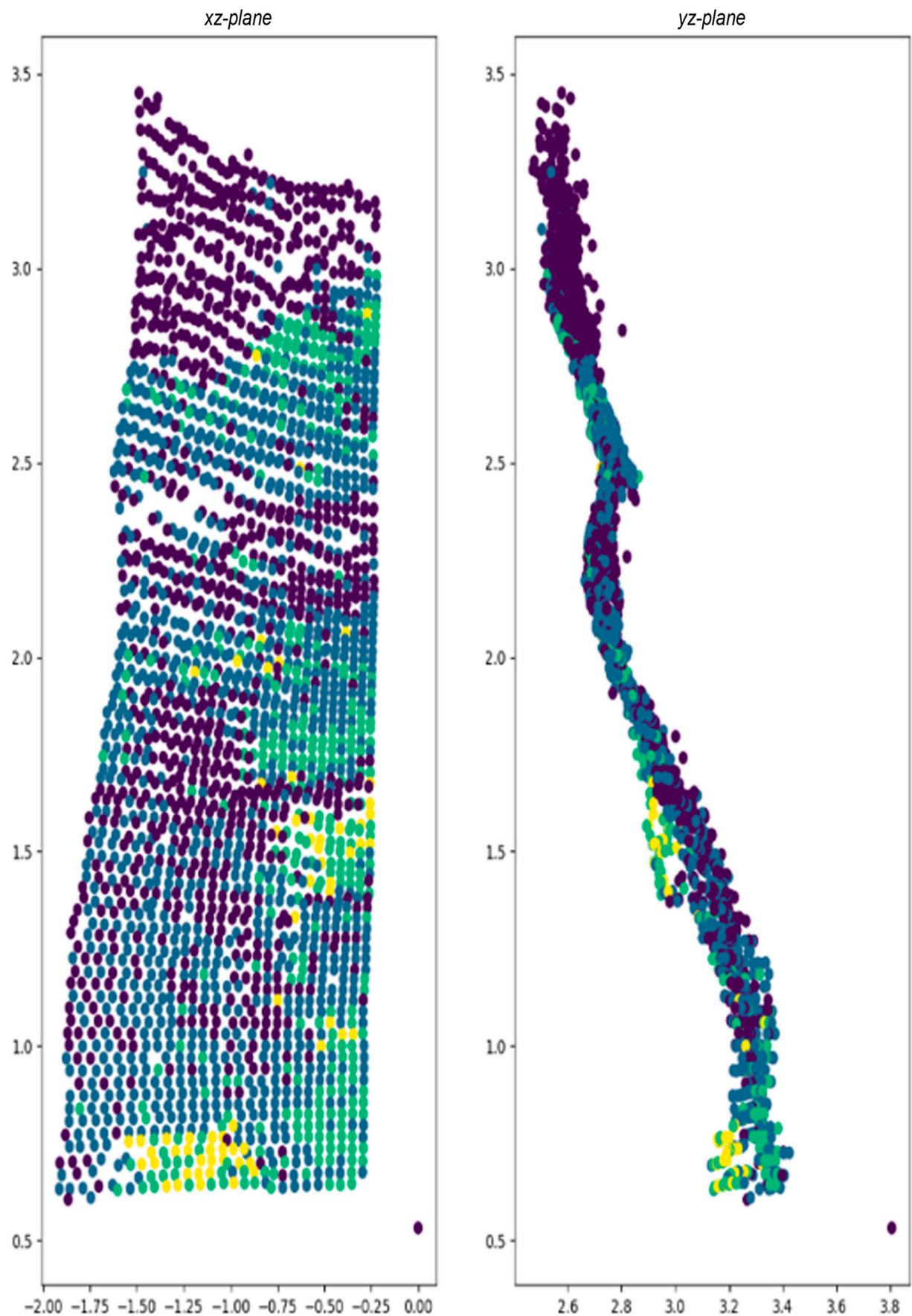


Fig. 11. Schematic diagram of the integrated solid segmentation of the 3D structure and material composition stratification of the internal wall of the lava tube.

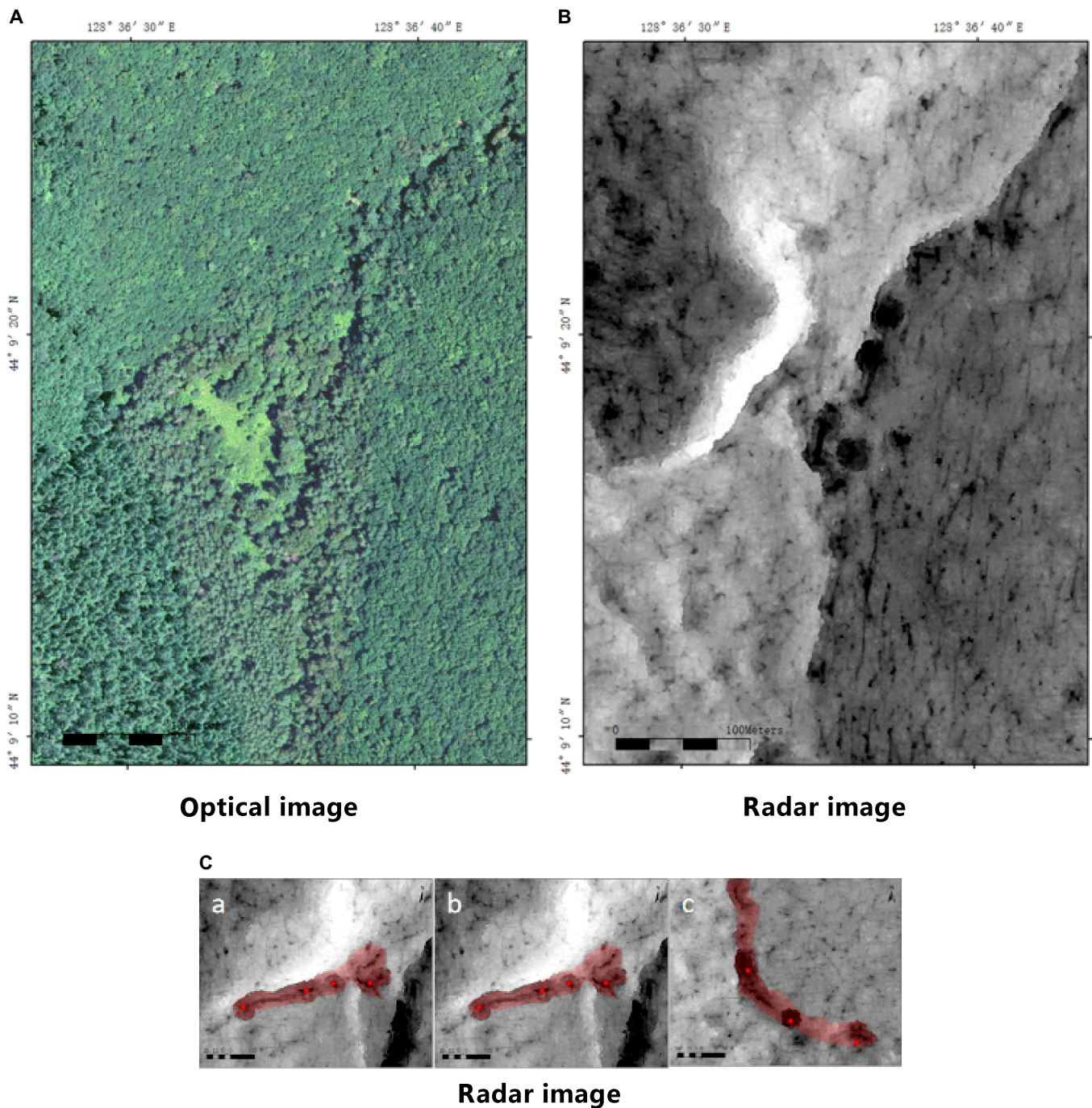


Fig. 12. Comparison results between optical and radar images of the area near the lava tube skylight. (A) Optical image. (B) Radar image. (C) Radar images, (a) and (b) are radar images of the same lava tube at different resolutions, and (c) is a radar image of another lava tube skylight; the red shaded area is the outline of the lava tube, and the red dot is the location of the lava tube skylight.

The cross-sectional model presented clearly revealed faults, rope-like lava flow patterns, and the collapse on the right side (Fig. 15). These features offered valuable insights into the internal structure and morphology of the lava tube, aiding in a more comprehensive understanding of its formation and evolution.

Lava tube internal wall segmentation results

Once the data had been verified and deemed acceptable, the timing of peak laser echoes was used to determine ranging distances, and point clouds were generated. Fig. 16 provides a schematic

illustration of the hyperspectral laser acquisition process, demonstrating the echo intensity across different bands.

After generating the point cloud, the pre-processing stage was initiated. This process included eliminating noise and removing points that had been affected by inaccuracies due to the presence of small holes in the scanned surface and the limited precision of the prototype. These factors can lead to discrepancies in distance measurements across different wavelength bands. The objective of this step is to ensure the validity of the hyperspectral point cloud for a given location across various wavelength bands.

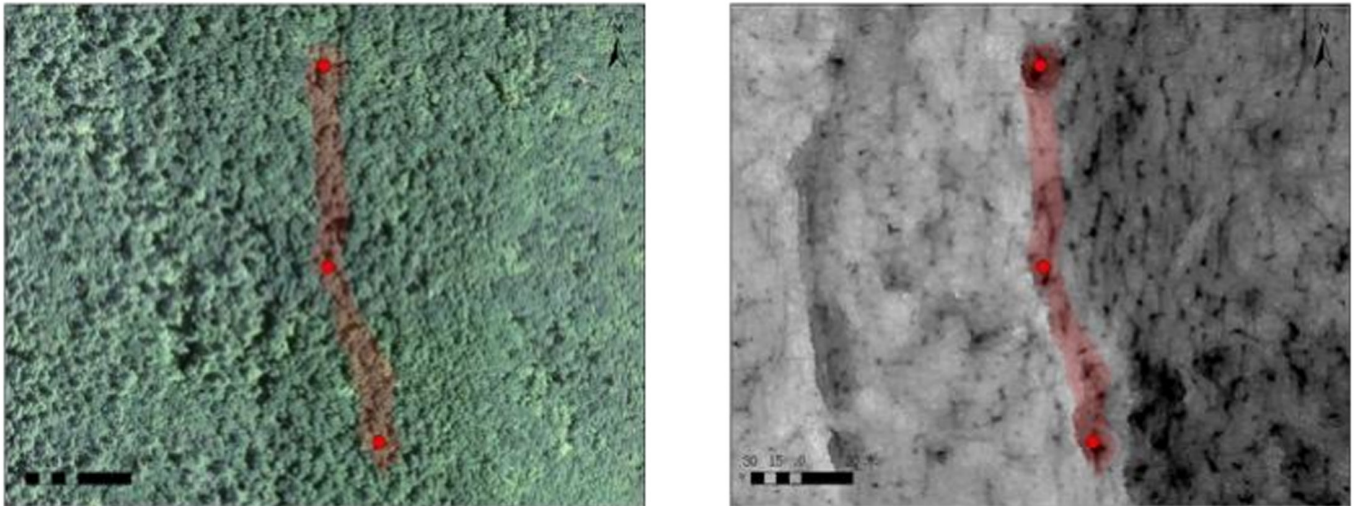


Fig. 13. Comparative validation of lava tube extraction results. Light red color highlights the range of lava tubes, while dark red dots indicate the locations of skylights.

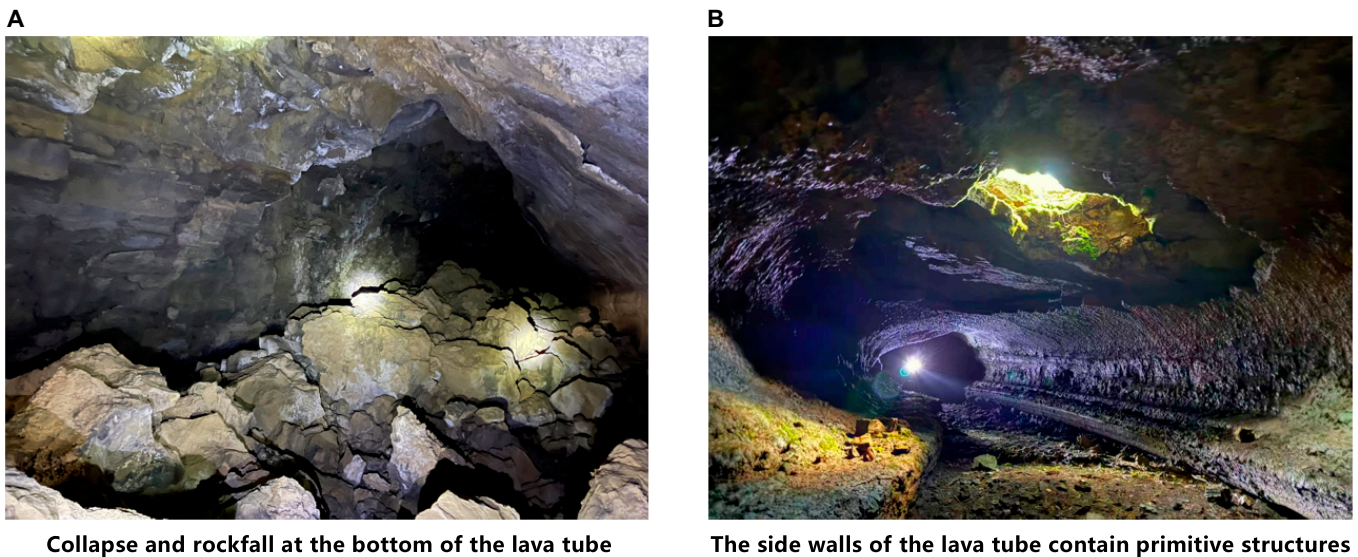


Fig. 14. The original structure preserved inside the lava tube and the presence of collapsed objects inside. (A) Collapse and rockfall at the bottom of the lava tube. (B) The side walls of the lava tube contain primitive structures.

Next, an unsupervised classification of the pre-processed point cloud was conducted using its spectral features. This classification process facilitated the identification and categorization of the material components present within the measurement area. The classification result of the hyperspectral LiDAR point cloud is illustrated in Fig. 17.

Discussion

Several major issues remained unsolved in the literature. The reliance on single-frequency GPR antennas or GPR with a uniform frequency often leads to limitations in the trade-off between data resolution and penetration depth, and there is a lack of comprehensive geological data on lava tube orientation. Additionally, the lack of measurements of critical landforms, such as skylights and collapses, hinders further research.

To address these issues, this study implemented several improvements based on the shortcomings identified in previous research. Our experiments began with an investigation of

lava tubes, including features like skylights, whereby tangent measurements were conducted along the tube's orientation and both cross and diagonal cross detection surveys were employed at various segments. GPR with frequencies of 50, 100, 200, and 400 MHz was utilized to perform repeated measurements at the same locations over known or suspected lava tubes to investigate their structure. By analyzing tangent measurements at various positions along the tube's orientation and comparing data across different frequencies, we obtained improved results, thereby validating the feasibility and effectiveness of GPR for characterizing and monitoring lava tubes and addressing the resolution versus penetration limitations associated with single-frequency GPR. At the same time, it should be noted that the velocity and attenuation of GPR waves are strongly controlled by the dielectric properties of the subsurface, which in turn depend sensitively on water content: even modest amounts of liquid water can markedly slow wave propagation and increase signal attenuation, limiting penetration depth and obscuring deeper targets. In our study area, the surveyed

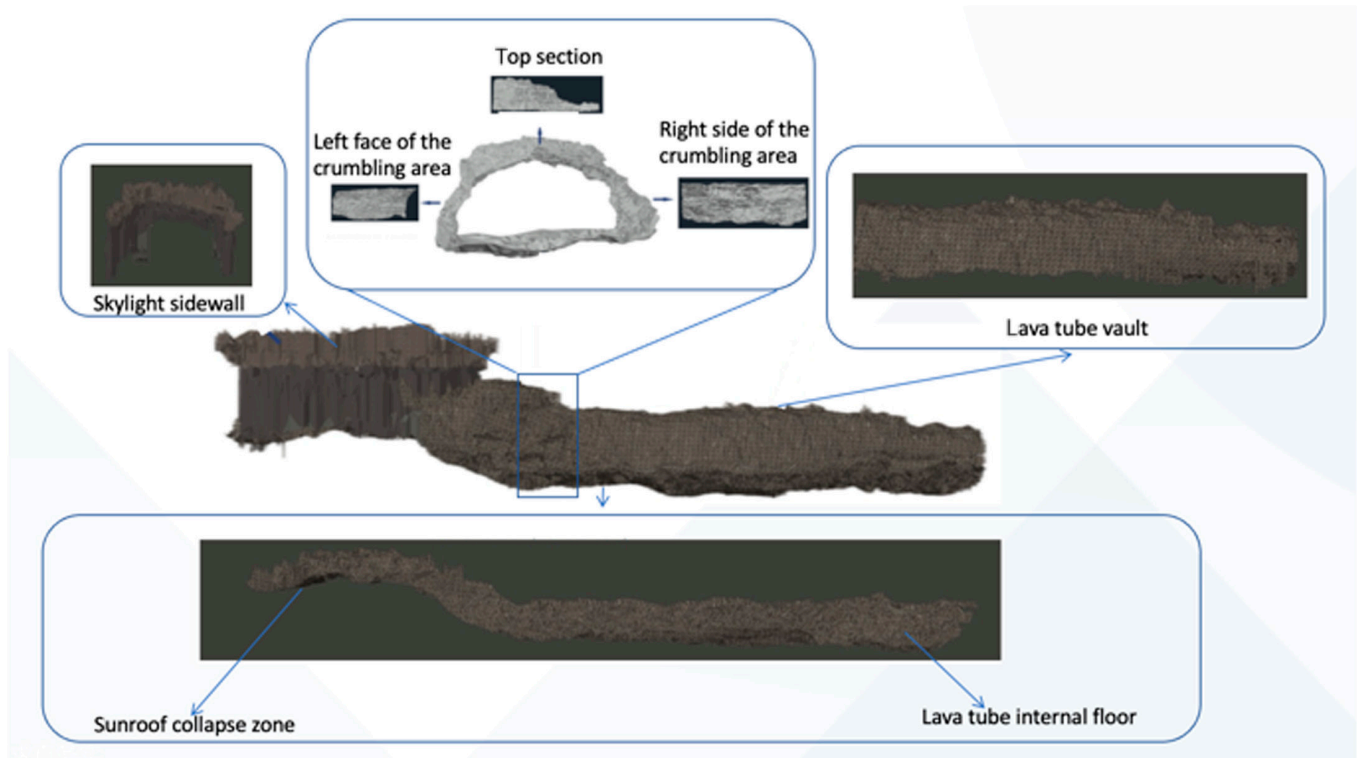


Fig. 15. Results of integrated modular modeling of lava tubes above and below ground.

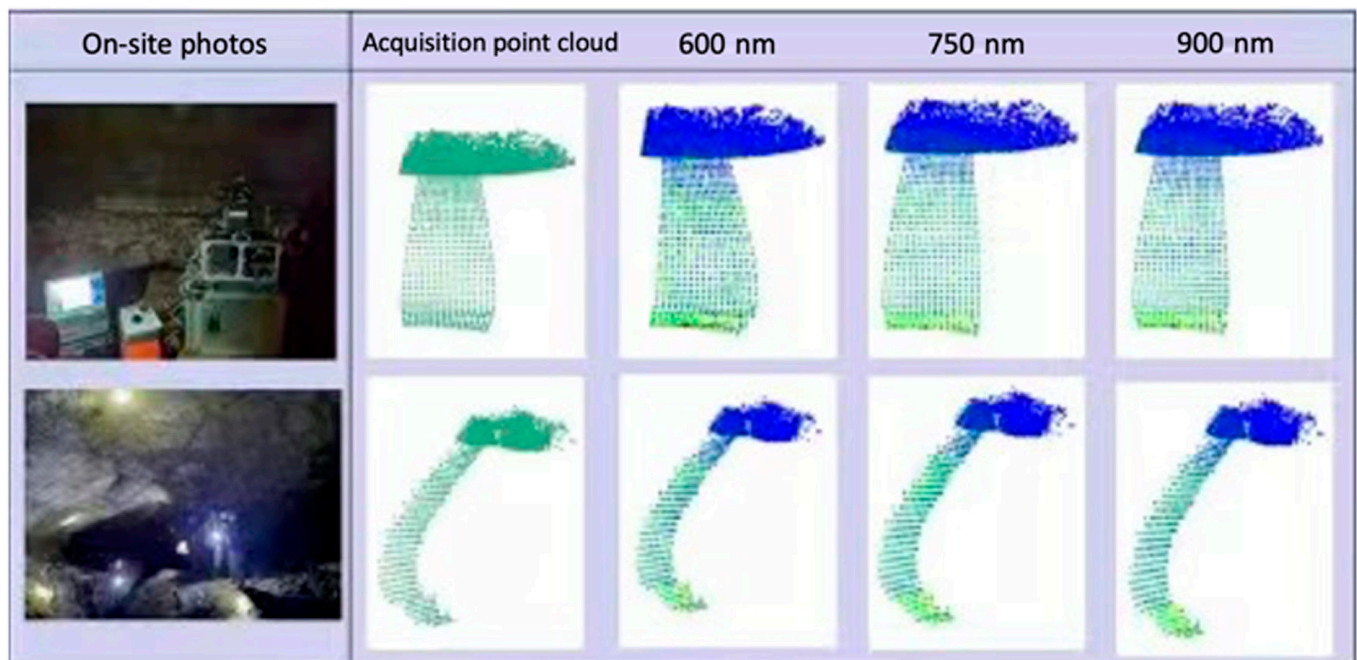


Fig. 16. Hyperspectral laser data collection and schematic diagram of echo intensity under different wavelengths.

lava tube is hosted in massive, largely dry basalt and no standing water or persistent seepage was observed along the profiles; thus, moisture-related effects are expected to be minor and the multi-frequency data can be interpreted mainly in terms of lithological contrasts and void geometry. However, for wetter terrestrial analogues or planetary targets where liquid water or brines may be locally present, water-controlled attenuation and

velocity variations will become a first-order limitation for structural imaging and depth conversion and should therefore be explicitly considered in survey design and when extrapolating the implications of our results.

Furthermore, a multi-source data fusion approach was employed. Satellite SAR data were employed to provide comprehensive SAR images of the Jingpo Lake region. The use of

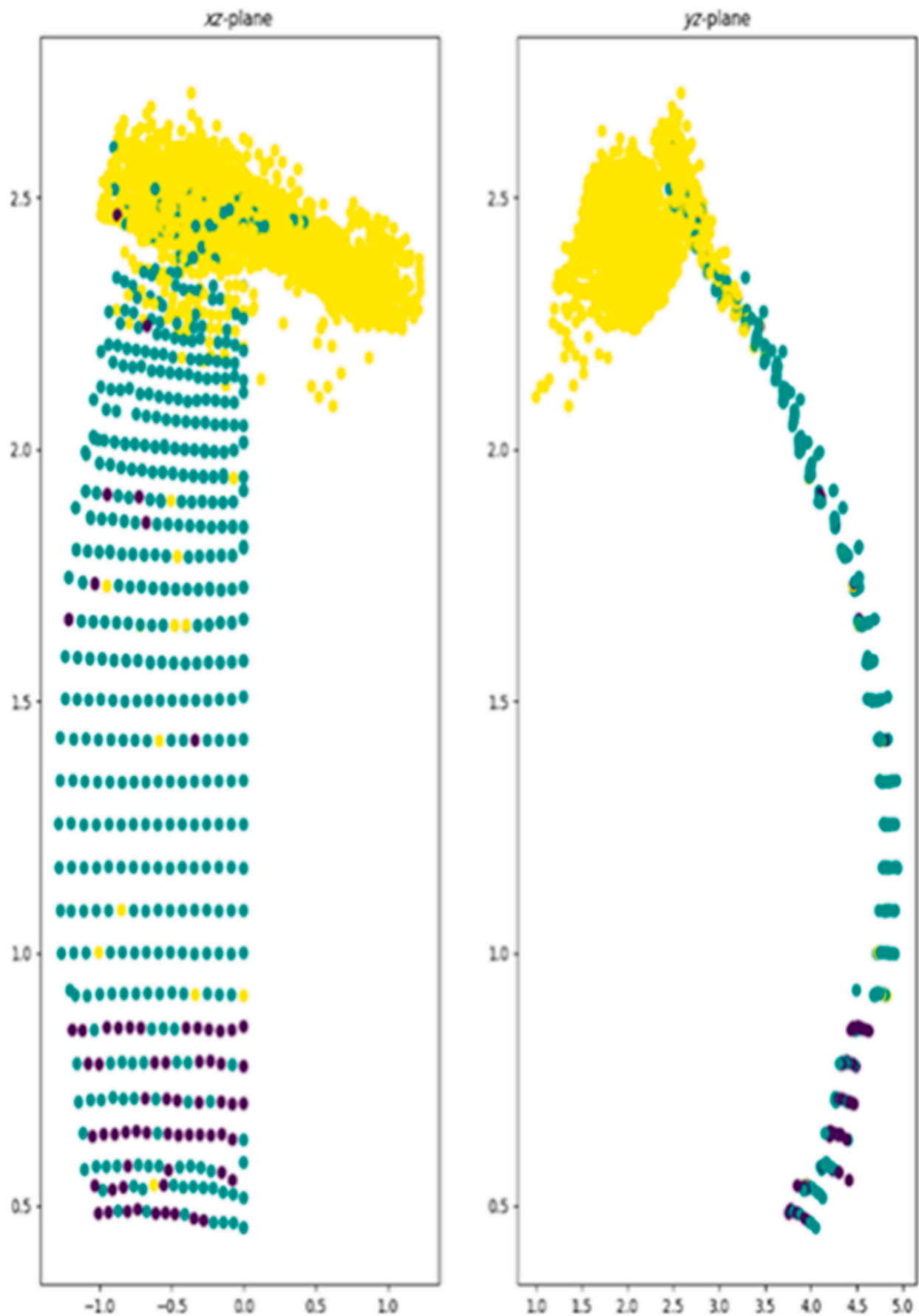


Fig. 17. Hyperspectral LiDAR classification results.

data from drones effectively bypassed the complex terrain and dense vegetation cover around the lava tubes, thereby yielding accurate images, point cloud data, and LiDAR data through the implementation of manual flights. The use of hyperspectral LiDAR data enabled the collection of spectral point clouds (from which intensity images can be derived) within the dim interior of lava tubes, facilitating the acquisition of data in poor visibility conditions. The use of GPR enabled the detection of the roof thickness and internal height of the underground tubes, and potentially aspects of the floor structure, and from the surface. Taking Shenyang Cave as an example, frequencies of 50, 100, 200, and 400 MHz can all identify the top of the lava tube and the overlying rock layers at a depth of 1 to 3 m. For 50 and 100 MHz, the contour information of the lava tube floor can be identified, and the internal height is generally 2 to 3 m.

Although hyperspectral LiDAR can accurately and synchronously obtain information on both morphology and material composition under dark conditions inside lava tubes, the spectral range in this study was limited to 500 to 1,000 nm, which was insufficient to cover the absorption peaks of minerals such as feldspar, pyroxene, and olivine. Therefore, future work should expand this range to 450 to 3,000 nm to improve the identification accuracy of key minerals.

The integration of multi-source data facilitated a comprehensive analysis of the lava tube morphology and other information. Compared to the utilization of a single data source, this approach enabled the creation of a model with an accuracy of approximately 0.1 m, thereby ensuring the reliability of the results. The utilization of hyperspectral remote sensing data facilitated effective differentiation of materials on the lava tube interior walls.

This integrated approach enabled a comprehensive and systematic analysis of the lava tube system's surface and subsurface features. This holistic framework combined multi-source observational data across 4 key dimensions—space-borne, aerial, ground, and in-tube—for a thorough investigation of the entire lava tube segment. Specifically, space-borne SAR was employed for large-scale regional analysis and the extraction and localization of potential skylights. Concurrently, UAV LiDAR and photogrammetry acquired high-resolution 3D point clouds for the fine characterization of surface morphology and the internal geometry of skylight walls. For subsurface characterization, multi-frequency GPR was deployed from the surface to estimate tube roof depth and cavity distribution and to analyze the strata sequences of the overburden rock layers. Furthermore, in-tube measurements utilizing handheld Geo-SLAM and hyperspectral LiDAR precisely surveyed the internal 3D geometric structure of the cavity and the rock wall material composition. A critical final step involved the spatial co-registration and quantitative cross-validation of the GPR interpreted roof reflections against the independently acquired high-resolution 3D point cloud model. This integrated methodology effectively overcame the inherent limitations of single-sensor approaches, significantly enhancing the geometric resolution and reliability of the resultant lava tube model, and establishing a robust scientific data foundation for subsequent geological research and hazard mitigation efforts.

Conclusion

The integrated remote sensing method developed in this study provides a reference for designing exploration payloads for both the interior and exterior of lunar lava tubes. The obtained

integrated surface–subsurface 3D model can also be combined with lunar topographic data to construct a comprehensive structural model, providing a foundational framework for subsequent detection, analysis, simulation, and mission planning.

The exploration of lunar lava tubes holds profound importance. It not only facilitates in-depth investigations into the Moon's geological evolution but also unlocks the enigmas surrounding its volcanic activities and internal architecture, presenting an optimal locale for the establishment of future lunar bases. Regarding the comprehensive detection of lava tubes, this study introduced an integrated ground–air–space detection technology framework. Taking the lava tubes in Jingpo Lake as the research subject, the study utilized multiple types of drones in combination with Geo-SLAM technology to construct a high-precision 3D model that seamlessly integrated above-ground and underground features. During the harsh winter when liquid water was completely absent (enhancing GPR signal penetration), a multi-frequency GPR was deployed to accurately map the subsurface structure of the lava tubes and surrounding rock formations. Inside the tubes, a hyperspectral LiDAR system was used to simultaneously collect topographical data and material composition information in the dark environment. Hyperspectral LiDAR can be used in the dark environment of the moon. At the elemental level, it primarily detects Si, Al, Fe, Mg, Ca, Ti, K, Th, U, and water-related H and O. At the molecular level, it can identify volatiles such as H_2O , OH^- , CO_2 , CH_4 , and NH_3 . At the mineral level, it can often detect pyroxene, olivine, plagioclase, ilmenite, and volcanic glass. Stable water ice and hydroxyl groups may exist in permanently shadowed areas, reflecting the capture and preservation of volatiles in extreme temperature environments [58]. The combined application of multiple detection methods not only reveals the chemical and mineralogical composition of the lunar soil but also provides key evidence for future lunar resource development and habitat assessment. Moreover, the SAR mounted on an orbiter scanned the skylights of the lava tubes, validating the unique advantages of SAR data in interpreting these geological features.

The verification results from the multi-sensor comprehensive detection of lava tubes in this study will serve as a foundation for future comparative research on the terrain, orientation, cave distribution, and internal environment of lunar lava tubes. Additionally, they offer significant references for designing comprehensive detection schemes for lunar lava tubes.

Hyperspectral LiDAR, as applied in the Jingpo Lake study, provides insights into the formation mechanism and geological characteristics of lava tubes by analyzing the material composition of their walls. However, current hyperspectral LiDAR systems are typically large and heavy, making them impractical for deployment on lunar missions. Therefore, future development must focus on miniaturizing hyperspectral LiDAR devices so that they can be integrated into lunar rovers or handheld tools for astronauts, enabling flexible in situ exploration. Such a portable system would significantly improve the efficiency of material analysis within lunar lava tubes, providing critical data for in situ resource utilization assessment and potential base site selection.

Similarly, multi-frequency GPR, as demonstrated in the Jingpo Lake study, provided detailed morphological information on deep lava tubes by probing subsurface structures. However, its data processing, particularly for multi-frequency datasets, is computationally intensive, posing a challenge for the limited computing capabilities available on lunar missions.

Future development should therefore prioritize efficient, real-time processing algorithms that allow for the rapid analysis and interpretation of GPR data directly on the onboard computers of lunar rovers or probes.

These technological advancements would significantly enhance lunar lava tube exploration capabilities. Portable hyperspectral LiDAR would provide high-resolution data on material composition, helping to identify potential resources (such as water ice and other valuable minerals). Optimized real-time GPR processing algorithms would enable autonomous probes to rapidly generate 3D subsurface models, mitigating mission risks, like structural instability or navigation hazards. As active sensors, both technologies are inherently suited for exploration in the low-light conditions of lava tubes, ensuring reliable data exploration. These technologies are applicable not only to the Moon but also to the exploration of lava tubes on other planets, such as Mars, thereby advancing human deep space exploration.

The integrated air-ground-subsurface detection scheme for lava tubes, along with its validated interpretation results, will play a critical role in informing the design of future lunar lava tube exploration strategies. This approach provides a robust data foundation for comprehensive studies, including the acquisition of integrated internal and external lava tube structures, the interpretation of skylight morphology, and the analysis of rock layer structures. Concurrently, the findings from this comprehensive lava tube detection study offer valuable support for the development of specialized payloads for lunar and Martian orbiter-based lava tube detection, as well as payloads designed for morphological and compositional analysis under low-light conditions within lava tubes. These results also provide a significant reference and guidance for planning scientific exploration tasks on the lunar surface in China's future crewed lunar missions.

Acknowledgments

Funding: This research was funded by the Major Program of the National Natural Science Foundation of China, Grant No. 62495033; and the National Natural Science Foundation of China, Grant No. 42371453.

Author contributions: T.H. contributed to the conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing (original draft), writing (review and editing), and visualization. H.Y. participated in data processing, writing, preliminary translation, and integrated modeling work. Z.K. contributed to the conceptualization, methodology, resources, writing (review & editing), supervision, project administration, and funding acquisition. X.L. contributed to the validation, investigation, resources, data curation, and writing (review and editing). C.W. conducted research on regional drone aerial photography and data collection. H.W. performed high-spectrum laser radar data processing and analysis. H.Z. performed high-spectrum laser radar data processing and analysis. X.W. performed high-spectrum laser radar data processing and analysis. Y.Z. conducted internal structural analysis of lava tubes. W.F. contributed to the conceptualization, methodology, and writing (review & editing). M.M. contributed to the methodology and writing (review and editing). S.Y. was responsible for ground radar instrument design and software construction. R.P. performed geological analysis. H.L.Y. performed SAR data processing. L.C. contributed to software, validation, and formal analysis.

Y.L. contributed to validation, investigation, and data curation. S.C. contributed to software, validation, and formal analysis. Y.Q. contributed to validation, investigation, and data curation. Q.Y. participated in lava tubes data acquisition and analysis. J.C. contributed to validation, investigation, and data curation.

Competing interests: The authors declare that they have no competing interests.

Data Availability

The data that support the findings of this study are available from the following sources: Satellite Data: The Synthetic Aperture Radar (SAR) data used in this research are obtained from Hi-Sea-1 and are publicly available for download from the official website. Field Measurement Data: The terrestrial point cloud data, internal lava tube point cloud data, Ground Penetrating Radar (GPR) datasets, and hyperspectral data were collected through independent measurements by the authors. Restrictions: Due to the proprietary nature of the field measurements and ongoing research constraints, the point cloud, GPR, and hyperspectral data are not publicly available at this time.

References

- Kang Z, Xu X, Xu Y, Yao S, Lei Z, Zhang B, Cai J, Xiao M, Hu T. Shallow subsurface structure of the moon: Key questions for future exploration. *Space Sci Technol.* 2024;4:0173.
- Xiao L, Huang J, Zhao JW, Zhao JN. Significance and preliminary concepts of lunar lava tube cave exploration. *Sci Sin Phys Mech Astron.* 2018;48(11):87–100.
- Du W, Yang J. The moon's early magmatic activities: From the perspective of lunar alkali-suite and Mg-suite samples. *Space Sci Technol.* 2024;4:0118.
- Ikeya K, Haruyama J, Miyake W, Tanaka M, Toyokawa K, Nozawa H. Simulation of light environments inside lunar holes and their associated subsurface caverns. *Earth Planets Space.* 2024;76:142.
- Qiu X, Ding C. Radar observation of the lava tubes on the moon and Mars. *Remote Sens.* 2023;15(11):2850.
- Duan Z, Xing GF, Zhu XK, et al. Study of the quaternary lava tunnel group in the Qiongbai region: Morphology and its comparative planetary significance. *Acta Petrol Sin.* 2023;39(08):2347–2364.
- Brož P, Poppe S, Sofge K, Stárek M, Gomes R, Boháček P, Kereszturi A, Łosiak A, Sauro F, Hauber E, et al. LUNAR geology orbiter concept to study lunar irregular Mare patches and lava tubes from orbit. *Acta Astronaut.* 2025;234:154–174.
- Hurwitz DM, Head JW, Hiesinger H. Lunar sinuous rilles: Distribution, characteristics, and implications for their origin. *Planet Space Sci.* 2013;79–80:1–38.
- Dong YL, Mu HX, Zhang LB, Pan ZC, Cheng XY. Investigation and study of typical lava tunnels in the Haikou Shishan Volcanic Group Geopark. In: *Proceedings of the 34th Annual Conference of the Tourism Geoscience and Geopark Research Branch of the Geological Society of China & Seminar on Longyan Geopark Construction and Tourism Development, Longyan, Fujian, China.* Beijing: Geological Society of China; 2019.
- Zhang P, Dai W, Niu R, Zhang G, Liu G, Liu X, Bo Z, Wang Z, Zheng H, Liu C, et al. Overview of the lunar in situ resource utilization techniques for future lunar missions. *Space Sci Technol.* 2023;3:0037.

11. Kereszturi A, Ori GG, Marques NKD, Grandjean P, Allemand P, Steinmann V, Alberti G, Mastrogiuseppe M, Gurgurewicz J, Kofman W, et al. FlyRadar—Targets for future drone based GPR survey on Mars. *Acta Astronaut.* 2025;229:113–127.
12. Li YB, Weng AH, Xu WL, et al. Magnetotelluric sounding reveals the trans-layer magma transport system of Jingpo Lake volcano. In: *Proceedings of the 14th China International Geoelectromagnetic Workshop (CIGEW)*. 2021. p. 27–28.
13. Guo KX, Liu YS, Nie BF, et al. Volcanic rock characteristics and magma evolution of the Xingshan volcanic group in the Jingpo Lake area. *Geol Rev.* 2024;70(01):137–154.
14. Carrer L, Gerekos C, Bruzzzone L. A multi-frequency radar sounder for lava tubes detection on the moon design, performance assessment and simulations. *Planet Space Sci.* 2018;152:1–17.
15. Pu CL, Guo L, Zhan T. Application of ground-penetrating radar in the investigation of lava tunnels in Jingpo Lake world Geopark. *Chin J Eng Geophys.* 2015;12(01):117–121.
16. Esmaeili S, Kruse S, Jazayeri S, Whelley P, Bell E, Richardson J, Garry WB, Young K. Resolution of lava tubes with ground penetrating radar the TubeX project. *J Geophys Res Planets.* 2020;125(5):Article e2019JE006138.
17. She XY, Wang J, Huang J, et al. Current status of lava tube exploration research in solar system bodies. *J Deep Space Explor.* 2024;11(04):313–327.
18. Xu Y, Chen R, Huang HJ, Meng X, Chen Y, Zhang L, Zhang J, Xiao L. Analog study of ground-penetrating radar technology for detecting lava tubes in celestial bodies. *J Deep Space Explor.* 2024;11(04):365–373.
19. Zhao X, Liang FX, Li JP, Yiping C, Bisheng Y. 3D exploration of extraterrestrial lava tubes and surface verification based on lightweight mobile measurement systems. *J Deep Space Explor.* 2024;11(04):385–393.
20. Yang Q, Kang ZZ, Hu T, Ye C, Liu D. Research on real-scene 3D modeling technology for lava tubes oriented toward future lunar scientific exploration. *J Deep Space Explor.* 2024;11(04):355–364.
21. Du YM, Chen YP, Zhang S, Zhang L, Zhang TP, Wu YZ, Chen S, Zhao JL. 3D exploration and morphological study of lava tubes in extraterrestrial bodies. *J Deep Space Explor.* 2024;11(04):346–354.
22. Ke Z, Meng Y, Yan XY, Li WK, Feng W, Zhong M. GRAIL gravity gradients evidence for a potential lava tube at Marius Hills on the moon. *Icarus.* 2024;408:115814.
23. Mai XZ, Zhang WL. Fine modeling method based on fusion of multi-resolution oblique imagery and GeoSLAM laser point cloud. *J Surv Mapp Spat Geogr Inf.* 2023;46(02):180–182.
24. Luo XD, Lai MZ, Lu Y, et al. Application of close-range photogrammetry in 3D modeling of material cultural heritage. *Bull Surv Mapp.* 2023;12:132–135.
25. Yang H, Zhang WQ. Application practice of real-scene 3D reconstruction and BIM technology in ecological restoration of open-pit mines. *Energy Environ Prot.* 2023;45(08):51–55.
26. Xie T, Wang YR, Lü SN, et al. Haisi-1 satellite and its application prospects. *Satell Appl.* 2021;10:40–44.
27. Sun JF, Ai Q, Tang H, et al. Adaptive window lee filtering algorithm based on improved edge direction. *Sci Technol Eng.* 2018;18(08):97–101.
28. Worasit S, McGee RJ, Sankaran S. Optimization of UAV-based imaging and image processing orthomosaic and point cloud approaches for estimating biomass in a forage crop. *Remote Sens.* 2022;14(10):Article 2396.
29. Chun X, Zhengxu L, Haiqin D, Lu X, Ma T, Shan C. Plane accuracy of aerophotogrammetry without image control points of DJI PHANTOM 4 RTK UAV. *IOP Conf Series Earth Environ Sci.* 2021;734(1): <https://doi.org/10.1088/1755-1315/734/1/012003>
30. Guo YB. Internal processing workflow for 3D modeling with DJI Phantom 4 RTK. *Heilongjiang Transportation Sci Technol.* 2020;43(06):190–192.
31. Salucci M, Poli L, Massa A. Advanced multi-frequency GPR data processing for non-linear deterministic imaging. *Signal Process.* 2017;132:306–318.
32. Sun CJ, Yu W, Wang W, Geng SB, Liu J, Gao XD, Guo JW, Zhang YH. Research on real-time imaging methods for multi-frequency array ground-penetrating radar data. *Aerosp Meas Technol.* 2024;44(03):48–54.
33. Lu GZ. Study on multi-frequency ground-penetrating radar data fusion methods [dissertation]. Zhejiang University; 2021.
34. Zhang W, Qi J, Wan P, Wang H, Xie D, Wang X, Yan G. An easy-to-use airborne LiDAR data filtering method based on cloth simulation. *Remote Sens.* 2016;8(6):501.
35. Cai S, Yu S, Hui Z, Tang Z. ICSF: An improved cloth simulation filtering algorithm for airborne LiDAR data based on morphological operations. *Forests.* 2023;14(8): Article 1520.
36. Zhu YB. 3D visualization and digital image fusion for detailed target reconstruction using GeoSLAM laser point cloud. *Laser J.* 2024;45(07):233–239.
37. Li X, Shao H, Lu Y, Chen Y, Sun L, Dai H, Hong T, Zhang X, Zhang H. An enhance ranging algorithm based on multi-waveform classification with hyperspectral LiDAR. *Measurement.* 2025;253(Part A):117489.
38. Wang SW, Shu QT, Ma X, Xiao J, Zhou W. Research progress on data fusion of LiDAR and hyperspectral imaging technologies. *Remote Sens Technol Appl.* 2024;39(01):11–23.
39. Man Z, Haolin L, Guanyong W. High-precision spotlight SAR imaging with joint modified fast factorized backprojection and autofocus. *Int J Antennas Propag.* 2020; <https://doi.org/10.1155/2020/2495050>
40. Yan W, Zegang D, Minkun L, Zeng T, Long T. Fast overlapped subaperture algorithm for high-squint spotlight SAR imaging. *Int J Remote Sens.* 2020;41(16):6051–6070.
41. Xue M. Study on SAR image denoising algorithm based on edge reconstruction and similarity metrics [dissertation]. Xidian University; 2023.
42. Fang J, Xu Z, Zhang B, Hong W, Wu Y. Compressed sensing SAR imaging with multilook processing. *CoRR.* 2013.
43. Mustafa ZA, Ibraheem BA, GissmAllah KM, Elmahdi R, Omara AI. Noise reduction for magnetic resonance imaging by using edge detection and hybrid mean lee filter techniques. *J Clin Eng.* 2023;48(1):21–28.
44. Mallet C, Bretar F. Full-waveform topographic Lidar: State-of-the-art. *ISPRS J Photogramm Remote Sens.* 2009;64(1):1–16.
45. Wu ZY, Qian RY, Ling JY. Study on 3D ground-penetrating radar data processing methods. In: *Proceedings of the 2023 China Geoscience Union Academic Conference, Zhuhai, Guangdong, China*. Beijing: Chinese Geophysical Society; 2023.
46. Yang TY. Research and application of ground-penetrating radar signal processing [dissertation]. University of Electronic Science and Technology of China; 2014.

47. Baso M, Efri S. The development of ground penetrating radar (GPR) data processing. *Int J Mach Learn Comput*. 2019;9(6):768–773.
48. Surajit K. Gain augmentation of a triple notched ultra-wideband antenna using compact uniplanar frequency selective surface for ground penetrating radar. *IETE J Res*. 2023;69(2):813–824.
49. Ali J, Abdullah N, Yahya R, Ullah I, Das B, Jusoh M. Ultra-wideband antenna development to enhance gain for surface penetrating radar. *Wirel Pers Commun*. 2020;115(3):1–18.
50. Zheng JX. Study on inversion algorithms for layered medium parameters in ground-penetrating radar [dissertation]. Guilin University of Electronic Technology; 2023.
51. Miller R. Fundamentals of radar signal processing (Richards, M.A.; 2005) book review. *IEEE Signal Process Mag*. 2009;26(3):100–101.
52. Li YJ, Niu HP, Yang GX, et al. Types of basic sequence interfaces and their application in lithostratigraphic unit division. *Geol Bull China*. 2016;35(08):1304–1313.
53. Wang SL, Pan GS, Meng QS, Li HX, Qi XP, Yang HQ, Liu W, Wang HB. Ground-penetrating radar data processing based on artificial intelligence and its application in detecting underground space hazards. *J Guilin Univ Technol*. 2025;45(01):43–50.
54. Zhang Q, Cui Z, Wang T, Li Z, Xia Y. Calibration-enhanced multi-awareness network for joint classification of hyperspectral and LiDAR data. *Electronics*. 2024;14(1):102.
55. Wang R, Ye X, Huang Y, Ju M, Xiang W. GASSF-net: Geometric algebra based spectral-spatial hierarchical fusion network for hyperspectral and LiDAR image classification. *Remote Sens*. 2024;16(20):3825.
56. Hao WSB. Remote sensing digital image analysis: An introduction. *J Japan Soc Photogram Remote Sens*. 2013;52(2):94–95.
57. Liu BY, Wang YC, Ma YK, Li F, Pan H, Ma Y, Liu Y, Zhang H, Han F, He T, et al. Development and prospects of hyperspectral LiDAR. *Inf Countermeas Technol*. 2025;4(02):1–17.
58. Kereszturi A. Polar ice on the moon. In: Cudnik B, editor. *Encyclopedia of lunar science*. Cham: Springer; 2023. p. 971–980.
59. Zhan T, Zhang HY, Zhang J, et al. Distribution characteristics and genesis of lava tunnels in Jingpo Lake world Geopark. *J Nat Sci Harbin Normal Univ*. 2017;33(05):87–93.

Integrated Ground–Air–Space Exploration Technology of Jingpo Lake Lava Tubes

Teng Hu, Haiting Yang, Zhizhong Kang, Xiaojun Liu, Changjun Wu, Haohao Wu, Haifeng Zhao, Xue Wan, Yuyan Zhao, Wenzhe Fa, Matteo Massironi, Shengbo Ye, Riccardo Pozzobon, Honglei Yang, Linsheng Chen, Yan Li, Sai Cheng, Yuanzhi Qu, Qiao Yang, and Jinhao Cai

Citation: Hu T, Yang H, Kang Z, Liu X, Wu C, Wu H, Zhao H, Wan X, Zhao Y, Fa W, et al. Integrated Ground–Air–Space Exploration Technology of Jingpo Lake Lava Tubes. *Space Sci Technol*. 2026;6:0438. DOI: 10.34133/space.0438

Lava tubes play an important role in base construction and understanding planetary geological development on extraterrestrial bodies. However, our understanding of lava tube morphology on Earth as a reference for extraterrestrial bodies remains limited. Existing research mainly focuses on their formation mechanisms and uses a single approach to study their morphology. To fill this gap, we conducted a multi-platform investigation of a lava tube near Jingpo Lake, Heilongjiang Province, China, employing space-, air-, and ground-based techniques. The method presented in this paper can assist in the comprehensive exploration of lunar lava tubes in the future. First, data covering this large lava tube area were collected using synthetic aperture radar (SAR), due to its all-weather capability, from which distribution information on lava tube skylights was retrieved. Furthermore, close-range point cloud data of the lava tube skylight areas were collected from drones equipped with the DJI Zenmuse L1 LiDAR sensor, which allows for high-resolution data acquisition and the creation of detailed models, providing local high-precision point clouds. Additionally, Light Detection and Ranging (LiDAR) was used for detailed point cloud collection inside the lava tubes, and through the registration of high-precision point clouds of the skylights both inside and outside the tube, comprehensive point cloud data of the entire lava tube were obtained. Hyperspectral LiDAR was also used to collect data of the tube walls under dark conditions, addressing the issue of consistency matching between hyperspectral imaging and laser far-field spots, enabling integrated spatial–spectral data acquisition. Finally, ground-penetrating radar was also employed for subsurface structural analysis, benefiting from its high penetration capabilities to acquire more detailed information on the underground morphology of the lava tubes. Our experiments demonstrate that this multi-sensor approach provides comprehensive information on terrain, lava tube orientation, cave distribution, and the internal environment of the lava tube system.

Image

View the article online

<https://spj.science.org/doi/10.34133/space.0438>

Use of this article is subject to the [Terms of service](#)

Space: Science & Technology (ISSN 2692-7659) is published by the American Association for the Advancement of Science. 1200 New York Avenue NW, Washington, DC 20005.

Copyright © 2026 Teng Hu et al.

Exclusive licensee Beijing Institute of Technology Press. No claim to original U.S. Government Works. Distributed under a [Creative Commons Attribution License \(CC BY 4.0\)](#).