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Multispectral Images Classification Applied to the Identification of Archaeological Remains: a Post-Dictive Perspective

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Abstract

Automated and semi-automated image classifications have made their way into archaeological applications, but early attempts have been strongly criticized. This study examines semi-automated detection methods of archaeological evidence through a comparison of pixel-based and object-oriented data classification. This research has been carried out on high-resolution imagery (WorldView-2) and the selected case study is located on the western slope of Etna (Sicily), the highest volcano in Europe, where a huge variety of settlements can be found from Prehistoric to Medieval times. The methodology of both pixel-based and object-based data classification is described and discussed over to specific case-study. The different nature of the two methods combined with the post-dictive approach adopted provides useful results in order to determine robustness and weakness of techniques presented here. In fact, our goal is to analyze advantages and disadvantages of the usage of pixel and object-based classification techniques and shed light on the significant change in pattern recognition. Finally, the obtained data are compared with manual visual interpretations and analyzed in terms of their accuracy.

Keywords: pixel-based classification, OBIA, volcanic environment

Introduction

In the last years, the archeological community is starting to take account of the advantages in employing computer-aided analysis techniques, which can help in classifying large area rapidly and high-resolution archaeological data. The starting point of this revolution is clear: it's a fact that we now have the capability to produce so much data of such high spatial, spectral and temporal quality that it is becoming extremely difficult to process and interpret it all manually. Consequently, the data explosion has generated new challenges and new scenarios. While in fields such as environmental remote sensing, medical imaging, security and robotics automated and semi-automated techniques are routine, they are still in its infancy in archaeology (Bennett, Cowley and De Laet 2014). The benefits and the limitations to which such approaches are applicable continue to be debated, and it seems there's certain reluctance in archaeology to accept the notion of computer-aided features detection. Interpretation of archaeological features is clearly heavily conditioned –in a positive and negative way- by the abilities and the experience of the interpreter. Algorithms will never replace the skills of an archaeologist but, at the same time, multiple interpretations are often ineluctable. The critical issue is embedded in the exact definition of what can be considered as "archaeological feature".

From this perspective, instead of declining the notion of computer-aided detection of archaeological information, the goal should be finding general procedures and work-flows in which we can use these techniques in archaeology (Calderone et al. 2022; Mangiameli et al. 2020; Gennaro et al. 2018). Automated and manual processes should not be evaluated as alternatives and separate methods but rather as complementary wheels of a holistic approach.

In this paper, we are going to discuss two different approaches to semi-automated features extraction of information that are frequently used nowadays in the fields of archaeology and image-analysis: pixel-based and object-oriented classifications. In particular, we evaluate the applicability of these methods for the identification of archaeological features in the western slope of Etna (Gangi et al. 2020), the European highest volcano, using a multispectral dataset (Candiano et al. 2019; Mangiameli, Mussumeci & Candiano 2018) and adopting a post-dictive approach (Gennaro et al. 2019 b). Therefore, the first part is dedicated to the geographic and archaeological context, while in the second, softwares are applied to obtain pixel-based and object oriented classification. The results demonstrate that photo interpretation and mapping can be performed much more effectively based on object-based classification.

The Archaeological Context

The selected case study is of great archaeological interest and it lies on the Western slope of the European highest active volcano, Etna (Figure 1). The mountain and its spectacular activity are rooted in the collective imagination and memory of modern and ancient inhabitants. So, it is not surprising that Etna has been the protagonist of numerous myths and legend since ancient times. According to Homer, for example, the forge of the god Ephestus was located in the volcano's bowels; Empedocles, the famous pre-Socratic rationalist, left his hometown, Agrigento, and died, throwing himself into the volcano, while he was studying the nature of fire and magma. Even Catania's patron saint, Saint Agata, is linked to Etna. Indeed, it is believed that, during a destructive eruption in 1169, the lava flow was miraculously stopped by the saint's veil and so the city of Catania was saved (Guidoboni et al. 2014). Mount Etna has been inscribed in the UNESCO World Heritage List in June 2013. It is worth mentioning that the scientific committee describes «*Mount Etna (as) one of the best-studied and monitored volcanoes in the world, and continues to influence volcanology, geophysics and other earth science disciplines. Mount Etna's notoriety, scientific importance, and cultural and educational value are of global significance* ».

Despite the human presence in the North-West side of Etna goes back to the Neolithic Age (Privitera, 1998; Spigo, 1985), unfortunately archaeological interest has never been strong (Orsi 1905; Orsi 1907). The prehistoric cave occupation is the only evidence that archaeologists have extensively studied for many years (Privitera, 2007). The western flank is much less studied than the southern and eastern ones. Our investigated zone lies between three districts, Balze Soprane, Santa Venera and, mainly, Edera; a national roadway (S.S. 120) constitutes the northern limit and the total extent of the sample area is around 1,3 sq.km. This portion of territory, located above 800-900 m a. s. l, is part of a large and characteristic lava plain of the Saracena's valley, a tributary of the Simeto river, in the territory of Bronte. Thanks to its great naturalistic interest from a geologic, floristic-vegetation and faunal point of view, the entire area, belonging to Etna Park, has been identified by European Union as a Site of Community Importance (SCI). The final result is an extraordinary and unique landscape. From an archaeological point of view, the geomorphological elements mentioned above represent some of the main problems encountered in the landscape analysis. In addition, all the ancient buildings are made of lava stone blocks and this produces another obstacle for the archaeological interpretation. In the Edera district systematic excavations undertaken by the Soprintendenza of Catania completely brought to light a dozen of circular and rectangular buildings (Puglisi & Turco 2015) (Figure 2). Most of them, dated to Byzantine era (VIII-IX century) are located in the

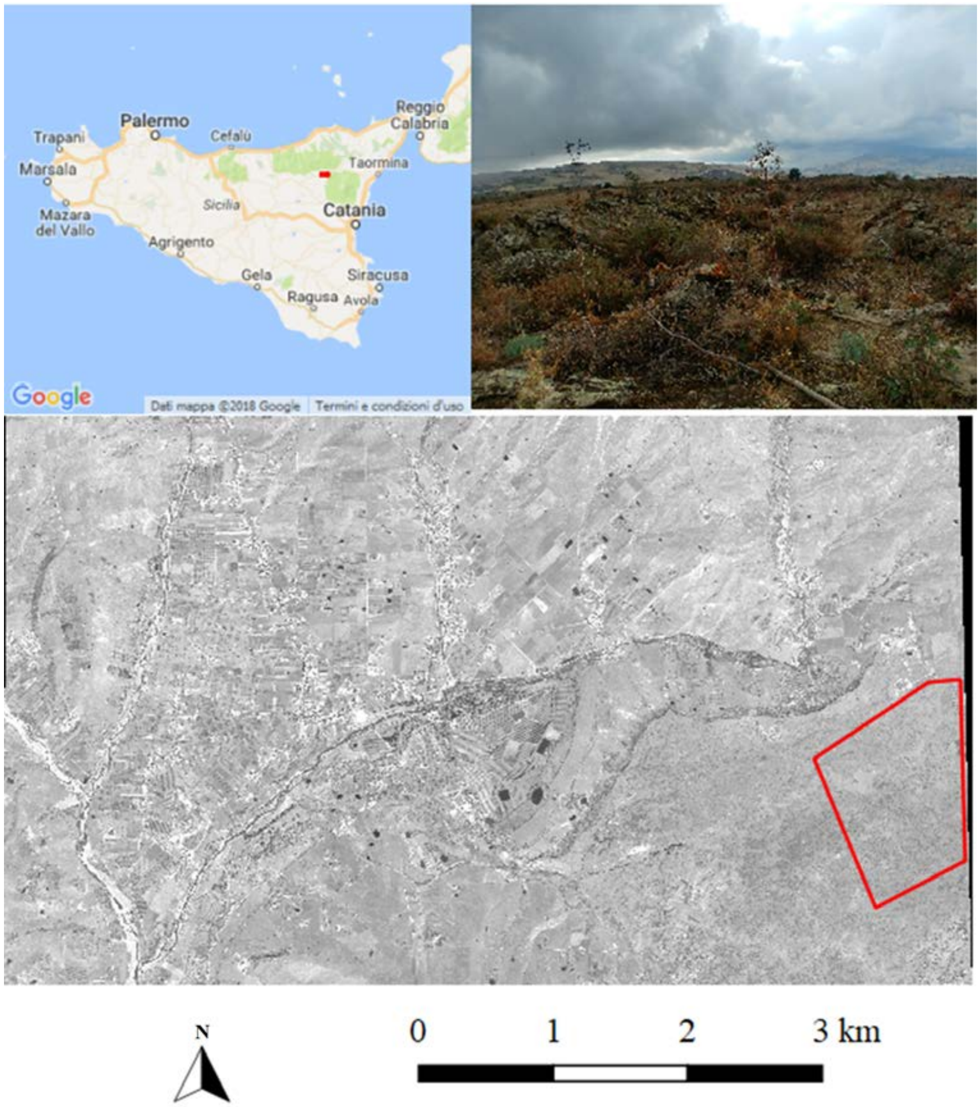

Figure 1. Location map of the study area.

southern edge of the district, not so far from the national road, and they are known as Building 1, Building 2 and so on; the remaining part, built in Greek times, has been discovered near the modern Masseria (farm) Edera. In addition, wall-structure runs across the districts for about 2 km (Figurer 3). Unfortunately, it is not easily framed chronologically and it's still today object of studies. However, some scholars have interpreted the structure as a Byzantine fortification wall dated to Early medieval times (Leone et al. 2007).

Dataset

The WorldView-2 satellite sensor provides panchromatic and multispectral data with geometric resolutions of 0.46-0.52 m and 1.85–2.07 m, respectively, depending upon the off-nadir viewing angle (0 to 20°). The panchromatic sensor collects information at the visible and near-infrared (NIR) wavelengths. The multispectral sensor acquires data in 8 spectral bands from coastal to NIR-2. Both panchromatic and multispectral sensors offer 11bits (2048 gray levels) resolution. The WorldView-2 imagery products are available at different processing levels (basic, standard, orthorectified) serving the needs of different users. The WorldView-2 data used for this study were acquired on April 19, 2013. In this research, the pansharpening was performed using Orfeo Toolbox in QGIS. The application of this algorithm allowed a noticeable improvement of the image quality in terms of spatial resolution. In particular, starting from the 8-band multispectral image with GSD equal to 2 m, we obtained the analogous multispectral image having GSD equal to 0.50 m.

Figure 2. Archaeological structures already excavated in Edera district (from Puglisi & Turco 2015)

Tools and Classification Techniques

The entire study was conducted using, mainly, free and open source software (FOSS) within a low-cost logic that allows study of landscapes using limited budgets. In particular, the processing of the acquired data was performed with QGIS and its plugins. QGIS is a GIS free software and open source that has potential similar to equivalent commercial GIS and it is possible to extend functionality via native or external plugins. In particular the Semi-Automatic Classification Plugin (SCP) was used, which is a FOSS plugin that allows to process multispectral images and to perform their supervised classification. Furthermore, ever within the QGIS platform, the tools of Orfeo Toolbox were used. OTB is an open-source C ++ library for processing remote sensing images that includes several feature extraction, filtering, classification and segmentation algorithms. Regarding eCognition, this is the widely used commercial software for OBIA solutions. It is used in earth science to develop rule sets for the automatic analysis of remote sensing data. Besides, the extracted features can be exported in raster or vector format allowing integration into GIS applications. This software has been already applied in archaeology for feature recognition. As mentioned above, we used SCP for the pixel-based classification and eCognition (trial version) for the object-based analysis.

Classification techniques can be distinguished into the following two main broad categories:

- Pixel-based techniques or PBIA (acronym for Pixel Based Image Analysis), based exclusively on the spectral information contained in the individual pixels in the image.

Figure 3. The wall-structure (photo by authors)

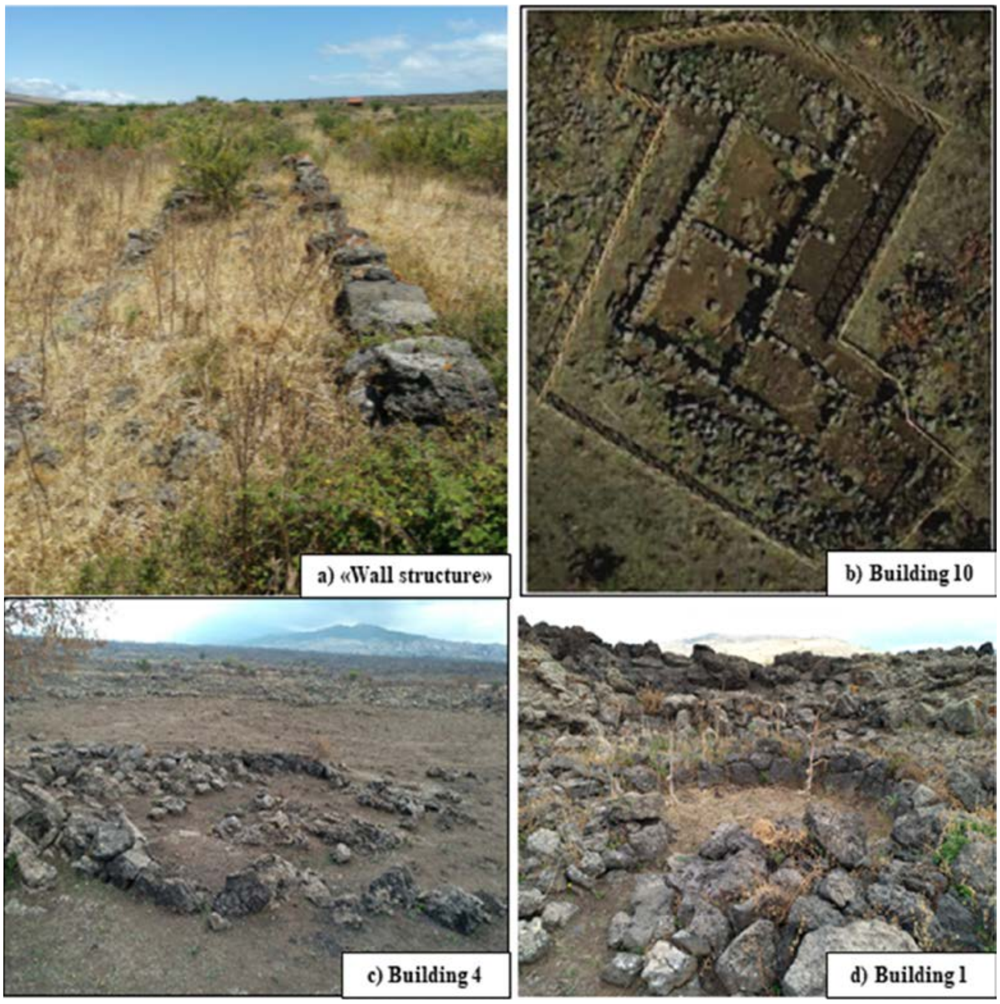

Figure 4. RMacro-class of rock divided in 4 sub-classes.

- Object-based or OBIA techniques (acronym for Object Based Image Analysis), which use information related to groups of pixels, considering the interrelations between adjacent pixels.

In the archaeological field, the classification procedures used have traditionally been pixel-based (De Laet, Paulissen, & Waelkens, 2007; D'Orazio, Palumbo, & Guaragnell 2012; Schuetter et al. 2013; Lasaponara et al. 2014); in recent years, scholars are moving towards the use of object-based techniques in order to obtain thematic maps characterized by a greater information content (Lasaponara et al. 2016; Sevara et al. 2016).

The detection of archaeological features, especially buried evidence, is a really complex task and modern techniques may be not so effective (Parcak 2009). Traces of archaeological remains include different features, which cannot be characterized by any specific color or tone of gray in the image, but rather by their huge heterogeneity. Archaeological marks (as crop, soil, shadow) might be easy to extract in a visual photo-interpretation process, but heir heterogeneity makes their automatic or semi-automatic classification problematic.

Pixel Based Classification

Pixel-based methodology uses the smallest entity within an image, the picture element (or pixel), in order to extract the feature information in relation to one or more predefined classes.

Therefore, the classification algorithms operate on individual pixels by analyzing the radiometric information, i.e. the value of the digital number (DN), of every single pixel present in the image. The assignment of the pixels to the classes takes place at the level of the single pixel and depends exclusively on its spectral content. The classes have either

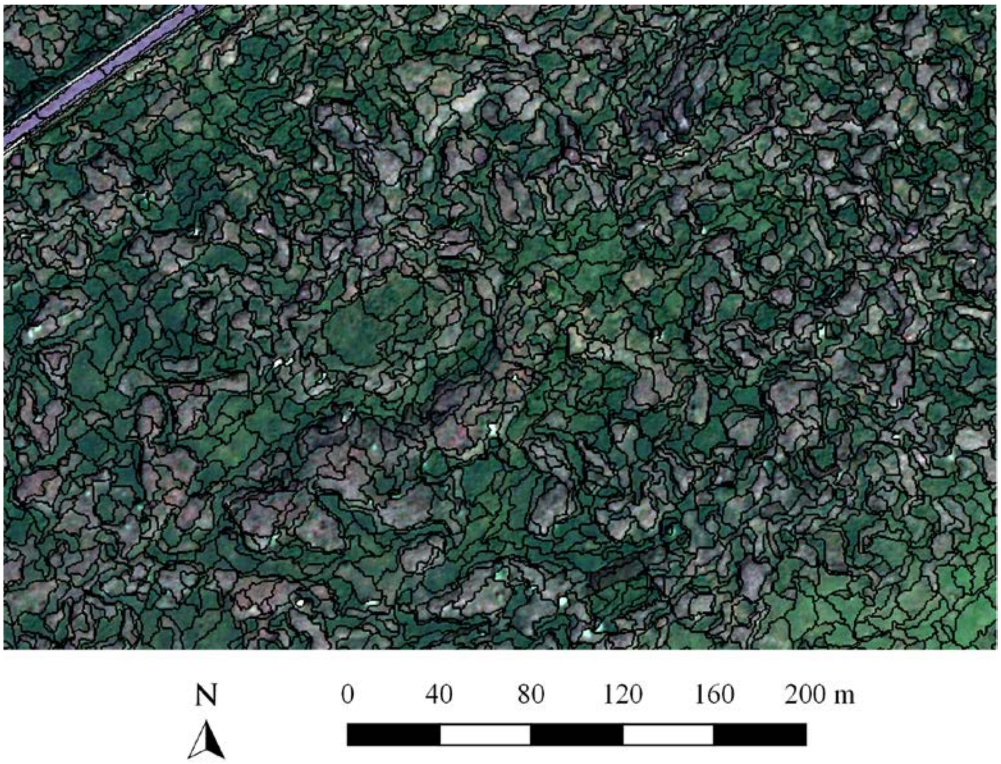

Figure 5. Segmentation process's results.

been predefined by the investigator in the form of a supervised classification approach, or identified by the software in an unsupervised approach based on grouping the spectral properties of the multispectral image's pixel.

Only the supervised pixel-based approach seems to be successful for archaeological feature detection, which first requires the definition of the number and nature of the classes to be represented in the thematic map. In the first phase (training), it is necessary to identify the thematic classes that will be extracted and represented in the classification. Moreover, the so-called training area or Region Of Interest (ROI) have to be identified in order to build a "model" of the thematic class, which consists in the creation of a characteristic and distinctive spectral signature of the considered class.

To start our classification, we identified 3 macro-classes of ROI

- Macro-class of rock, that includes the following classes of rocks (Figure 4):
  - **a.** Area taken from a double facing "wall structure" in the district of Santa Venera;
  - **b.** Area from emerging structure "Building 10", the biggest structure in the area, with a different spectral signature than the "Building 1"'s one.
  - **c.** Area from the floor of "Building 4";
  - **d.** Area from emerging archaeological structures called "Building 1";
- Macro-class of road;
- Macro-class of vegetation.

These last two macro-classes are defined exclusively to create spectral separability between the pixels in the image and to "train" the software, but they are not important for the research of archaeological remains. Once the training phase is over, the assignment phase is carried out by comparing, through specific classification algorithms, the spectral signature of the generic pixel to be classified with the spectral signatures of the previously created training areas.

Over the years, a huge number of algorithms have been developed. Analyzing the spectral signatures of the classes and the ROI's scatter plot, it seems that

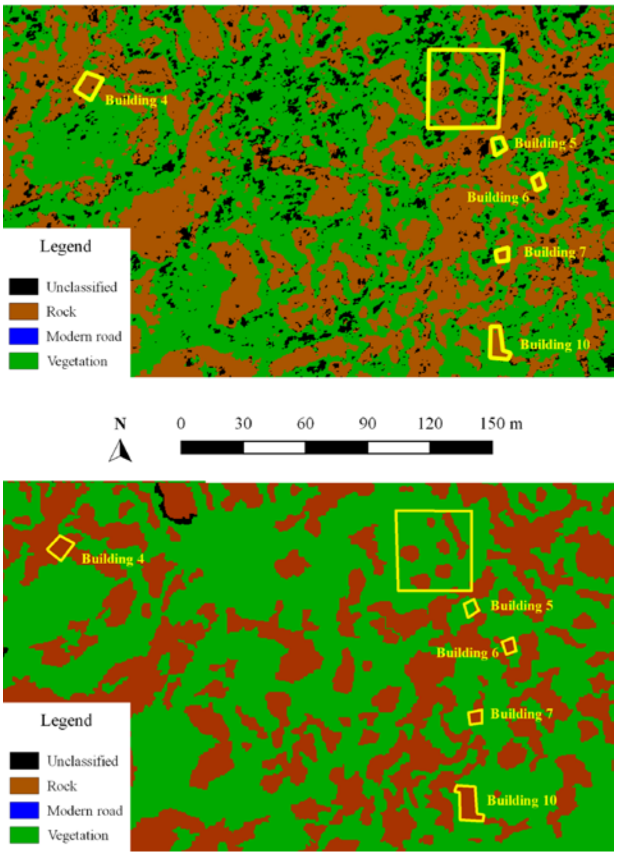

Figure 6. Comparison between pixel-based and object-oriented classification.

the Minimum Distance algorithm could be considered as the best one for our context and our purpose.

After completing the classification assignment phase, we move on to the last phase of the classification: validation phase. It consists in ascertaining the final accuracy of the produced image, realized by comparing the 'test area' with what the classifier has provided for the same locations.

Therefore, several test areas were identified in order to evaluate the accuracy of the image obtained from the classification.

Object Based Classification

In contrast to the pixel-based approach, an object-based image analysis (also called OBIA) uses the entire image or data set and breaks it down into meaningful segments (Blaschke et al. 2014). Generally, object-orientation is a programming paradigm based in the concept that the functions which are applied to data shall be assigned to a certain object. Object oriented approaches are usually based on two main steps: I) first, the segmentation, which consists in the delineation of homogenous regions in a data set; II) then, the classification, controlled by a knowledge base that describes the characteristics of output object classes (Lasaponara et al. 2016). In fact, based on initial segmentation, the single segments (i.e. sets of pixels) containing information about pixel values, object shape and topology are the input in the classification step (Benz et al. 2004). As the classified objects of interest can be used seamlessly in a GIS, OBIA is known as a technique combining remote sensing and GIS analyses (Rutzinger et al. 2006). Due to the complexity of data sources, creating a model or a "computer-based representation" is often a challenging task.

In archaeology, object-based image are discriminated not only on the different geometric and spec-

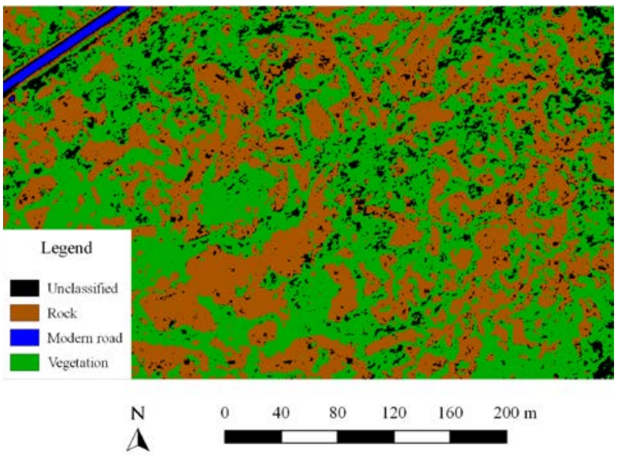

Figure 7. Pixel-based classification.

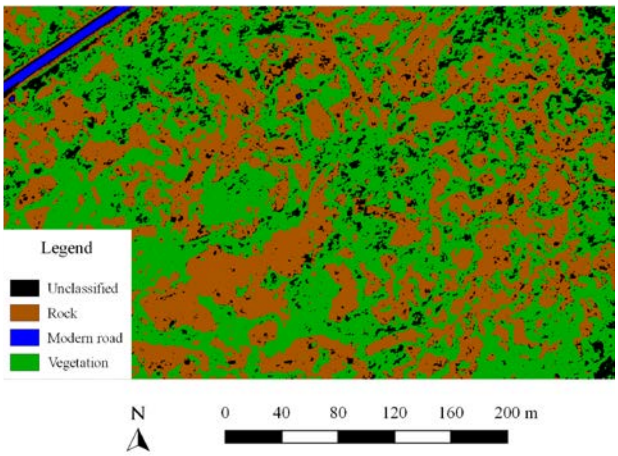

Figure 8. Object-based classification.

tral properties but also because of their semantic meaning and their association within dataset. OBIA techniques should not be used as a substitute for archaeological interpretation, but they can nevertheless increase productivity especially when dealing with large datasets. Our analysis was designed specifically for archaeological purposes. Our primary goal was to distinguish vegetation from volcanic rock and, then, identify regular shapes possibly linked to archaeological buildings. In particular, we focus on circular and rectangular shapes since the main interest of our investigations is the detection of these geometric shape features. We already know where archaeological evidence are located, because they have been already brought to light years ago. In this way, the post-dictive approach, as already stated by scholars (De Guio 2015), allows us to evaluate instruments and techniques at our disposal, emphasizing weaknesses and strengths. We performed the OBIA classification using eCognition software. In order to make archaeological feature pattern more easily recognizable, we used Red Edge, NIR-1 and NIR-2 bands.

Image Segmentation

The main aim of this phase is to find the optimal parameters for segmentation and extraction of rocky buildings using a Multiresolution Segmentation (MS), which is a segmentation technique provided by eCognition. Because MS is a bottom-up region-merging technique, it is regarded as a region-based algorithm. MS starts by considering each pixel as a separate object. Subsequently, pairs of image objects are merged to form bigger segments (Darwish, Leukert & Reinhardt 2003). The merging decision is based on local homogeneity criterion, describing the similarity between adjacent image objects. The pair of image objects with the smallest increase in the defined criterion is merged. The process terminates when the smallest increase of homogeneity exceeds a user-defined threshold (so called Scale Parameter – SP). Therefore, a higher SP will allow more merging and consequently bigger objects, and vice versa. The homogeneity criterion is a combination of color (spectral values) and shape properties (shape splits up in smoothness and compactness) (Darwish, Leukert& Reinhardt 2003). In particular, the value "one" on the color side will result in very fractal segments with a low standard deviation for pixel values, whereas a zero color value would result in very compact segments with higher color heterogeneity (Lasaponara et al. 2016). Furthermore, the shape parameter controls the shape features of an object by simultaneously balancing the criteria for smoothness of the object border and the criteria for object compactness.

Summing up, the segmentation process can be managed and modified by the three parameters seen: (i) scale (ii) shape/color and (iii) compactness/smoothness. Applying different combinations of these parameters, the user is able to create a hierarchical network of image objects. The configuration of the parameters depends on the desired objects to be segmented and, at the same time, segmentation does not have a unique solution, changing the scale parameters in multi-resolution algorithm can cause different solution; when the segmentation scale is not appropriate, the image can be under or over segmented.

In our analysis, we selected the three parameters and evaluated the goodness of the segmentation carried out, through a systematic trial-and-error approach validated by the visual inspection of the quality of the output. It is also possible to proceed with the classification process and then indirectly assess the goodness of segmentation process through the accuracy of the classifications produced (Darwish, Leukert& Reinhardt 2003). In order to make archaeological feature pattern more easily recognizable, in this step we have used Red Edge, NIR-1 and NIR-2 bands. In particular, we have taken SP equal to 25, shape/color equal to 0.85 and compactness/smoothness equal to 0.25. This means that 85% of the criterion dependent on shape and 15% on color. The shape factor was divided between compactness and smoothness in the ratio of 1 to 3. The results of the segmentation process are shown in Figure 5.

Image Classification

The segmentation results have fundamental implications because they form the basis of the subsequent classification; in this phase, classes are defined and each individual segment is assigned to a single class based on the employed target object's properties.

In the present case study, we selected the same thematic classes and the same ROIs used for pixel-based

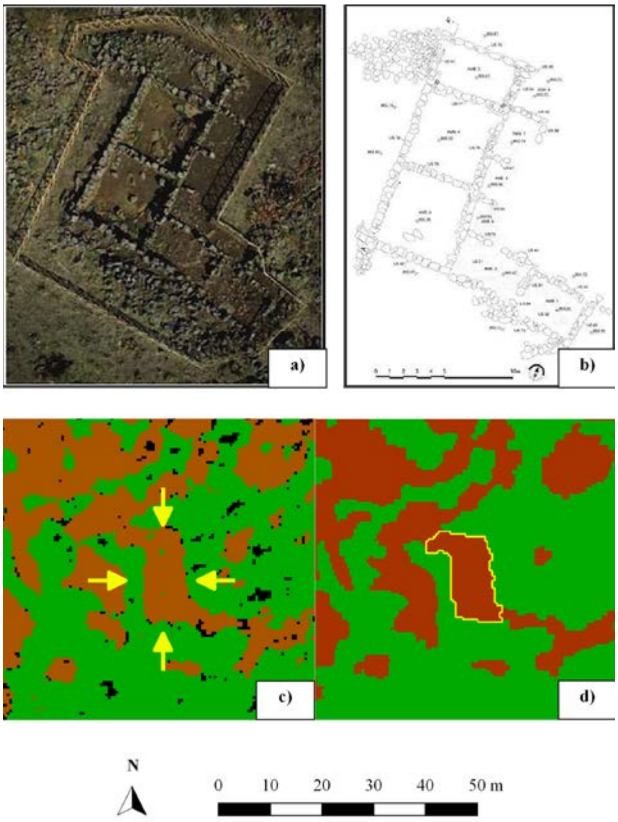

Figure 9. Building 10 from two different classifications: pixel-based (left), object-based (right).

classification. This will allow us, with the same boundary conditions, to make a comparison between the pixel and object approach applied to the particular context under examination. Like pixel-based classification, once the training phase is over, the next phase is assignment. However, unlike what is seen with the pixel-based classification, this assignment phase is performed using specific classification algorithms, which take into account not only the spectral characteristics of the previously created training objects, but also the geometric and topological features. In our analysis, we have used the Nearest Neighbor algorithm, which seems to be the best for our context. In particular, this algorithm has been appropriately calibrated to perform the classification taking into account both the spectral characteristics and the geometric ones (appropriately identified for the particular context under examination). The last phase of the classification is the validation phase, which consists in ascertaining the final accuracy of the produced image by comparing the 'test area' with what the classifier has provided for the same locations.

Results and Discussion

Now we want to compare the results from both traditional pixel-based and object-oriented classification. It is worth mentioning that the legend used is the same used for both approaches: this facilitates the comparison (Figure 6).

Pixel-based method allows us to classify emerging walls and structures especially, while other archaeological features were not correctly detected (Figure 7). In particular:

Building 10 is clearly recognizable also because it's the biggest and best conserved building;

with regard to Building 3, it is possible to identify just the emerging North-Western wall.

Building 4 is clearly recognizable, despite the modest dimension and the fact that it is mostly buried for its circular shape;

Buildings 5-6-9 cannot be easily distinguished from the surrounding lava rock; probably, the structures were built in that peculiar position in order to use the lava hill as a form of northern and cold wind protection; the "wall structure" in Santa Venera district is easy to recognize also because either its length and its wall's thickness.

Analyzing the results obtained, it is clear that the classification achieved through the minimum dis-

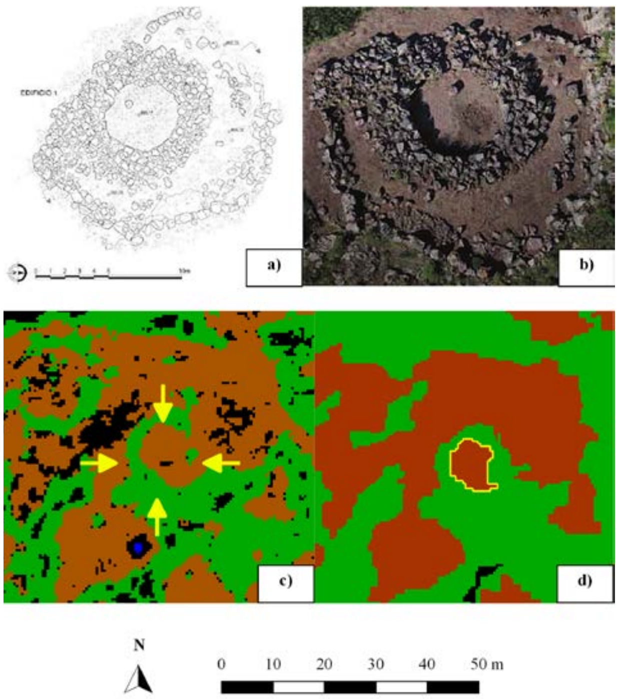

Figure 10. Building 1 from two different classifications: pixel-based (left), object-based (right).

tance algorithm has an overall accuracy of 45%. Also from the value of Cohen's Kappa it is clear that the classification is middling.

A further analysis of this value showed that one of the main problems is the classification of small objects, whose contrast to the surrounding environment is low. This is one of the most challenging problems, especially examining our situation. First of all, archaeological buildings have small dimension, considering that the biggest one is approximately 100 square meters. In addition, the material used for the construction of huts is not brick but, unfortunately, lava stone. So, we were looking for wall and structures made by volcanic stone in a volcanic plateau.

The final results of the object-based classification are shown in the following image (Figure 8).

Unlike what was obtained with the pixel-based approach, in the object-based procedure only a few of the archaeological buildings remained difficult to recognize, while most of them were detected correctly, despite the dense vegetation and the complex environment. In particular, the buildings already recognizable in the pixel-based classification map (such as the building 10, 4 and the wall structure) are here even better identified and defined (Figures 9 & 10). In addition, buildings that were not clearly recognizable in the pixel-based classification map (such as buildings 3, 5, 6 and 9) are more easily identifiable here

The positive final outcome is certainly to be found in the segmentation phase, in which operating with three types of parameters, adopting a trial-and-error approach, it is possible to segment the entire scene; so, the subsequent classification phase will be performed on objects and not simply on pixels. In addition, the classification algorithm used here takes into account not only spectral features, but also features related to the created objects (i.e. geometry, shape, etc.). All these elements allow us to obtain a thematic classification map characterized not only by a higher OA, but also by the absence of the classic "salt and pepper" effect typical of a pixel-based classification.

Although the object-based classification is considerably more accurate than the respective pixel classification, some unresolved issues remain. In fact, even if with a smaller entity, the problem concerning the classification of small buildings with a low contrast with the surrounding environment persists. As we have already mentioned above, this issue is closely related both to the size of the archaeological buildings sought and to the material with which the huts are made. In fact, the huts are not made of bricks but, unfortunately, of lava stone.

Conclusions

This paper has outlined two strategies for the semi-automated extraction of archaeological features from multispectral data, comparing the results of pixel and object-based approaches in the same archaeological environment.

The results discussed above represent a positive step forward for recognizing the value of different approaches. However, as we have demonstrated here, the use of an automated classification algorithm, as a complete substitute for manual interpretation, would result in a series of errors.

The final outcome is even more critical taking into account the pixel-based classification, where a number of archaeological buildings have not been classified in the correct way. The main issue deals with the problem of separating, using spectral signature, lava rock from archaeological structures made of lava stonewalls. In addition, many variables, as environmental conditions, greatly reduce successful classification rates.

In the object-based procedure, just few of the archaeological buildings remained hard to recognize, while most of them were detected correctly. The post-dictive approach, with targeted detection and classification of known classes already in mind, clearly helped in obtaining a good performance.

So, at least automatic identification of archaeological features procedure provides a functional benefit in a time-saving perspective, reducing the necessity to manually digitize features. In addition, rapid detection of potential objects of interest can be a perfect starting point for more detailed and subsequent interpretations.

In our opinion, the development of semi-automated techniques for the analysis of remote sensing data is priority and what this work makes evident is that the skilled interpreters role will be crucial to any process. Clearly, we still need to create general framework for archaeological feature detection in specific contexts, especially for the volcanic one here presented, without having to rewritten rulesets completely.

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