GeOBIA approaches to remote sensing of fossil landscapes: two case studies from Northern Italy

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GeOBIA Approaches to Remote Sensing of Fossil Landscapes: Two Case Studies from Northern Italy

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Abstract:
This paper presents the preliminary results of an object-based image analysis aimed at the implementation of a package of procedures of remotely sensed object/ pattern/ scenery recognition specifically designed for the semi-automatic and automatic recognition of a batch of critical archaeological and ethnoarchaeological features. The research focuses on the guided recognition of mountain and plain features with elliptic, linear and polygonal shape on high resolution aerial photographs and near-infrared imagery. Case studies from Northern Italy are investigated, stating the image processing steps and highlighting the pros and cons of using an artificial intelligence for the analysis in the domain of Remote Sensing.

Keywords:
Remote Sensing, Geobia, Automatic And Semi-Automatic Recognition, Prehistoric Rural Landscape, Landscape Archaeology

1. Introduction

One of the major problems of remote sensing is the complex and palimpsestic origin of most archaeological contexts. The long-term human/ environment interactions have often cumulatively produced what has been defined as a fossil landscape (Balista et al. 1998): an intricate overlapping of diachronic signatures and traces, each one characterised by a different degree of residuality. The distinction and differentiation of these various features is, therefore, a matter of central concern for the understanding of the historical, cultural and archaeological development of a given territory. It should be emphasised, moreover, the significant ambiguity/equifinality (Skyttner 2005; von Bertalanffy 1956) that some of these features present in the final state of their morphogenetic paths.

Photo-interpretation of the archaeological site and off-site features is usually carried out case-by-case, resulting in a highly time consuming and economically expensive task. In order to avoid errors and bias (e.g. pareidolia) that may, in some circumstances, affect the human mind and to improve the comparability of analytical data, we decided to use a specific software designed for semi-manual, semi-automatic and automatic spatial analysis. This procedure simultaneously examines a wide range of data – dimensional, but also chromatic, formal, textural, structural, spatial-relational – with a sound methodological consistency allowing to critically reduce the range of random variability of the output data.

Hay and Castilla (2008) defined Geographic Object-Based Image Analysis (i.e. GeOBIA; also generically OBIA) as: "a sub-discipline of Geographic Information Science (GIScience) devoted to developing automated methods to partition remote sensing imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scales, so as to generate new geographic information in GIS-ready format". This means that the conceptual unit of the process is no more represented by single pixels (or voxels, in a three-dimensional coordinate system), but by homogeneous image objects and their relationships. For a systematic overview of the researches on the topic the reader is referred to the recent synthesis of Blaschke (2010) and to the related bibliography.

The OBIA approach has been applied in archaeology for the development of predictive maps using high-resolution DEMs by Verhagen and Drăguț (2012), but until now only a few attempts were made in order to classify fossil or buried archaeological structures via their residual traces on the ground – like for example soil-marks, grass-marks etc. (Magnini 2011).

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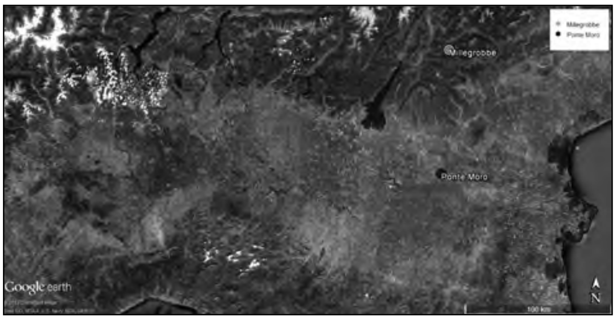

***Figure 1**. The location of Millegrobbe (Lavarone, TN) and Ponte Moro (Cerea, VR) in the context of Northern Italy.*

2. Know Why to Know How: Methodology and Preliminary Steps of the Research

Object-based image analysis can be divided in two main steps: segmentation and classification, that can be repeated in sequence as many times as needed (Benz et al. 2004). Segmentation uses a series of mathematical and logical operations on the image-data in order to obtain meaningful groups of pixels. To simplify, segmentation cuts the image into multiple crude objects, which can therefore be further edited, hierarchised and then classified.

We found that multi-resolution segmentation with varying scale, shape and compactness parameters was the optimal option to analyse our multilayered archaeological landscapes. In fact, the multi-resolution algorithm (Baatz and Shäpe 2000) divides the image into polygons, maximising at the same time the mutual heterogeneity and the internal homogeneity. It is essentially a bottom-up technique which merges single pixels to create larger image objects. The following step, called classification, involves the systematic grouping of image objects into categories on the basis of colour, shape, texture and/or structural and spatial relationships.

Definiens/eCognition, although proprietary, is the most common software for GeOBIA applications (see Anders, Seijmonsbergen and Bouten 2011; Dronova, Gong and Wang 2011; Peña-Barragàn et al. 2011; Vieira et al. 2012); this is the reason why we decided to use it as well.

At the beginning of our research we chose to test in our study areas (Fig. 1) four different kinds of classification in order to understand the pros

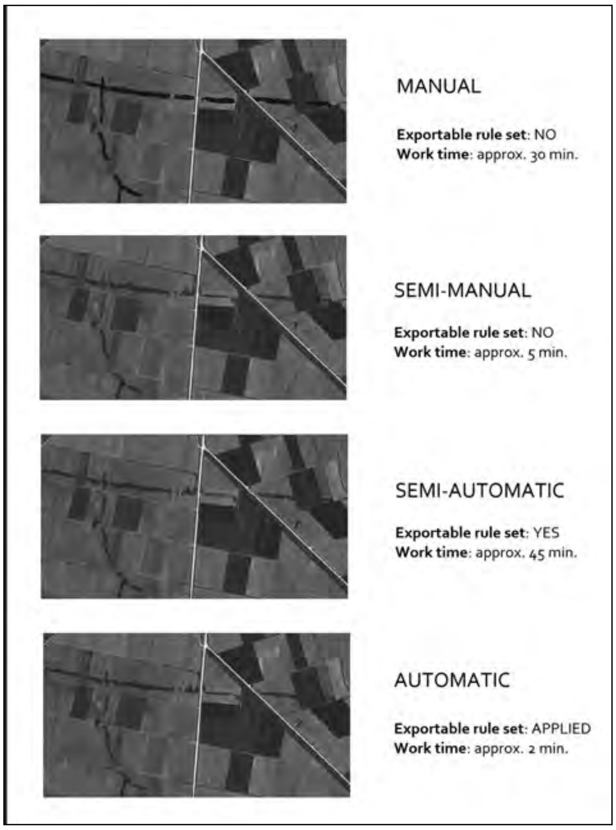

***Figure 2**. Comparison of outcomes and timing to classify the roadway in Ponte Moro through: a) manual recognition (Quantum Gis); b) semi-manual recognition (eCognition); c) semi-automatic recognition (eCognition); d) automatic recognition (eCognition).*

and cons of one compared to the others. Thus, as showed in Figs 2-3, we used: 1) a classic visual/manual approach (Quantum GIS); 2) a semi-manual approach (eCognition); 3) a semi-automatic approach (eCognition); 4) an automatic approach (eCognition).

The visual-manual classification with a GIS-based software (in this case we used Quantum GIS, but many other options are also available) is primarily based on the operator's experience, while the degree of detail is linked to the work time/quality ratio that best suits the specific project. This is what archaeologists usually do for the purpose of photo interpretation.

For the semi-manual approach to classification as shown in Figs 2-3, we started from the raw segmentation data and manually selected the image

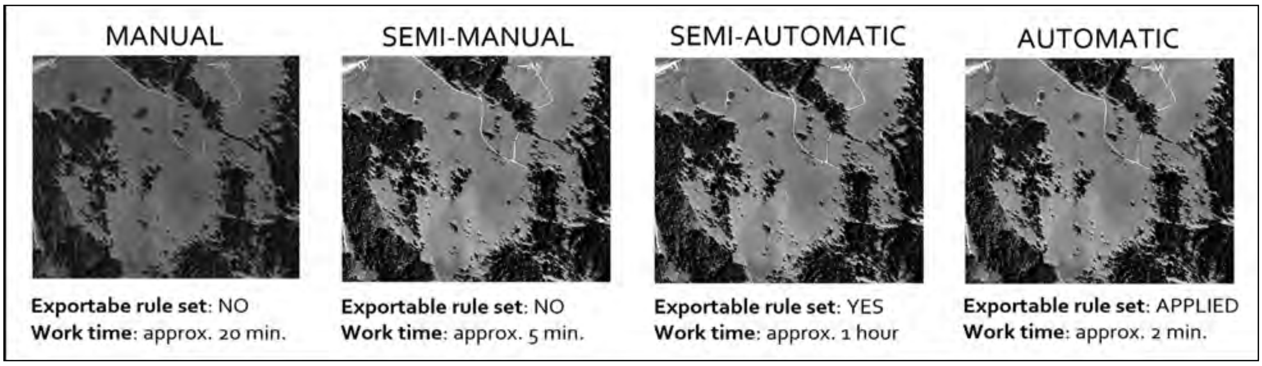

Figure 3. *Comparison of outcomes and timing to classify the mountain pools in Millegrobbe through: a) manual recognition (Quantum Gis); b) semi-manual recognition (eCognition); c) semi-automatic recognition (eCognition); d) automatic recognition (eCognition).*

objects to classify. This methodology, though still largely depending on the operator's expertise and his cognitive maps, provides a somewhat objective basis (because the shape of the polygons/image objects is generated by the software according to the properties of the image) to direct all the subsequent processing. It also makes possible to obtain a good level of detail in a relatively short work time; but, of course, reusable rule-sets cannot be created using a semi-manual procedure.

In order to successfully classify in an automatic or semi-automatic way the intended landscape features, it is essential to understand their characteristics and recognise their peculiarities with respect to the context where they can be found in. This means that the operator must have a mental model of the expected results to identify the specific parameters of the features to be selected for analysis; in other words, during the selection of the classification parameters and the creation of a rule-set the artificial intelligence has to be instructed and guided by the human mind. In the next paragraphs (3.1 and 3.2) we will present a semi-automatic procedure for the creation of a rule-set aimed at the classification of a series of ancient man-made and natural features. As for the automatic classification shown in Figs 2-3, we run the rule-sets derived from the semi-automatic classification over the same image-data: as proved by Drăguţ and Blaschke (2006) this procedure gave identical results, ensuring the reproducibility of the outcomes. The software can – in a following stage – repeat the same procedure for an unlimited number of times, applying an identical rule-set to different images which possess the same or comparable geographic, anthropogenic and/or physical features: it is the crucial shift from a semi-automatic to an automatic photo interpretation and it will be in fact the main focus of our future research. Needless to say, this latter approach can involve a number of risks whose impact needs to be assessed according to the cost/benefit ratio and the complexity of the project.

3. Case Studies

This section will present two case studies in mountain and plain environments that will involve distinctive mental models implemented by selecting the appropriate, locally sensitive object features and by considering them in a logical succession. These steps allowed us to achieve a semi-automatic photo interpretation with a quite higher heuristic impact in comparison to the manual procedure.

The preliminary study which will also be summarised below is also an essential phase of the work. In fact it highlighted the basic information on the features of interest (shape, average area, dimensions etc.) which were subsequently used as classification parameters.

The detailed explanation of each *object* feature which will be mentioned in the following paragraphs and the related formulae can be found in eCognition's Reference Book (Trimble Germany GmbH 2011).

3.1 Ponte Moro (Cerea – VR, Italy)

Ponte Moro is a rural, off-site area located in the low Po Plain near the terramara settlement of

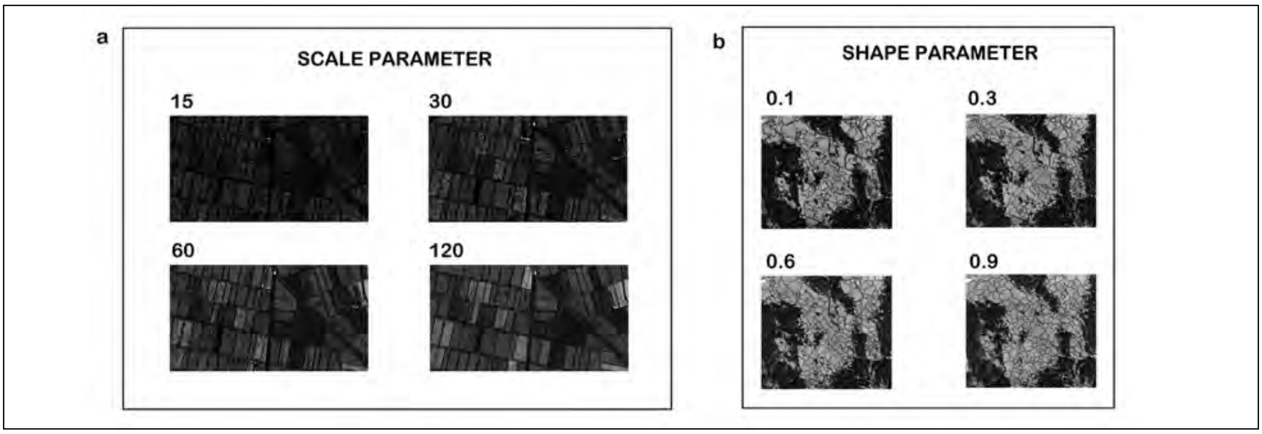

Figure 4*. a) Ponte Moro: comparison of the outcomes of a segmentation with scale parameter of 15, 30, 60 and 120; b) Millegrobbe: comparison of the outcomes of a segmentation with shape parameter of 0.1, 0.3, 0.6 and 0.9.*

Castello del Tartaro, occupied between the Middle Bronze Age (MBA) and the Late Bronze Age (LBA). The area is currently under investigation by the AMPBV (Alto Medio Polesine Basso Veronese) project (Balista et al. 1986; De Guio, Betto and Balista 2011 and related bibliography), co-directed by the Department of Cultural Heritage: Archaeology and History of Art, Cinema and Music (University of Padua) and the Institute of University College (London), in collaboration with the Archaeological Superintendence of Veneto, Boston University, Clarke University (USA-MASS), Accordia Research Centre (London), Center for Remote Sensing (Boston), Nanotechnology Lab (Boston). The aim is to examine the extremely well-preserved fossil landscape of the Valli Grandi Veronesi, a true 'landscape of power' arisen during the MBA and characterised by a massive occupation of the wider middle to low Po plain. In particular, Ponte Moro shows the buried remains of a roadway and a palaeochannel both related to the prehistoric occupation. Geoarcheological studies and C14 results carried out in the area confirm the hypothesis proposed on the basis of the Remote Sensing analysis and support the dating of the road to the Bronze Age (Betto, De Angeli and Sartor 2006).

In order to classify the subsurface archaeological features and the related surface patterns, we first applied a multi-resolution segmentation (parameters: scale 30, shape 0.1, compactness 0.5) to an aerial orthophoto (copyright CGR - Compagnia Generale Ripreseaeree Parma, 2008) overlaid with a near-infrared digital

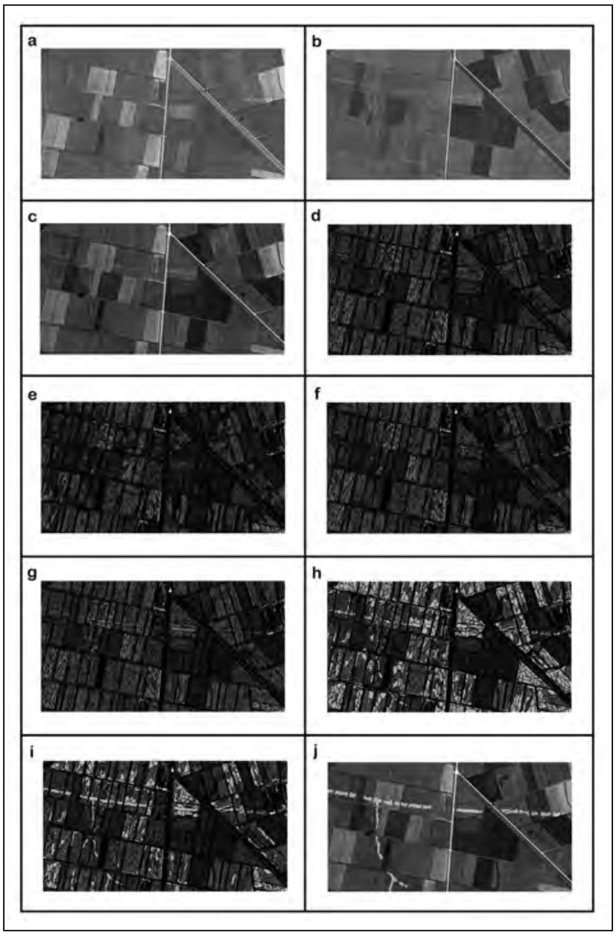

Figure 5*. Creation of a rule set (through semi-automatic recognition) for the classification of a paleochannel (blue) and a buried roadway (yellow) in Ponte Moro. Step of the project and final results.*

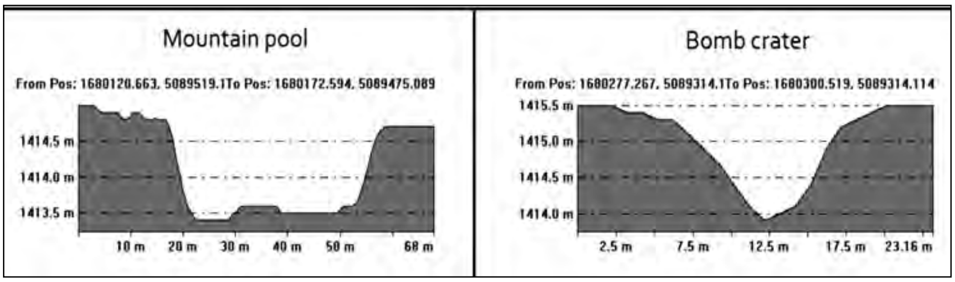

***Figure 6**. Comparison between the sections of a mountain pool (left) and a bomb crater (right) from Millegrobbe. Global Mapper reworking of lidar data.*

orthophoto (copyright CGR Parma, 2008) at the same spatial resolution of 0.5 m. The reason for this choice is that the two images offered significantly different data: the palaeochannel was well recognisable only from the near-infrared image, while the roadway was clearer on the simple aerial orthophoto. The selection of the scale parameter was obtained by comparing the results achieved using values of 15, 30, 60 and 120. The higher the values, the larger the image objects. As shown in Fig. 4a, an apparent over-segmentation was thus necessary to distinguish image objects pertaining to the buried archaeological structures from those related to agrarian features of adjacent fields. The homogeneity criterion is based on the ratio between colour and shape: higher values of 'shape' (max 0.9) involve a lower weight of the spectral characteristics in the overall homogeneity parameter (for technical details and algorithms, see Benz et al. 2004). Since the chromatic level was the most important factor for our analysis, we chose to use a low shape value.

We started the project with the classification of the palaeochannel (blue in Fig. 5) by considering the 'mean' feature of the near-infrared layer (layer 4). The palaeochannel, in fact, can be recognised basically due to the different vegetation growth (grass-marks and crop-marks) and considering that the vegetation has a high reflection in the near infrared channel, this was the first characteristic we used to select the image objects of interest. Segmentation, due to the presence of modern roads and canals, split the palaeochannel into many very small image objects, so we used the object feature 'area' to unclassify the biggest image objects, related to fields and recent infrastructures. Then we considered the 'max diff' and the 'standard deviation' (on the near infrared layer) features, because the image objects of the palaeochannel are relatively inhomogeneous in terms of texture and colour, being the final outcome of anthropogenic and post-depositional processes. We also used the 'merge region' algorithm, to combine the adjacent image objects belonging to the palaeochannel class so that we could obtain a shape more and more similar to the profile of the prehistoric watercourse as seen on the near infrared image. The software also identified a further structure on the eastern side of the image which had never been recognised before by traditional photo interpretation. The area presents all the spectral and textural characteristics of fossil riverbeds: upcoming field checks will allow to clarify its detailed nature (ground truth).

The recognition of the roadway was then implemented as a new class, starting from the same segmentation data. At this point, it was clear that the continuity of the roadway alignment was interrupted by a series of modern roads and irrigation canals. In order to remove such sources of noise, we classified all of the image objects that had middle to low values of the 'length/width' feature. Then, by elimination, we considered the 'mean' feature of the green layer, so that we could choose only the light-coloured image objects, mainly related to the ancient roadway. Subsequently, we selected the image objects with small to medium 'area' and to improve the image reading we used the 'merge region' algorithm that joins neighbouring image objects of the same class. In the end we eliminated the remaining background noise thanks to the 'brightness', 'area' and 'rectangular fit' features.

3.2 Millegrobbe (Lavarone - TN, Italy)

The mountainous area of Millegrobbe (Fig. 1) is a cumulative landscape, massively occupied since Late Bronze Age for metalworking. Later on, it was centre of a complex mountain economy (woodland exploitation, pastoralism, stone quarrying etc.) and finally it became a well-known bloody theatre of the First World War. History has left impressive signature of marks on the ground, which are currently under investigation in a series of projects promoted by the University of Padua (De Guio and Zammatteo 2005; De Guio et al. 2013 and related bibliography; Magnini 2011; Pearce and De Guio 1999).

The current research is mainly focusing on: 1) project Ad metalla, centered on palaeometallurgy (Bronze-Age roasting and smelting); 2) Archaeology of War, linked to the impact of the Great War on the Vezzena-Luserna-Lavarone plateaux (thousands of kilometres of military roads and trenches and millions of bomb craters); 3) ethnoarchaeology and 'Archaeology of Us' (actualistic studies), all connected to a wide spectrum of mountain economy as well as to a softer archaeology of the mind (from pasture pools to stone piles, deforestation holes, charcoal pits, lime kilns, toponyms, local traditions, legends and fairy-tales etc.).

In order to differentiate all these traces from a remote point of view, it is necessary to recognise their differences in shape, section, dimensions, colour, and – even more importantly – their reciprocal and contextual relationships on all kinds of available imagery of the area, such as aerial photos, near-infrared digital orthophoto, NDVI, lidar, and RADAR data.

In particular, we decided to refer to the following three types of features that, although very different from each other, share a high degree of ambiguity with other structures present in the same reference area (De Guio et al. 2013):

a. Trenches (linear equifinality with roads, trails, muleteers, cross trampling traces, land divisions and boundaries): long, narrow and zigzagging ditches in the ground dug by soldiers during the First World War as a defence against enemy fire. They were of variable size: about two meters deep, equally wide, stretched from a few meters to several kilometres in length. The historical maps (copyright IGM - Istituto Geografico Militare, 1969) allowed the identification in the Millegrobbe surroundings of an area called 'ex-trenches' in which we will attempt to remotely identify the remains of any possible ground structure associated with the Great War.

b. Mountain pools (circular/ elliptic equifinality with cairns, treethrows, charcoal pits, lime kilns, smelting platforms, ice storage pits, bomb craters, sinkholes): typical alpine and pre-alpine seasonal pools, occasionally derived from natural depressions but usually man-made, especially in karst regions. The diameter varies between five and sixty meters, but frequently it ranges from ten to thirty meters, while the approximate depth is between half a meter and a meter and a half (Fig. 6). The Late Bronze Age roasting/ smelting furnaces and slags of Millegrobbe are strictly linked with some of these structures, as they are the only basins (often trapped by local morphology and quite recognisable even at the post-abandonment stage) that can provide the water reserve required for metallurgical activities. The correct identification of mountain pools (both active and fossil, normally in clustered distributions across different pastures) plays therefore a considerable role not only from the ethnographic, but also from the archaeological and paleometallurgical point of view.

c. 'Malga' (i.e. shepherd's huts, poligonal/ rectangular equifinality with military warehouses, barracks, outposts, artillery emplacements, stockyards): traditional residential-productive unit of the mountain landscape, centre of the pastoral economy (breeding, dairy production etc.). Characterised by widely varying shapes

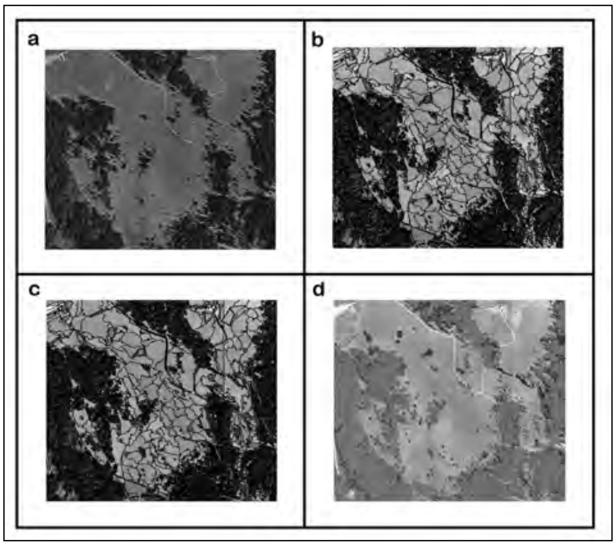

***Figure** 7. Creation of a rule set (through semi-automatic recognition) for the classification of mountain pools (red), malgas (yellow), woodland (green) and war trenches (blue) in Millegrobbe. Step of the project and final results.*

and sizes, they can sometimes consist of several compartments connected one to each other (stable, poultry, piggery, cistern, cheese storage room, living spaces and so on).

The semi-automatic multi-class recognition of the target features was set on an aerial orthophoto (CGR Parma 2000) overlaid with a near-infrared digital orthophoto (CGR Parma 2008). The first step of the analysis was to perform a multi-resolution segmentation with the following parameters: scale 100, shape 0.1, compactness 0.5. The selection of the values of the segmentation parameters is subject to the same logic already discussed for the case study of Ponte Moro; to evaluate the resulting segmentation in relation to the variation of the 'shape' parameter, see Fig. 4b. This comparison shows quite clearly that reducing the colour significance, proportionally reduces the recognition of the structures of interest.

The second level concerns the creation of a new class, here called 'trenches' and identified with the colour blue (Fig. 7). The obvious attributes of the trenches in both the selected images are linear shape and colour, which differ significantly from that of the surroundings. We began the creation of our rule set by selecting all image-objects with a middle-to-high length and width ratio, through the use of the 'length/width' feature. However, we chose to exclude those image objects with the highest ratio, which corresponded to the modern roadways. Also, we unclassified image objects with the largest and smallest areas, that were not related to the structures of interest. Subsequently we considered the 'mean' feature of the green layer (to remove part of the vegetation) and of the near-infrared layer, where the profile of the trench was better delineated. Once the objects belonging to the trench were identified, we used the 'merge region' algorithm to join the adjacent image objects. In this way we could identify the trench as a limited number of image objects, which are easier to work with. Finally the features 'brightness' and 'standard deviation' were used in sequence on the near-infrared layer, in order to eliminate the remaining background noise not related to our analysis.

In addition to the recognition of different types of individual classes, the software simultaneously classifies different types of evidences starting from the same raw segmentation data. Therefore we decided to set up a multi-class project, taking into consideration, beyond the trenches, also mountain pools (red), malga (yellow) and woodland (green).

Pools were classified mainly thanks to their circular shape, their peculiar colour and the absence or presence of water inside. The features considered are in order: 'roundness', 'area' (in relation to the average size of the alpine pools as outlined by the related bibliography), 'mean' on the red layer and 'brightness', to take advantage of their colour and reflectance characteristics.

The malga, being man-made structures rather regular and quadrangular-shaped, have been classified with the 'rectangular fit' feature. Then the smaller image objects, related to shadow within the trees, were eliminated by taking into consideration their 'area'. Ultimately 'brightness' allowed us to remove those image objects with high contrast values, which corresponded to modern buildings.

Classifying the forest coverage, although it may seem difficult because of its irregular shape, is extremely fast, as demonstrated by numerous case-studies (e.g. Dorren, Maier and Seijmonsbergen 2003; Heyman et al. 2003). In our case the 'mean' feature on the green band made it possible to obtain highly accurate results and also to identify individual trees in open field.

4. Conclusion and Perspectives

These study cases confirm the applicability of object based image analysis to archaeological photo interpretation and strengthen its role to identify features evident at ground level as well as remains exclusively detectable from aerial or near-infrared view. However, implementing a geospatial analysis on surface structures or landscape-related features (our original purpose) is very different from the identification of buried archaeological remains, whose peculiar characteristics have been informed by the succession or interaction of a variety of depositional and post-depositional formation processes: these involve specific actors (physio-genetic, bio-genetic and anthropo-genetic) and related behavioural scripts. Such a complexity in the epigenetic path outlines the difficulties to formalise an unambiguous heuristic model.

The software also ensures some kind of 'controlled automation' of the photo interpretation process and the exportability of the supporting rule sets in a way that seems particularly useful when working on large scale projects to speed up the object/ pattern/ scenery recognition task. It should however be considered, given the high internal variability of the outcomes on the ground of the archaeological surface and subsurface structures, that in the case of a fully automatic approach the operator's control on the obtained results is still essential in order to fine-tune or recalibrate the parameters according to the specific research targets, locally sensitive info/noise ratio and and/or ground-truth feedback.

OBIA methodology provides innovative hints, pointing to interesting archaeological developments in the near future. The research here presented is a work in progress, which is now focusing on the use of different types of data (NDVI, lidar, RADAR, etc.) and trying to explore both their specific potential as well as their possible cross-validating redundancy. This will, ultimately, help to develop more and deeper rule/knowledge based approaches to landscape archaeology.

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