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Clearence cairnfields forever: combining AI and LiDAR data in the Marcesina upland (northern Italy)

1. Introduction

The ‘Piana di Marcesina’ is a vast upland located in the north-eastern side of the Asiago Plateau (Vicenza province, Italy) at an average altitude of 1350 meters above sea level, best known for being one of the widest (approximately 15 km^2) and more spectacular pastures of the whole pre-alpine Veneto region (fig. 1). Cairnfields are the major landmark of the area: they are constituted by groups of variously sized, un-cut rock piles, intentionally created by human workforce. Such structures can be made up of a few or hundreds of stones, individually with a dimension suitable to be moved by one or two people. Cairns are typical elements of the contemporary Alpine environment, but they can also be observed in multiple geographical and chronological settings, each characterized by culturally-specific functions which include, e.g. a connection to grazing and agricultural activities, their employ as funerary monuments, or as markers of ritual sites (Leech, Quartermaine 2012). Occurrences of stacked loose stones and cairns are indeed well known in global ethnohistorical and archaeological accounts e.g. in Alaska, Scandinavia, or Wales, with a dating from the Bronze Age to modern times (Hunt *et al.* 2016; Ward 1989; Widgren 2010).

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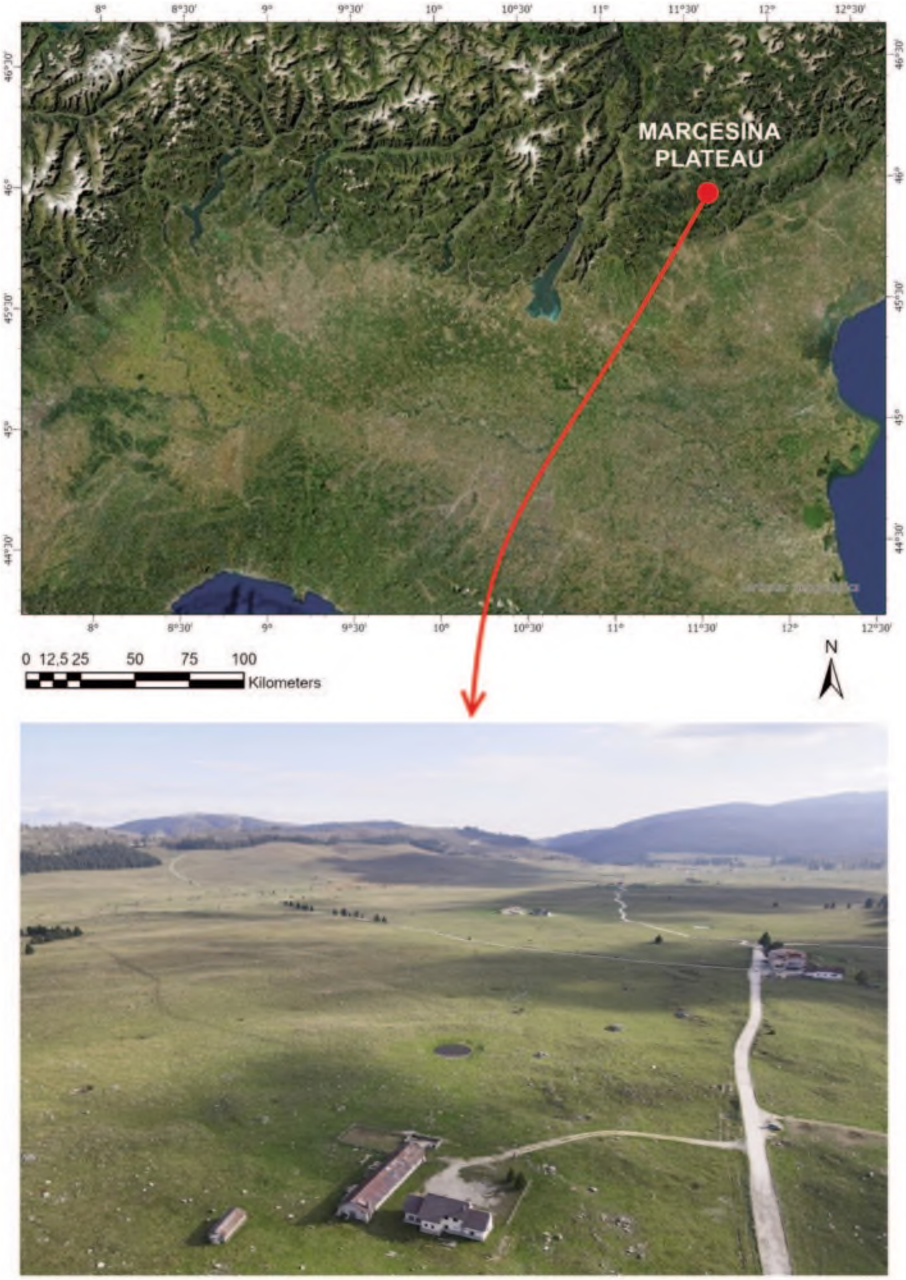

Fig. 1. Localization of the Marcesina plateau in the framework of northern Italy (top) and drone-derived aerial view of the area (bottom).

In Italy, despite a few sporadic attempts (Paltineri 2002; Montanari, Guido 2013; Montanari, Stagno 2015), these structures are still mostly neglected by the mainstream academia. However, they possess a tremendous potential for cultivation history because cairns generally constitute one of the very first man-made interventions during the opening of a landscape for agriculture or grazing, together with slash-and-burn, tree roots eradication resulting in a *trous-monticule* morphology (De Guio *et al.* 2013), and the construction of land divisions (also known as reaves, *sensu* Fleming 2008), and terraces. Cairnfields can also occur in equally important phases of agricultural/ farming/ economic expansion of marginal mountainous areas or in contexts of post-abandonment reopening, as it is the case of many medieval and modern examples. In addition, the fossil soil sealed by cairns is a precious container of paleo-ecological evidence, often easily datable due to the frequent occurrence of charcoal (Overland, Hjelle 2013).

Mapping cairns and cairnfields is thus a crucial task for contemporary archaeologists, due to their intrinsic historical and archaeological relevance. As recently highlighted, the peculiar, elevated morphology of cairns and cairns-like structures makes them particularly suitable for manual identification or automatic classification through LiDAR visualization techniques and AI (Roiha, Heinaro, Holopainen 2021; Küçükdemirci *et al.* 2021), which rank among the forefront research lines of current remote sensing and landscape archaeology (Magnini, Bettineschi 2019; D. Davis 2021; Verhagen 2012).

In this paper, we will present the first attempt to automate the recognition of Alpine cairns by combining a dedicated pre-processing protocol with rule-based AI classification and object-based image analysis (OBIA). The results will hopefully constitute a crucial prerequisite to monitor and protect the fossil landscape in our target area, but also a fundamental step for efficiently planning excavation interventions and promoting further in-depth botanical and radiocarbon analyses in view of the chrono-cultural characterization of the local cairnfields.

2. Materials and methods

2.1. The archaeological context

The present morphology of the Marcesina area is the result of a long-term evolution of an original paleo-valley modelled by last glacial (Würm) and post-glacial geomorphic processes (Pellegrini, Sauro 1994). The environmental and biological richness, including flora, fauna, peat bogs, and water-fed formations induced by ephemeral karstic springs, has gained a special European protection status.

An anthropogenic impact is attested since Paleolithic times (Bassetti, Dalmeri 2000), starting with rare mousterian lithics and continuing with more widespread

Upper Palaeolithic and Mesolithic seasonal settlements. The most internationally renowned site is the Riparo Dalmeri (Epigravettian phase, ca. 16,000-12,000 cal. BP), which preserves an extraordinary fossil surface very rich in eco-factual and (infra)structural evidence, and an exceptional instance of Paleolithic painted art on pebbles in a ritual layout (Cristiani, Lemorini, Dalmeri 2012; Dalmeri *et al.* 2009). Surprisingly, distinct sources of paleo-ecological record (especially carpological/ palynological, and micro-faunal), converge to suggest for the post-glacial Allerød climatic oscillation an environment similar to the present, when a long-term human-induced deforestation accounts for a comparable opening of the landscape, with a native prairie constellated by small pine woods and few *Thermophylous* broadleafs of mixed oaks.

Furthermore, Marcesina preserves traces of the World War I, including two former military cemeteries (Italian and Austro-Hungarian) that used to host the remains of over two thousand soldiers and limited trenching systems on the slopes surrounding the plateau. The area is now entirely devoted to seasonal pasture with a diffuse presence of dairy farms (in Italian 'malghe') and an even more frequent occurrence of traditional *blockbau* buildings (both abandoned – in varying states of preservation – and re-activated as ephemeral touristic residences) that used to host generations of woodcutters.

The cairns of Marcesina are characterized by variable shape, size, spatial settings – from random, to linear, to cluster –, and different preservation state including occurrences which are fully buried, others covered in mixed vegetation, or in open-air (fig. 2). Their relative and absolute age is hard to determine without

Fig. 2. Detail of one of the biggest cairns of Marcesina during the ground survey of April 2021.

further investigations, but they most likely belong to multiple chronological phases as suggested by their diverse typologies and spatial distribution patterns.

Looking at the historical trajectory of the Marcesina plateau, the significance of its cairnscape is further increased by the liminal nature if its location. In fact, Marcesina has long represented a highly contentious ecotonal band between a prealpine and a proper Alpine region, with distinct ethnic, linguistic, cultural, and political traditions.

On the base of cumulated sources of evidence coming from strictly comparable, but better known nearby areas, we expect three major phases of landscape opening that correspond to: a) the colonization of the mountains for pastoral, agricultural, and metallurgical activities from the Middle to the Final Bronze Age, approx. 15th-11th century BC (Addis *et al.* 2016; Pearce 2016); b) the arrival of the Cimbrians, i.e. an allochthonous, German-speaking population in 12th-14th century AD (Bortolami, Barbierato 2009); c) a recent climax of mountain deforestation dated to the 18th-19th century AD. Particularly, we can rely on a detailed archival history of boundary conflicts and conciliations mainly related to grazing rights starting from the 16th century and culminating with the final land division devised by the Austrian Empire and the Republic of Venice in the year 1752 (Cacciavillani 2000).

2.2. Data source and preprocessing

Earth observation data constitute crucial sources of information in multiple archaeological fields and their value is now widely recognized in the scientific literature (Chen, Lasaponara, Masini 2017; Magnini *et al.* 2019; Risbøl, Gustavsen 2018; Campana 2017). Considering the expert knowledge derived from previous research on cairns – including their average elevation, diameter, the chromatic and textural differences with respect to the surrounding grassland – for this case study we employed a combination of aerial orthoimages and LiDAR data.

The 2007 orthoimages by the Veneto Region (ReVen) are freely available on the local Geoportal; they have 3-bands (RGB) and a pixel resolution of 0.5 meters. LiDAR data were acquired by the private company Etra in 2013 with a ground resolution of 1 meter per pixel and were offered as Digital Terrain Models (DTMs) and Digital Surface Models (DSMs); the point cloud is not freely downloadable for further, alternative processing. Since the DTM was subject to an aggressive filtering that eliminated our target cairn-features, we employed a normalized Digital Surface Model (nDSM). nDSM is considered particularly useful for building extraction and had a massive role in remotely sensed urban planning; this difference image results from the algebraic subtraction DSM-DTM to obtain the absolute height of structures and trees in the study area (Cal 2020; Kodors 2019; Aval *et al.* 2019).

DSM data were also processed with Positive and Negative Openness (Yokoyama, Sirasawa, Pike 2002; Doneus 2013) using RVT - Relief Visualization Toolbox (Kokalj, Hesse 2017; Kokalj, Somrak 2019). Openness estimates the mean horizon elevation angle within a definite search radius: the Positive Openness (PO) takes into account the zenith angle of all estimated horizons; instead, the Negative Openness (NO) considers their nadirs. In short, PO emphasizes convexities (rims, ridges, etc.), while the NO tends to highlight the lower section of concavities (Sevara *et al.* 2016). As for the computation settings, we conformed to what is generally suggested in the previous literature for flat surfaces, employing a radius of 10 pixels and 16 search directions.

2.3. Methodological framework: ArchaeOBIA and rule-based classification

Within the agenda of computer-aided image analysis of earth observation data for archaeology, object-based image analysis (OBIA) has gained significant recognition over the last decade, for its potential to overcome some of the major weaknesses associated with the per pixel approach, that ignores geometric, textural, and contextual information, and hierarchical properties (Blaschke 2010; Blaschke *et al.* 2016; D.S. Davis 2019; Magnini, Bettineschi, De Guio 2017).

OBIA – also known as GeOBIA with a geographic connotation (Blaschke *et al.* 2014) and ArchaeOBIA, with an archaeological focus (Magnini, Bettineschi 2019; 2021) – builds on classic object/ pattern/ scenery recognition applications, including edge-detection, feature extraction, and classification. Unlike its predecessors, however, OBIA starts from defining coherent image segments (the so-called image-objects), which constitute the basis for further classifications. This first step, i.e. segmentation, can be achieved through different algorithms, the most relevant being the multiresolution segmentation or MRS (Benz *et al.* 2004; Munyati 2018). MRS is a region-growing method that starts from random generator pixel called seeds. Seeds increase in dimension by incorporating neighboring pixels up to a critical heterogeneity threshold defined by the user, thus generating multiple, non-overlapping image-objects of assorted shapes and dimensions.

Classification is then implemented in the form of a rule-based system built starting from the empirical and theoretical knowledge of the archaeologists. This symbolic AI paradigm, born in the mid-1960s, relies on the idea that intelligent systems should focus on well-defined areas of applications, instead of trying to solve general problems (Franklin 2014). For this reason, the AI needs to be fully equipped with the *a priori* knowledge of the human expert in relevant research fields, that is followingly stored into the knowledge base of the system. In expert systems, knowledge is usually formalized as a set of rules that take the form of if-then statements (e.g. "if the area of the image-object is higher than 30 m^2, then include it in the class *cairn*"). This approach can be essentially based on two reasoning strategies: progressive and regressive deduction, both particularly useful to classify or declassify specific image-objects according to their spectral, textural, morphometric, and relational characteristics using well-defined algorithms and object-features (Hay, Castilla 2006).

For this case study, we employed the commercial software package eCognition Developer 10.2, which is widely adopted across the scientific community for OBIA investigations (Inomata *et al.* 2017; Magnini *et al.* 2022; Sevara *et al.* 2016; Verhagen, Drăguţ 2012).

3. Results and discussion

3.1. Segmentation and classification

Within the Marcesina upland, approximately half of the area (ca. 7 km^2) is covered by arboreal vegetation in aerial and satellite imagery. Following the disastrous Vaia storm that impacted the area in October 2018, the forest cover was partially reduced (fig. 3) and several segments of the plain still appear to be unexplorable due to the presence of fallen trees and mechanical vehicles for clearing the area (Vaglio Laurin *et al.* 2021). In the remaining 8 km^2, only part of the pasture is marked by cairnfields. A large portion of the stones removed was also used in the construction of reaves (fig. 4). For these reasons, the selected study area covers the central and southern side of the plain for a total of 4.5 km^2. Within this framework, we selected a small test area (from here on Area 1) of approximately 5 hectares as a training set for the model (fig. 5). It should be noted that Area 1 contains numerous abandoned pastoral structures and fragments of boundary walls which can occasionally become equivocal with our target cairn-features, thus posing a further challenge for automatic image classification and AI (for and in-depth discussion on the role of equifinality and multifinality in archaeological RS and AI see Magnini, Bettineschi 2019).

The first step in object-based image analysis is segmentation. Despite this step can be theoretically

Fig. 3. Damage caused by the Vaia storm.

Fig. 4. Drone-derived aerial view of the Marcesina plateau showing a land division in dry stones, two mountain pools, and a cairnfield in the background.

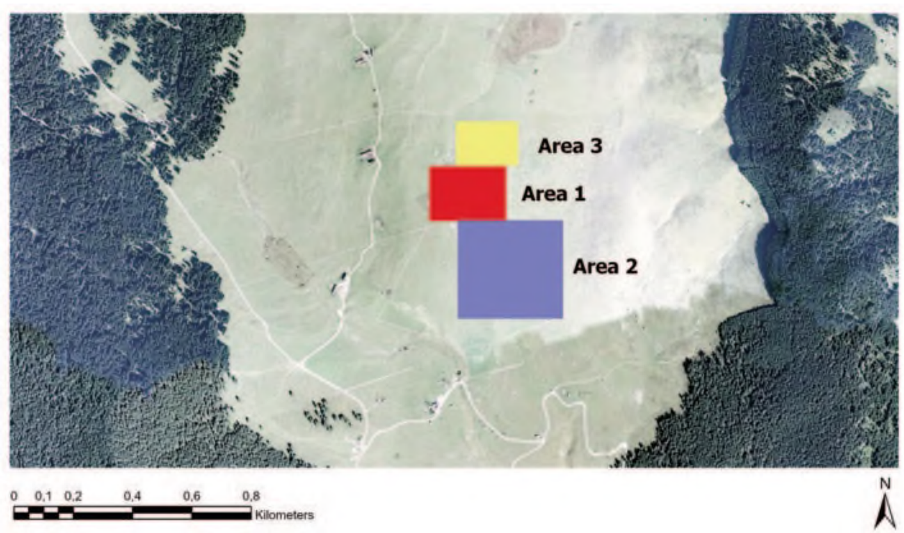

Fig. 5. Orthoimage of the area of investigation, highlighting the training area (Area 1) and the two assessment areas (Area 2 and Area 3).

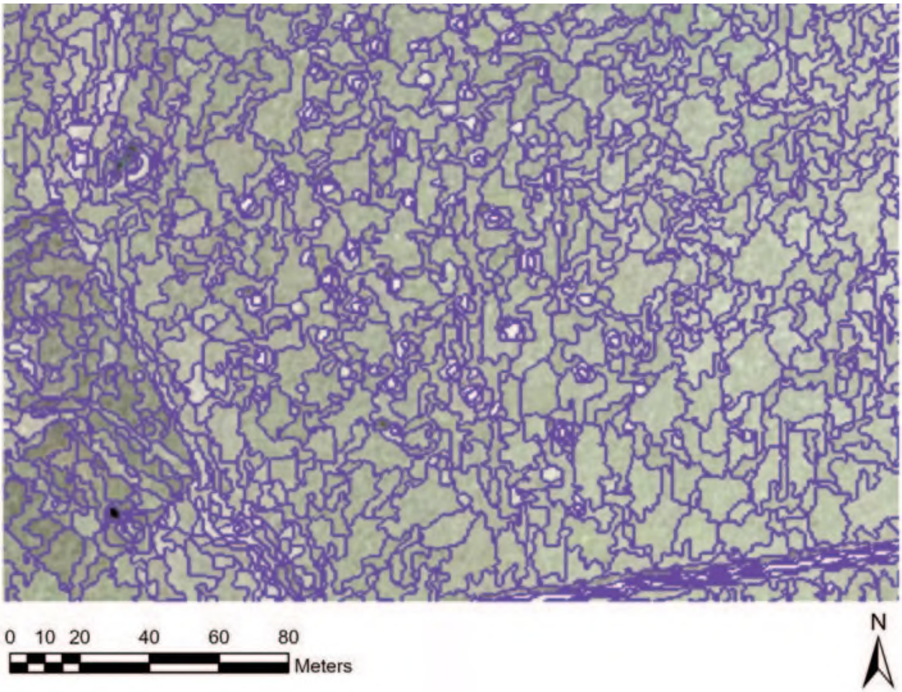

Fig. 6. Multiresolution segmentation of Area 1 over ReVen orthophoto.

repeated as many times as needed, we opted for one segmentation cycle using the multiresolution algorithm, employing a low scale parameter (15) and giving the same weight to all layers. Practically, a low scale parameter creates very small image objects, which are required to univocally circumscribe single cairns (fig. 6). This phase resulted in a very detailed delineation of our target features, that was undoubtedly facilitated by the presence of the nDSM among the considered layers. nDSM is indeed particularly helpful for highlighting elevated structures and is very effective in flat areas such as the Marcesina plateau. However, the presence of buildings, infrastructural remains, and arboreal vegetation would hamper the automatic recognition of the cairns on the nDSM alone. The multi-resolution protocol employed, which combines morphological with optical data (cf. section 2.2), guarantees an increased discriminatory potential, and improves the efficacy of knowledge-based object/ pattern/ scenery recognition (OPSR). In this perspective, we first isolated the tree and shrub vegetation from the surrounding pastures by using the spectral difference feature on the green band of the aerial orthophoto.

Subsequently, the cairns were classified on the nDSM layer considering their non negligible height above the surrounding terrain. The values were selected to include all possible natural or man-made structures elevated from the zero quote

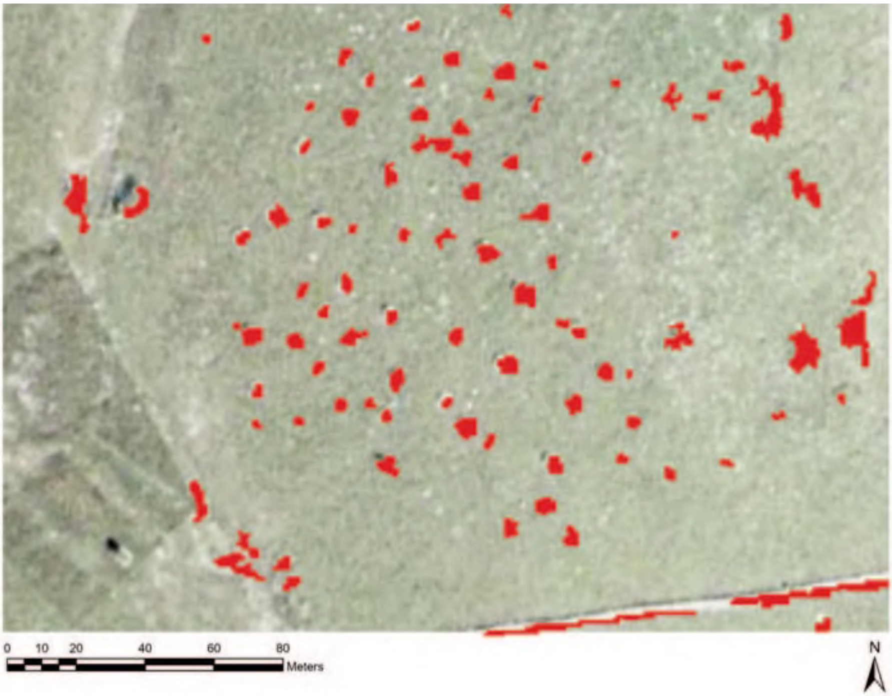

Fig. 7. Intermediate step of the classification process in Area 1 over ReVen orthophoto, showing potential cairns and other elevated structures as red image-objects.

of the nDSM (fig. 7). This rule ensured the classification of all cairns, even those that are less evident or partially damaged due to formation and taphonomic processes. However, given the contextual presence of buildings, boundary walls, and other elevated structures, these rules were not sufficient to accurately identify our target objects.

Additional morphological parameters were thus selected according to our specific diachronic semantic model (DhSM): proceeding with a regressive approach, a maximum length/width ratio was defined for the cairns to exclude boundary structures. We also extracted the minimum and maximum area of the cairns visible in the training area to assign a dimensional range to our target class. A value of 10 m^2, corresponding to a diameter of approximately 3.5 m, was chosen as the minimum value, while 158 m^2, corresponding to a cairn diameter of 14 m, was chosen as the maximum value. This operation allowed us to discount most of the erratic boulders that are part of the natural landscape. The third morphological parameter considered was based on the pseudo-circular shape of the cairns. Specifically, we classified all image-objects included in the first quartile of the object-feature “roundness”, for accounting to slight morphological changes that cairns might have undergone through time.

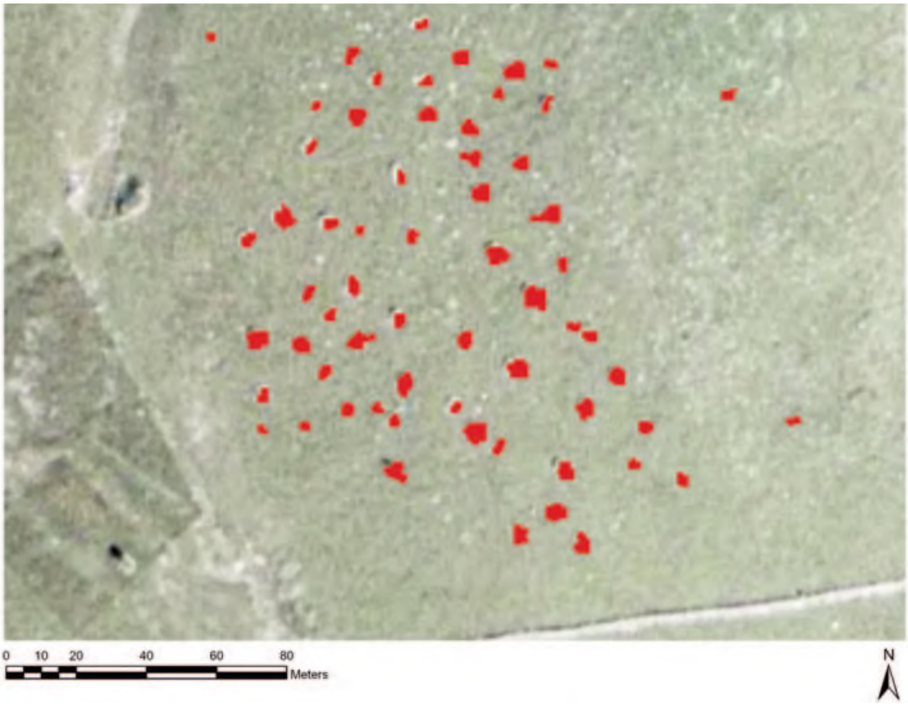

Fig. 8. Final classification results in Area 1 over ReVen orthophoto, showing the automatically identified cairns as red image-objects.

Ultimately, two relational parameters were applied. The first object-feature chosen considers the difference between an image-object and its neighboring image-objects in terms of average layer intensity values. As the cairns have a significantly higher average intensity value on the red band than the surrounding pasture, we opted for using that layer. This feature proved to be essential to better isolate the cairns from the grassland. Since the cairns might at times be subject to partial collapse or limited rockslides caused by atmospheric agents, we also employed the relational object-feature “Rel. border to”, in which the user can define the minimum or maximum border length that an image-object can share with neighbor objects of a specific class, in our case other cairns. Essentially, we merged all image-objects which shared a substantial portion of their perimeter with other image-objects identified as cairns for obtaining a more accurate quantification of the total occurrences in the area.

3.2. Validation

The total number of cairns identified by our knowledge-based rule-set in Area 1 is 62 (fig. 8). To validate the model, we carried out systematic Unmanned Aerial

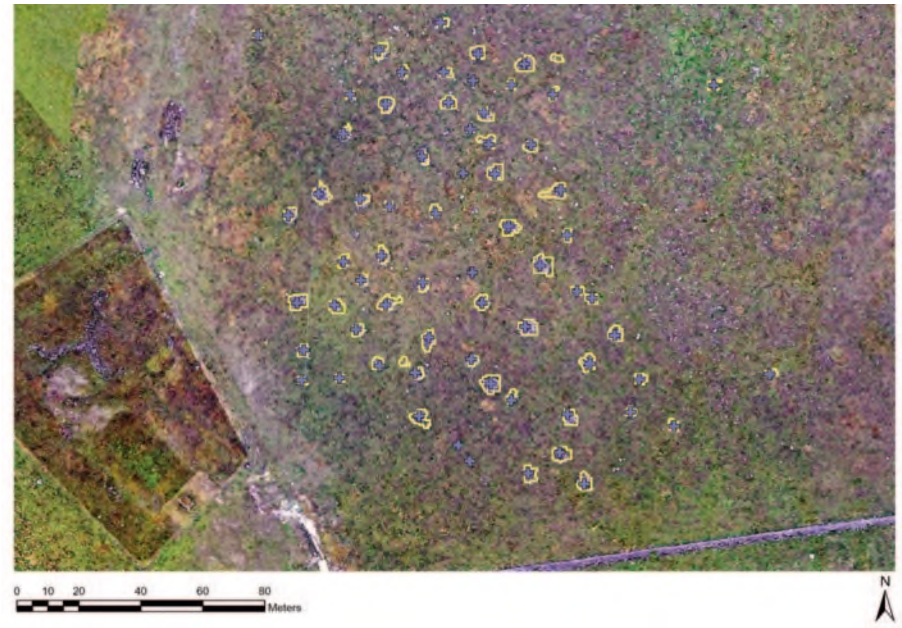

Fig. 9. Results of the validation survey in Area 1 over UAV-derived orthophoto: yellow lines circumscribe the image-objects automatically classified as cairns, while the blue crosses show the real-world cairns identified after the drone and ground-based survey.

Vehicle (UAV) acquisitions and ground surveys which took place at the end of April and the beginning of May 2021. The aerial images were acquired via multiple UAV flights at a height of 100 m. All the image-sets were processed using the Structure-from-Motion software Agisoft Metashape Professional to create an orthophotomosaic of the whole area with a spatial resolution of 5 cm.

During our aerial and ground-based surveys we could demonstrate that 60 out of the 62 image-objects automatically classified by our model were indeed cairns (fig. 9), with only two commission errors related to big erratic boulders naturally present in the plateau, with a percentage of commission errors of only 3.2% (tab. 1). The number of omission errors is slightly higher, with a total of 6 occurrences out of 66 cairns identified during the aerial and field surveys, meaning that 9.1% of the real-world cairns were not identified by the proposed rule-set. Based on these data, the automated method that we are proposing recorded user's and producer's accuracies of 96.8% and 90.9%, respectively.

The results obtained for Area 1 can be considered extremely satisfactory as they range in the highest values of the precision and accuracy rates derived from the review of a significant set of papers dealing with automated archaeological mapping (Trier, Cowley, Waldeland 2019), and slightly outperforms the first results obtained by connective AI approaches for cairn detection, which were able

	Test Area 1
Total number of cairns automatically classified by our rule-set	62
Total number of cairns correctly classified by our rule-set after the UAV	60
Total number of cairns identified during UAV and ground surveys	66
Omission errors	6
Commission errors	2

Table 1. Cairn number in Area 1 based on both automatic classification and field surveys, including the values of omission and commission errors.

to achieve 86% accuracy values (Küçükdemirci *et al.* 2021). The same processing protocol was thus reapplied independently in the Marcesina plateau for mapping and quantifying the local cairnfields in their entirety.

3.3. Export and ground truthing

The semi-automatic or totally automatic replicability of the same rule-set in a variety of contexts sharing similar geographical and/or cultural characteristics is among the most promising prospects of AI for the automatic recognition of archaeological objects. Looking at the Marcesina case study, the number of cairns automatically identified on the whole plateau amounts to 491 occurrences (fig. 10). For evaluating the quality of the rule-set performance outside the training area (i.e. Area 1), we ground truthed two different portions of the Marcesina plateau characterized by a high density of cairns (Area 2 and Area 3 in fig. 5). The UAV and ground assessment was carried out at the end of August 2021 with the same methods and tools already described in section 3.2.

Table 2 summarizes the results of the automated reapplication of the rule-set and compares them to the data emerged from UAV and ground surveys. For Area 2, the total number of cairns automatically classified is 41 (fig. 11). However, only 32 of them were effectively confirmed after UAV and ground controls, with a percentage of commission errors reaching ca. 22%. This is essentially due to the quantity of natural, erratic boulders, which is higher in this part of the plateau. Contrarily, the model missed only 3 real world cairns, which implies a 8.6% rate of omission errors. Omission errors are totally absent in Area 3, with a striking value of 100% (25 properly classified out of the 25 real world examples in the area). However, 4 commission errors are present, mostly related to residual portions of reaves in dry stones (fig. 12). Commission errors thus correspond to the 13.8% of the total occurrences.

When it comes to the user's and producer's accuracy calculated outside the training area, the percentages are 78% - 91.4% for Area 2 and 86.2% - 100% for Area 3, with an average of 81.4% - 95% for the two areas combined.

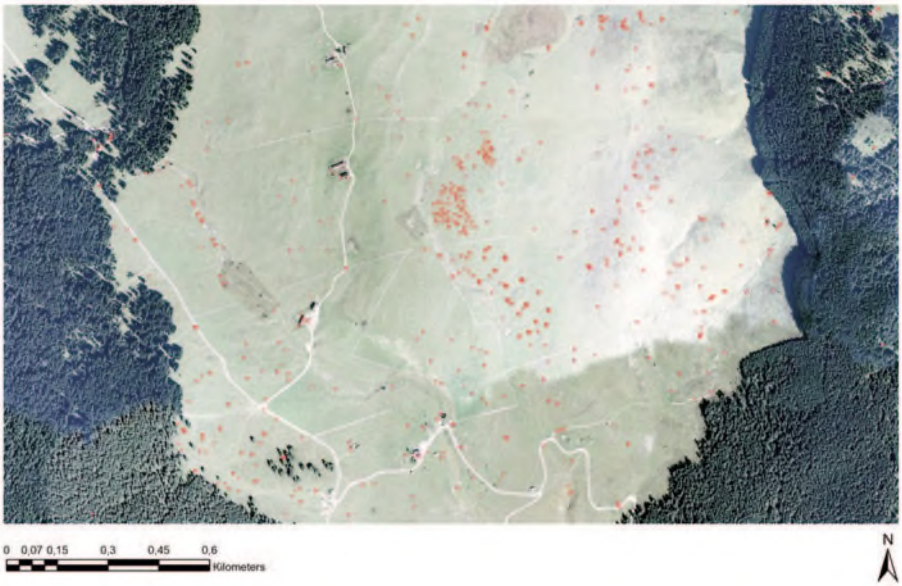

Fig. 10. Final classification results of the whole study area over ReVen orthophoto, showing the automatically identified cairns as red image-objects.

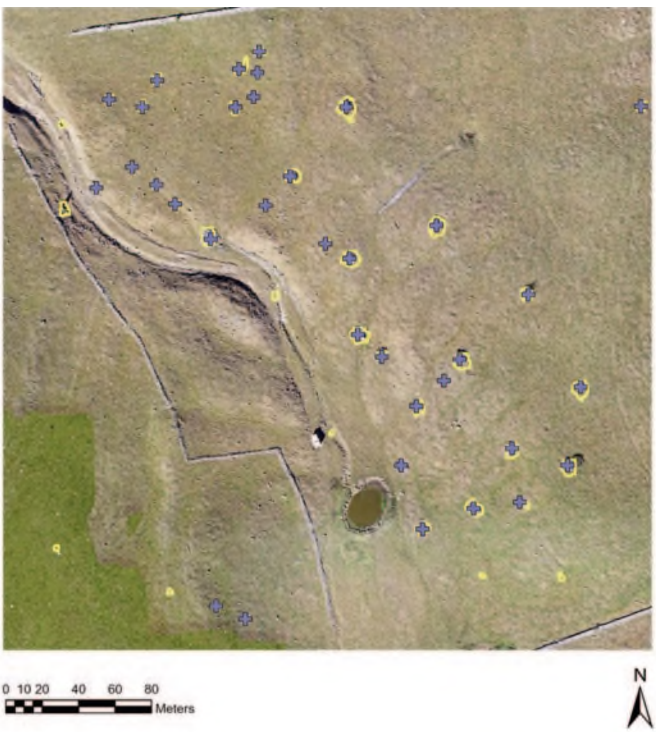

Fig. 11. Results of the validation survey in Area 2 over UAV-derived orthophoto: yellow lines circumscribe the image-objects automatically classified as cairns, while the blue crosses show the real-world cairns identified after the drone and ground-based survey.

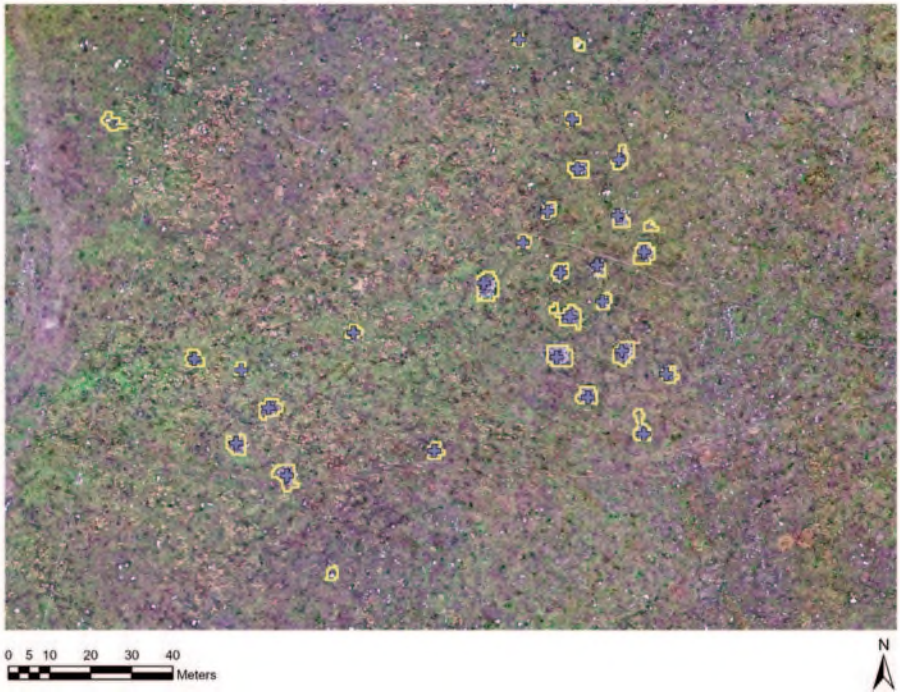

Fig. 12. Results of the validation survey in Area 3 over UAV-derived orthophoto: yellow lines circumscribe the image-objects automatically classified as cairns, while the blue crosses show the real-world cairns identified after the drone and ground-based survey.

	Area 2	Area 3	Total
Total number of cairns automatically classified by our rule-set	41	29	**70**
Total number of cairns correctly classified by our rule-set after the UAV and ground truthing	32	25	**57**
Total number of cairns identified during UAV and ground surveys	35	25	**60**
Omission errors	3	0	**3**
Commission errors	9	4	**13**

Table 2. Total cairn number in Area 2 and Area 3 based on both automatic classification and field surveys, including the values of omission and commission errors.

In both Area 2 and 3, commission errors outnumber omission errors: this means that even the smaller cairns, or those with a lower preservation state, as well as those which are partially hidden by mosses and grass turf were correctly identified with the proposed protocol. The major problems are due to commission errors, which are related to the equifinal appearance of several natural (erratic boulders) and man-made structures (collapsed stone walls, terraces, reaves, or buildings) that are widespread in the Alpine uplands, and especially in the Marcesina plateau. This issue is strictly related to the limited spatial resolution of the ReVen orthophotos and would be almost entirely solved by using higher resolution data, such as UAV-borne imagery.

However, in general terms, the scores obtained in the training area and those in the two assessment areas are extremely convincing, suggesting that the proposed set of rules satisfactorily accounts for the wide variability in the Marcesina cairnfields.

4. Conclusions and perspectives

This paper clearly demonstrates the effectiveness of combining knowledge-based AI and ArchaeOBIA for the identification, quantification, mapping, and monitoring of cairnfields in Alpine environment. This approach not only has the potential to speed up image classification and subsequent archaeological photointerpretation, but also offers an alternative to the bias induced by the human operators. The work presented here constitutes the first step of a complex ethno-historical and archaeological project centered on the area of Marcesina. In the immediate future, we also aim to implement a tentative automatic seriation covering the variability in cairn taxonomy and evaluate its chronological implications. In addition, we wish to explore the temporal evolution of the cairnfields formation thanks to a combination of half-excavations and radiocarbon dating on the fossil layers. This approach will set the base for establishing reliable and diagnostic relationships with the topography, but also the other local features, structures, and infrastructures such as ecotones, slope classes, land-divisions, connectivity network, and "malghe" in diachronic perspective.

The importance of fieldwork, ground truthing, and other types of external validation strategies has been underlined by multiple authors (Magnini, Bettineschi 2019; Davis 2021, and cited literature). Without *in situ* calibration, the resulting data may produce misleading historical interpretations, or worst, damaging policy suggestions. However, this phase is not only fundamental in terms of data quality assessment but also becomes a crucial moment of interaction with the communities who are the principal actors in the education, communication, and protection of the local heritage. This participatory approach, which is now rightfully gaining more and more visibility in the archaeological research and practice (see the "Research" section in volume 9 of this journal, 2019), is critically important in the field of remote sensing and AI, where it is too easy to analyze and publish data without ever setting foot in the area of investigation. And while sometimes this might be appealing, as it offers the opportunity to investigate and monitor sites and contexts endangered by natural hazards, looting, or armed conflicts, and similar emergency situations (Lasaponara, Masini 2018), it is always worth remembering that knowledge should be co-produced with all the relevant stakeholders and that archaeologists have the ethical duty to negotiate adaptive solutions to cope with the goals and expectations of each community involved (Johnson *et al.* 2021; Sanger, Barnett 2021).

Abstract

The plateau of Marcesina, in the municipality of Enego (Vicenza, Italy), was selected as a test site to develop an automated protocol for the recognition and quantification of cairns and cairnfields in Alpine environment coupling object-based image analysis (OBIA) and artificial intelligence (AI). The segmentation was implemented starting from a combination of aerial orthoimages and LiDAR-derived visualizations (nDSM and Openness), which were subsequently classified with a knowledge-based approach. Our rule-set was able to identify 491 cairns in an area of approximately 4.5 km^2; the average user's and producer's accuracy were calculated thanks to an assessment strategy based on drone flights and ground survey and returned values of 81.4% -95%, respectively.
Keywords: cairns and cairnfields, artificial intelligence, object-based image analysis, LiDAR visualizations, UAV and ground survey, mountain archaeology.

La piana di Marcesina, nel comune di Enego (Vicenza, Italia), è stato scelto come sito test per sviluppare un protocollo automatico per il riconoscimento e la quantificazione dei cumuli da spietramento e dei campi di cumuli da spietramento in ambiente alpino tramite una combinazione di analisi d'immagine basata su oggetti (OBIA) e intelligenza artificiale (IA). La segmentazione è stata implementata partendo da una combinazione di ortofoto aeree e visualizzazioni LiDAR (nDSM e Openness*), che sono state successivamente classificate con un approccio* knowledge-based*. Il set di regole così creato ha identificato 491 cumuli di spietramento in un'area di circa 4,5 km^2; la* user's *e la* producer's accuracy *sono state calcolate grazie a una validazione incrociata basata su* survey *da drone e ricongnizioni di superficie, che hanno restituito valori rispettivamente nell'ordine dell'81,4% e 95%.*
Parole chiave: *cumuli di spietramento, campi di cumuli da spietramento, intelligenza artificiale, analisi d'immagine basata su oggetti, visualizzazioni LiDAR, ricognizioni da terra e da drone, archeologia di montagna.*

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