

Article

LiDAR-Assisted Survey Locates Unregistered Rock Shelters in the Blue Mountains, Australia

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Highlights

Main findings

- GIS-based models combined with an archaeological survey successfully locate rock shelters in UAV-based and aircraft-based LiDAR datasets.
- Coordinates of detections are more accurate than ones included for previously mapped rock shelters in online databases.

Implications of main findings

- Provides an efficient methodology for correcting legacy data and locating unregistered rock shelters within and beyond Australia that carries benefits for local communities, archaeology, and cultural heritage management.

Abstract

Rock shelters are important cultural and archaeological sites in Australia, often containing evidence of Aboriginal occupation and symbolic expression. While rock shelters have been investigated across Australia, locating them in rugged environments through pedestrian surveys remains challenging. This research contributes a methodology which integrates remote sensing, GIS analyses, and archaeological survey to locate rock shelters in the Blue Mountains. We produced models in ArcGIS Pro that analyse high-resolution, UAV-based LiDAR datasets and publicly available, low-resolution, aircraft-based LiDAR datasets from the New South Wales government. Our models yield locations of potential rock shelters, which can be visually evaluated in 3D LiDAR point clouds and ground-truthed through archaeological survey. Ground-truthing confirmed the successful detection of six known rock shelters on UAV and NSW LiDAR datasets, producing more accurate coordinates than the ones listed in online databases. Significantly, we identified three previously unregistered rock shelters that preserve rock art and lithics. These promising results indicate capacity to improve the spatial accuracy of legacy site records and locate unregistered archaeological rock shelters within, and potentially beyond, Australia. Our methodology promotes targeted and efficient survey of rock shelters that can produce regional datasets benefitting local communities, archaeology, and cultural heritage management.

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Keywords: remote sensing; LiDAR; GIS; archaeology; Australia; drones; rock shelters; rock art; lithics; archaeological survey

1. Introduction

Rock shelters constitute globally significant contexts for understanding human occupation across diverse environments and timescales. They are visible geomorphic features associated with bedrock weathering processes and surface sediments [1–3]. They are typically lit by direct or indirect sunlight and can be accessed from the surrounding landscape, offering protection for people and animals [1–3]. For this reason, they provide focal points for investigating how people lived in expansive landscapes in the past [2]. Investigations of rock shelters have uncovered crucial cultural and archaeological evidence ranging from artwork and lithics to faunal and floral remains, which have played key roles in the construction of regional chronologies, the reconstruction of paleoenvironments, and the study of cultural change [1,2]. Such studies have transformed understandings of human evolution in Africa and Europe [4,5] as well as early settlement and high-elevation adaptation in the New World and Australia [6–8]. Conducting further archaeological research in rock shelters is crucial for learning more about the human past, but locating them in rugged environments through pedestrian surveys remains challenging.

Remote sensing offers a powerful, non-destructive way to address this issue, enabling archaeologists to identify and map geomorphic features and archaeological sites and landscapes in difficult-to-access environments [9]. Light detection and ranging (LiDAR) is an active remote-sensing technique that has substantially changed how archaeological landscapes are documented and investigated and has contributed to major advances in archaeological site detection [10,11]. LiDAR systems mounted on crewed aircraft or uncrewed aerial vehicles (UAVs) emit short laser pulses toward the ground and measure the time required for the reflected energy to return to the sensor. These range measurements are combined with the scanning geometry and the position and orientation of the platform, typically determined using integrated Global Navigation Satellite System (GNSS) and inertial measurement unit (IMU) observations, to calculate georeferenced three-dimensional coordinates for individual laser returns [11,12]. The resulting measurements form a 3D point cloud representing the sampled surfaces and objects within the landscape. Point-cloud density and spatial distribution are influenced by factors including pulse repetition frequency, scan angle, flight altitude and speed, flight-line overlap, and sensor configuration [11].

A major advantage of airborne LiDAR for archaeological applications is its capacity to record multiple returns from individual laser pulses. In vegetated environments, some pulses penetrate gaps in the canopy and produce returns from both vegetation and the underlying ground surface. Classification of these returns allows ground points to be separated from vegetation and other objects and used to generate high-resolution terrain models [10,12,13]. Unlike passive optical imagery, and complementary to photogrammetric surface reconstruction, this capacity to sample terrain beneath partial vegetation cover makes LiDAR particularly effective for identifying subtle topographic and archaeological features in forested landscapes [10,13]. Consequently, LiDAR has enabled the identification and mapping of archaeological features previously obscured by vegetation, contributing to significant (re)discoveries and reinterpretations of archaeological landscapes in the Americas [14–20], Europe [21,22], and Asia [23–25]. Archaeological applications of LiDAR in Australia, however, have been limited, tending to focus on specific sites and areas as opposed to broader landscapes [13,26,27].

This paper combines remote sensing, GIS analyses, and archaeological survey to produce and test a transferrable and scalable methodology for geomorphological mapping and

the identification of potential rock shelters in the Blue Mountains, Australia. Aboriginal groups such as the Dharug, Wiradjuri, Gomeroi, Darkinjung, Tharawal, Wonnarua, and Gundungara peoples hold connections to the Greater Blue Mountains area. The named sites in this paper are in Dharug Country. The Blue Mountains are marked by steep sandstone cliffs, dense eucalyptus forests, and deeply incised valleys, making the terrain exceptionally challenging to survey on foot, yet they represent an important area for learning about Aboriginal symbolic expression and adaptation to mountain environments. Previous investigations have documented rock art sites across the region [28,29], long-distance movement of people through the mountains [30], and extended occupation of rock shelters [7].

Here, we report on a pilot study conducted in collaboration with the Dharug Custodian Aboriginal Corporation (DCAC) that develops a geomorphological mapping workflow for locating potential rock shelters within, and potentially beyond, the Blue Mountains. Potential rock shelters were then visited to verify if they represent occupiable rock shelters with surviving material culture, such as lithics or rock art. To evaluate the effectiveness of LiDAR-based detection methods, we tested publicly available low-resolution airborne LiDAR data from the New South Wales (NSW) government and high-resolution UAV LiDAR data collected during our own missions against pedestrian surveys. The 1057 km² study area (Figure 1) contains numerous known archaeological rock shelters, providing an ideal setting for testing this approach. Four focal areas (Mount Irvine Area 1 (MTI-A1), Mount Irvine Area 3 (MTI-A3), Djulpura Area 1 (DJ1), and Djulpura Area 2 (DJ2)) were selected in consultation with DCAC because they contain known shelters and represent potential movement corridors for Aboriginal groups, increasing the likelihood of identifying additional, unregistered sites with cultural evidence (Table 1). Please note, site coordinates and photographs of lithics and rock art are not included in the paper in accordance with the Dharug Custodian Aboriginal Corporation's requests.

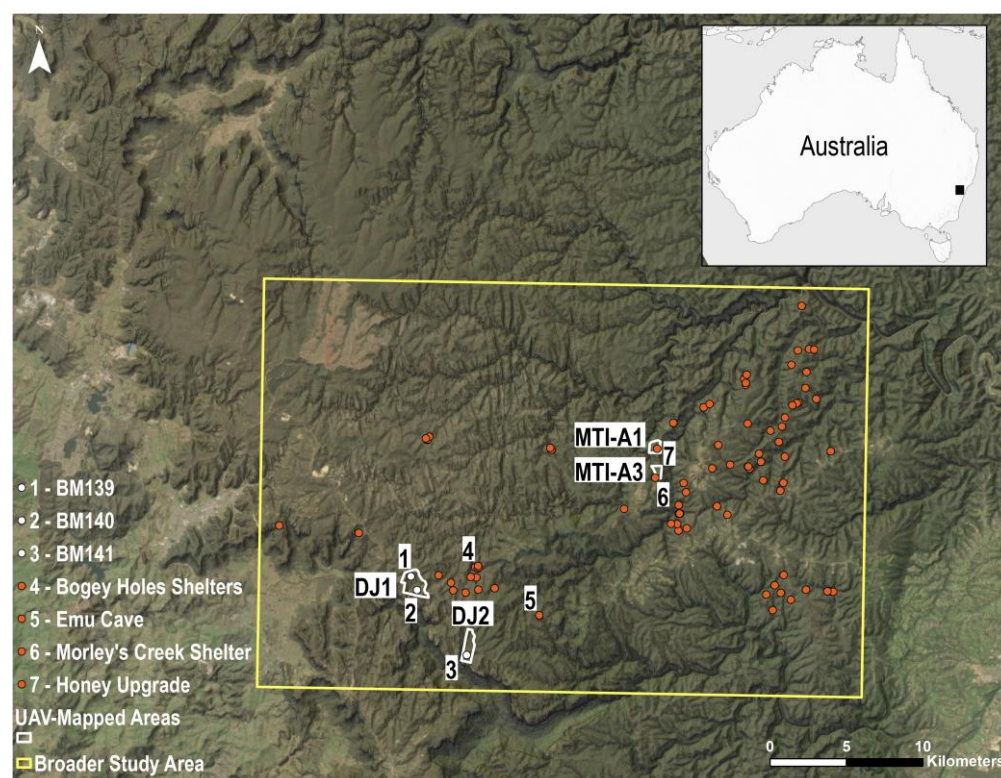


Figure 1. Map of the study area, showing locations of rock shelters and UAV-mapped areas. Rock shelters are represented by circles. Previously known rock shelters are shown as orange circles, and previously unregistered rock shelters are shown as white circles. Named rock shelters in the legend are discussed in the text. The Bogey Holes label represents three individual rock shelters. Basemap

imagery was obtained from Esri World Imagery. The Australia inset uses the NGS Black Line Base (National Geographic Society).

Table 1. Area (km²) and number of UAV and NSW LiDAR detections for each UAV-mapped zone.

Zone	Area (km ²)	Total NSW LiDAR Detections	Total UAV LiDAR Detections
MTI-A1	0.53	336	385
MTI-A3	0.37	288	397
DJ1	2.05	965	567
DJ2	1.21	1250	668

2. Materials and Methods

Our methodology for locating rock shelters combines pedestrian ground-truthing with both low- and high-resolution LiDAR analyses (Figure 2, Table 2). Low-resolution NSW LiDAR data from the study area was obtained from the ELVIS Elevation and Depth—Foundation Spatial Data (<https://elevation.fsdf.org.au/> (accessed on 1 September 2026)) cloud-based system. These data are within MGA1994 Zone 56 (EPSG: 28356) and are already classified, sourced from multi-generational airborne sensors at a point density of at least 0.5 points/m², with ± 0.30 m and ± 0.80 m vertical and horizontal accuracies respectively (Table 2). For the high-resolution UAV data, we conducted our own missions using a YellowScan Explorer V2 (version 2) (YellowScan, Saint-Clément-de-Rivière, France) sensor mounted on a DJI M350 UAV (DJI, Shenzhen, China). The UAV was flown over four zones in the study area (Figure 1, Table 1) at 75 m above ground level (AGL) and between 7 and 10 m/s. We employed crosshatch flight patterns with 50% side overlap and 50–70% front overlap to maximise point density and coverage. This enabled us to collect LiDAR data at a point density of at least 100 points/m² for the four study zones (Table 2). UAV GNSS/IMU and flight trajectories were corrected using the Qinertia OEM in YellowScan CloudStation Ultimate (version 2608). UAV LiDAR data are within MGA2020 Zone 56 (EPSG: 7856).

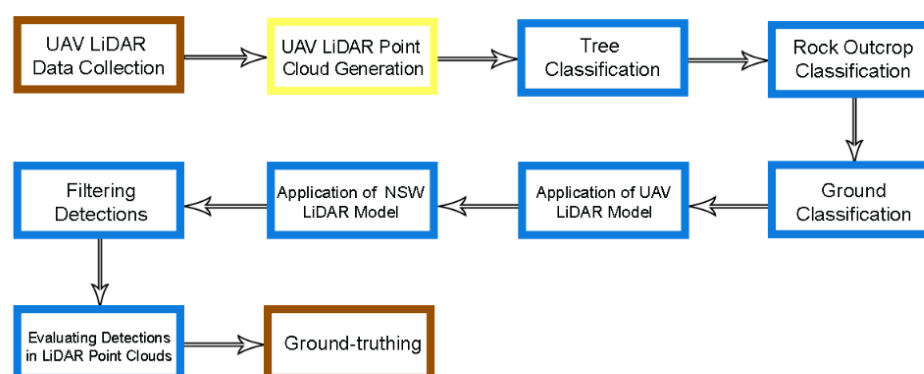


Figure 2. Flowchart of broader workflow for locating and verifying rock shelters, which involves fieldwork (brown boxes), analyses in YellowScan CloudStation Ultimate (yellow box), and analyses in ArcGIS Pro (blue boxes).

Table 2. Comparison of sensors and parameters used to acquire high-resolution UAV LiDAR and low-resolution airborne LiDAR datasets.

Sensor	Vehicle Type	Acquisition Height (m AGL)	Average Horizontal Accuracy	Average Vertical Accuracy	Total Return Point Density Range (pts/m ²)
YS Explorer V2	UAV	75	±0.05 m	±0.05 m	113–229
ALS50	Aeroplane	varies ca. 700–1700	±0.80 m	±0.30 m	1.0–1.50
ALS80	Aeroplane	varies ca. 700–1700	±0.80 m	±0.30 m	0.53–4.0

We processed UAV and NSW LiDAR datasets in YellowScan CloudStation Ultimate and ArcGIS Pro (version 3.6.2). UAV LiDAR point positions were post-processed in SBG Systems Qintertia (version 5.1.2457) using observations from a Leica GS16 base station (Leica Geosystems AG, Heerbrugg, Switzerland), achieving sub-10 cm horizontal and vertical accuracy. To ensure a consistent coordinate reference system for spatial comparison between the LiDAR datasets, the NSW LiDAR dataset was reprojected from MGA1994 Zone 56 to MGA2020 Zone 56 in ArcGIS Pro. Point clouds (i.e., LAS datasets) were then generated in YellowScan CloudStation Ultimate and exported to ArcGIS Pro for further processing and analysis. We employed the New Zealand Tree Point Cloud Classification Deep Learning Package (<https://www.arcgis.com/home/item.html?id=0e2e3d0d0ef843e690169cac2f5620f9#overview>) (accessed on 1 September 2026) [31] to classify trees as “high vegetation” and non-tree points as “unassigned” in UAV LiDAR datasets. This package, however, misclassifies some outcrops situated near trees, including those containing potential rock shelters and overhangs, as vegetation. To address this issue, we developed a model in ModelBuilder within ArcGIS Pro that generates an elevation raster and uses a slope threshold of greater than 55 degrees to identify and restore potential outcrop surfaces removed during tree classification (see Supplementary Material Section S1 for Python script exported from ArcGIS Pro version 3.6.2). We removed high vegetation points before classifying ground points in ArcGIS Pro using standard classification. High-noise points positioned 10 m or more above ground were removed. Resulting UAV LiDAR datasets therefore contain points classified as “unassigned,” “ground,” and “outcrops.” These processing steps were not necessary for the NSW LiDAR dataset because vegetation and ground points were already classified; only ground points were retained for analysis.

We developed models in ModelBuilder for identifying locations of accessible rock shelters and overhangs (Figures 3 and 4). These models are built around four variables: difference between the highest elevation and the lowest elevation in each cell (“vertical separation”), slope, height relative to the surrounding landscape (“relative height”), and spatial relationship to areas outside of shelters (“open area”) (Figures 3 and 4). The vertical separation and slope variables capture topographic and elevation-derived characteristics associated with rock shelters, while the relative height and open area variables are designed to exclude potentially inaccessible rock shelters and overhangs. While the UAV LiDAR and NSW LiDAR models share the same core steps (Figure 3), their parameters differ because the UAV LiDAR datasets have higher point densities (at least 100 points/m²) compared to the NSW LiDAR dataset (at least 0.5 points/m²) (Table 2). During the preparation of this manuscript, we used ChatGPT 5.6 Sol to assist with developing and refining the logic and workflow of the ArcGIS Pro models used to detect rock shelters. We determined the model parameters, reviewed and implemented all outputs, and take responsibility for the methodology. Python scripts detailing specific parameters for the UAV and NSW LiDAR models are in Supplementary Material Sections S2 and S3 respectively.

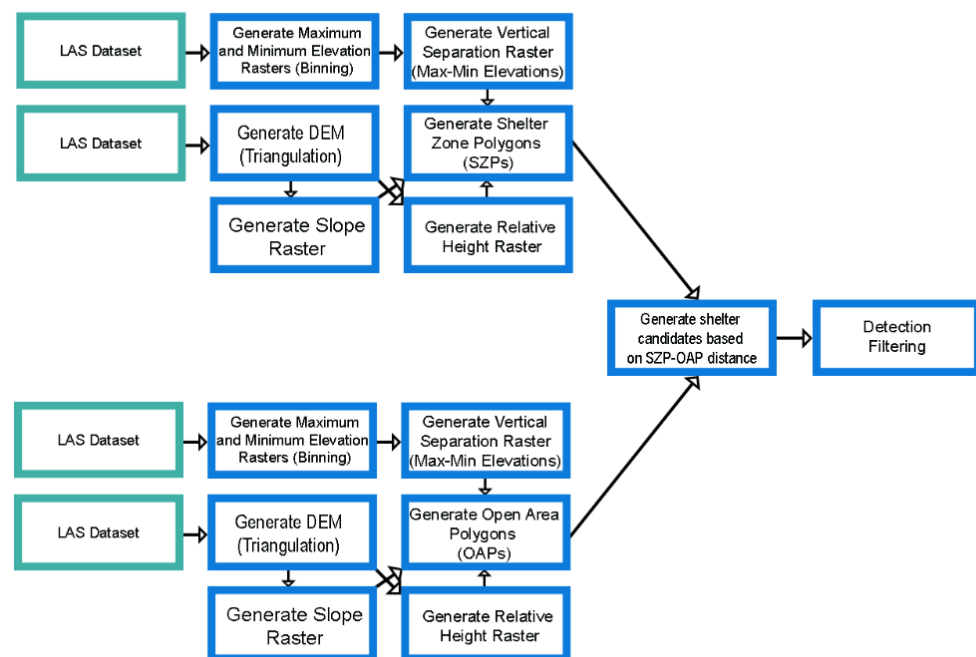


Figure 3. Flowchart of ArcGIS Pro models for locating accessible rock shelters and overhangs. Green boxes represent the LAS datasets, and blue boxes represent analyses carried out in ArcGIS Pro.

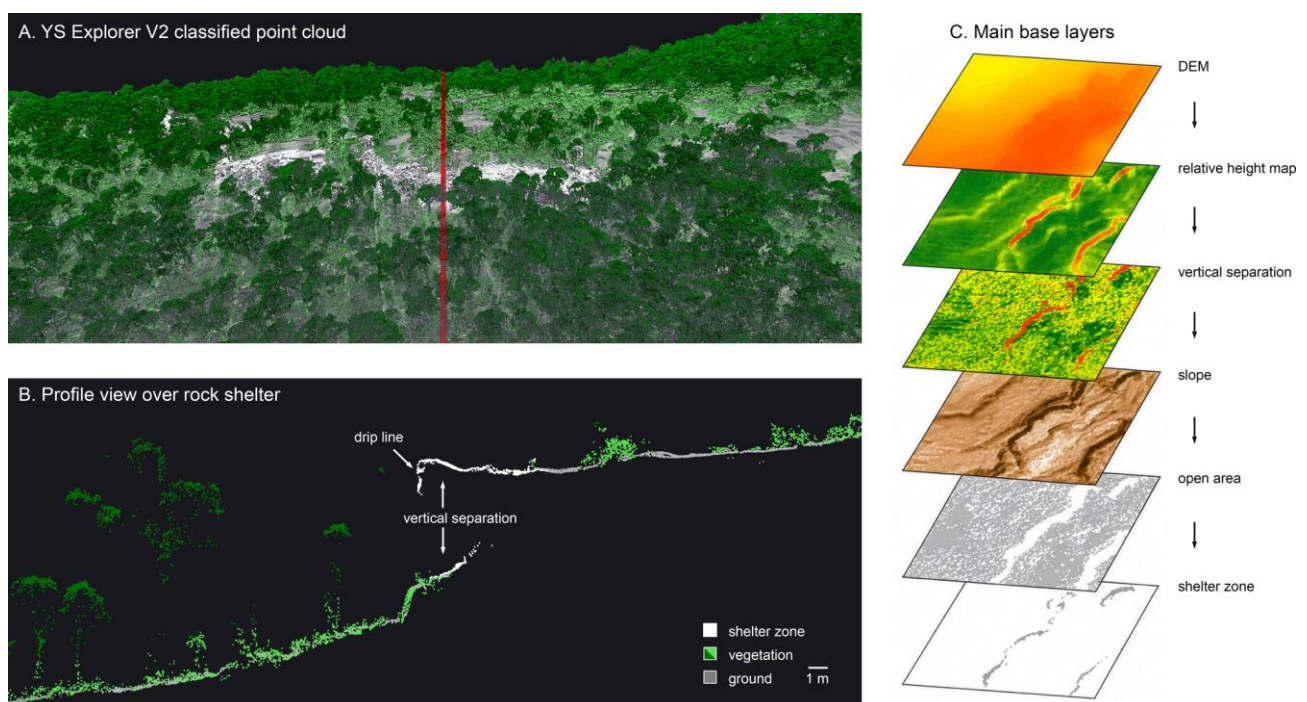


Figure 4. Schematic displaying a YellowScan Explorer V2 classified point cloud (A), profile view of the Honey Upgrade rock shelter (B), and the main base layers generated by the ArcGIS Pro models for locating rock shelters and overhangs (C). Point clouds (A,B) were visualised in YellowScan CloudStation Ultimate.

To detect rock shelters (Figure 3), we employed ArcGIS geoprocessing tools “LAS Dataset to Raster,” “Focal Statistics,” “Slope,” and “Raster Calculator” on both the low- and high-resolution LiDAR datasets. Our models derived digital elevation models (DEMs) from the respective LiDAR point clouds (LAS datasets), using a cell size of 1 m (UAV LiDAR

model) and a cell size of 3 m (NSW LiDAR model). A DEM generated using triangulation interpolation was used to generate a slope raster. Slope mask rasters were then generated using thresholds of greater than 55 degrees (UAV LiDAR model) and greater than 35 degrees (NSW LiDAR model). Focal statistics were subsequently applied to these slope masks using a maximum statistic within 5×5 -cell neighbourhoods, effectively expanding areas of steep slope in both models. Focal Statistics were applied to this same DEM to calculate the minimum elevation within 10×10 -cell neighbourhoods (UAV LiDAR model) and 7×7 -cell neighbourhoods (NSW LiDAR model). The resulting minimum-elevation raster was then subtracted from the DEM in Raster Calculator to generate a raster representing relative height above the surrounding terrain. Two DEMs representing minimum-elevation and maximum-elevation rasters were generated using binning interpolation and subtracted from each other in Raster Calculator to produce a vertical separation raster.

Potential rock shelters and overhangs (“shelter zones”) were identified using Raster Calculator as cells within the slope mask with vertical separation values ≥ 2 m (UAV and NSW LiDAR models) and relative height ≤ 3 m (UAV LiDAR model) or ≤ 7 m (NSW LiDAR model). Open areas were identified using Raster Calculator as cells that are not within shelter zones with vertical separation values < 2 m (UAV and NSW LiDAR models), slope values < 35 degrees (UAV and NSW LiDAR models), and relative height ≤ 3 m (UAV LiDAR model) or relative height ≤ 7 m (NSW LiDAR model). Such model parameters are consistent with measured horizontal depths and floor-to-ceiling heights of rock shelters (see Results). Detections of potential rock shelters and overhangs (“shelter candidates”) were defined as shelter zones within 1 m of open areas (UAV LiDAR model) or within 3 m of open areas (NSW LiDAR model). At this stage, we retained UAV LiDAR candidates located within the mapping zones and with areas between 10 m^2 and 250 m^2 . Candidates smaller than 10 m^2 were considered unlikely to represent sufficiently large rock shelters or overhangs, while those larger than 250 m^2 are more likely to represent extensive cliff faces or other landforms. This size filter was not applied to NSW LiDAR candidates.

Shelter candidates were then examined in 3D LiDAR point clouds to assess their shape and potential to preserve cultural information. In YellowScan CloudStation and ArcGIS Pro, we generated profile views (Figures 4 and S1–S4) of shelter candidates to determine if recessed or overhanging geomorphology was visible. This is useful for distinguishing between promising candidates worth visiting and formations that appear inconsistent with rock shelter geomorphology. Therefore, this important step takes advantage of LiDAR’s capacity to visualise landscapes in 3D and can potentially reduce the number of candidates requiring field verification. Following this visualisation, pedestrian surveys were deployed to ground-truth promising detections and determine whether they were (a) occupiable rock shelters and (b) whether any archaeological evidence was present. For confirmed archaeological rock shelters, we mapped the drip line [3] using a centimetre-accurate Leica GG04 GNSS receiver. We measured horizontal depths (distance between drip line and back wall) and floor-to-ceiling height with a Leica DISTO laser distance meter and recorded the compass heading of each horizontal depth measurement. Mapped drip lines as well as horizontal depths and their associated headings were then used to produce projected rock shelter area polygons in ArcGIS Pro. LiDAR detections were categorised as successful if they overlapped or were within 1 m of mapped drip lines or projected rock shelter areas.

3. Results

3.1. Model Outputs and Candidate Density

We applied the NSW LiDAR model across the broader Blue Mountains study area (1057 km^2), generating 751,655 detections. We compared these detections against 85 known rock shelters recorded within our study area in the Aboriginal Heritage

Information Management System (AHIMS) database that were previously mapped with GPS devices (Figure 1). The Aboriginal Heritage Information Management System is the NSW digital database for Aboriginal cultural heritage [32]. Distances between known rock shelters and the nearest LiDAR detection ranged from 0 to 38.32 m, which is consistent with the reported horizontal positional uncertainty of the legacy GPS records (0 to 50 m). Field verification is required to determine whether these nearby detections correspond to the known rock shelters and, ultimately, to evaluate the model's detection success.

We generated 2017 detections across UAV LiDAR datasets collected from Mount Irvine Area 1 (MTI-A1), Mount Irvine Area 3 (MTI-A3), Djulpura Area 1 (DJ1), and Djulpura Area 2 (DJ2) (Figures 1 and 5–8, Table 1). We ground-truthed 19 promising detections within the UAV-mapped areas and confirmed that all represented rock shelters, overhangs, or recessed cavities underneath rock formations. Horizontal depths and floor-to-ceiling heights of rock shelters with archaeological evidence were recorded (Table 3). Because these 19 candidates were deliberately selected following visual assessment, these observations cannot be used to estimate model accuracy.

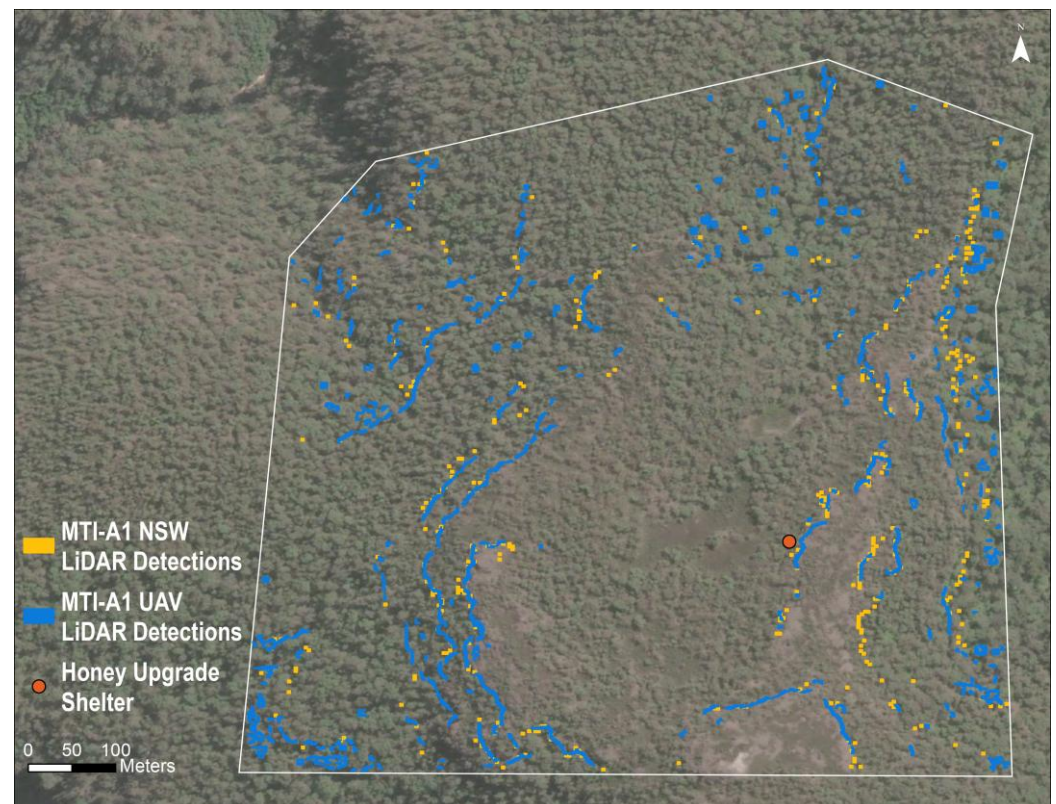


Figure 5. UAV and NSW LiDAR detections in MTI-A1. Basemap imagery was obtained from Esri World Imagery.

Table 3. Rock shelter attributes, including floor-to-ceiling heights, horizontal depths, and distances between mapped drip lines and shelter coordinates recorded in online databases (drip line-legacy coordinate distance).

Shelter	Range of Floor-to-Ceiling Heights (m)	Range of Horizontal Depths (m)	Drip Line—Legacy Coordinate Distance (m)
Honey Upgrade	1.49–3.91	1.19–5.89	8.97
Morley’s Creek	1.48–2.99	2.37–5.68	14.10
Emu Cave	1.21–4.50	1.11–5.35	23.66
45-4-1129	2.78–3.10	2.34–2.84	30.10
45-4-1141	1.30–4.45	0.99–3.37	15.68
45-4-1130	1.88–2.36	2.72–3.68	1.78
BM139	2.80–7.46	1.88–4.65	N/A
BM140	2.26–3.75	1.29–4.10	N/A
BM141	3.03–5.34	0.8–3.3	N/A

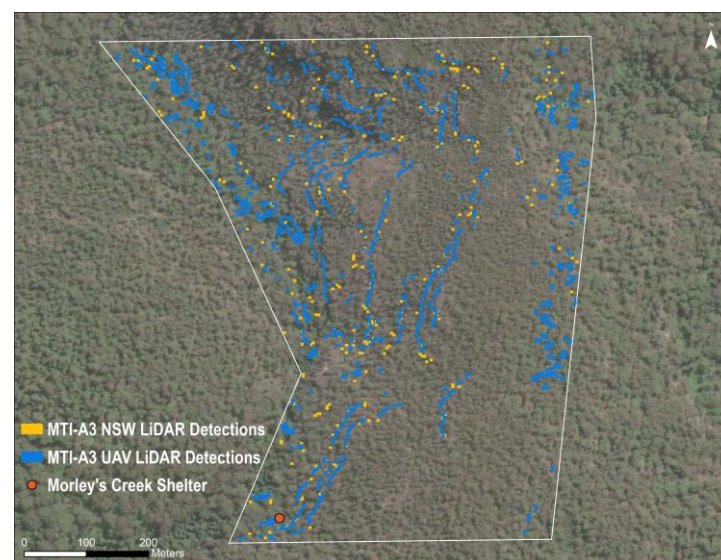


Figure 6. UAV and NSW LiDAR detections in MTI-A3. Basemap imagery was obtained from Esri World Imagery.

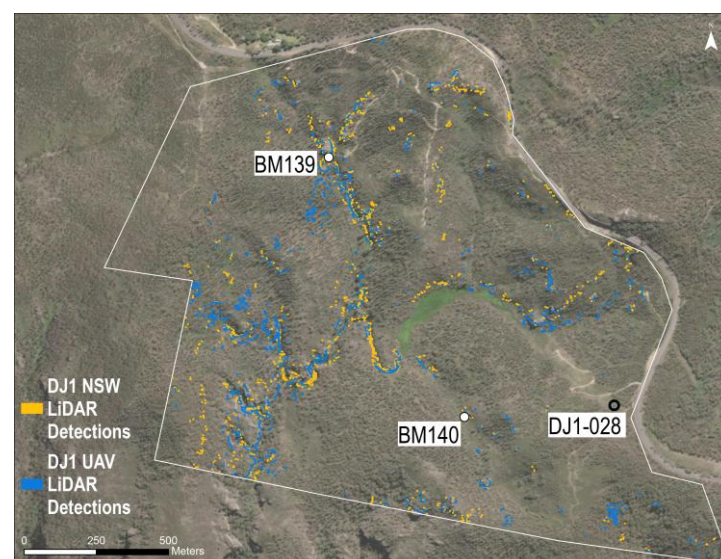


Figure 7. UAV and NSW LiDAR detections in DJ1. Basemap imagery was obtained from Esri World Imagery.

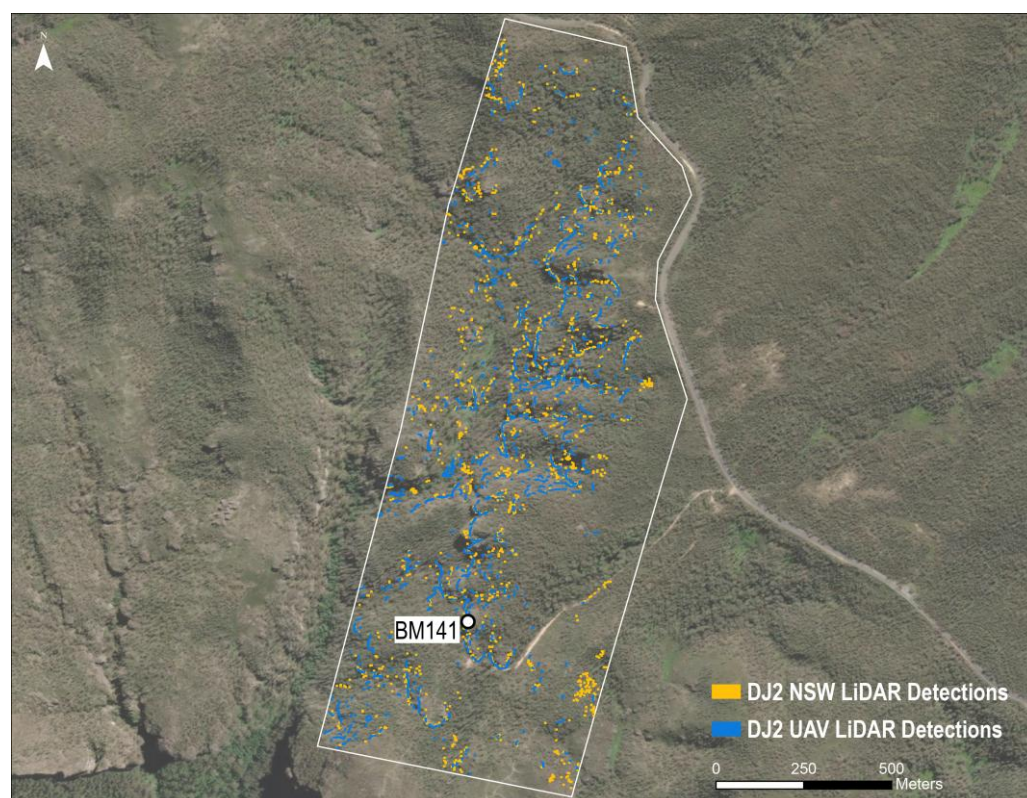


Figure 8. UAV and NSW LiDAR detections in DJ2. Basemap imagery was obtained from Esri World Imagery.

3.2. Field Verification of Previously Recorded Shelters

UAV and NSW LiDAR detections overlap, or are within 1 m of, the drip lines of the Honey Upgrade and Morley's Creek shelters in MTI-A1 and MTI-A3 respectively (Figures 9 and 10). Honey Upgrade (AHIMS ID#45-1-3009) is a relatively small, low, and west-facing rock shelter, with two panels of red pigment motifs and several grinding grooves across three distinct work areas [32]. The massive quartzose sandstone fabric of the Honey Upgrade shelter is consistent with the Narrabeen Group sandstones, specifically the Burra-Moko Head Sandstone member, which is the dominant cliff-forming lithology within the Blue Mountains, and the overlying Banks Wall sandstone [33]. A thick red-brown band is apparent in the Honey Upgrade Shelter fabric (Figure 9). This is provisionally interpreted as a claystone horizon, most likely representing the Wentworth Falls Claystone Member [34,35], which suggests that the Banks Wall Sandstone is the dominant unit at this shelter. The weathering of the claystone (as the less competent unit) may also be at least partially responsible for the formation of the shelter overhang.

Morley's Creek Shelter (AHIMS ID#45-1-2912) (Figure 10), located in the vicinity of Mount Irvine, contains rock art and artefacts [32]. At least 35 lithics have been documented at the site. This shelter is most likely comprising Banks Wall Sandstone, although, based on current observations, the Burra-Moko Head Sandstone member cannot be excluded from consideration. Morley's Creek Shelter has wet pigment art and charcoal drawings relating to the Burbung Ceremony of southeastern Australia. This site is very important to the Dharug because it was a starting point for this ceremony, which took place at Teselate Hill in the Mount Irvine precinct.

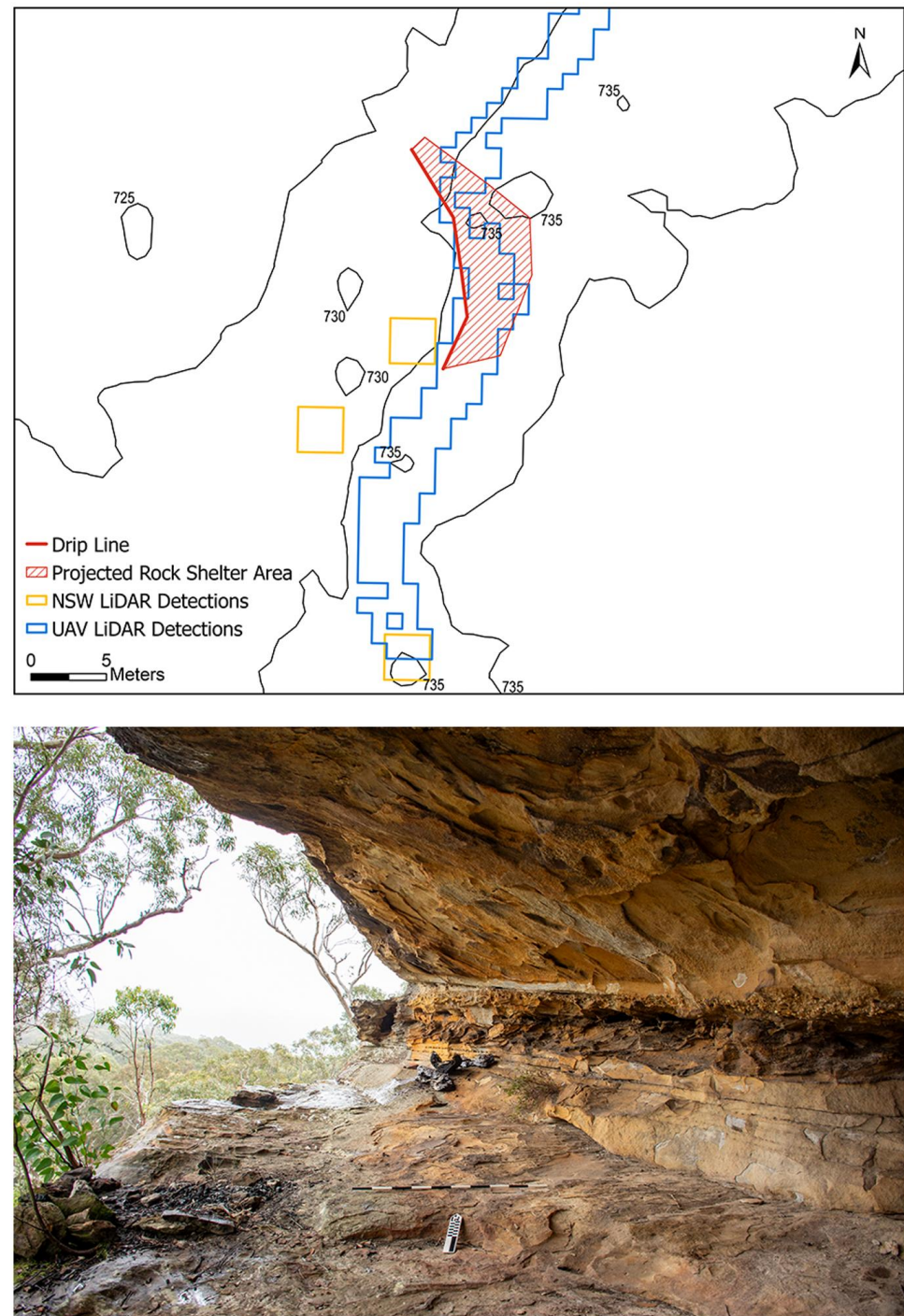


Figure 9. Honey Upgrade rock shelter in MTI-A1: UAV and NSW LiDAR detections overlapping or within 1 m of the drip line (**top**) and photo of interior (**bottom**).

NSW LiDAR detections also overlap drip lines of rock shelters located outside of UAV-mapped areas, including Emu Cave (Figure 11) and multiple sites in the Bogey Holes area (Figure 12). Emu Cave (AHIMS ID#45-4-0018, also referred to as Shearwood's Cave and Caves Hotel), which is at least 2000 years old [36], is the only site within the Blue Mountains that has a large array of engraved animal tracks, mostly bird [36]. There are at least 172 vertical engravings. Regarding geology, the massive quartzose sandstone fabric of the shelter is broadly consistent with several Narrabeen Group units; however, considering the location and elevation of the cave, the Banks Wall Sandstone is deemed more likely than the Burra-Moko Sandstone [37].

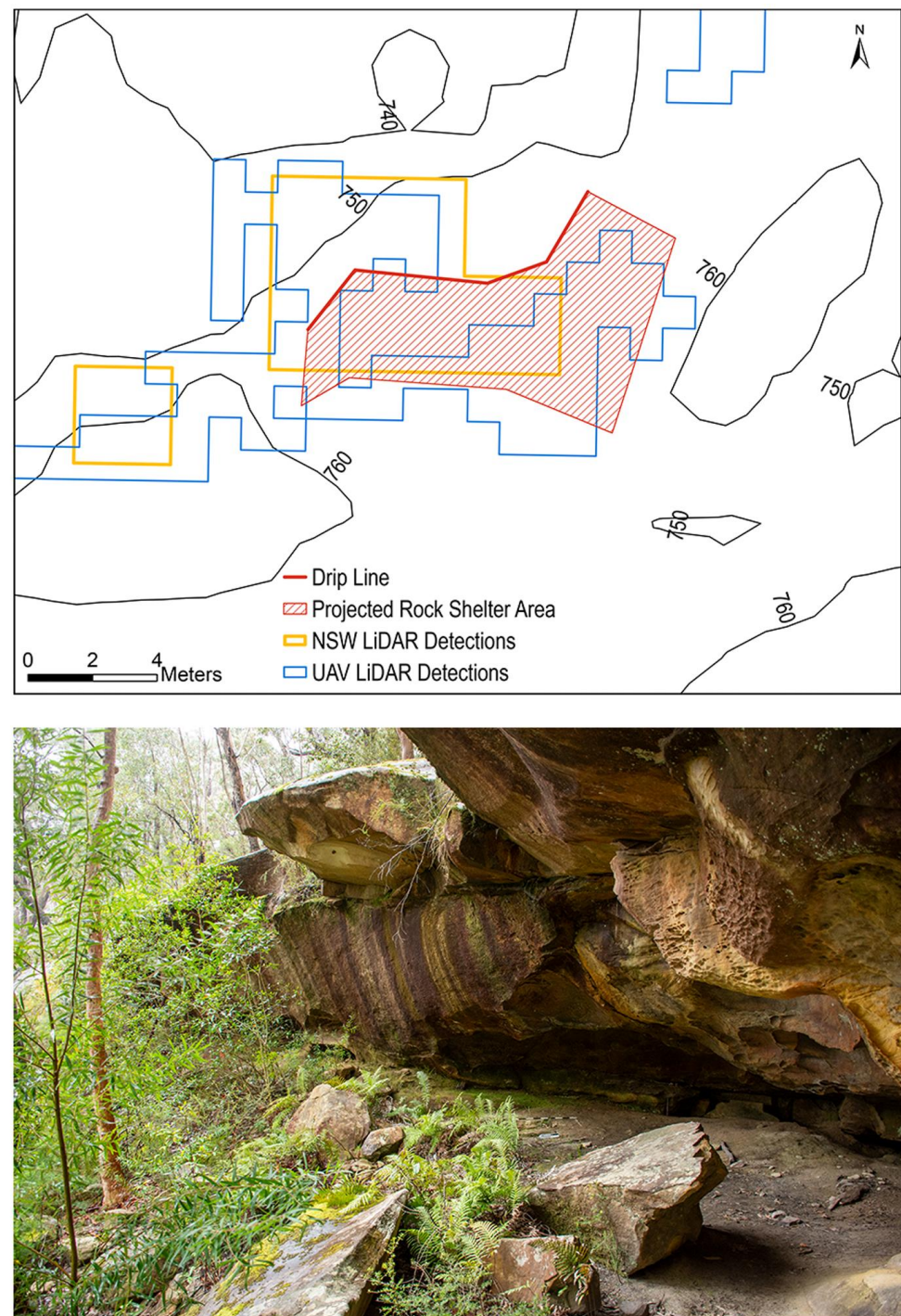


Figure 10. Morley's Creek rock shelter in MTI-A3: UAV and NSW LiDAR detections overlapping the drip line (**top**) and photo of interior (**bottom**).

The Bogey Holes area is a cultural precinct comprising multiple shelters near Mount Wilson and was likely used for resource gathering and as a staging point for ceremonies to the north at Mount Irvine. We focus on three rock shelters within this area that have rock art and lithics: The Occupation Site (AHIMS ID#45-4-1141), the Old Ochre Shelter (AHIMS ID#45-4-1130), and the Manuport Cave (AHIMS ID#45-4-1129) (Figure 12). Planar cross bedding is apparent in the quartzose sandstone fabric of these shelters. Large planar cross beds are a common feature of the Burra-Moko Head Sandstone member [33,37].

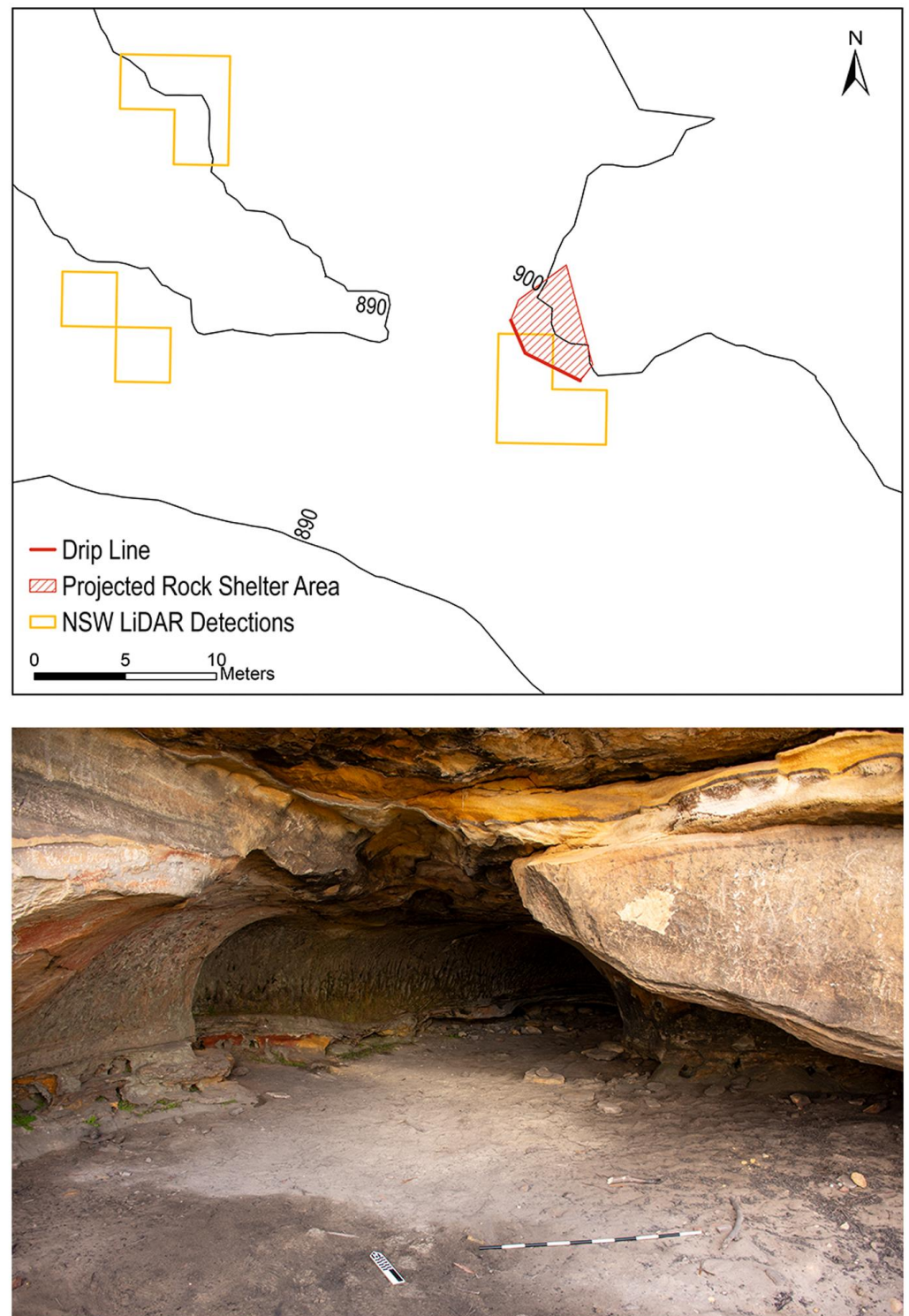


Figure 11. Emu Cave: NSW LiDAR detection overlapping with drip line (**top**) and photo of interior (**bottom**).

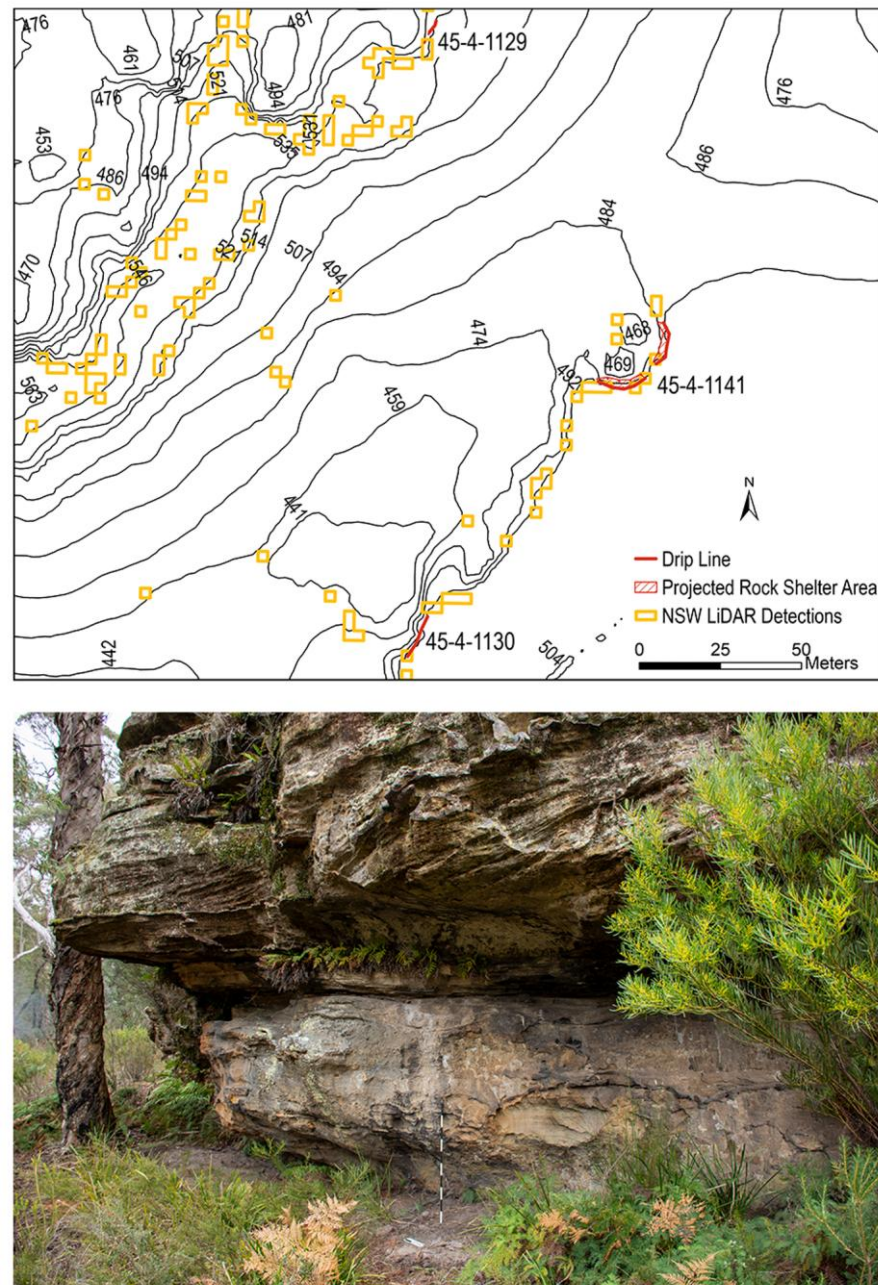


Figure 12. Bogey Holes shelters: NSW LiDAR detections overlapping with drip lines (**top**). Photo of interior of The Occupation Site (45-4-1141) (**bottom**).

3.3. Unregistered Rock Shelters and Archaeological Evidence

UAV and NSW LiDAR detections also overlap with the drip lines of unregistered rock shelters that have cultural features. These shelters include BM139—Djulpura 1 Shelter with Artefacts (AHIMS ID#45-4-1831) and BM140—Djulpura 2 Shelter with Art and Artefacts (AHIMS ID#45-4-1830) in DJ1 (Figures 13 and 14), and BM141 in DJ2 (Figure 15). The BM139 and BM140 shelters comprise a similar quartzose sandstone as the other shelters, with the fabric of BM140 evidencing a thin layer of a finer red-brown sedimentary rock. Although similar laminations are noted within the Burra-Moko Head Sandstone member around Capertee and the Wolgan Valley, they are not present further south. Accordingly, this layer is interpreted as a claystone horizon within the Banks Wall Sandstone [33].

BM139 (Figure 13) is located south of the Bells Line of Road and north of the Grose Valley, just east of Bell. At BM139, three large stone artefacts were recorded on the surface of the rock shelter floor (Supplementary Material Section S4).

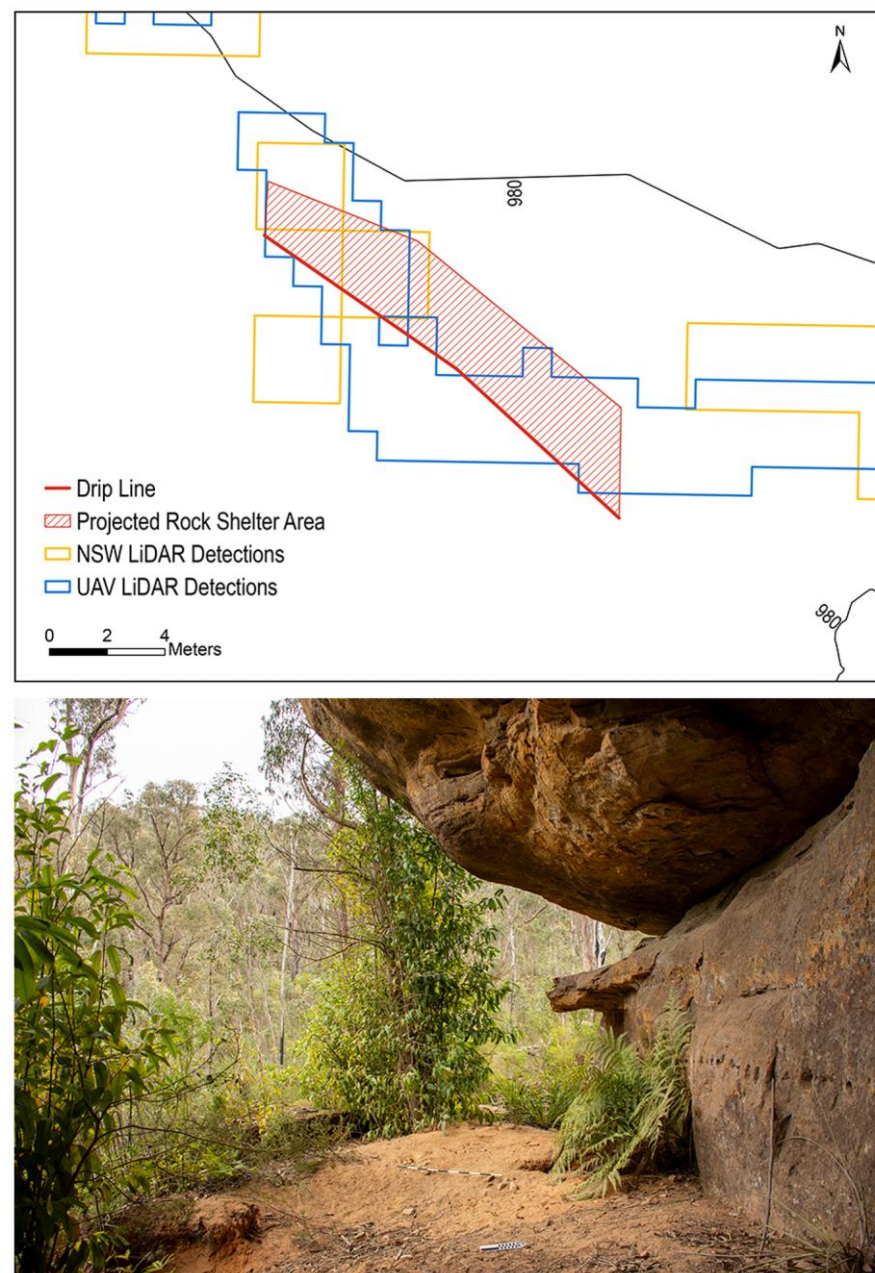


Figure 13. BM139 rock shelter in DJ1: UAV and NSW LiDAR detections overlapping with drip line (top) and photo of interior (bottom).

At BM140 (Figure 14), we documented 21 stone artefacts on the floor surface (Supplementary Material Section S4) as well as one art panel consisting of two red pigment hand stencils placed side by side, in total measuring approximately 35×15 cm. The motifs include a left-hand stencil directly next to a right-hand stencil, likely created in one event from the same individual. The stencils are located on a slightly angled panel underneath a band of iron-rich stone, with some exfoliation at the top of the stencils.

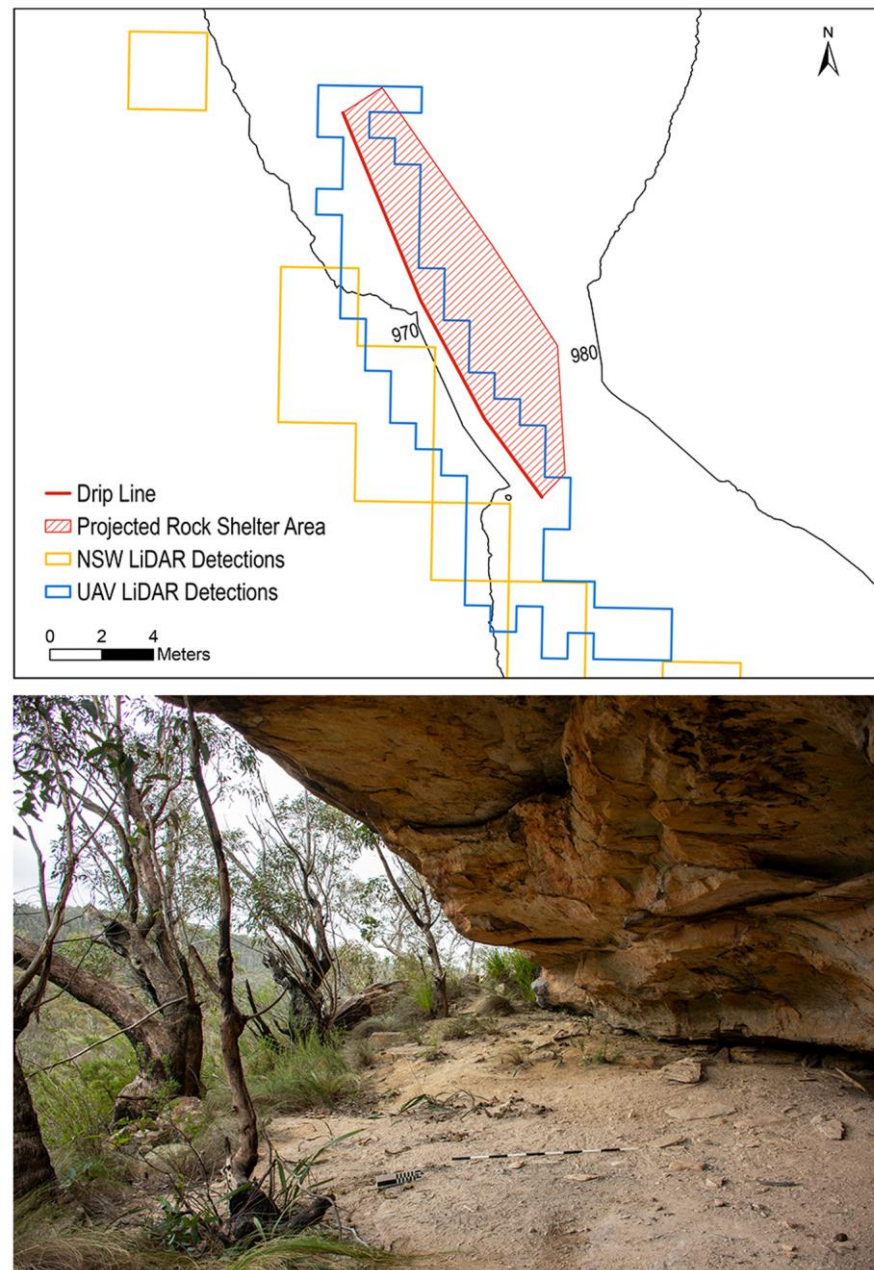


Figure 14. BM140 rock shelter in DJ1: UAV and NSW LiDAR detections overlapping with drip line (**top**) and photo of interior (**bottom**).

BM141—Djulpura 3 Shelter with Artefacts (AHIMS ID#45-4-1829) is located in proximity to the Pierces Pass walking track. The cross-bedded quartzose sandstone fabric of the BM141 shelter possesses thin lenses of pale, fine-grained sedimentary material (Figure 15). This is provisionally interpreted as a claystone lens within the Banks Wall Sandstone member. As some of the lithic raw materials from the DJ1 and DJ2 areas are macroscopically consistent with various claystone units, the larger claystone horizons within the shelter fabric may have been exploited by past people for stone artefact production. A total of 26 stone artefacts were identified during a brief surface inspection of BM141 (Supplementary Materials Section S4).

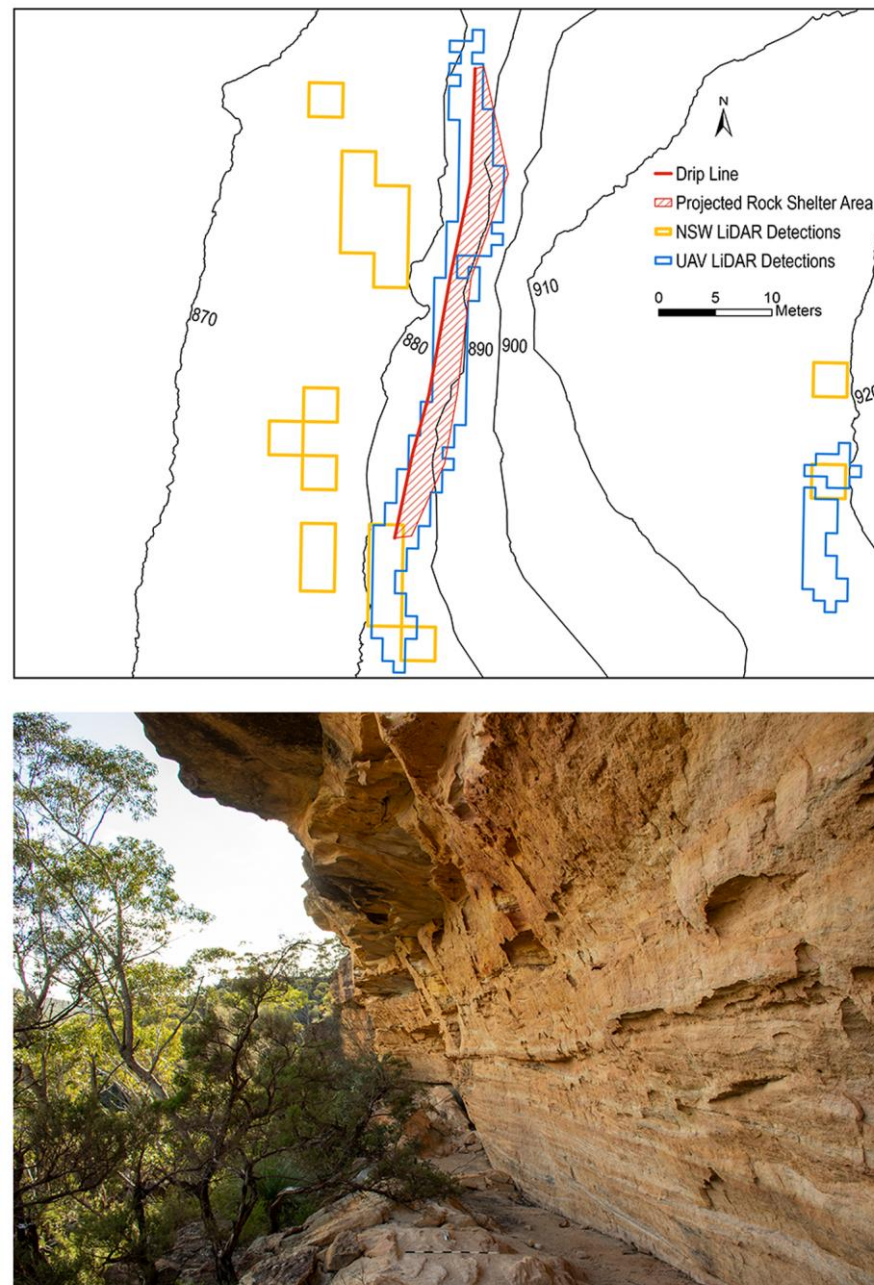


Figure 15. BM141 rock shelter in DJ2: UAV and NSW LiDAR detections overlapping with drip line (**top**) and photo of interior (**bottom**).

3.4. Candidate-Prioritisation Framework

We assigned priority levels to LiDAR detections based on their dataset and spatial relationship. Given limited time and resources, determining which sites and how many to ground-truth can be challenging [11]. Since UAV LiDAR datasets have substantially higher point densities than the NSW LiDAR dataset (see Section 2), UAV-derived detections are more likely to capture rock shelter morphology. For example, DJ1-028, a rock shelter in DJ1 lacking visible archaeological evidence, was detected by the UAV model but not the NSW model (Figures 7 and 18). Notably, all UAV detections corresponding to known and previously unregistered rock shelters also spatially overlap NSW detections, indicating that agreement between the two independent models provides a useful basis for prioritising detections for further investigation. We therefore classified UAV detections that are within 1

m of NSW detections as high priority, UAV detections located more than 1 m of NSW detections as middle priority, and NSW detections as low priority (Table 4, Figures 16–19).

Table 4. Area (km²) and number of detections for each UAV-mapped zone, categorised according to priority level. UAV detections that are within 1 m of NSW detections are high priority, UAV detections that are more than 1 m from NSW detections are middle priority, and NSW detections are low priority.

Zone	Area (km ²)	High-Priority Detections	Middle-Priority Detections	Low-Priority Detections
MTI-A1	0.53	114	271	336
MTI-A3	0.37	102	295	288
DJ1	2.05	214	353	965
DJ2	1.21	282	386	1250

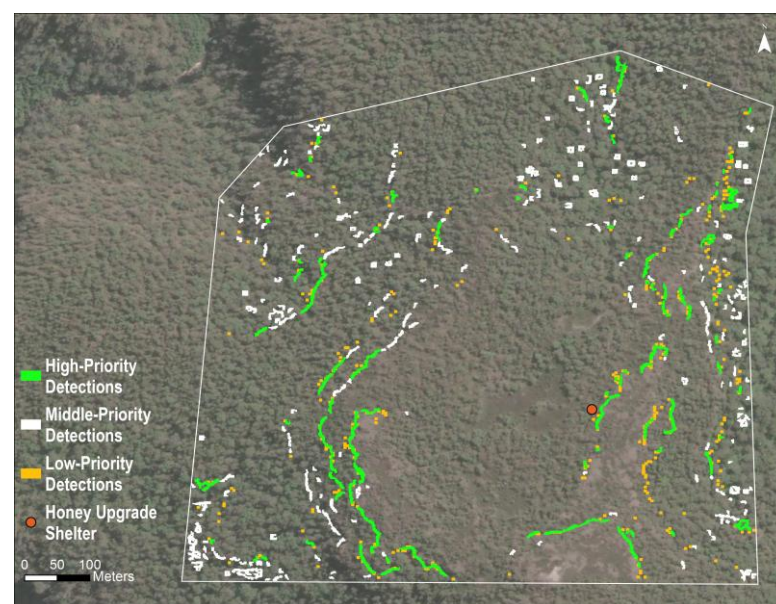


Figure 16. LiDAR detections in MTI-A1, categorised by priority level. Basemap imagery was obtained from Esri World Imagery.

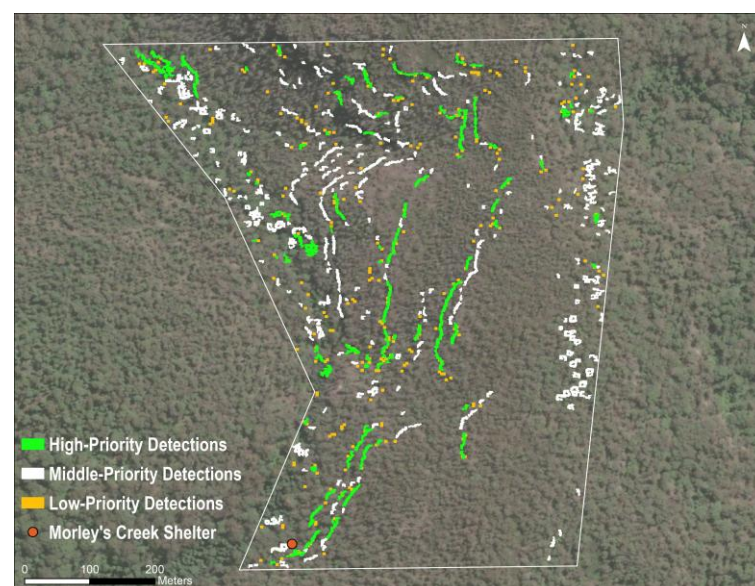


Figure 17. LiDAR detections in MTI-A3, categorised by priority level. Basemap imagery was obtained from Esri World Imagery.

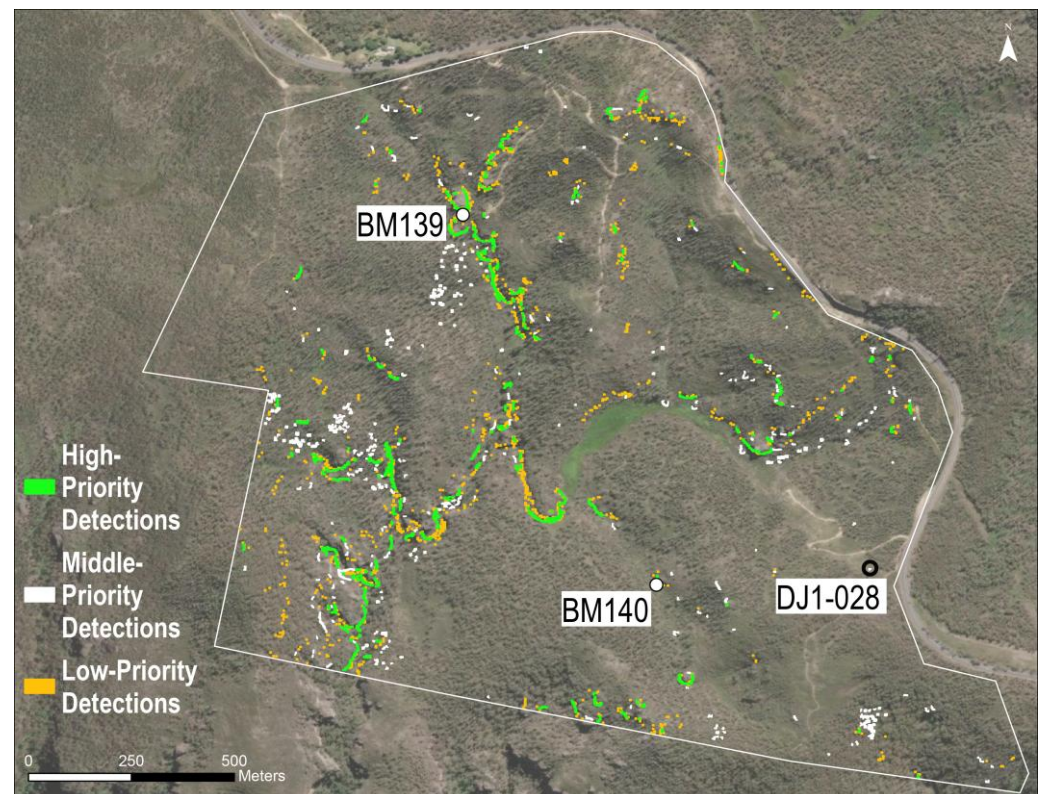


Figure 18. LiDAR detections in DJ1, categorised by priority level. Basemap imagery was obtained from Esri World Imagery.

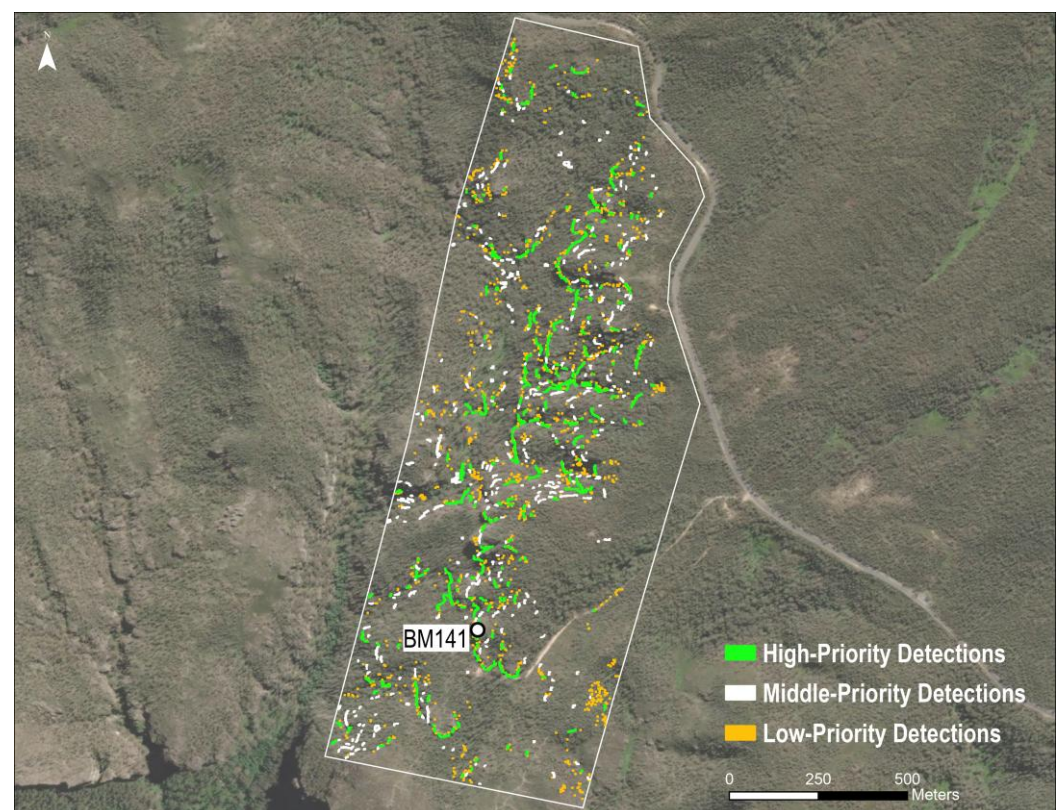


Figure 19. LiDAR detections in DJ2, categorised by priority level. Basemap imagery was obtained from Esri World Imagery.

3.5. Legacy-Coordinate Offsets

UAV and NSW LiDAR detections provide more accurate locations of known shelters than the coordinates recorded in the AHIMS database. The AHIMS database has frequent issues with coordinate accuracy, particularly in more remote areas. As of 2026, the process requires uploaders to input the coordinates in UTM GDA1994 and to keep the horizontal accuracy under 50 m, and to input the location method (phone GPS, non-differential or differential GPS, or CAD system). However, AHIMS records can be uploaded by anyone with an account, and there are no checks on the accuracy of coordinates. Additionally, many older records have been converted from older coordinate systems and paper maps, and there have often been errors during this process, meaning that coordinates are often incorrectly listed and sometimes hundreds of metres off from site locations. Consequently, relocating sites can be challenging, particularly in remote areas of rugged terrain such as the Blue Mountains. In response, we have created an online database known as the 'Coolamon' in collaboration with Environmental Systems Solutions. This database allows us to record sites which have not previously been recorded in AHIMS but also to re-record sites and update the information as necessary.

We examined the distances between the mapped drip lines of six known rock shelters and their recorded coordinates in the AHIMS database (Table 3). While variable, these results show discrepancies between the ground-truthed locations of rock shelters and their existing database coordinates, which is an issue identified by other studies [13]. This highlights the potential of our workflow for improving the spatial accuracy of legacy site records (see Section 4).

3.6. Limitations and Model Performance

Several limitations should be considered when interpreting the performance and broader applicability of the workflow. First, ground-truthing focused on candidates judged to be promising following inspection of the LiDAR point clouds, rather than a random or exhaustive sample of detections, and the resulting field verification therefore cannot be used to estimate model precision. Similarly, because areas without detections were not systematically surveyed, the false-negative rate remains unknown. Consequently, quantitative performance metrics such as overall model precision, recall, and F1-score cannot be reliably estimated from the present sample. Additional systematic validation is required to quantify model performance across the broader landscape. Model performance is also dependent on morphology-specific thresholds for slope, local relief, relative elevation and candidate size, as well as variation in LiDAR point density and classification accuracy between the UAV and NSW datasets, meaning that shelters with different geometries or poorly represented surfaces may not be detected. An additional constraint is that the raster-based analyses represent terrain as 2.5-D surfaces in which each horizontal location is assigned a single elevation value, limiting the direct representation of vertically complex or undercut overhangs and requiring the derived variables to be treated as proxies for shelter morphology rather than measurements of complete shelter geometry. Finally, because the thresholds employed here were developed for the sandstone landforms, vegetation and LiDAR datasets of the Blue Mountains, application in other regions will require evaluation and potentially recalibration against local geology, topography, shelter morphology and data characteristics before comparable detection performance can be assumed.

4. Discussion

As a pilot study, our primary objective was not to quantify model performance by determining rates of true and false positives, but rather to evaluate the workflow's potential for

confirming the location of registered sites and detecting previously unregistered rock shelters. Our methodology integrated high- and low-resolution LiDAR datasets with GIS analyses and pedestrian surveys in the Blue Mountains study area, resulting in the successful detection of nine registered and unregistered rock shelters containing lithics and rock art.

Our work demonstrates the value of LiDAR-based geomorphological mapping as an important, non-destructive approach to archaeological investigation that offers perspectives on the landscape not readily attainable through fieldwork alone [9]. This approach complements and enhances archaeological survey rather than replacing it, producing detections of geomorphic features that need to be ground-truthed to confirm their archaeological significance [13,38]. Moreover, coordinates of successful detections in this pilot study were more accurate than those listed in the AHIMS database, providing a method for checking the accuracy of legacy site coordinates.

This methodology can generate regional datasets of rock shelters relatively rapidly, thereby better positioning communities and researchers to investigate past occupation, particularly in rugged environments. From deserts to forested landscapes, systematically surveying these types of terrain is arduous, time-consuming, and expensive, constraining the reach of archaeological fieldwork and, consequently, our understanding of human activities. This is especially relevant in areas such as Australia, where many bioregions “lack high quality regional data sets with chronological scaffolding” [39].

Employing LiDAR technology for rock shelter detection can also potentially be leveraged across landscapes beyond Australia [13]. Our research complements a growing body of studies employing automated detection methods to locate archaeological sites across diverse landscapes, from tombs in Oman [40] and circular ritual enclosures in Sweden [41] to earthworks in Tonga [42]. By extending LiDAR methods to topographic and elevation-derived attributes associated with rock shelter geomorphology, our workflow can potentially be adapted to different environmental contexts. Model parameters and detection filtering can be adjusted according to locally available data on rock shelter geomorphology, geology, topography, and other landscape characteristics.

Our results indicate capacity for landscape-scale remote sensing to facilitate targeted pedestrian surveys and improve the spatial accuracy of legacy site records. For future surveys, our approach provides a scalable framework integrating LiDAR datasets of varying point densities. Access to LiDAR datasets is an important ethical issue because it is often disproportionately available to Western researchers [9,43–45]. Publicly accessible, airborne LiDAR datasets are not available in all regions. Where such data exist, however, our low-resolution LiDAR model can be applied to generate an initial set of rock shelter detections across broad areas. These low-priority detections can serve as a regional filter for identifying areas in which high-resolution UAV LiDAR data collection and targeted survey can be effective. Within UAV-mapped areas, correspondence between UAV and low-resolution LiDAR detections provides an additional basis for prioritising detections. Such detections represent high-priority candidates for rock shelters that can be targeted for verification in 3D point clouds and through survey. Candidate detections can be further filtered by excluding those in areas considered unlikely to have supported human occupation, such as flood-prone locations, significantly reducing the area requiring survey to locate rock shelters. Additionally, if a powerful laptop is available, LiDAR data processing of local high-resolution data and 3D point cloud visualisations can be carried out in the field to provide coordinates of shelter candidates to survey teams in real time.

Our approach can also improve the accuracy of legacy site coordinates by relocating known rock shelters previously mapped by low-accuracy GPS devices and recorded in online databases such as AHIMS. Inaccurate coordinates can hinder the relocation of archaeological sites for further research, condition monitoring, and protection from wildfires and other threats. Successful detections of Emu Cave and the Bogey Holes rock

shelters outside of UAV-mapped areas indicate that low-resolution, airborne LiDAR datasets can be sufficient for relocating known rock shelters. We propose generating circular polygons around legacy site coordinates, with radii corresponding to their reported horizontal positional uncertainty. Low-priority LiDAR detections within the search areas can then be prioritised for ground-truthing using high-accuracy GNSS. Confirmed site locations can be subsequently used to update legacy records with more accurate coordinates.

5. Conclusions

This research therefore offers significant benefits for Aboriginal communities and cultural heritage management. The ability of our workflow to identify rock shelters in rugged terrain can contribute to more nuanced assessments of archaeological potential across diverse landscapes and inform land management strategies [46,47]. Model detections provide a baseline for targeted ground-truthing and can support Aboriginal communities in identifying unregistered archaeological sites and expanding existing cultural heritage datasets [13]. In this way, the workflow provides an additional tool that communities can use alongside existing knowledge and practices to engage with cultural heritage.

Our results lay the groundwork for future regional-scale, archaeological remote sensing research in Australia undertaken in collaboration with Aboriginal communities. We are continuing to collaborate with the Dharug Custodian Aboriginal Corporation to ground-truth candidate detections in the Blue Mountains and quantify false positives, providing a more robust assessment of model performance that can inform refinements of model parameters. We also plan to work with Aboriginal communities to test and adapt the workflow for identifying unregistered rock art sites in different environments, including the tropical savanna zone of western Arnhem Land and semi-arid western New South Wales. As this research develops, we envision this methodology not simply as a tool or guide for locating archaeological sites, but as an additional platform through which Aboriginal communities can document, manage, and safeguard cultural landscapes.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18203495/s1>. These materials provide the Python scripts for the outcrop model in Section S1, the UAV LiDAR model in Section S2, and the NSW LiDAR model in Section S3. Descriptions and interpretations of stone artefacts from BM139, BM140, and BM141 are provided in Section S4. Figure S1: Profile view of the 3D LiDAR point cloud of Morley's Creek rock shelter, Figure S2: Profile view of the 3D LiDAR point cloud of the BM139 rock shelter, Figure S3: Profile view of the 3D LiDAR point cloud of the BM140 rock shelter, Figure S4: Profile view of the 3D LiDAR point cloud of the BM141 rock shelter.

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Data Availability Statement: All data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Information. Site coordinates are not publicly available at the request of the Dharug Custodian Aboriginal Corporation because of the cultural sensitivity of these locations.

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