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INTEGRATED AIRBORNE LIDAR-UAV METHODS FOR ARCHAEOLOGICAL MAPPING IN VEGETATION-COVERED AREAS

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KEY WORDS: Airborne Laser Scanner (ALS), morphology analysis, DSM/DEM, supervised automatic classification, multi-scale 3D survey and modelling, Archaeological and landscape heritage,

ABSTRACT:

The research focuses on using 3D digitization in Landscape Heritage conservation processes, specifically in the context of the Spina Verde Park in Como, Italy. The aim of the research is to improve knowledge of the proto-urban archaeological sites of the park and its network of trails, which represent a significant heritage of the area. The study employs low-altitude airborne Light Detection and Ranging (LiDAR) and terrestrial survey methods to obtain high-resolution data, which are structured into a 3D geospatial database in a GIS environment. The integration and harmonization of multisensory 3D data, both airborne and terrestrial originated, and available cartographic datasets, allows for a flexible monitoring tool and supports the interpretation of the archaeological sites and landscape context. The research proposes a methodological approach that has applications in different built and natural heritage contexts and can monitor the conservation status of both archaeological heritage and natural components of the territorial context. The research focuses on testing automated classification algorithms that are useful for identifying and classifying archaeological sites and features within landscapes. By analysing the high-resolution raster generated from the airborne LiDAR point cloud, the research inquiries about the detecting, identifying, and mapping proto-historic archaeological traces efficiently and accurately, leading to better preservation and conservation of built and landscape heritage.

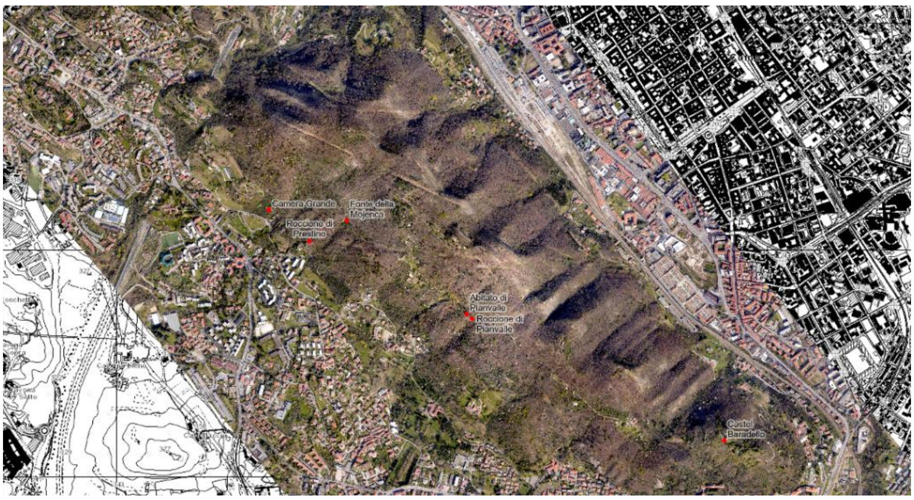

Figure 1. Map view from the GIS database of the park area, showing the high scale and high resolution orthophoto derived from ALS data based on the helicopter flight. Archaeological sites object of terrestrial image and range based 3D survey are highlight.

1.INTRODUCTION

The significance of 3D digitization in Cultural Heritage conservation processes is nowadays becoming more and more relevant. Certainly, preserving the landscape and archaeological heritage increasingly depends on the strategies in place to document, manage and analyse data and foresee possible valorization opportunities. As well as the archaeological sites to which they lead, the hiking trails are particularly important for the landscape context stratification to which they belong, as the ancient settlements and generally any of traces of anthropization. The network of trails within a park or archaeological site or protected areas, such as the one to which this research refers, assumes significance both as a way of access to the site and as a cultural element itself, resulting from multiple stratifications that have evolved during history and representing historical traces of connection between settlements. The location, measurement and 3D mapping of these are therefore not only documenting actions but also a

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support to the knowledge and interpretative action about human evolution in a geographical scale perspective.

In this direction, thanks to the evolution of geospatial science and remote sensing technologies for surveying and automation in data processing, multi-sensor terrestrial and aerial methods are nowadays available in researches and applications for 3D mapping with dense and accurate Digital Elevation Models (DEM).

In this research, the common goal, shared with the scientific community of archaeologists studying archaeological landscapes, is focused to improve knowledge of the proto-urban site of the Spina Verde Park (see par. 1.2). In addition, the park's network of trails represents a significant heritage of the area since it was used in the proto-historic age. Due to the sites' complexity, which cannot always be easily distinguished from the ground context, and the spatial dissemination itself, the research analyses the territorial framework of the proto-settlement system, using airborne and terrestrial LiDAR solutions, together with photogrammetry, to obtain high-resolution data.

The activities were planned at two different times: the LiDAR flight from a helicopter, for monitoring purposes, performed by CNR – IRPI in March for seasonal plant coverage reasons, and the terrestrial and UAV acquisition activities, performed by the team of Politecnico di Torino in the 2022 summer. One of the first aims was to inquire about the area of the park, by analysing the relations among archaeological sites and the environmental morphology, exploiting high-resolution data derived from Airborne Laser Scanner (ALS) and supervised automatic classification methodologies.

1.1 Related works

In recent decades, LiDAR airborne, also identified as Airborne Laser Scanner (ALS), data processing and applications have been widely studied (Maas & Vosselman, 2010; Chen et al., 2017). Related previous research demonstrates the potential of airborne LiDAR and automated classification techniques in archaeological prospection and the importance of considering multiple data sources for identifying archaeological features (Freeland et al., 2016; Guyot et al., 2018; Niculiță, 2020). In this framework, the cited works inquire about the use of 2.5D raster products in order to acquire and analyse data concerning archaeological sites that covers large areas. While this research studies adopt the processing of converted raster from 2.5D to 2D, the most recent trend is moving towards directly analyzing the original data from 3D point clouds acquired through LiDAR sensors equipping aerial vectors. In particular, the aim is to try defining a new standard methodology, that could be largely transferrable, for detecting archaeological features with the aid of Machine Learning (ML) techniques, even if in complex contexts, such as a highly forested environment (Mazzacca et al., 2022). Considering that these approaches are already consolidated for airborne Digital Surface Model (DSM) data, the research is also orienting toward UAV DSM, both from newer LiDAR equipment solutions and photogrammetric DSM (Spanò et al., 2018). Due to high-resolution technologies, it's possible to enhance the built heritage knowledge and simultaneously monitor the morphological and micro-topographic aspects of the territory.

Previous research works also demonstrated the flexibility of a 3D GIS multiscale database, that manages to operate in different built and natural heritage contexts and to monitor the conservation status of vegetation and other natural components of the territorial context, such as water and soil shapes (Mohamed, 2020). In fact, structuring the obtained dataset onto a 3D geospatial database in a GIS environment, where both available geographic datasets and collected data are integrated and continuously updated, allows multiple possibilities not only for data visualisation and archiving, but mainly for geographical data correlation and supporting interpretation. Developing territorial analyses can return products that can be further treated to semantically label entire territory layers (Chen et al., 2016), especially with the help of regional/urban digital cartography and survey data acquired in the field. On the other hand, obtaining an overall multiscale model – resulting from the integration and harmonisation of multisensory 3D data, both airborne and terrestrial originated – allows a flexible monitoring tool, due to the essential multi-temporal nature of geospatial data, as previous acquisitions, historical data, etc. (Rabbia et al, 2020; Brocchini et al., 2017; Gawior et al., 2017).

1.2 Case study: The Spina Verde Park in Como, Italy

The methodological approach above presented has been applied and proposed in this research, in relation to the study framework of the area of Spina Verde Park in Como (Italy) (Figure 1). As briefly mentioned in the introduction, The Spina Verde lies in a hilly high forested area in the southern part of Como Municipality. Throughout the park's territory, there are numerous sites and archaeological traces belonging to a series of widespread proto-historic settlements active during the first millennium b.C. (De Marinis et al., 2001). Moreover, some of the hiking connections within the Park, which are essential for reaching archaeological sites and for the usability of the Park itself, are an active testament to the protohistoric ways that served as connections and communication routes between the various settlements.

Therefore, since the morphology of the research area is characterized by large dimensions, steep slopes, and almost total forest cover, the application of low-altitude airborne LiDAR survey technology, optimally designed, has allowed for the rapid acquisition of homogeneous and widespread data. A series of ground-based surveys were also planned to analyze and monitor individual archaeological areas, to be carried out in a widespread survey campaign. These data, in addition to ensuring a multi-scale approach that increased the scale itself, are essential for a combined valuation approach based comparison between the aerial and terrestrial data.

However, these trails are not always are mapped in the regional geographic dataset, and the proposed methodology wants to move in the direction of exploiting the integrated 3D data to map these morphological elements.

2.METHODOLOGY

2.1 LiDAR airborne survey

In order to obtain a suitable points density of the area for archaeological investigation, an ALS / Photogrammetric flight was planned, in March 2022 using an Eurocopter / Airbus AS350 with Litemapper 6800 LiDAR System (Figure 2) equipped with a RiEGL LMS-Q680ì full waveform laser head, using 400 Khz PRR (Pulse Repetition Rate), with a 70%-50% photogrammetric/LiDAR in over and side lap, according to the flight pattern (Figure 3).

Due to the hilly vegetation coverage, the flight was executed before spring to minimize plant growth. However, the presence of evergreen plants in some areas creates zones of variable point clouds density. For this reason, a photogrammetric flight was planned to acquire images blocks using a 150Mpixel PhaseOne iXM medium format aerial camera (50mm focal length), with a resulting mean Ground Sampling Distance

(GSD) of 4 cm/px. The flight plan was designed to obtain an average raw point density of 40-50 pts/m^2 over the border areas and more than 100 pts/m^2 over the top hilly area where the AGL (Above Ground Level) of the sensor was smaller.

Figure 2. Eurocopter / Airbus AS350 with Litemapper 6800 and particular of EASA certified POD equipped with the LiDAR/Aerophotogrammetric system of CNR-IRPI

Figure 3 Flight Pattern over the Spina Verde Park.

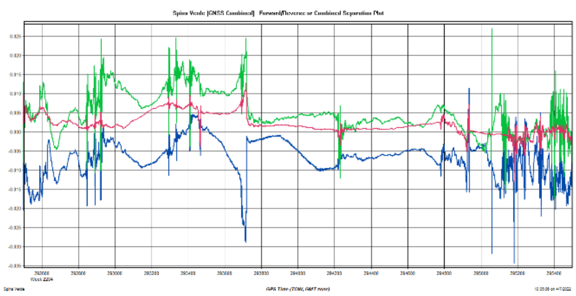

Figure 4. E,N,H combined separation (std.dev) during the flight survey.

Prior to this, a calibration flight composed by 8 cross-flight strips at different AGL over the helipad base was executed to calculate a boresight calibration correction and to issue a camera certification valid for the flight; thanks to 27 Ground Control Points (GCPs) taken with Real-time GNSS positioning technique, marked all around the area. Kinematic trajectory, acquired with a 256 Khz IGI IMU (calibration certificate of 29/09/2021) and a Septentrion GNSS multi-constellation, was adjusted using the close-by COMO CORS Station pertaining to the SPIN3 GNSS Reference Network.
Additionally, two aerial cross-strips, over the investigation site, helped to improve the boresight calibration parameters estimation under the flight conditions over the site.

Final Combined separations in E,N,H of adjusted trajectory over the survey area were estimated with an rms. of +/-2,5cm (datum ETRF2000; ellipsoidal height). (Figure 4)
Moreover, properly distributed GNSS GCPs acquisition is essential for accurate assessment of LiDAR airborne point cloud data, to improve the positional accuracy of the LiDAR data, verify its accuracy, correct systematic errors, and improve the quality of 3D models generated from the data (see par.2.3).

2.2 Terrestrial and UAV 3D metric survey campaign

As mentioned in the previous section, after the ALS data acquisition and the subsequent post-processing, a ground survey campaign has been scheduled.
The fieldwork campaign was organized by the research team with a multi-sensor and multi-scale survey approach (Monego et al., 2019), that was planned and executed aimed at investigating the different micro-topographic situation and at obtaining 3D multiscale documentation of the most significant archaeological and heritage sites, such as the proto-historic settlement of Pianvalle, the Rock Chambers (De Marinis et al., 2001) and the tower of the Castle of Baradello (Figure 5).

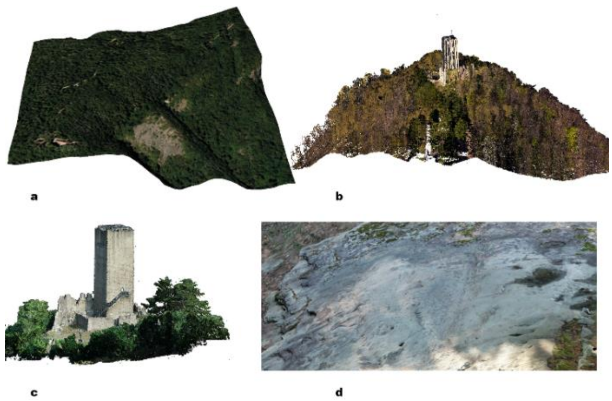

Figure 5. Digital 3D data derived from multi-scale integrated survey campaigns: (a) a sample of aerial LiDAR flight with (b) zoomed view on the Baradello tower and (c) Baradello tower from photogrammetric flight 3D model and (d) the textured LiDAR mesh particular of a carved rock in Pianvalle.

The purpose of the ground survey, in addition to archaeological sites 3D documentation, was to analyze and metrically compare the integrated terrestrial and aerial data, evaluating the 3D reconstruction and ensuring data reliability. Moreover, by integrating and comparing the absolute and relative position of both the terrestrial and aerial measurements, any misalignment or co-registration inaccuracies in the data positioning can be identified and corrected by sensors calibration and vector shift. In addition, by acquiring by terrestrial GNSS RTK measures the position of GCPs, the data can be accurately georeferenced, which is important for spatial analysis.
During May 2022 the terrestrial survey campaign consists in the use of range-and image based approaches, using: two Time of Flight (ToF) TLS from Faro Technologies, a UAV photogrammetric-based surveys, carried out using a DJI Phantom, and finally some of the cart tracks carved on some rocky routes segments, in the remotest areas of the Park have been mapped using a GeoSLAM Mobile Mapping System (MMS). The coordinate of the control network of vertices, to which all the acquired dataset refers, has been determined by the integrated GNSS and traditional topographic methods, as the GCPs measurements distributed on the ares, with a final

adjustment that delivers an overall accuracy of the vertices between 5-10 mm.
In Table 1 main characteristics of the surveys are reported. For the entire Spina Verde area, 27 GCPs were acquired, located at the edges of the hilly zone of the park, with a mean accuracy of 3 cm. This set of points has been used to perform the registration of the airborne LiDAR point cloud.
Both the Pianvalle site, divided into two separate work areas, and the Baradello tower area were documented, integrating terrestrial LiDAR and UAV photogrammetry methodologies. Four different datasets have been collected. As it is possible to observe in Table 1, the accuracies – ranging from 1 to 4 cm – are consistent with the prefixed requirements of the survey.

Methodology		***Spina Verde***	***Baradello***
GNSS GCPs	*instrument*	Leica GS18	
	n° points	27	
	accuracy assessment	avg ≈ 0.03 m	
LiDAR	*instrument*		Faro Focus 330
	n° scans		22
	accuracy assessment		ICP 6 mm target 11 mm
UAV SfM	*instrument*		DJI Phantom 4 Pro RTK
	n° images		631 h 42.5 m
	accuracy assessment		GCP 4.1 cm CP 3.8 cm
Methodology		***Pianvalle*** *Settlement area*	*Rock area*
LiDAR	*instrument*	Faro Focus 120	Faro Focus 120
	n° scans	11	13
	accuracy assessment	ICP 8 mm / TB 10 mm	ICP 5 mm target 10 mm
UAV SfM	*instrument*		DJI Matrice 210 V2
	n° images		73 h 5.5 m
	accuracy assessment		GCP 2.1 cm CP 3.3 cm

Table 1. Resume table of the collected data and the post-processing accuracy assessment.

2.3 Data analysis and comparison

As mentioned, in order to perform the comparison check, combining aerial and terrestrial datasets, a ground survey campaign has been planned, to be carried out after the flight, both to acquire 3D metric data to compare with the Airborn Laser Scanner (ALS) point cloud, and to acquire the position of GCP for georeferencing and data validation. Overall, the ground survey campaign is an important step in comparing and ensuring reliability of the data collected during the flight, providing higher scale valuable information for subsequent analysis and interpretation about the archaeological heritage. The ground GNSS real-time campaign composed of 27 GCP, an aerial UAV photogrammetry flight, was executed to integrate the multi-scale documentation and punctually compare and analyze the LiDAR aerial campaign, estimating a best-fitting rubber-sheet algorithm, and investigate with more resolution some of the archaeological sites that have been involved in the terrestrial survey activities. The following step of the research consisted in comparing directly the airborne 3D point cloud data with those collected during the on-field campaign.

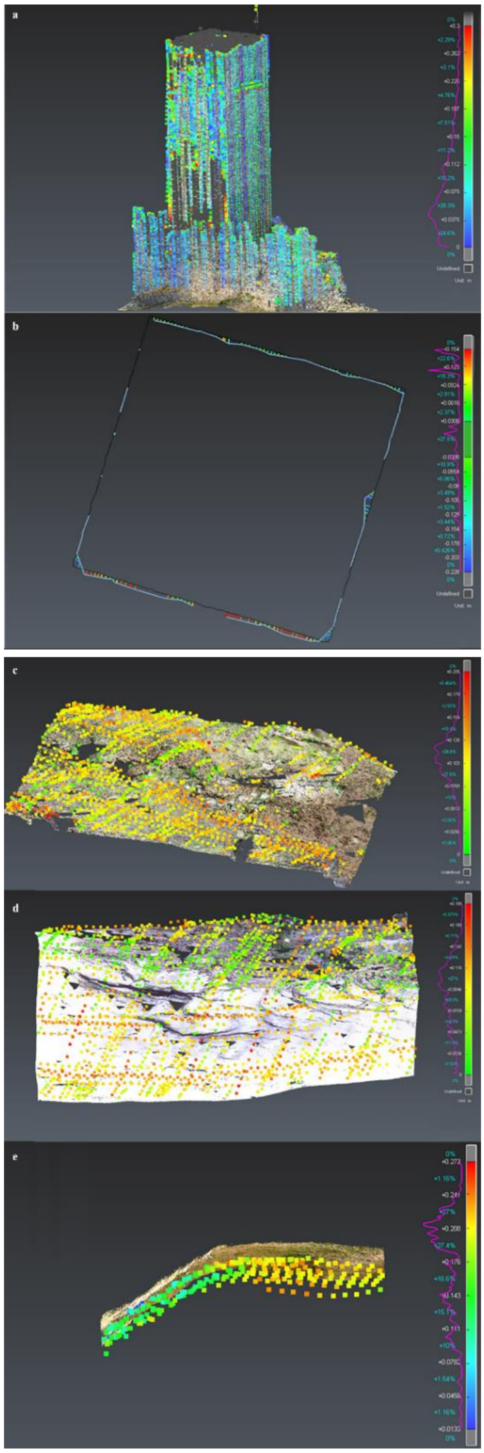

Figure 6. Examples of data comparison between close-range data as *ground truth* in RGB and aerial LiDAR in scalar colour. Baradello site (a) and (b) section of the two dataset. Pianvalle sites, comparison between terrestrial and aerial LiDAR: (a) great rock area and (d) settlement area. Baradello site, (e) comparison between terrestrial and airborne LiDAR

Two different areas were chosen as comparison samples: the Pianvalle site, which is located at the foot of the hill, and the tower of Baradello, which is one of the highest points of the area. The comparison of ALS ground class data and the segmented terrestrial TLS and UAV clouds (Figure 6c-d) demonstrates in the first step of ALS processing an altimetric shift between the data acquired in the field and the airborne ones that underline an co-registration shift between 5 cm and 20 cm, with lower error at the lower altitudes, where most of the GCP was positioned. Moreover, comparing the terrestrial LiDAR point cloud of the Baradello site with the building class of the airborne point cloud, demonstrate a lower overall deviation that varies between 3 cm and 10 cm.

3.DEM GENERATION, ANALYSIS, CLASSIFICATION

3.1 Aerial LiDAR point cloud processing and classification

To approach the analysis of the data, the crucial first step was to operate a preliminary filtering of the point cloud, so as to be able to quickly generate DEM of ground data. The entire raw airborne LiDAR and stereoscopic images dataset was processed using the TERRASOLID package suite on Microstation environment. LiDAR dataset was filtered and classified using a geometric and echo-based macro classification routine to obtain a first ground preliminary surface (DTM) and a secondary overground class. These first classes were useful to check the consistency of *ground*, helping to recognize that other classes (like trees, bushes or buildings) were correctly excluded from the first ground surface.
Upon the first DTM ground being validated, a secondary vegetation class (low/medium/high trees classes and building) was extracted using a height and shape-based algorithm.
At this step, normally, lots of points not yet classified but pertaining to the ground class are excluded because they don’t improve the reconstruction of terrain (for normal use) and they are more time-expensive for calculation. Moreover, they are also the first error source for DTM detection especially when they are close to a slope change or near a complex chain like a tree or building. Thanks to a complex check made by the operator, was so possible to manually change (with a second consistency validation) to manually assign all remaining point to a final DTM class. This tip allowed to maximize the overall point cloud assigned to the ground class; very useful to search trails and man-made shapes in a heavily forested environment with lots of slope changes. After the first classification operation, the entire dataset was divided into 67 tiles of 500x500m, choosing for the work sample 5 tiles (Figure 8), corresponding to the area related to the terrestrial 3D metric survey campaign applied to the archaeological sites. The statistical information, such as point count, the average distance between points, and minimum and maximum elevation, were calculated as well in order to verify the consistency of the final dataset, resulting in an average point distance for the class ground of 20 cm (Table 2).

ID	FileName	Class	Pt_Count	Pt_Spacing	Z_Min	Z_Max
1	*pt000021.las*	2	8130434	**0.175**	325.11	513.81
2	*pt000023.las*	2	4793430	**0.228**	364.24	535.97
3	*pt000032.las*	2	7328882	**0.185**	307.27	514.23
4	*pt000020.las*	2	4176807	**0.245**	345.77	426.57
5	*pt000034.las*	2	6058295	**0.203**	341.4	545.59

Table 2. Statistical information of the 5 work sample tiles of the “ground”, as class (2)

To achieve an organized structure of the dataset in the GIS environment and also being able to obtain a manageable GeoDatabase (GDB) for the analysis operations, the original tiles were subsampled. The 5 given tiles were subdivided into 125 100x100 m sub tiles, to easily generate DEM products.

The DTM has been generated by triangulating temporarily the point cloud into a triangulated irregular surface (TIN) and then rasterizing the TIN into a DEM; the same process has been batched for every single tile, merging them afterward in order to manage efficiently the dataset.

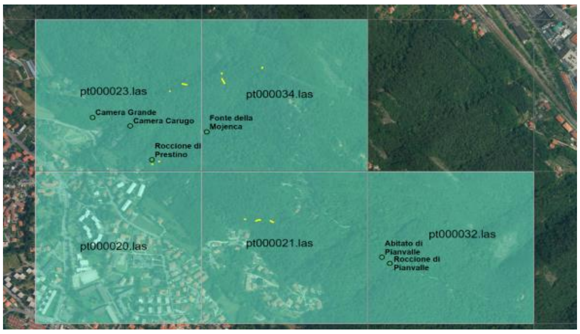

Figure 7. The 5 work sample 500x500m tiles.

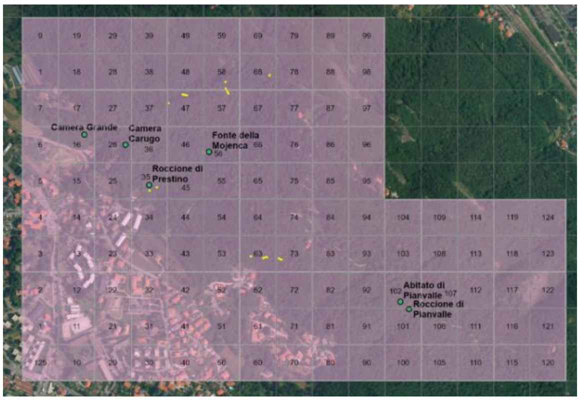

Figure 8. The sub-sampled tiles, with indication of the surveyed areas of interest.

3.2 Geomorphologic analysis

It should be noted that when using an Airborn Laser Scanner (ALS) technique to investigate archeological highly forested areas, also features such as trails, standing stones, walls, roads, canals, earthworks, and similar features must be reflected in the final DTM. Precisely for this reason, it was clear from the beginning how the traces of the current trails, which could partially correspond to the proto-historic ways, were not immediately visible and recognizable in the 2.5D produced from ALS point cloud and further raster interpolation from the DTM. In addition, 11 areas of reduced extension (20 m by 20 m) were extracted and selected for photo interpretation of orthoimages and point cloud analysis. As long as the average spacing through the ground class points was 20 cm, a DTM was calculated with a 20 cm pixel dimension corresponding to the initial data density. Starting from the 11 micro-sample, morphological analyses of DTM have been tested and combined as (Figure 9): intensity-based hillshade visualization; b slope direction; aspect calculation; roughness statistical calculation; combined aspect and slope direction; flow direction.
In particular, the calculation of the roughness statistic, was crucial in the intention to determine the distinction between concrete driveways and the raw earth trails inside the park area.
The roughness of the surface of the terrain has been quantified by calculating or the normalized topographic position index (NTI), which is based on the difference between the mean and minimum of the flow accumulation and the maximum and minimum of the flow accumulation both of the DTM. The focal statistics calculations were based on the distance search radius of 5 pixels (1m) in order to apply the more tailored method to search for raw

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earth trails in a heavily sloped area. That was, in fact, to develop a strategy for trail detection thanks to the analysis of the soil morphology in different contexts, depending on the level of tree cover and slope of the land.

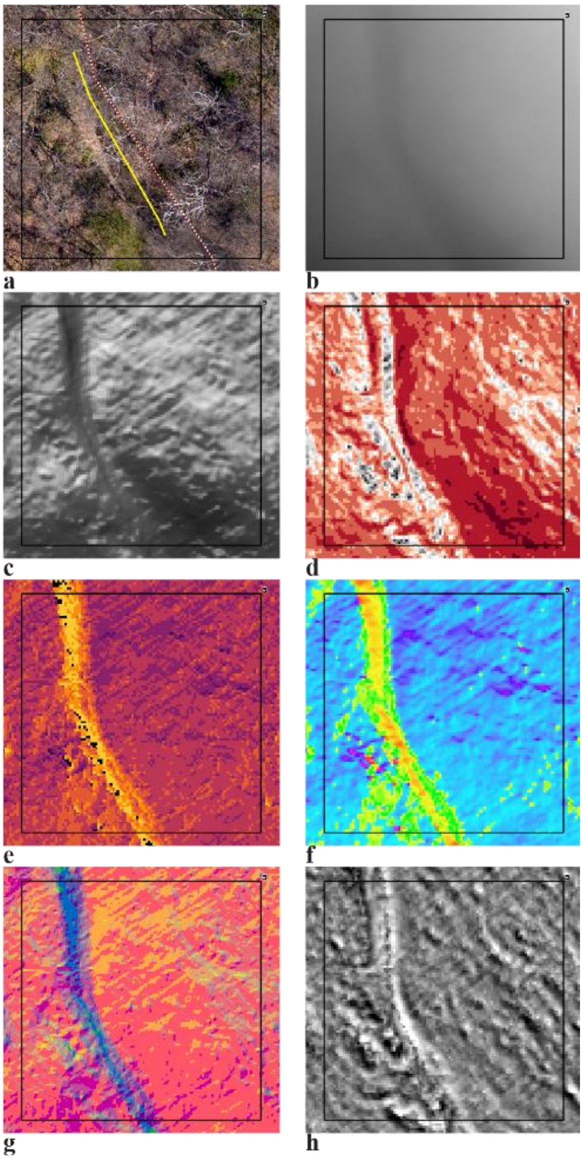

Figure 9. Examples of morphological analysis performed on one of the samples, showing a trail with traces from an ancient cart: orthoimage (a) and LiDAR DTM interpolation (b). Hillshade visualization of DSM and a trail area (c), slope (d), aspect direction (e), simultaneous aspect direction and steepness (f), flow direction (g), roughness statistic (h).

In fact, starting from a so-treated ground surface and thanks to a high dense point per square resolution, different shaded surfaces using visual enhancements (like true or relative slope gradient visualizations) are very useful to recognize immediately smooth ways typically traceable to human-made trails. That is also true if they are in part or completely covered by vegetation. They are in fact characterized by blocks with a constant slope following natural neighborough of hills, or represented by breaklines made by human activities to sweeten too high values gradients.
In addition to the just mentioned morphological analysis, two further elaborations were useful to define strategies adoption for the application of supervised automatic classification pipelines from visualization techniques (VTs) methodology (Mazzacca et al., 2022). A false color gradient shade surface (Figure 10), orientated by a magnetic direction, helps to divide hills or mountain peaks into two subdomains: two opposite color palettes, defines orientations and direction of hill gradients, allowing one to understand just a glance, if the trail follows down or up, locally, the morphology of the area. In fact, a shaded surface with a grey gradient in 256, or more color palette definitions, is very useful to recognize a human pattern but does not give any information about the relative altimetry of the track.

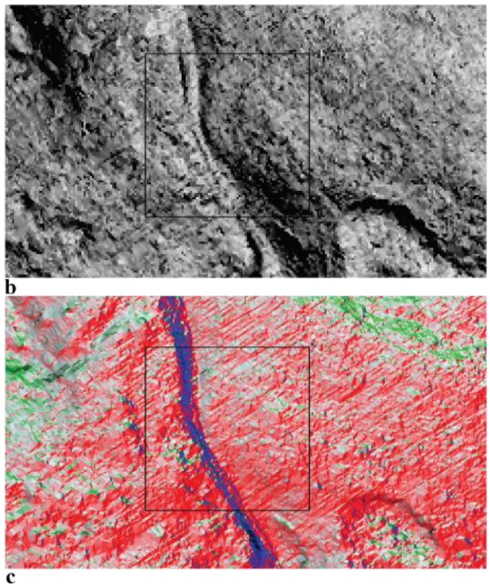

Figure 10. Single (a) and false color gradient (b) shade surface magnetic north oriented

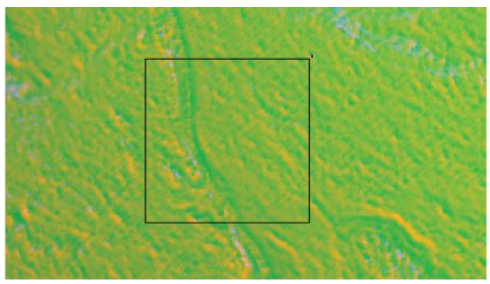

Figure 11. Composite band rasters: Red band Roughness-Green band Flow Direction-Blue band Slope.

Finally, fixing the method to generate a valid mixed multiband shade composition made by the DTM, the aspect relative direction steepness, the hillshade visualization, the roughness statistics, and the flow direction return a multiband raster RGB for better visualization in the GIS environment (Figure 10).
Beyond allowing a more visual-attractive appearance processed image, that keeps also altimetric information immediately evident , various composite raster can be analyzed using supervised automatic classification techniques, querying at the same time both the geometric details of the pixel composition and all the bands simultaneously.

3.3 Visualization techniques (VTs) and ML for supervised automated classification

The classification process began with a preliminary attempt to perform classification directly within the geodatabase, using ESRI's enterprise functionality and fine-tuning procedures on existing Deep Learning-trained networks for pixel-based land use classification. An attempt was made to create a multi-class

definition file that included urban features, but given the scarcity of data, it was not possible to obtain a validation distinguishable from an accuracy parameter.
In an attempt to overcome this obstacle, efforts were made to focus on reduced areas, with a minimal number of classes, in order to try to distinguish between the bare ground and trails. Two different classification strategies (Figure 11) were adopted for studying the method and applying on the samples (Figure 12), first according to the method based on pixels and then based on an object. While the conventional pixel-based approach involves determining the class of each pixel independently without considering any information from adjacent pixels, the object-based approach utilizes segmentation to group neighboring pixels together based on their similarity in color and shape. With the integration of structured geographic datasets in the GDB environment and averaging pixel values, this approach generates objects that closely resemble real-world features in the image and produces more precise classification results.

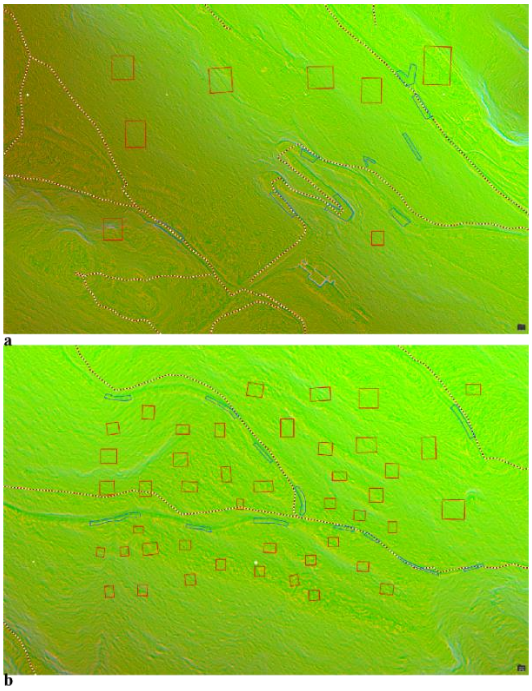

Figure 12. Examples of a two-class definition model labels for the two different areas (a, b): bare earth/generic terrain (red) and raw earth trails (blue).

	Area 1 (a)		Area 2 (b)	
	% m²/total	*m² average*	*% m²/total*	*m²average*
Trail class	15.67%	21.89	26.27%	87.92
Terrain class	84.33%	32.11	73.73%	277.54

Table 3. Summary of the average and percentage of labelled polygons area in each sample site.

4.DISCUSSION

The pieces of evidence in Figure 13 represent the result of applying object-based and pixel-based classifications in two different areas selected as samples. From this preliminary analysis and class-assigned dataset, it's clear that a combination of the different visualizations and products of the ALS point cloud DTM can be helpful to boost the semi-automatic recognition of the trails of the Park. Many stretches of the investigated trails have a rocky bottom and, moreover, cart tracks carved into the rock have been observed in several sectors. This means that most likely many of the trails that today constitute the possible access to the archaeological areas of the park, or more generally run through this naturalistic area with public access and for public recreation and enjoyment, are certainly characterized by an ancient attendance.

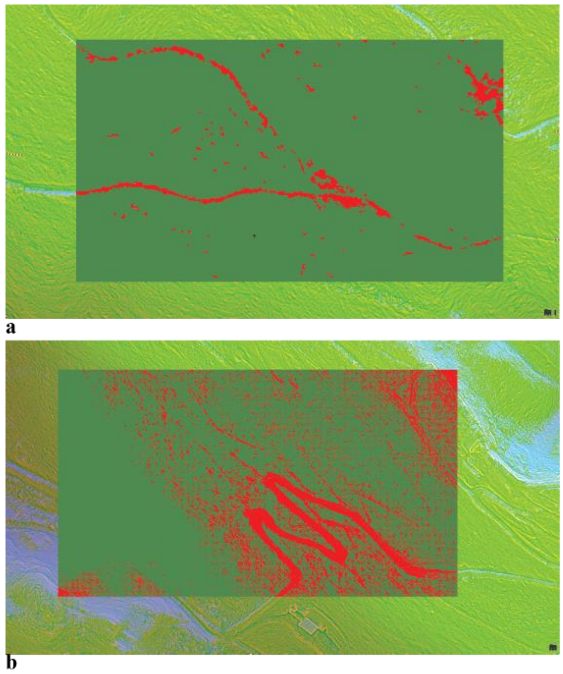

Figure 13. Resulting rasters of the two different areas from the Machine Learning algorithms applied to the composite band raster from Figure 11a. Object based classification (a) and pixel based classification (b).

Being able to count on a reliable framework of the trails network, prefigured this research, in the future can be compared with the distribution of archaeological sites and the simple discoveries of ancient objects of which the park area is very rich. That may mean being able to allow an archaeological reading of the settlement that is richer in information than was possible before this work. To recap we can say:

- the semi-automatic analysis of the DTM from ASL data and obviously their ascertained reliability, allows overcoming the criticality of the difficult survey of the paths on the ground, given the dense and often permanent trees cover along the course of the seasons which characterizes the park.
- In fact, the comparison between the new orthophoto, the results of the DTM analysis from the ASL, and the datasets available from ground mapping indicates that the best result from the point of view of the georeferencing of the trials is the one provided by the ASL data
- the large-scale DTM obtained, which significantly improves the micro-topographic knowledge of the park area, can allow archaeological research in the future to be able to count on an overall framework and where data of interest are found, they can inform in-depth investigations on the ground, solving the critical issue of georeferencing terrestrial data. This investigation approach can help to knowledge enrichment of the park site and locate shapes and geometries attributable to anthropic activities over the area, as the research applied to the trails demonstrated.

4.1 Future perspectives

As observed in the previous sections, the results obtained from using the airborne LiDAR data for supervised automatic classification are characterised by a significant potential. This is true not only for the case highlighted here, but also for different applications involving digital surface models. Nowadays, different consolidated enterprise solutions are currently used for classification of aerial point clouds. However, many of these solutions may lead to data loss in terrain extraction, especially where the studied features (e.g., sites characterised by low vertical development) can be interpreted as terrain or natural features due to a lack of continuity between adjacent elements. In these cases, the use of customized algorithm represents a significant opportunity to solve this crucial problem. In fact, a custom point cloud classification algorithm – tailored to steeply-sloped and forested archaeological sites – should be firstly developed, in that areas where remains may not be clearly defined. ML algorithms can be trained to analyze LiDAR data and identify key characteristics of the terrain and vegetation, leading to more accurate classification results. Another perspective for exploration is represented by the use of deep learning for neural network training. By using the entire dataset to train the network, with fine-tuning solutions applied as necessary, it may be possible to identify subtle features from archaeological sites, and morphology features such as topography, trails, and geological formations, that may not be apparent to the human eye. Moreover, it will be crucial to validate the studied methodology through testing on additional case studies. This will ensure robustness of the approach and valid across different archaeological sites with varying conditions.

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