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Drone-Based High-Resolution LiDAR for Undercanopy Archaeology in Mediterranean Environment: *Rusellae* Case Study (Italy)

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ABSTRACT

This paper presents a novel methodology and workflow successful in identifying and mapping undercanopy archaeology in woodland Mediterranean areas. The study area is characterized by dense vegetation typical of the Mediterranean area, located in southern Tuscany (Italy), within the territory of the ancient city of *Rusellae* next to the Tyrrhenian seaside. In February 2021, a drone-based LiDAR acquisition was led over an area of 550 ha, with an average of ~700 points/m^2. Specifically, the combination of aerial drone and LiDAR sensor enabled us to obtain high-resolution and high-quantity data, requiring significant processing efforts facilitated by the collaboration among various expertise in different fields, such as archaeology, computer science and geomatics. Among the most significant, this experience demonstrates the implementation of a methodology that, under certain circumstances, can be effective for the archaeological study of Mediterranean landscapes covered by dense canopy and undergrowth vegetation. The results provide new insights into these areas by shedding light on previously unknown archaeological features and enhancing our understanding of past landscapes.

1 | State-of-the-Art of Undercanopy Archaeology in Mediterranean Environment

Since the mid-20th century, topographical studies in archaeology have grown in both quantity and refinement, not only in the Mediterranean region but across the globe. Millions of hectares of open landscapes have been investigated, significantly enhancing our understanding of settlement patterns, rural populations, productive systems and both large-scale and local trade networks compared to earlier periods (Broodbank 2013). However, wooded areas remain a particularly challenging environment for archaeological surveys. From a strictly archaeological perspective, this difficulty stems from the lack of effective survey methods tailored to the unique characteristics of forested environments. In these often-impenetrable areas, which are unsuitable for arable farming and have thus been largely undisturbed by soil movement in recent centuries, traditional field-walking surveys prove entirely ineffective, as do most other techniques commonly used in more open landscapes. Aerial photography has achieved some limited success in these upland regions, but

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only in areas where tree cover is sparse or entirely absent, such as the highest elevations (Cosci 2013). This gap in methodology highlights a critical need for innovative approaches to uncover the archaeological potential of wooded landscapes.

From around early 2000s, the growing use of airborne light detection and ranging (LiDAR) technology in topographical mapping and archaeological surveys has opened new opportunities for exploring previously undocumented archaeological features hidden beneath forest canopies. Over the following years, LiDAR applications have expanded significantly across Europe, North America, Central America and Southeast Asia, showcasing its transformative potential for enhancing archaeological and landscape understanding, conservation, management and the scientific study of settlement dynamics throughout history. However, in the Mediterranean region, the adoption of LiDAR remains relatively limited. The reasons for this have been systematically analysed in recent studies (Vinci et al. 2024). The effectiveness of LiDAR largely depends on several factors, including the characteristics of material culture, depositional and post-depositional processes, vegetation cover and data resolution/quality (Doneus et al. 2022). These factors explain why LiDAR has yielded exceptional results in tropical rainforests, where large-scale structures are often well-preserved, compared to temperate regions like the Mediterranean. In the latter, archaeological evidence, though abundant and widespread, tends to be smaller in scale and frequently obscured by the dense and thorny vegetation typical of the Mediterranean maquis. This contrast highlights both the potential and the challenges of applying LiDAR in Mediterranean environments.

In the early decades of the 21st century, LiDAR applications in the Mediterranean predominantly utilized data acquired for non-archaeological purposes (Vinci et al. 2024). While the coverage of open-access LiDAR data is often extensive (typically spanning thousands of square kilometres), the ground resolution is generally very poor, with few points per square metre. This severely limits the ability to detect archaeological features beneath Mediterranean forest canopies. These low-resolution datasets, often collected outside the optimal seasonal window for archaeological surveys (such as winter, when vegetation is sparse), are primarily useful for identifying hillfort sites. This limitation represents a significant challenge for archaeological research, as it restricts the collection of data largely to central places, leaving much of the broader landscape—including structures and infrastructures—poorly understood.

It was only from the 2010s onwards that LiDAR acquisitions specifically tailored to archaeological needs began to emerge. Among these, pioneering work in Italy and Croatia stands out, demonstrating advanced vegetation filtering techniques and assessing the impact of such methods on the visibility of archaeological features (Campana 2017; Doneus et al. 2020; Mazzacca et al. 2022). These efforts have marked a turning point in the application of LiDAR for archaeological purposes in the Mediterranean, paving the way for more detailed and comprehensive landscape analyses.

2 | Introduction

As part of the Emptyscapes project (Campana 2023, http://www.emptyscapes.org), in 2019, the Landscape Archaeology and Remote Sensing Laboratory of the University of Siena (LAP&T, https://lapet.unisi.it) started a field-walking survey of two wooded environments: the hill of Moscona and the hill of Mosconcino near Grosseto, Tuscany, Italy. Both areas are next to the lowlands intensively surveyed in the past decades by a multimethodological approach (Campana 2018). Despite of the very dense wooded vegetation, survey activities allowed the field work team to identify several archaeological features, highlighting the importance of the highlands in this environment (Cirigliano 2023). The overall outcomes improved the understating of the rural landscape and the suburbs of the ancient city of *Rusellae* (Angelini and Farinelli 2013; Mangiavacchi 2002). However, despite the initial positive results, limitations were encountered. Indeed, the dense undergrowth vegetation, which, in some cases, has contributed to the favourable preservation of the archaeological evidence, represents also a substantial hindrance to the visibility, restricting the access to several areas and preventing our understanding of the totality of the ancient landscape.

In the early 2000s, the LiDAR sensor introduced new opportunities to explore undercanopy archaeology, thus enabling, under certain circumstances, the mapping of archaeological evidence through dense vegetation (Baltsavias 1999; Holden et al. 2002; Devereux et al. 2005). Beginning in 2005, through a Culture 2000 project of the European Union titled 'European Landscapes: past, present and future', LAP&T took its first steps into LiDAR data acquisition, processing and interpretation, targeted at four sample areas in the counties of Siena and Grosseto. Further experience was gained in 2009 when the laboratory team took the lead in the BREBEMI project in northern Italy, for a motorway construction project that aimed to connect the cities of Brescia, Bergamo and Milan over a total distance of ~100 km (Campana and Dabas 2011). These initial experiments showed some interesting trends and equally obvious limitations emerged. The primary limitation can be attributed to the character and density of the Mediterranean tree cover including undergrowth vegetation and the presence of dense scrub in many areas, combined with the relatively low resolution the LiDAR systems used within the region. For all intents and purposes, the results range from poorly effective to ineffective.

The key problem was that LiDAR surveys had not been done in the Mediterranean region with a focus on proper methods pertaining to the characteristics and prerequisites of the method. These include details of the density of woodland canopy, undergrowth vegetation and thickness of any associated scrub. But also important is the timing of data acquisition (for instance, avoiding late spring and summer when the leaves are at their densest), the characteristics of expected archaeological remains (buildings, earthworks, natural features, etc.), the estimated ground resolution (in recorded points per square metre) and simply the details of the type of LiDAR system to be used (whether discrete or full waveform).

To overcome all those issues, we turned our attention to drone-based LiDAR. In March 2016, within the Emptyscapes project, we initiated a test flight in collaboration with the Italian company Microgeo (Florence) and Austrian RIEGL Laser Measurement Systems to do data acquisition over a small area of dense woodland in the Maremma region of southern Tuscany. Tests undertaken enabled the collection of LiDAR measurements for a limited area of the woodland (~16.5 ha) at high resolution (200 points/m^2). The experiment was successful, proving that it was possible to penetrate the dense vegetation and reveal a number of potential archaeological and environmental features beneath the obscuring canopy and undergrowth.

In February 2021, a drone-based LiDAR survey was planned and carried out by LAP&T in collaboration with Alto Drones and Global Digital Heritage (GDH) gathering 550 ha of wooded landscape (Figure 1). The survey produced a massive amount of data (about 3 billion points, 10.000 aerial photographs, etc.) requiring advanced techniques for management, processing and interpretation with machine learning (ML) methods.

3 | Case Studies

We focused this study on the sites of Moscona and *Rusellae*, both of which fall within the territory of the ancient Etruscan and Roman city of *Rusellae*, originally known as the *Ager Rusellanus*. This landscape encompasses prominent archaeological features from Prehistory to the Medieval period. The investigations focused on these two areas that because they posed the more significant challenges due to the dense, multicanopy vegetation.

The first case study is the hilltop section of Moscona, where the presence of a medieval settlement of about 1 ha in size is well known (Collavini 1998; Mangiavacchi 2002). Here is found the remains of a fortified settlement dating to the 12th century, built at the behest of the Aldobrandeschi family, a comital family of the medieval period that had properties in southern Tuscany. The foundation date of this settlement is known to be 1179 (Collavini 1998; Farinelli and Francovich 2000). Despite the presence of visible archaeological remains, Moscona lacks of any systematic and basic archaeological investigation. The remains of the fortified settlement of Moscona encompass a circular tower, which measures approximately 30 m in diameter, and a surrounding wall connected to the tower itself, enclosing a settlement of ~1 ha (Bianchi 2023, 63–86). One hypothesis is that these structures replicate the plan of buildings from earlier periods, particularly referring to the circular tower. This hypothesis refers to the possibility that they reproduce the walls of the 7th century BC hill fort (Donati 2012). This first case was selected due to the combination of several factors that contributed to the verification and reliability of the data: richness of archaeological data, availability of pivotal reference works, an environmental context almost entirely covered by dense vegetation and the possibility to rely on ground truth surveys to evaluate the results.

The second case study is associated with areas neighbouring the city walls of *Rusellae* where excavations conducted during the second half of the 20th century have identified sites now completely covered by vegetation (Bocci 1975, 6–9). The city of *Rusellae* was founded in the 6th century BC by the Etruscans (even though the area has been permanently inhabited at least since the 8th century) and was inhabited until the 14th century AD (Celuzza 2013). *Rusellae* hosts rich architectural heritage, which shows details of complex archaeological stratigraphy, city walls, an amphitheatre and the *forum* area. Key features are also found outside the city, including Etruscan cemeteries located along the road system leading to the city (Campana 2018).

More specifically, the second case study includes a section of landscape along the western slopes that surround *Rusellae*. This is a funerary area located outside the city's walls. This region is characterized by round barrows characterized by stone vault and dating back to the Etruscan archaic period (6th century BC). Currently, the area is entirely covered by vegetation. The necropolises of *Rusellae* have never been systematically investigated. Occasional excavations were carried out starting from the second half of the 18th century (Capei 1862). The overall pattern depicts necropolises located along main roads connecting the city. The funerary architecture includes in this area and in a longue durée perspective, the following types: pit graves,

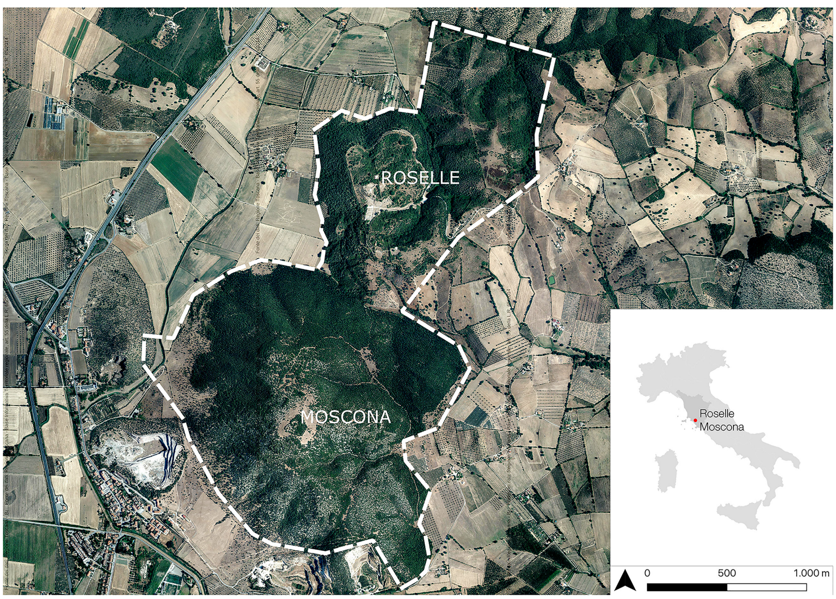

FIGURE 1 | Aerial photography from the regional geoportal of Tuscany of the surveyed area. The Etruscan-Roman city of Rusellae was included in the acquisition. The acquisition data were managed in collaboration with Alto Drones in February 2021.

trench graves, *cappuccina* graves, round barrows and rock-cut tombs. The case study concerns burials belonging to the last group, namely, those of rock-cut tombs. This funeral monument is reported in a map published in 1975 by the Archaeological Superintendence (Bocci 1975). The report shows the city's layout with the location of various necropolises here distinguished by type (Bocci 1975, 6–9; Bettini 1998). However, the exact extent of this necropolis and the number of burials was unknown.

4 | Data Acquisition

As reported above, a 2021 LiDAR survey was conducted in mountainous areas covered by forest vegetation, spanning a continuous area of 550 ha at an average point density of 750 points/m^2 (Figure 1). Due to the high density of the local vegetation, the team conducted laser scanning during winter because of the lowered vegetation cover. The survey generated 2.7 billion points and 10.000 aerial images. The acquisition was managed by Alto Drones and LAP&T who conducted flights over the entire area in automatic mode, by maintaining a constant speed and height of 60 m. The RIEGL miniVUX-3 was equipped with the Applanix APX-20 IMU. From the laser scanner data and flight trajectory, a 3D point cloud was derived. The individual flight strips overlap was generated using RiPRECISION software, a strip adjustment calculated on the trajectory provided by the IMU, allowing a high-resolution alignment of the individual scan strips and providing a homogeneous point cloud. The accuracy of the point cloud in both planimetry and elevation is ±2 cm.

4.1 | Data Processing

4.1.1 | Methodology

To generate the necessary digital terrain model (DTM) raster files used to study the microrelief of the area, we first semantically enriched the acquired data through a semantic segmentation process, aiming at subdividing the points into three classes: *ground*, *structure* and *vegetation*. We processed the data through a similar pipeline as the one presented in our previous publication (Mazzacca et al. 2022), with a few modifications according to recent developments and research goals. We applied a similar multilevel (ML) approach (Teruggi et al. 2020), sequentially performing two binary semantic segmentation processes, aimed at mapping both the *ground* class and the above-ground archaeological structures (Figure 2). Because the purpose of this study is to investigate microrelief, we decided to focus primarily on *ground* class detection, and differently from our prior work, we first mapped the point cloud into *ground* points and *nonground* points, while discriminating between structures and vegetation in a later stage. This approach aimed to produce a precise, accurate and low-noise DTM, essential to generate a readable DTM raster file required for the success of the study's subsequent stages. That said, the pipeline's final goal would be to generate a high-resolution, comprehensive digital feature model (DFM), which is a DTM that includes archaeologically relevant above-ground elements as well (Štular et al. 2021). For this reason, two areas of the acquired data, containing known archaeological structures, were selected to test the capabilities of the algorithm to map archaeological above-ground evidence.

Another distinction between our study and the previously reported pipeline (Mazzacca et al. 2022) lies in using a deep learning (DL) technique to carry out the semantic segmentation process rather than one based on traditional ML. More specifically, we used an internal implementation of the Point-Transformer architecture (Zhao et al. 2021). To train the DL algorithm we used a manually labelled part of the archaeological site of *Rusellae* and an area of the archaeological site of Santa Marta, which features a similar Mediterranean vegetation signature to the *Rusellae* and Moscona contexts. The labelled data were then given to the DL network to generate segmentation models and automatically divide the acquired point clouds into classes. Similar to our previous work (Mazzacca et al. 2022), the labels were combined with sensor-based features and geometric features calculated at different radii (Weinmann et al. 2015) in order help the network converge towards better results. At

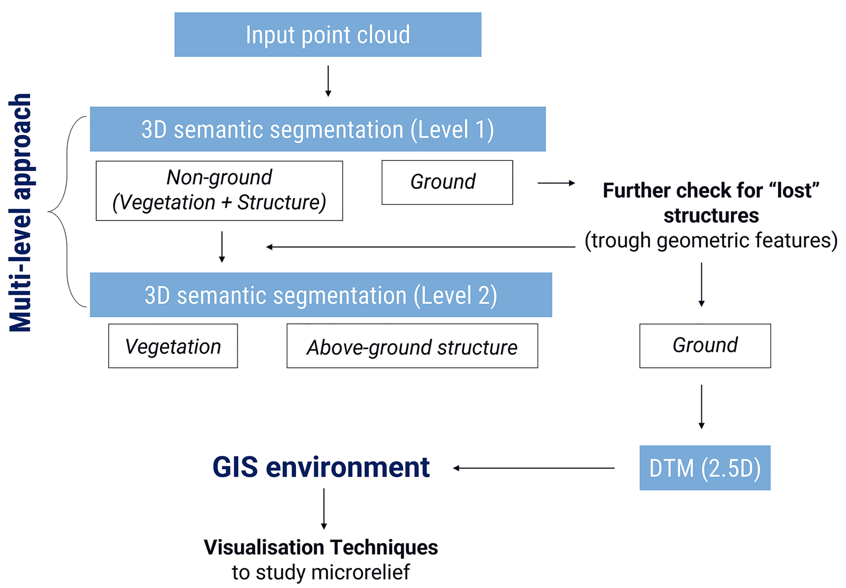

FIGURE 2 | The project pipeline for LiDAR data processing and undercanopy structure identification.

the end of the first level, we generated DTM raster files starting from the predicted ground point clouds, while the nonground point clouds were passed on to the second stage of the classification procedure to distinguish the above-ground structures from the vegetation.

The first level of the pipeline was performed at a lower resolution compared to the acquired raw point clouds, subsampling the data at a 0.2-m resolution. Moreover, the entire dataset was divided and processed in tiles through both stages of the segmentation workflow. The choice to tile and subsample the data is due to the large size of the dataset, which otherwise would require lengthy machine times to process. The well-known compute-intensive nature of DL methodologies has to be considered when approaching these technologies, bearing in mind that the necessary hardware requirements must be fulfilled to take advantage of these techniques.

A few tests were made to understand which level of data subsampling was more suitable to obtain the best possible results. After testing the pipeline's first level on selected areas of the dataset, subsampled at 0.1-, 0.2- and 0.5-m resolutions, we achieved the clearest and more readable DTM by processing the data at 0.2-m resolution and reprojecting the results on the raw data before generating the DTM raster files from the ground labelled points by kriging interpolation at 0.3-m resolution.

The second level was performed at a higher resolution (0.1 m) to better discriminate the above-ground structures from the vegetation, recognizing that the latter is characterized by high values of the *anisotropy* feature when calculated at very small radii. Eventually, we passed the DTM raster files, resulting from the ground classified points interpolation, onto the next phase of the pipeline by importing them into a GIS environment to perform the archaeological analysis with the help of different visualization techniques. The second level of the classification pipeline was visually evaluated to evaluate the network capabilities to detect above-ground structures, comparing the results with our prior work.

4.1.2 | First Level of Classification (DTM Raster Generation)

During the first phase of the process, the network was able to successfully differentiate the *ground* from the *nonground* class (Figure 3), overcoming with a high degree of success the specific difficulties that characterize the *Rusellae*/Moscona area, namely, the presence of low-standing archaeological structures and the extensive shrub's low vegetation. Although largely successful, these problems were not completely solved.

In particular, the dense low vegetation cover does not allow the sensor impulse to pass through and hit the ground in many areas, causing the generation of empty data patches on the ground. Furthermore, the shrub cover sometimes makes it difficult for the algorithm to clearly distinguish ground and nonground points close to the ground surface, which results in widespread noise. That said, the metrics calculated on the evaluation set at the end of the training phase (Table 1) show a high level of accuracy, and the resulting ground point cloud shows improved noise removal compared to our previous work, resulting in a cleaner DTM.

4.1.3 | Second Level of Classification (Structures Detection)

Several challenges are associated with the structures mapping process, the two main ones being (a) the intrinsic differences

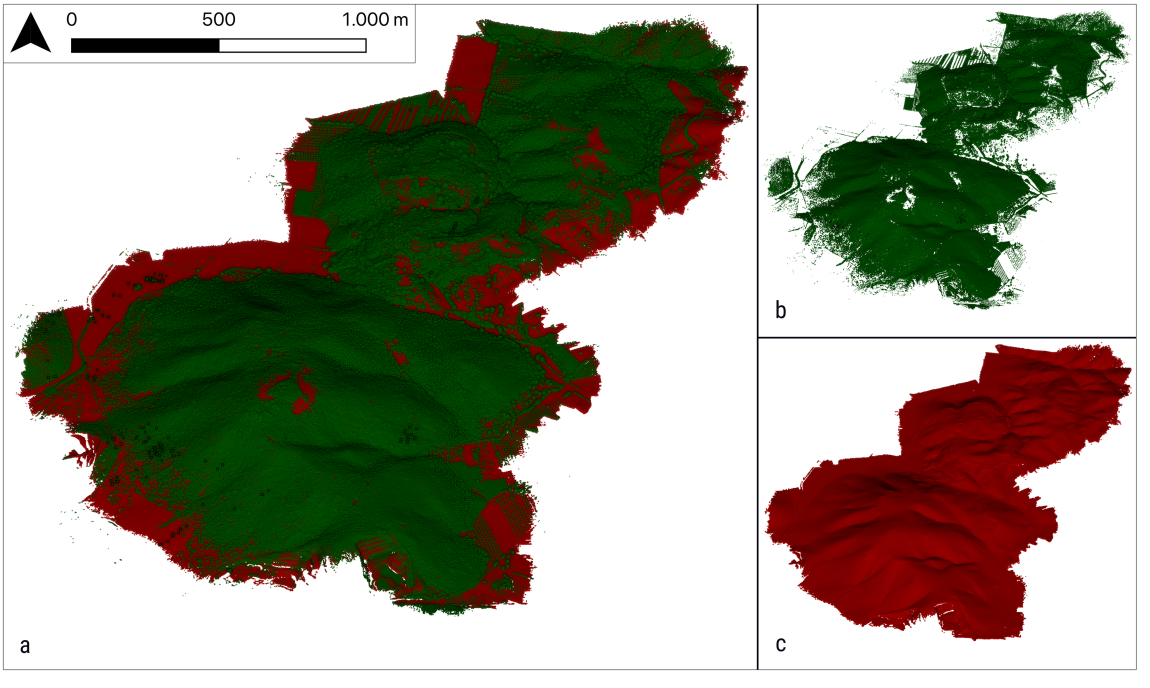

FIGURE 3 | Results of the first level of segmentation: (a) Point cloud segmented in ground (brown colour) and nonground (green colour), (b) nonground point cloud and (c) ground point cloud.

TABLE 1 | Evaluation metrics at the end of the first level (L1) of the semantic segmentation process and explanation of the metrics calculation.

	L1 (overall accuracy = 96.76%)	
(%)	Ground	nonground
Precision	95.58	97.35
Recall	94.75	97.78
F1 score	95.16	97.56

$$\textbf{Precision} = \frac{Tp}{Tp + Fp}$$

$$\textbf{Recall} = \frac{Tp}{Tp + Fn}$$

$$\textbf{F1} = 2 * \frac{Recall * Precision}{Recall + Precision}$$

Tp = True Positive;
Fp = False positive;
Fn = False negative.

TABLE 2 | Evaluation metrics at the end of the second level (L2) of the semantic segmentation process.

	L1 (overall accuracy = 96.76%)	
(%)	Ground	Nonground
Precision	95.58	97.35
Recall	94.75	97.78
F1 score	95.16	97.56

among structures in functionality (e.g., public monuments, houses and production), size (e.g., monumental complexes or small settlements buildings) and period (e.g., classical age, medieval age and contemporary age) and (b) the low amount of available training data to train a DL network to map all the above-mentioned structure types, characterized by large differences in their geometrical signature.

We decided to visually evaluate the results of this stage of the segmentation process through an on-site visual inspection. As mentioned earlier in our explanation of the challenges involved in mapping archaeological structures, we could not rule out the presence of substantially different structures from the ones that were used to train the algorithm; therefore, the metrics calculated on the evaluation set (Table 2) are not sufficient to assess the correctness of the results, and a field survey was deemed necessary to confirm the accuracy of the outcomes.

The model successfully detects above-ground structures, especially vast archaeological structures and complexes (Figure 4), discriminating them from the vegetation. Although the algorithm proved to be successful for the most part, the predicted *structure* class shows a significant number of false positives, resulting in widespread noise across the landscape.

4.2 | Ground Verification

Due to the challenging context characterized by dense vegetation, ground verification played a significant role in confirming and validating data interpretations. Additionally, we were able to rely on a vast dataset from the Emptyscapes project, which has been operating in this area for over 20 years (Campana 2023). The opportunity to cross-reference multiple results from previous surveys facilitated classification with a high degree of reliability.

Each feature identified in the LiDAR data was described in a digital record of the GIS providing relevant information such as the description of the evidence, interpretation, reliability and preliminary dating. Field campaigns were managed by transferring the GIS database to a mobile GIS, implemented by Qfield, the mobile version of the QGIS desktop software (Chyla and Bulawka 2020). The mobile GIS enabled the efficient organization of the fieldwork, a reliable navigation through woodland environment and real-time data recording. Once the feature was identified, the position was recorded by GNSS RTK (Trimble R12i). Despite the challenges posed by dense vegetation, which limited survey activity, it was still possible to verify all identified archaeological features.

However, the results presented in this paper represent only a small portion of the area analysed so far, and the focus has been on the contexts already verified through surface surveys. Indeed, across the 550 ha examined by LiDAR, over 700 features have been identified, many of which were previously unknown. These include features interpreted as terraces, charcoal kilns, road systems, burials, buildings and fortifications. Further field work activities are planned to verify the entire corpus of evidence.

5 | Results

5.1 | Moscona

The building named locally 'Tino' is a circular structure that has dimensions and landscape visibility that make it a regional landmark. The same cannot be said for the rest of the settlement, which is currently entirely covered by dense vegetation, making it difficult to interpret the nature and extent of the hidden archaeological evidence (Figure 5). During 2002, a local architect, Fabio Mangiavacchi, conducted a survey that produced a detailed plan of the structures. However, the report indicates that some areas of the settlement were not surveyed due to dense vegetation, which hindered any survey activities (Mangiavacchi 2002, 127–132).

Processing data by using the *local dominance* method (Hesse 2016) allowed us to obtain a new visualization of the DTM. By adjusting the DTM parameters, it was possible to generate a more detailed representation of the settlement's organization (Figure 6). The result of this work is a more detailed plan compared to previous studies. Focusing on the summit area of the hill, we were able to identify 97 archaeological features.

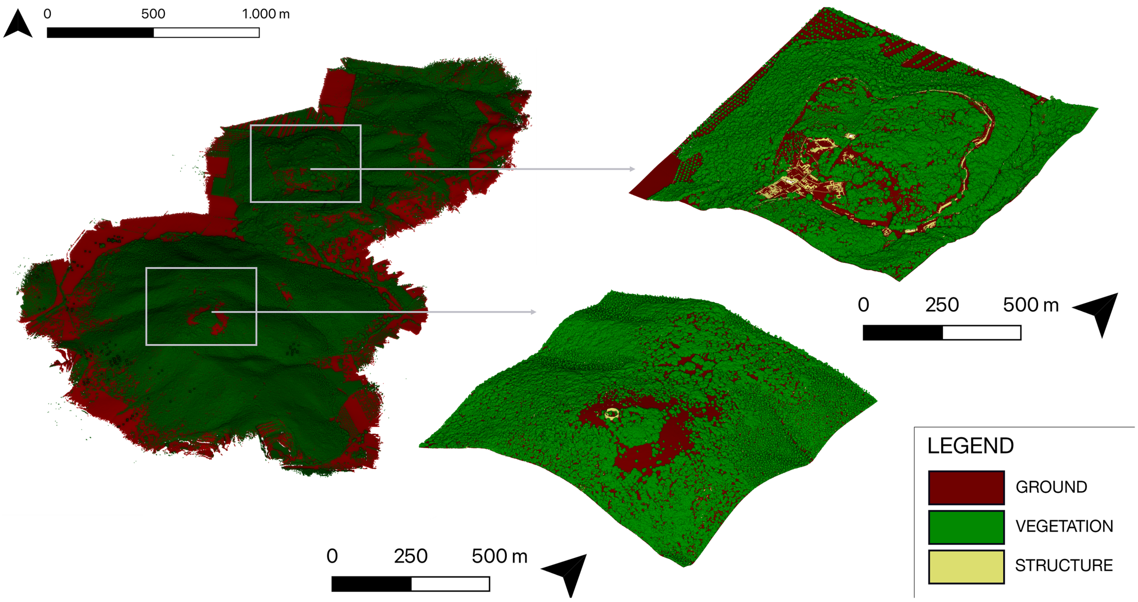

FIGURE 4 | The semantic segmentation L2 results for the Rusellae city area and the Tino of Moscona area.

FIGURE 5 | Orthophoto obtained from regional acquisitions during the same year of the LiDAR acquisition. Here, it is possible to see how the interior of the Moscona fortification is covered by vegetation, hiding any view of the archaeological features.

Starting from the area located within the enclosure, which encompass a surface of nearly 1 ha (Figure 7, No. 58), it is possible to distinguish groups of buildings of various sizes. A first group of rectangular plan structures is located along the north–northwest perimeter; among these, five buildings stand out with dimensions of ~10 × 6 m (Figure 7, Nos. 2–5 and 8), along with other small portions of walls that could be connected to similar structures (Figure 7, Nos. 1 and 7).

Other possible dwellings are arranged radially within the fortified area, oriented east–west and smaller in size compared to the previously mentioned structures. These 42 buildings (Figure 7, Nos. 9–51) appear to be arranged symmetrically relative to each other. In some cases, it is possible to discern the complete plan, as with Building Nos. 30–35, while in others, only fragments are visible. These structures generally have a quadrangular plan measuring approximately from 6 × 5 to 7 × 4 m.

Additional portions of walls (Figure 7, Nos. 53 and 54) have been identified within the area associated with the 'Tino' (Figure 7, Nos. 55 and 56). This interpretation is based on previous surveys, where it was possible to observe the use of hydraulic mortar typical of impermeable structures, as well as the compact and enclosed shape. It was also possible to interpret some depressions visible in our DTM as cisterns, as in the case of Trace Nos. 60 and 62, while the presence of a third cistern is hypothesized at Trace No. 61. Trace No. 59 could indicate the presence of a well due to the shape (Figure 7).

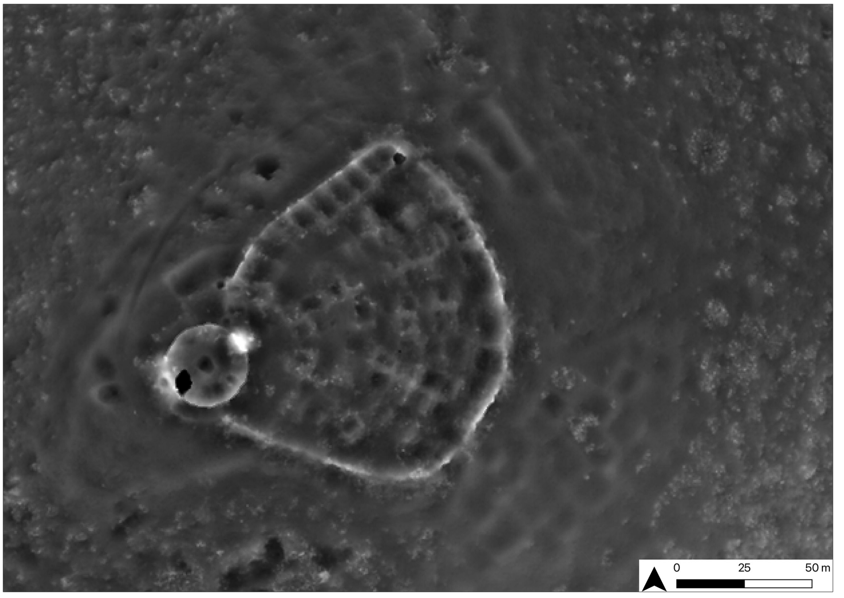

FIGURE 6 | Local dominance analysis performed on the DTM resulting from previous steps. In the image, it is possible to clearly observe the residential structures within the fortified structure that are below dense vegetation. Additionally, rectangular-shaped structures can be observed on the outer part to the southeast.

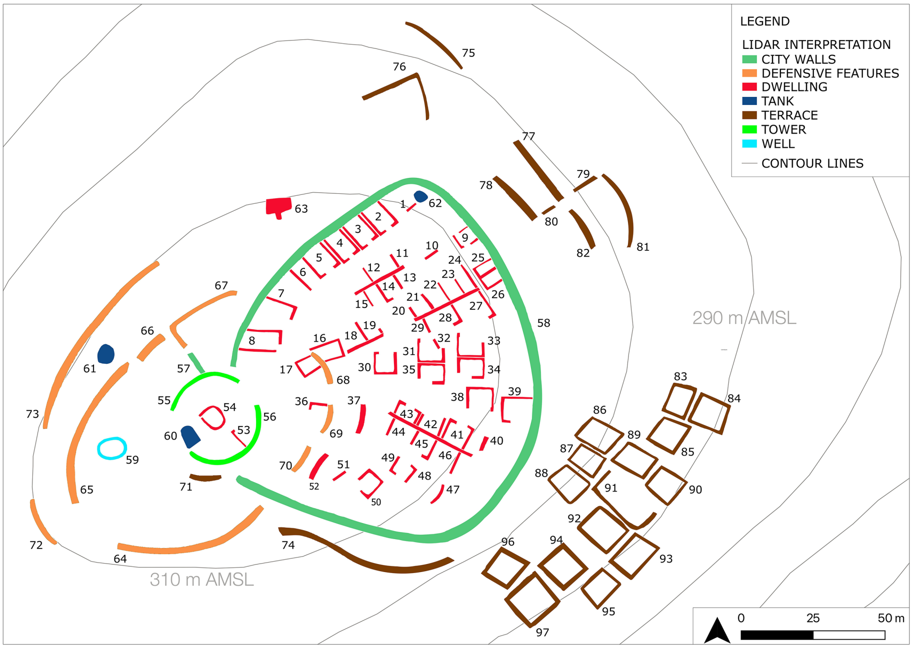

FIGURE 7 | Distribution map of the Moscona settlement, generated by DTM using the Local Dominance method. The map highlights 97 features including building structures, wall fragments, possible cisterns and terraces.

Outside the castle, a series of traces attributable to possible terraces or additional fortification structures have been identified. Feature Nos. 64–73 are likely to depict circular enclosures around the 'Tino' tower, while Feature Nos. 74–82 are likely to be agricultural terraces (Figure 7).

Terraces with an almost quadrangular shape have been identified among Feature Nos. 83–97, located in the southwest part of the hilltop and not far from the fortified settlement. Their dimensions range from a minimum of approximately 7 × 8 m to a maximum of approximately 12 × 10 m. Given their orientation and shape, it is hypothesized that these areas were intended for agricultural production, although currently, there is no direct evidence to support this hypothesis (Figure 7).

5.2 | Rusellae Funerary Landscape

The cemetery presented here has never been analysed through systematic research. The graves are currently not visible from aerial photographs as they are beneath dense vegetation (Figure 8). Therefore, by means of LiDAR data, we can now provide a map of the burials identifiable in the DTM and visualized through the processing obtained with the anisotropic sky-view factor

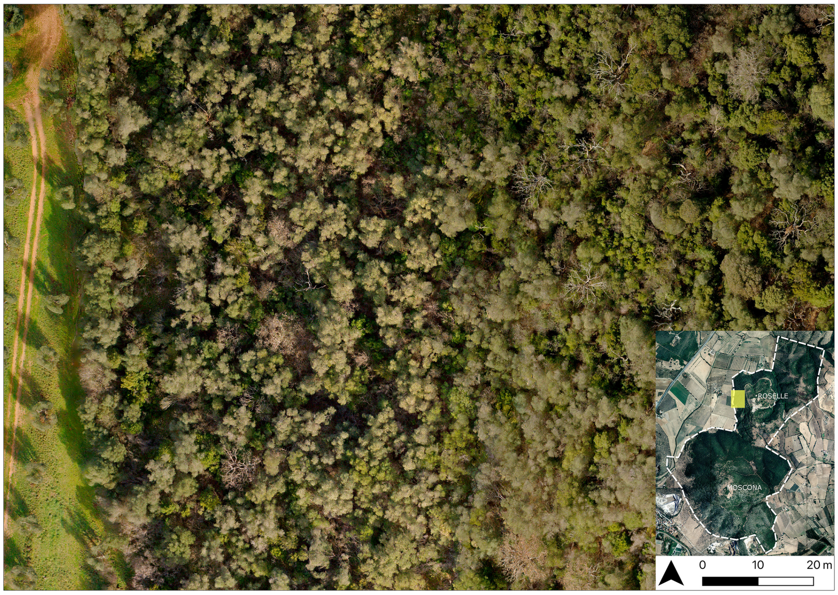

FIGURE 8 | Aerial photograph of the Tuscany region showing the necropolis area. As can be seen from this image, it is impossible to observe the ground due to the high density of woodland vegetation.

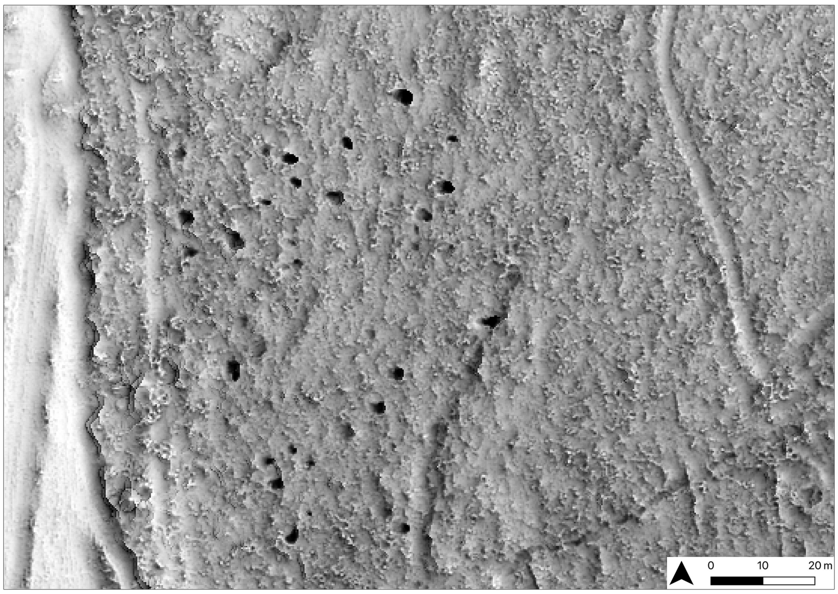

FIGURE 9 | The image displays the results of visualizing the DTM by using sky-view factor. In this case, the tombs are made visible because their interiors are empty.

visualization (Figure 9; Kidd and Chapman 2012; Hesse 2016). Through this analysis, we can identify 51 tombs (Figures 10 and 11). These are scattered over an area of more than half a hectare and are arranged so that the remains of this necropolis can be identified through the hole at the entrance, which creates visible voids in the DTM resulting from processing of LiDAR data.

6 | Discussions and Conclusions

The dataset collected and processed lacked preclassified results or an existing DTM. Among the key challenges faced was the development of tools for effective data segmentation. Several difficulties were encountered, particularly in overcoming dense ML vegetation and accurately classifying high-density ground points. Both challenges were directly related to the dense vegetation cover of the study area. Analysing historical aerial images revealed that extensive deforestation occurred between 2010 and 2013 across almost the entire surface of Moscona hill. This led to a regrowth of even denser vegetation, creating a barrier that was difficult to penetrate through field surveys and posed significant challenges even for high-resolution LiDAR analysis.

The methodology presented here adopted a multiresolution, multilevel approach. The primary goal was to produce a DTM as free as possible from vegetation. At the first level (L1), the neural network is trained to differentiate the ground class from all other elements, which are labelled as 'nonground'. At the second

FIGURE 10 | The pictures show two of the 51 tombs identified during the surface reconnaissance. From the images, it is possible to see how these graves are covered by dense vegetation. The sizes of the entrances vary widely and never exceed 1 × 1 m; however, the context is different for the interior part where spaces excavated in the rock measure up to 3 × 4 m with heights of up to 1.80 m. In all cases, these are single-chamber rock-cut tombs.

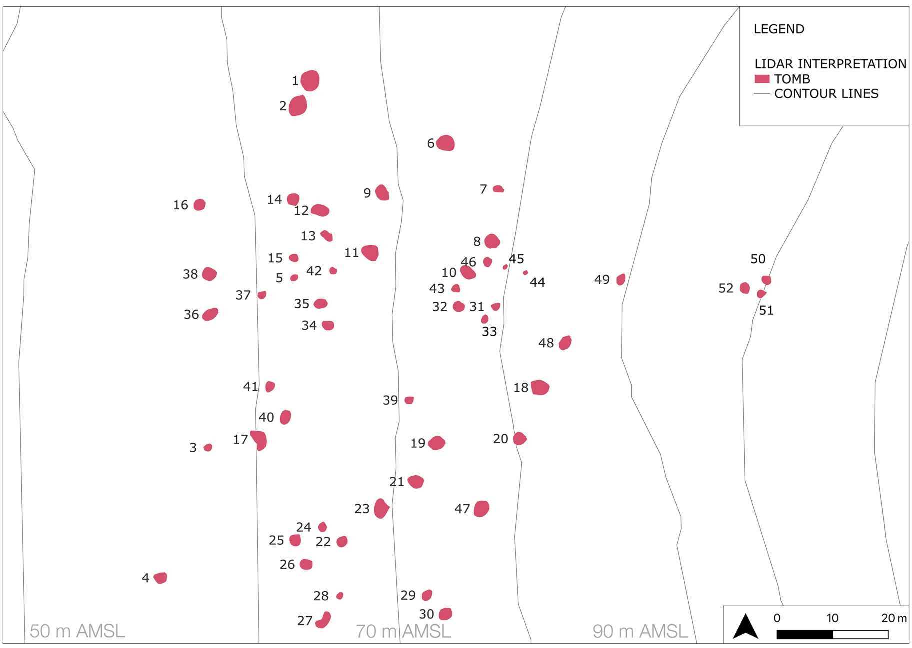

FIGURE 11 | Map of the identified tombs which have been surveyed by filed verification. The mapping, carried out through the analysis of LiDAR images, made it possible to accurately identify the distribution of the burials, clearly distinguishing anomalies in the DTM. Field verifications confirmed the presence of burial structures, improving the understanding of their layout and extent.

level (L2), the nonground point cloud, at a higher resolution, is used to calculate geometric features at very small radii, assisting the model in distinguishing between structures and vegetation. Finally, the third level (L3) focuses on identifying different types of structures (e.g., low walls, architectural complexes and modern buildings), starting from the inferred structure class.

By comparing historical aerial images from 1954 onward, we observed that some archaeological evidence, such as the example of the 'Tino' structure, are easily identifiable. These features are also prominent in LiDAR data due to their significant size and impact on the landscape. Often, such features are located on hilltops where vegetation density is usually lower. This method of identification through aerial photography has long been established in Tuscany (Cosci 2013). Significant challenges remain in identifying smaller archaeological features or those situated along slopes. Furthermore, focusing solely on hillforts and other central place evidence—typically located on hilltops—reinforces a site-based approach that overlooks broader landscape contexts.

Nevertheless, one of the most significant outcomes of this study is that such methodology can effectively support archaeological research in Mediterranean territories (and beyond) covered by dense vegetation, including undergrowth and scrub. The combination of high-resolution LiDAR data collected for archaeological purposes, identifying the optimal time window for data acquisition, processing the data using DL techniques to identify archaeological features, field verification and the collaboration of a multidisciplinary research team allowed us to develop a comprehensive, end-to-end workflow with highly reliable results.

The processing of these LiDAR data has led to the discovery of previously unknown archaeological features, enhancing our understanding of the past. In Case Study 1 (Moscona), the results revealed a more detailed and complex archaeological framework. Despite the challenges posed by dense vegetation, LiDAR processing enabled the identification and mapping of additional settlement features and landscape structures including enclosures, charcoal burner, terraces and previously unknown chronological phases, demonstrating the effectiveness of this technology in overcoming visibility limitations in woodland environments. Similarly, in Case Study 2, the investigation of the necropolis outside the city walls of *Rusellae* revealed previously undocumented monumental barrows scattered across a large area.

The integration of LiDAR technology, drone-based aerial platforms and traditional archaeological methods has proven to be a valuable approach for investigating densely wooded landscapes. However, it is important to note that this research is still in its early stages. Several challenges remain, particularly the high costs associated with drone-based LiDAR equipment, the management and processing of large datasets, the semantic segmentation of scrub and undergrowth vegetation and the development of semiotic tools for identifying and interpreting landscapes and archaeological features.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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