Theory and practice for an object-based approach in archaeological remote sensing

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1. Introduction

In recent years, archeological research has seen an increasing number of remote sensing (RS) applications with the use of new sensors and data types, such as multi/hyper-spectral imagery (Traviglia, 2011; Lasaponara, Masini, 2012; Doneus et al., 2014; Agapiou et al., 2014; De Guio, 2015; Moriarty et al., 2019), radar (Wiseman, El-Baz, 2007; Lasaponara, Masini, 2013; Chen et al., 2016; Tapete, Cigna, 2017; Burigana, Magnini, 2018) and LiDAR data (Bewley et al., 2005; Devereux et al., 2005; Doneus et al., 2008; Challis et al., 2011; Opitz, Cowley, 2013), that have joined the classic aerial photographs. However, these innovations had only little impact on the traditional photointerpretation, which remains essentially a work for the human operator via visual inspection (Brophy, Cowley, 2005; Cowley, 2015; Crutchley, 2015; Wilgocka et al., 2016; Quintus et al., 2017).

The reduction of the instrumental costs and the exponential increase in the volume of datasets of the last few years prompts for an overall revision of the methods traditionally used in archaeology (Bennett et al., 2014). In this context, the automation or semi-automation of image analysis seems to offer an opportunity to speed up and grant better reproducibility for the classification and the subsequent interpretation of the remotely sensed imagery, even in the archaeological field. This approach has a long history in the domains of environmental, material and biomedical sciences (Heidrich et al., 2013; Caie et al., 2016; Feuchtinger et al., 2016; Hawkins et al., 2016), but its potential is yet to be fully exploited for systematic research on cultural heritage.

As previously pointed out, the number of papers dealing with object, pattern and scenery recognition (OPSR) of archaeological contexts is still very limited and includes applications of template matching, machine learning, convolutional neural network (CNN), custom algorithms and object-based methods (see Traviglia, Torsello, 2017 and Davis, 2018 for a general overview on the topic). In this paper, we will focus our discussion on object-based image analysis (OBIA or GeOBIA, with a geographic connotation) which was described as "an evolving paradigm with specific tools, software, methods, rules, and language (that) is increasingly being used in studies which need to conceptualize and formalize knowledge representing location based reality" (Blashke et al., 2014).

In order to promote the interoperability of the rule-sets, it is necessary to make explicit what it is implicit in the classification and interpretation process. For this purpose, we propose a theoretical

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framework aimed at formalizing expert archaeological knowledge using ontologies (i.e. formal, explicit specifications of a shared conceptualization, according to Gruber, 1993). Moreover, we introduce the concept of Diachronic Semantic Models (DhSM), developed to better explain the long-term evolution of the landscape in machine-readable language (§ 4.1).

As object-based applications make their way into archaeological practice, it becomes increasingly important to find a shared language and a common protocol of investigation, ideally passing from operational practice to operational routine. In this paper, we suggest a general workflow for OBIA applications in archaeology built from a wide range of published and unpublished case-studies to ease the comparability of data. Finally, we argue that there is a growing urgency to find a common way for publishing rule-sets and rule-set libraries to be semi-automatically or automatically implemented for archaeological investigations. This topic is of general interest for the OBIA community, but it should be stressed with a particular emphasis in view of further increasing the role of object-based applications in archaeology, as most of the operators have a humanistic background and, consequently, longer learning times in the development of customized rule-sets.

2. Overview of the method

2.1. The OBIA approach

RS imagery are composed of pixels (or voxels, in a 3D coordinate system), whose dimension is a function of the sensor used and of the parameters employed for the acquisition (Gonzalez et al., 2008). While pixel-based classifications rely only on the information contained in each single pixel (Lillesand et al., 2004), the basic entity of OBIA is represented by image-objects (sometimes also called image-segments) (Hay et al., 2001; Blaschke et al., 2004). An image-object is "a discrete region of a digital image that is internally coherent and different from its surroundings" (Castilla, Hay, 2008); each image-object is characterized by a set of additional spectral, textural, morphometric and relational parameters that can be used to fine-tune the results of the image classification if compared to the per-pixel approach (Baatz et al., 2008; Gamanya et al., 2009; Wuest, Zang, 2009; Blaschke et al., 2014). Moreover, image-objects can represent geographic objects (*sensu* Castilla and Hay, 2008) more accurately than single pixels and, thus, they offer an improved basis for classification.

Image analysis using object-based methods can be essentially divided in two main sequential steps: segmentation and classification. Segmentation is used to partition the image into homogeneous regions, called primitive-objects. However, primitive image-objects are not always meaningful, i.e. they do not always readily correspond to the real-world entities (Castilla, Hay, 2008). This is the reason why numerous cycles of segmentation and classification are sometimes employed for further refining.

The typology of segmentation algorithms is wide (Pal, Pal, 1993) and in constant increase, starting from the simplest (such as the chessboard and the quad-tree algorithms) to the most complex procedures (as the multi-threshold or the multiresolution segmentation). The multiresolution segmentation (MRS) is generally recognized as one of the best performing solutions both in the fields of biomedical sciences and RS. MRS is a bottom-up technique designed to emulate human perception. Basically, it maximizes intra-object homogeneity while maximizing inter-object heterogeneity (Baatz, Shape, 2000). The algorithm starts from generator-pixels called seeds and groups adjacent pixels in numerous subsequent steps. When the computed heterogeneity surpasses the threshold value defined by the scale parameter, the process interrupts and image-objects are generated (Benz et al., 2004). Simplifying, the higher is the scale parameter, the bigger will be the resulting image-objects (Drăguţ, Blaschke, 2006). The homogeneity criterion can also be manually adjusted by operating on the shape and compactness of desired values. It has been stated that omitting the influence of the shape parameter during the segmentation can offer better results in the task of landform classification (Eisank et al., 2011).

As previously noted, image-objects produced via image segmentation possess a series of intrinsic (object features) and extrinsic (class-related features) descriptors which can be used to direct the classification process. In fact, the classification phase is intended to distinguish image-objects into meaningful classes based on their attributes and relationships and according to the specific aims of the research (Castilla, Hay, 2008). The selection of the classification parameters and their threshold values can be both derived from selected training areas and a set of derived statistics (standard nearest neighbor classification, NN) or directly evaluated by the operators according to their expert knowledge (rule-based classification). It was demonstrated that rule-based classification outperforms pixel-based and object-based NN classifications in the accuracy of the results (Gibril et al., 2017). It should, however, be noted that the expert knowledge is subjective and cannot be used as such for the creation of exportable rule-sets, if not in very limited cases (Andres et al., 2012) as it will be better discussed later.

The most common software for object-based image analysis is eCognition Developer, owned by Trimble Inc.; however, in recent years the interest for Free and Open-Source Software (FOSS) for GeOBIA is progressively increasing as testified by numerous papers employing combined solutions using Orfeo ToolBox, R, GRASS GISS, QGIS or Doker (Van De Kerchove et al., 2014; Böck et al., 2016; Grippa et al., 2016; Knoth, Nüst, 2017) but also by the development of specific tools such as GeoDMA (Körting et al., 2013) and InterIMAGE (Costa et al., 2010).

2.2. OBIA in archaeology: a general outline of the literature

Automation is still a controversial issue in archaeological photo-interpretation (Hanson, 2008, 2010) as clearly highlighted by the quote "Why does there even need to be an automated process for satellite archaeology?" (Parcak, 2009). The answer is strictly entangled with the potential of OPSR to speed-up the examination of large amounts of data and to grant a better reproducibility to the task of image analysis, contributing at the same time to the management and protection of the archaeological record (see, among others: Magnini et al., 2017; Davis, 2018; Lasaponara, Masini, 2018).

Despite the challenges and misunderstandings between the traditional archaeologists and the RS experts, the scientific literature on the subject is rapidly growing (Traviglia et al., 2016). Among the papers dealing with (semi)automated OPSR in archaeology, however, only a minority employ object-based image analysis (Lambers, Traviglia, 2016; Davis, 2018).

The earliest employ of OBIA in archaeology dates back to 2007, when Jahjah et al. (2007) applied this approach for change detection analysis around the area of the ancient Babylon (Iraq). In the same year, De Laet et al. (2007) tested a procedure for the extraction of archaeological structures from multispectral satellite images comparing a set of different automated methods and visual inspection. The outcomes of this last case study were discouraging and contributed to a contraction in the archaeological applications of OBIA *stricto sensu*. However, starting from the same period, there was a progressive growth of OPSR applications (such as Bescoby, 2006; Menze et al., 2006; De Boer, 2007; Trier et al., 2009; Menze, Ur, 2012; Trier, Pilø, 2012; Schuetter et al., 2013; Caspari et al., 2014; Schneider et al., 2015; Sanger, 2015; Toumazet et al., 2017; Guyot et al., 2018; Trier et al., 2018; Matos-Machado et al., 2019), which are well worth mentioning here as they provided the foundation for a combined use of OBIA and OPSR, which is one of the most recent trends in automated detection (Davis et al., 2019).

It was only in 2012–2013 that object-based image analysis *stricto sensu* was given a second chance, this time for automating the delineation and classification of landforms starting from Digital Elevation

Models (DEMs) (Verhagen, Drăguţ, 2012, 2013). The promising results of this project triggered a new season of experimentation. In 2013, the method was used with success in the identification and classification of mountain pools on aerial photographs for ethnoarchaeological purposes (De Guio et al., 2013). In the same period, it was employed for the textural characterization of ancient marbles from petrographic micrographs (Hofmann et al., 2013). The following year, OBIA was tested for analyzing magnetic anomalies deriving from geophysical surveys (Pregesbauer et al., 2014) and it was cited as an engaging novelty for archaeological RS in a theoretical paper by Sevara and Pregesbauer (2014). An article on semi-automatic photointerpretation of aerial images combined with near infra-red (NIR) data was published in 2015 (De Guio et al., 2015). From 2016 to 2018, there was a steep increase in the quality and quantity of the publications, pointing to rapid advancements in the near future. Sevara et al. (2016) compared pixel-based and object-based image analysis in two test areas starting from different LiDAR visualizations. Moreover, Freeland et al. (2016) reported the results of a study in the Kingdom of Tonga, where they compared the results of the GeOBIA approach with an inverted pit-filling algorithm called iMound. OBIA was also experimented for the first time at artifact-level for classifying a set of prehistoric stone tools based on morphometric characteristics (Lamotte, Masson, 2016). A custom procedure was tested by Cerrillo-Cuenca (2017) for the detection of megalithic barrows on LiDAR data. Furthermore, it proved helpful in predicting the location of control places suited for human occupation in mountainous environment (Burigana et al., 2017) and for mapping and monitoring of the vanishing heritage connected to the First World War (WWI) (Magnini et al., 2017). New approaches were employed on Maya sites for the classification of the land cover connected with different types of archaeological structures (Inomata et al., 2017); in the USA, the method was employed for the identification of ethnoarchaeological charcoal hearths (Witharana et al., 2018) and, again, for mound and shell-ring detection (Davis et al., 2018, 2019).

What emerges from this general chrono-history of OBIA applications in archaeology is that the method is generally used to identify small, round archaeological structures: most often mounds, but also barrows, charcoal pits and shell-craters. The source datasets for landscape-level analyses are usually constituted by LiDAR-derived DEMs and their visualizations. However, aerial and satellite imaging (both orthophotos and multispectral data) were also used, sometimes in a multi-layer process. Moreover, it should be noted that there is a wide variability in the scale of the analyses, from the regional to the microscopic level (Hofmann et al., 2013; Heidrich et al., 2013; Gerisch et al., 2018).

3. Results and discussion

3.1. Practical issues

Despite the strengths and opportunities offered by OBIA, a series of drawbacks and weakness must be taken into account when considering the slow emergence of this method in archaeological RS. The criticism of conservative archaeologists has significantly slowed down in the last few years as the technological advances in the field of computer-aided OPSR have demonstrated their significant contribution to the research (Bennett et al., 2014); however, a series of practical issues is still preventing from an extensive diffusion of the method beyond the restricted circle of RS experts.

The basic obstacle should probably be associated to the software solutions (both proprietary and FOSS) for object-based image analysis, which are far from being user-friendly. Back in the early days of GeOBIA, Hay and Castilla (2008) noted that "under the guise of 'flexibility', some commercial object-based software provides overly complicated options, resulting in time-consuming analyst 'tweaking'". If this was true for computer scientists less than a decade ago, it is even more true for most of today's archaeologists that have just managed to reach a systematic integration of Geographic Information Systems (GIS) into the everyday field practice. The recent birth of eCognition Essentials (Trimble Inc.) has tried to overcome this problem and to offer an intuitive workspace for object-based classifications, especially with NN. However, the Developer version still retains the most complete collection of tools and algorithms which are crucial for rule-based classification of archaeological RS data.

Segmentation is a second point of interest. This phase is in fact the most criticized step of an OBIA project, as highly dependent on the personal choices of the operator. Different supervised and unsupervised methods have been proposed over the years to automate the selection of the scale parameter, as recently synthetized in the review paper by Zhang and Du (2016). However, the problem is yet to be completely solved, as segmentation is highly dependent on the data source, the aim of the study, the geographical context, the surrounding contrast and the internal heterogeneity (Zhang et al., 2018). In general terms, it was stated that over-segmentation is usually preferable than under-segmentation (Witharana and Civco, 2014); in fact, any specialized software offers the chance to refine the image-objects to better fit with the real-world objects during all the steps of the workflow. This is particularly obvious for archaeological case studies, where an apparent over-segmentation is often necessary for granting the necessary detail to traces that may appear secondary in the investigated context, such as in the case of evanescent crop-marks in cultivated and uncultivated fields, within a network of agricultural channels and rural houses (De Guio et al., 2015).

The incompleteness of the residual record is a major problem archaeology. This is even more evident in the field of RS, because this approach mostly relays on mediation factors (vegetation/soil/snow/shadow-marks, micro-morphology, etc.) which can sometimes limit the interpretative potential of the work, if disconnected from ground-truth assessment strategies. In fact, the archaeological remains are always affected by post-depositional processes which progressively alter their original characteristics, with different degrees of impact (Schiffer, 1972; Wood, Johnson, 1978; Nash, Petraglia, 1987; Leonardi, Balista, 1992; Harris, 1997). These processes can often lead to multifinality, i.e. a high variability in the physical outcomes of the same category of evidences (von Bertalanffy, 2003; Forbes, 2017). On the other hand, different archaeological entities can end up sharing similar characteristics at a certain point of their morphogenetic path, so much as to be not easily distinguishable from a remote point of view. This problem can be framed in the general context of equifinality, which accounts for the possibility of a convergent or similar behavior in open natural and anthropic systems of high complexity (Fig. 1) (von Bertalanffy, 2003; Graham, Weingart, 2015; Forbes, 2017).

Moreover, the archaeological traces on RS imagery are often associated to a complex palimpsest of historical and contemporary infrastructures of both natural and anthropic origin. Their presence affects the spatial continuity and/or the integrity of the ancient remains and can significantly hamper a proper semi-automatic recognition.

As previously noted, human perception can differ widely from a digital classification based on numeric values. For example, despite the straightforward nature of mountain pools in Alpine environment, applying the object-feature "roundness" is often not enough to correctly identify them all (De Guio et al., 2013). This kind of logical consequentiality has value in the conceptual domain, but can rarely be applied to real-world case studies. The presence of outliers (i.e. the twin pools) requires a revision of the original mental model and the use of different morphometric, textural, chromatic or relational parameters able to incorporate the widest variability of the considered archaeological entities.

Further limits sometimes highlighted in the literature are the reproducibility of the method and the exportability of the rule-sets (Sevara et al., 2016; Freeland et al., 2016). These questions are strictly entangled with the willingness of sharing the descriptors and parameters used in the classification process and are primarily connected to the operators rather than with the method *per se*. Nevertheless, both are

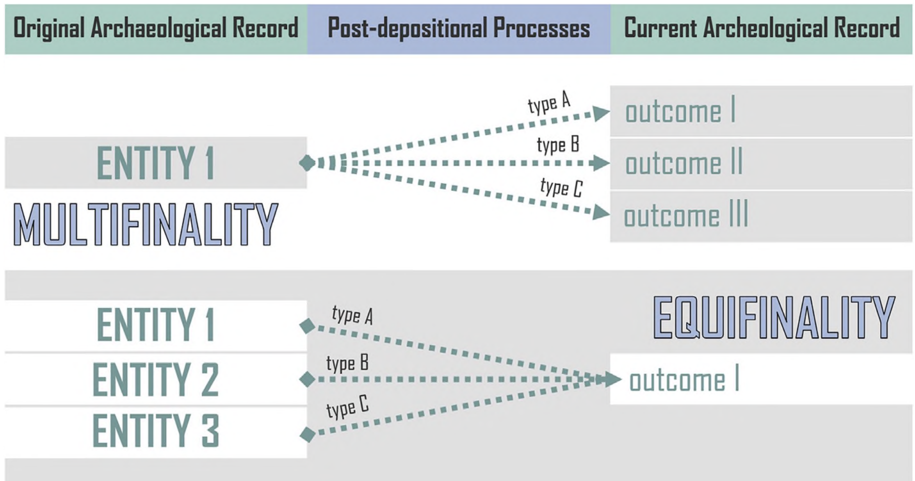

Fig. 1. The multifinality (top) and equifinality (bottom) problem from an archaeological RS perspective.

also rooted in the dilemma posed by the so-called *semantic gap*, which is the lack of coincidence between the information extracted from the visual data and the interpretation given by one or more experts on a given dataset (Smeulders et al., 2000). In this sense, the association of semantics based on formal and material ontologies (Husserl, Moran, 2001) to the archaeological domain seems one of the most promising answers, as it will be better discussed in the following paragraphs.

3.2. Towards a theoretical framework

The application of OBIA in archaeology is essentially based on expert knowledge. This means that the archaeologist retains an essential role in the whole process of image classification and data interpretation. Hence, automation should be regarded as an aid rather than a substitute of traditional visual inspection. At the same time, "the process transforms object-based image analysis into a type of computer-aided photointerpretation in which two experts analyzing the same data will obtain two different results because of their different experiences", as it was already pointed out in the field of Earth Observation (EO) (Arvor et al., 2013).

With this in mind, it is now necessary to propose an explicit theoretical framework to provide a common ground for further developments of the method in the archaeological practice and to foster object-based applications in archaeology towards higher levels of heuristic awareness. In turn, this will help to minimize the human bias introduced during the classification, contribute to the performance of (semi)automatic image interpretation and ease the interoperability of the data.

In this chapter, we discuss the use of ontologies as a mean to formalize archaeological knowledge. We also stress the role of the archaeological landscape, which is a four-dimensional entity derived from long-lasting human/nature interactions. Moreover, we define the notion of archaeological objects in the context of OBIA and we use them to explain the complexity of the archaeological palimpsest. By doing so, we also suggest a possible method to address the problem of classifying multi-/equi-final entities.

3.2.1. Diachronic Semantic Models (DhSM)

The use of ontologies and semantic modeling has been proposed on various occasions as an approach for linking the conceptualized idea of the geographic entities and their digital representations (among others: Dehn et al., 2001; Eisank et al., 2011; Arvor et al., 2013; Ghazouani et al., 2018). As already noted, ontologies were defined as a formal, explicit specification of a shared conceptualization (Gruber, 1993) easily transferrable in machine-readable language. Shared conceptualizations can be also regarded in terms of mental models, that are meant to simplify complex real-world situations and are often discipline-specific (Bishr, 1998). The same author describes semantics and semantic modeling as "the relationship among the computer representations and the corresponding real world feature within a certain context". This process involves three main domains of knowledge: 1) the real-world domain, made up of concrete entities (e.g. an existing village, cemetery, road); 2) the conceptual domain, constituted by abstract ideas of real-world entities based on expert knowledge; 3) the digital domain, associated to the virtual representation of real-world entities in computer-generated data.

However, the application of this approach to the archeological research is not straightforward as the chronological depth introduces a new variable in the system. Consider the case of an ancient settlement. In the real-world domain, it was subject to specific transformations (during use, obliteration, destruction, re-use …) that altered its original characteristics irreversibly. When trying to formalize a general ontology, it is necessary to consider its history through time: how could have it looked like in the past? How could it be now, after the transformations induced by the post-depositional processes in that specific context? And finally, how does it effectively appear, from a RS perspective?

In extreme synthesis, landscape archaeology is the study of the relationship between humans and nature in a diachronic perspective. The combined transformations in the landscape promoted by these two actors trigger the formation and the evolution of the archaeological record that can be studied through RS imagery. As shown in the scheme of Fig. 1, this uneven and often unpredictable succession of anthropic and natural actions can cause both a high rate of morphogenetic variability within the same class of archaeological evidences (multifinality) and similar outcomes deriving from the nonlinear development of different entities (equifinality). This palimpsest results in varying degrees of shift between the conceptualized idea of a specific archaeological evidence and its physical, real-world appearance.

For this reason, semantic models should be applied with a diachronic perspective. Fig. 2 summarizes the biunivocal connections between the digital, the conceptual, and the real-world domains in the study of the archaeological record at landscape-level. At the same time, it introduces the core concept of Diachronic Semantic Models (DhSM), which integrates the idea of evolution/transformation in the formalization of ontologies derived from expert knowledge. In other words, having a clear picture of how an ancient context should have looked like is not enough. One needs to be aware of the possible modifications that occurred during the millennia to develop an efficient conceptualized model that can be translated in machine language and

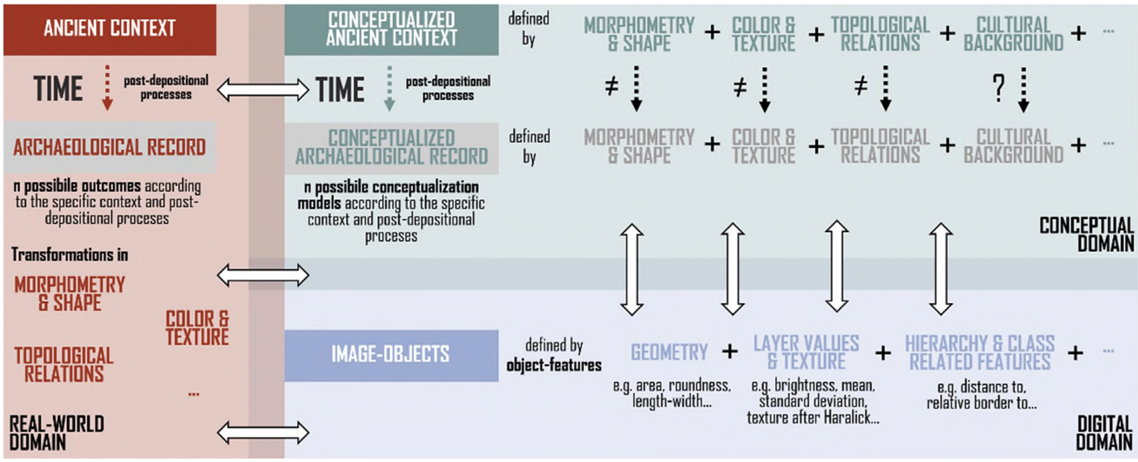

Fig. 2. Graphical representation of the biunivocal connections linking the real-world, the conceptual and the digital domains for modeling the evolution of the archaeological landscape through time.

used to maximize the results of a semi-automatic image analysis.

Further consequence is that classification does not necessarily coincide with interpretation. While classification can be neutral (parametrically speaking), interpretation is subjective because it relies both on the information extracted from the actual data and from additional knowledge sources which can be *a priori* and contextual (Ghazouani et al., 2018). Interpreting is giving meaning; in the case of OBIA, it consists in assigning a semantic label to a group of image-objects that share a set of meaningful parameters. According to this view, developing ontologies based on DhSM is an essential point within the OBIA framework because it helps in formalizing explicit knowledge models which can be shared among the archaeological RS community and thus offer a common ground in the image interpretation and decision-making domain.

3.2.2. *Archaeological objects: simplifying complexity*

In computer vision, 'objects' are autonomous portions of the real-world defined by specific properties which express an enduring identity in contrast with the characteristics of the surroundings (Smith, 2001). To avoid any misunderstanding, it should be stressed that objects are real-word entities, while image-objects in OBIA are self-coherent segments of a digital image (Castilla, Hay, 2008).

According to our proposal, archaeological objects (in short, archaeo-objects) constitute a sub-set of geographic objects as defined by Castilla (2003). Specifically, archaeo-objects are scale-dependent, bounded geographical areas with archaeological significance that can be identified as the residual referent of the original archaeological record at a specific stage of its morphogenetic path. Despite the focus on the current situation, archaeo-objects are intrinsically dynamic and their transformations through time can be broadly modeled using DhSM.

Demarcating the boundaries is the result of a cognitive process and can be viewed as a conceptual activity; the borders of an archaeo-object may be gradual or abrupt, and eventually a single archaeo-object may be physically split up by the presence of modern disturbance. However, as Castilla and Hay (2008) have demonstrated, this constitutes the peculiarity of certain geo-objects with respect to the conventional geographic entities that are ontologically autonomous.

It is possible to distinguish two main categories of archaeological objects: simple and complex. Complex systems theory distinguishes between simple, complicated and complex systems (Forbes, 2017). Simple systems are composed by few elements, are fully predictable and can be easily modeled. Complicated and complex systems, instead, possess a higher number of parts and require more information to be described. Yet, while complicated systems are fully predictable, complex systems are characterized by a certain degree of entropy that prevents the possibility to fully model or predict them. As all archaeological objects share a certain degree of unpredictability, our definitions of simple and complex archaeo-objects will also relay on the concept of heterogeneity, according to what was proposed by (Weinberg, 1975) who developed a classification based on small-number, middle-number and large-number systems.

Essentially, simple archaeo-objects are made up of one or a few homogeneous parts with similar behaviors and can be defined with a limited set of descriptors and parameters. Despite their unpredictability, it is however possible to model them with a decent level of accuracy within a given context (Fig. 3). It seems no coincidence that most object-based archaeological case studies have dealt with the investigation of simple archaeo-objects such as mounds (among others: Kramer, 2015; Freeland et al., 2016; Davis et al., 2018), shell-craters (Magnini et al., 2017) and charcoal hearths (Witharana et al., 2018).

Complex archaeo-objects comprise a low to high number of heterogeneous parts, require a vast amount of information to be described, are not fully predictable and can be modeled as a whole in a given context only with a low degree of accuracy. In other words, despite being generally perceived by the human observer as a single entity, complex archaeo-objects are composed by elements belonging to one or more hierarchically interconnected sub-classes. This is clearly exemplified by the remains of an ancient settlement (Fig. 4a) or by the fortification published in Sevara et al. (2016).

It is interesting to note that even archaeological objects that might be conceptualized as simple, in specific environmental (season, level of disturbance, etc.) and representational (sensor typology, scale, etc.) conditions are more consistent with the category of complex archaeo-objects. Consider for instance the case of the paleo-channel and the ancient road in Fig. 4b, where the presence of modern structures affects the spatial continuity and alters the integrity of the crop/soil-marks to such an extent that the traces can be no more classified with a limited set of descriptors and parameters (e.g. high ratio between length and width, uniformity in color) (De Guio et al., 2015).

For this reason, it is crucial to work on multiple layers with a variety of datasets and/or to use OBIA in conjunction with other OPSR approaches for accurately identifying objects at landscape scales (e.g., De Guio et al., 2015; Cerrillo-Cuenca, 2017; Davis et al., 2018).

The formal distinction between simple and complex archaeo-objects is important as it can help to address the problem of semi-automatic, digital classification of multifinal entities or of complex archaeo-objects, which are a long-lasting problem in applying an object-based approach to archaeological RS.

As already noted, complex archaeo-objects can be seen as a hierarchically interrelated group of simple archaeo-objects. Hence, the next

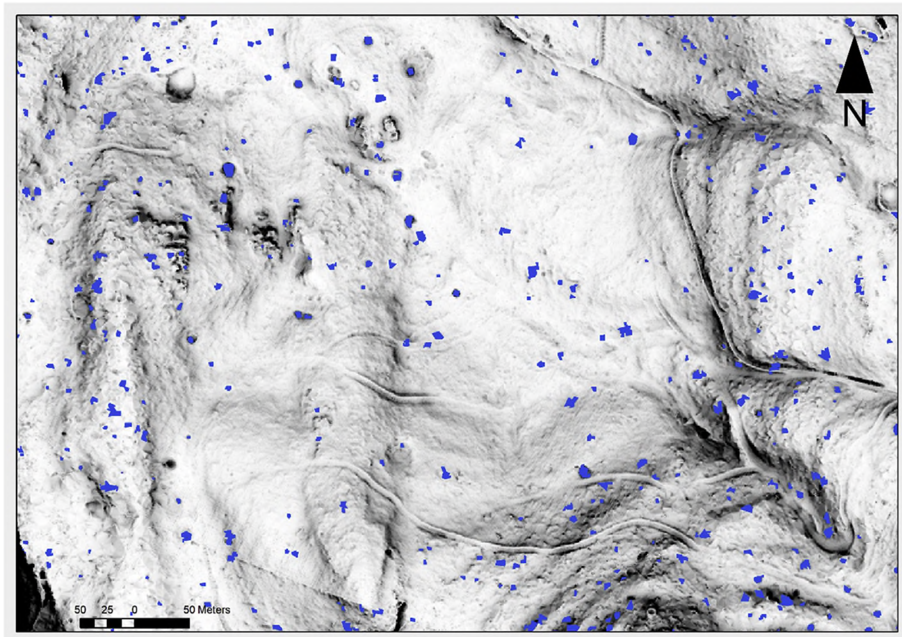

Fig. 3. Classification of simple archeo-objects: an example of WWI shell craters in Alpine environment (68).

step in the analysis of complex archaeo-objects is to split up the overall DhSM into single, hierarchically interconnected elements, to evaluate their presence/absence in the scene and then to reconstruct the complex object through relational parameters between the individual subclasses. The opportunity to create specific rule-sets for each element and to modulate them in a global rule-set through a hierarchical procedure opens new perspectives for the use of this method also in a multiplicity of palimpsestic archaeological contexts.

Fig. 5 shows a preliminary classification of the multifinal class "trench" related to the WWI trenching system around the Austro-Hungarian fort in Luserna (province of Trento, Italy). The trenches were first classified according to their post-depositional history and their appearance on the LiDAR visualizations in the three sub-classes: restored, filled and residual. Secondly, the three classes were merged to obtain a general representation of the class "trench".

The expression Archaeological Object-based Image Analysis or ArchaeOBIA was first introduced in its French form (ArchéOBIA) by Lamotte and Masson (2016), who intended to promote "une méthodologie d'extraction automatique d'informations quantitatives sur des collections archéologiques quelle que soit la période" ("a methodology for the automatic extraction of quantitative information from archaeological collections regardless of the period"). The authors limited the

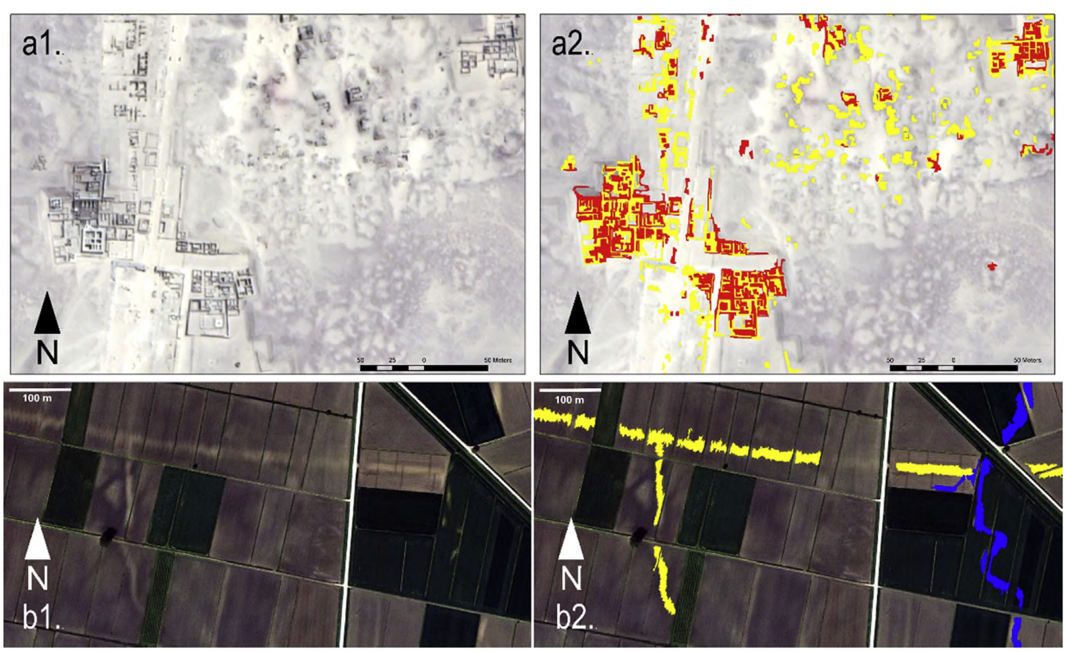

Fig. 4. Classification of complex archeo-objects. (**a1**) Multispectral WorldView 2 satellite image of the ancient village of Tebtynis (Egypt), with classification of the excavation progress (**a2**) for time series analysis; (**b1**) aerial image of Ponte Moro (Po Plain, Italy) with crop/soil-marks related to a Bronze Age infrastructural system interrupted by a modern hydric and road network, (**b2**) with classification of a paleo-channel (blue) and an ancient crossroad (yellow). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

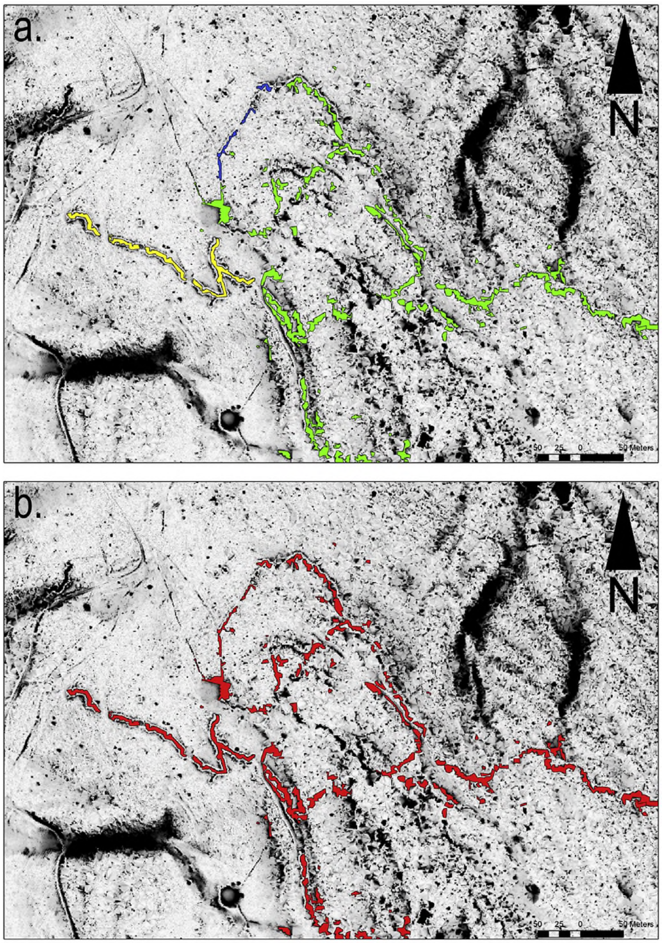

Fig. 5. Complex archeo-objects: the case of the WWI trenching system around Fort Lusern (province of Trento, Italy). (**a**) Classification according to the post-depositional history in 3 different classes: restored trenches (yellow), filled trenches (blue) and residual trenches (green); (**b**) merging of the previous classes in the multifinal class "trenches". (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

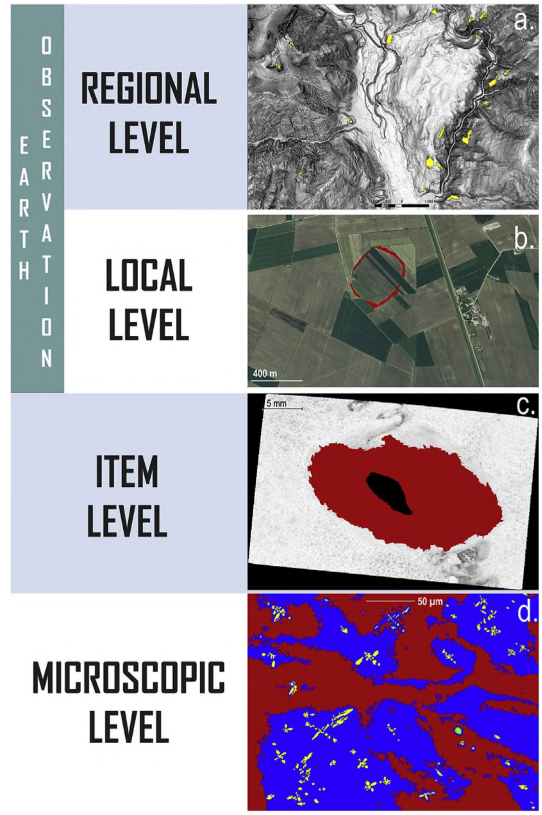

Figure 6. ArchaeOBIA levels of application. (**a**) regional-level: classification of "control places" in Alpine environment (Isarco Valley, Bolzano Province, Italy) starting from LiDAR data; (**b**) local-level: classification of the perimetral bank of the Bronze Age Terramare settlement of Castello del Tartaro (Po Plain, Italy); (**c**) item-level: classification of the recalcified osteological tissue in a Bronze Age cranium of the Olmo di Nogara necropolis (Po plain, Italy) after medical surgery; (**d**) classification of the glassy matrix and the different types of crystalline inclusions in a SEM-BSE image of a Ptolemaic glass sample from Egypt.

field of applications of object-based methods in archaeology to the morphometric computation of material remains at item-level, in terms of artifacts and ecofacts (Lucas, 2012). However, as we hope to point out throughout this chapter, the potential of the OBIA approach impacts various fields of the archaeological research, from EO at regional and local scale, to material studies at item and microscopic levels (Fig. 6).

3.3. *ArchaeOBIA in action*

For this reason, we propose a conceptual revision of the term. In particular, ArchaeOBIA will be employed throughout the text when referring to the use of object-based methods in archaeology within the theoretical framework of DhSM and archaeo-objects. The workflow concept of an ArchaeOBIA project is summarized in Fig. 7. The envisaged workflow is constituted by 5 main interconnected steps, comprising: data input, segmentation, classification, data output and validation, which can eventually lead to refining or to a direct re-application of the rule-set. The first step includes the know-why represented by the mental model of the operator formalized as DhSM and the raster/vector files that constitute the basic data for the analysis. Subsequently, segmentation and classification are performed in iterative cycles to produce meaningful image-objects; the more suitable descriptors and parameters for the specific case study are evaluated accordingly. The results consist of new raster/vector files, a rule-set and a series of numerical values which can be used for further statistical processing. The final phase is the systematic validation of the results by means of ground/aerial and geophysical surveys, excavation trenches, remote cross-validation or literature research to minimize the bias derived from the equivocality of the archaeological record. According to our view, assessment needs to be fully integrated in the workflow and not treated as a separate, optional component (as previously suggested in e.g. Ainsworth et al., 2013; Bennett et al., 2014; Freeland et al., 2016; Magnini et al., 2017; Davis, 2018). At a following stage, verified rule-sets can be exported and applied in different (but similar) contexts, with eventual refining to cope with differences in scale, contrast, resolution etc. of the new case study.

3.3.1. *A matter of scale*

The following paragraph will provide a scalar overview of OBIA in archaeology, with the aim of exemplifying the variety of the possible applications and the potential of the method in answering specific archaeological questions. The discussion will distinguish four scale-levels, the first two related to EO and the others to material studies: 1) the regional-level considers extensions bigger than fifteen square kilometers; 2) the local-level ranges between fifteen square kilometers and metric scale; 3) the item-level goes from metric to millimetric scale; 4) the sub-item, microscopic level considers magnifications in the order of millimeters to nanometers (Fig. 6). The thresholds used are arbitrary but based on the average values derived from a selection of OPSR/OBIA case studies published in the archaeological literature (see Table 1).

The earliest approaches of regional-level OBIA in archaeology can

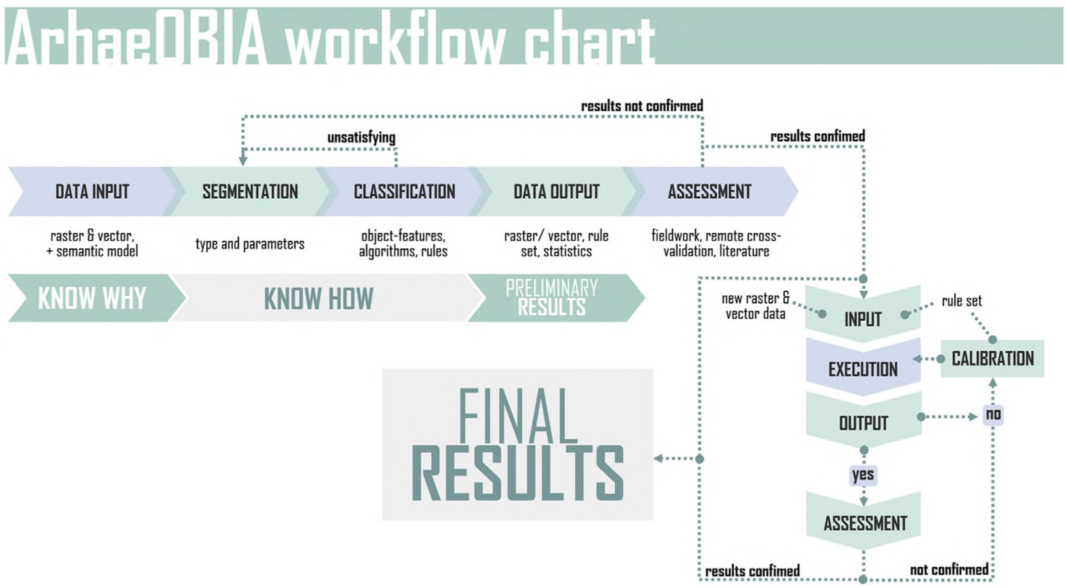

Fig. 7. Chart representing the general workflow of an ArchaeOBIA project.

be traced back in the works of (Veraghen, Drăguţ, 2012, 2013), who used the method to create geomorphological maps from LiDAR data for assisting the archaeological predictive modeling. The results are of high significance from a methodological point of view, as they show the reliability and speed of OBIA in automatically classifying landforms at regional scale. Starting from those pioneering experiences, our research group further explored the potential of object-based image analysis for archaeological predictive modeling, by testing a protocol for locating "control places" in two test areas in Alpine environments (Northern Italy). The rule-set was developed on the Western Asiago Plateau (Vicenza province, Veneto) (Burigana et al., 2017) and subsequently re-applied automatically in the Isarco Valley (South Tirol). Firstly, we

Table 1
A selection of 35 archaeological papers using OBIA (white background) and other OPSR approaches (gray background) divided per scale range. If more than one case study is present in the same publication, the various areas analyzed are separated by semicolons (;). Whenever the dimensional information is not explicitly defined in the text, we estimated the values using the images available (signaled in the table with *).

Article	Year	Dimension of Area/s	Scale	Notes
Hoffmann et al. (2013)	2013	micrographs/not reported	Microscopic	
Aprile et al. (2014)	2014	*10–12 mm^2	Microscopic	Area of each thin section (14)
Bettineschi (2018)	2018	10 mm^2	Microscopic	Mean area of 64 SEM-BSE images
Hein et al. (2018)	2018	6 mm^2	Microscopic	Area of each thin section (59)
Lamotte, Masson (2016)	2016	*46 cm^2	Item	Mean area of 52 artefacts
Magnini (2017)	2017	8.87 cm^2; 86.91 cm^2	Item	
De Laet et al. (2007)	2007	*4–5 km^2	Local	
Jahjah et al. (2007)	2007	7.74 km^2	Local	
Schneider et al., 2015	2014	total not reported/*8–9 km^2 (validation)	Local	
De Guio et al. (2015)	2015	0.78 km^2; 1 km^2	Local	
Kramer (2015)	2015	*3.5–4 km^2; *1 km^2	Local	
Sevara et al. (2016)	2016	0.26 km^2; 0.9 km^2	Local	
Magnini et al. (2017)	2017	4 km^2	Local	
Toumazet et al. (2017)	2017	2 km^2	Local	
Lasaponara, Masini (2018)	2018	*0.24 km^2; *0.75 km^2	Local	
Witharana et al. (2018)	2018	10 km^2; 10 km^2	Local	
Davis et al. (2019)	2019	*10 km^2; *15 km^2; 3 km^2	Local	
De Boer (2007)	2007	12 km^2; 15 km^2; 52 km^2	Local/Regional	
Caspari et al. (2014)	2014	not reported	Local/Regional?	
Bescoby (2006)	2006	42 km^2	Regional	
Menze et al. (2006)	2006	38400 km^2	Regional	
Trier et al. (2009)	2009	not reported/no scale bar	Regional?	
Menze, Ur (2012)	2012	23000 km^2	Regional	
Trier, Pilø (2012)	2012	29.3 km^2; 400 km^2	Regional	
Veraghen, Drăguţ (2012)	2012	192 km^2	Regional	
Schuetter et al. (2013)	2013	69 km^2	Regional	
Veraghen, Drăguţ (2013)	2013	192 km^2	Regional	
Freeland et al. (2016)	2016	259 km^2	Regional	
Burigana et al. (2017)	2017	52 km^2	Regional	
Inomata et al. (2017)	2017	441 km^2	Regional	
Magnini (2017)	2017	110 km^2	Regional	
Davis et al. (2018)	2018	2481 km^2	Regional	
Guyot et al. (2018)	2018	246.7 km^2	Regional	
Trier et al. (2018)	2018	0.92 km^2 (training); 400 km^2	Regional	
Matos-Machado et al. (2019)	2019	100 km^2; 2.9 km^2; 4.2 km^2	Regional	

considered the physiographic, climatic and morphological characteristics of the selected areas. After a preliminary evaluation of the local landscape, it soon became apparent that numerous factors classically used for predictive modeling, such as the availability of water, timber, pastures and quarries, were essentially ubiquitous in the area (Burigana et al., 2017). For this reason, we applied three DEM processing techniques: slope, local dominance and solar radiation. Classification was implemented with a rule-set that selected only image-objects with high local dominance and solar radiation, but low slope, which were considered more suitable parameters for human occupation and territorial control (Fig. 6a).

The project returned five areas on the Asiago Plateau that were ground controlled, confirming an anthropic exploitation covering a time span from protohistory to WWI. Subsequently, the same model was applied to the Isarco Valley to verify the replicability of the method. The procedure resulted in 36 potential "control places", the majority of which (24) found good correspondence with the archaeological sites known in the area. The remaining 12 archaeo-objects identified by the predictive model were remotely controlled analyzing orthophotos and, where available, a LiDAR-derived DTM with 0.5 m resolution. The interpretation of the data confirmed a possible anthropic exploitation covering a time span from protohistory (Bronze/Iron Age) to the XIX century for half of them (Magnini, 2017). The outcomes of the analysis proved the feasibility of the approach that can be exported and applied to similar mountainous landscapes for site predictivity analysis.

A significant portion of the archaeological efforts in the use of OBIA were performed at local scale (Fig. 6b, Table 1). The aim of the works is generally to implement an automated approach for identifying and/or mapping archaeological sites or specific types of ancient (infra)structures in a given area (De Laet et al., 2007; Jahjah et al., 2007; Kramer, 2015; De Guio et al., 2015; Witharana et al., 2018; Davis et al., 2019). In certain cases, mapping is not only devoted to quantifying the archaeological record, but also performed for monitoring its evolution through time in view of improving the management of the cultural landscape (Sevara et al., 2016; Magnini et al., 2017).

The average rate of true positives in landscape-level OPRS and OBIA applications, calculated from the review published by Trier (et al., 2018), ranges in the order of 81%; a similar accuracy (84%) was also reached in other publications, considering both omission and commission errors (Magnini et al., 2017). The study by Trier (et al., 2018) covers a selection of papers published in the period from 2012 to 2018 and one can perceive a progressive increase in the performance of the classification, up to a pick-rate of 98% true positives and 1% false negatives touched in 2018. In other words, the value of OPSR and OBIA for archaeology is no more in question, as demonstrated by the abundant bibliography and the high number of successful case studies. What is still missing at this point is the development of dedicated, sound and shared theoretical bases, that can surpass the boundaries of pure computer sciences for adapting to the specificities of archaeological research. With this paper, we hope to offer a further contribution towards this goal.

Looking at the published literature on OBIA, there are only two papers dealing with item-level applications (Lamotte, Masson, 2016; Masson, Lamotte, 2018). In their research, the authors were able to characterize a group of prehistoric handaxes in terms of colorimetric, textural and morphometric indices. The results were used as a statistical guide to compare the different objects and to propose typological correlations with chronological significance. In fact, manual measurements are characterized by limited repeatability due to the difficulty of identifying the correct orientation of the object and of choosing the reference points. By combining OBIA and 3D models, it is possible to obtain repeatable and exportable metric data. Fig. 6c presents the application of LiDAR visualizations and OBIA on the laser scanner data of Late Bronze Age (XIV-XII century BC) cranial samples for the quantification of the recalcified osteological tissue linked to the life expectancy of the human subjects after medical surgery.[1] The possibility to reapplying the original rule-set on various crania optimizes time and workload, providing an objective and repeatable methodology for the measurement and therefore the comparison of the different wounds. The accuracy was evaluated with reference to a repeated set of manual trials. The results obtained are essentially comparable with the manual extraction of the measures; yet, there is a substantial advantage in terms of time necessary to perform the task. Tentative tests using pixel-based classification, instead, offered very little advice as they were unable to detect the textural changes that distinguish the original bone from the recalcified tissue.

Again, OBIA has been tested for the analysis of archaeometric data only in very limited occasions, as well as OPRS in general (e.g. Aprile et al., 2014; Hein et al., 2018). Looking at OBIA applications, Hoffmann et al. (2013) proposed a method for the extraction of mineral grains in microscopic images of marbles thin sections. The data were used as a basis for the morphological and textural measurements intended for the identification of the provenance of the material. Recently, Bettineschi (2018) employed OBIA for analyzing SEM-BSE (Scanning Electron Microscope – Backscattered Electrons) images selected to represent the most significant color classes of the investigated set of opaque archaeological glasses[2] (Fig. 6d). After the classification, the data were quantitatively analyzed to obtain indications on the number of the coloring and opacifying inclusions, their maximum and average dimensions and on the ratio between the total volume of the glassy matrix and the volume of the crystalline inclusions, porosity excluded (as proposed in a per-pixel approach by Artioli et al., 2008). The accuracy in terms of phase identification and classification was evaluated based on a combination of chemical analysis and visual inspection on a subset of the 64 analyzed micrographs and it returned a preliminary value of over 90%. This objective and reproducible method provided a quantitative and qualitative estimation of the textural characteristics of the different glasses, offering new hints on the production technologies used and on the standardization of the manufacturing processes.

It should be stressed that, up to now, the application of OBIA to material studies is mostly devoted to quantification, rather than identification. In fact, there are multiple benefits in employing OBIA as an automated method of quantification at item and sub-item level. While manual measurements are generally subject to random errors of variable magnitude, automatic procedures generate precise and repeatable data. Assuming the existence of systematic errors (of omission/commission), the resulting shift from the real value will be constant for all measures, thus granting better comparability of the data. Moreover, OBIA can simultaneously consider morphometry, color, texture and relational parameters, helping in refining the final classification, if compared to the traditional per-pixel approaches.

4. Conclusions and perspectives

OBIA is a growing trend in archaeological RS. In this paper, we offered a synthesis of its basic principles and discussed the most relevant papers dealing with archaeological case studies. Moreover, we showed the practical problems which still preclude a wider diffusion of the method among the archaeological RS community and the field operators. It was argued that some of these issues can be overcome by introducing a theoretical framework able to formalize expert knowledge. The incompleteness and dynamic nature of the archaeological record led us to propose the use of ontologies based on Diachronic Semantic Models (DhSM). This formal approach can provide a possible key for the description of the evolution of the archaeological record through time. Moreover, it can prove particularly useful for the classification of multi-/equi-final entities which constitute a long-lasting

[1] The publication is currently in preparation.

[2] A dedicated paper is currently in preparation.

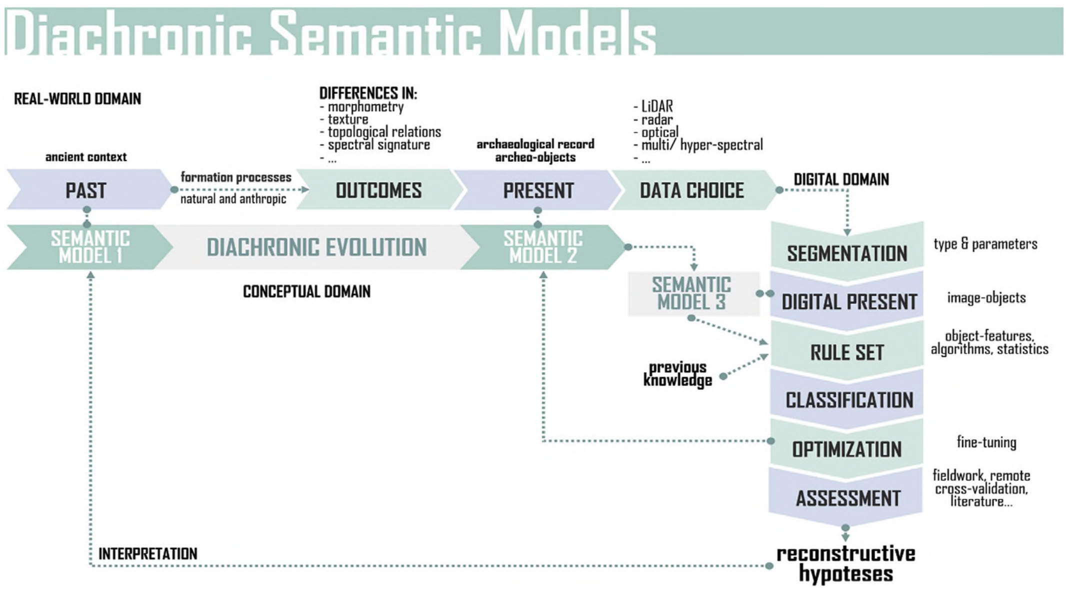

Fig. 8. Integration of Dhiacronic Semantic Models (DhSM) into the general workflow of an ArchaeOBIA project. Semantic model (SM) 1 represents an approximation of how the ancient context was expected to be in ancient times; SM2 includes the multi-/equi-final appearance it may have today; and SM3 considers its possible representation on different types of RS imagery.

problem in archaeological photointerpretation. Additionally, we introduced a formal definition of archaeo-objects, which are the focus of all RS applications in archaeology, especially in the field of computer-aided methods for automated and semi-automated image analysis.

This overall theoretical framework represents the backbone of the ArchaeOBIA concept. In general terms, ArchaeOBIA can be defined as the application of object-based image analysis to archaeological research, irrespectively of the scale of investigation. Furthermore, this approach is designed to systematically integrate OBIA and result assessment, to achieve an appropriate balance between processing speed and reliability of results. A scheme on the integration of DhSM and ArchaeOBIA is proposed in Fig. 8.

The paper also presented a series of case studies at regional, local, item and microscopic scale to highlight the versatility of the method. Judging from those data, ArchaeOBIA shows promising growth opportunities with regards to the fields of application and the type of sensors whose data might be processed in the near future. Besides, it proved as a reliable and reproducible method to deal with the complexity of the archaeological record. In fact, ArchaeOBIA offers an efficient and robust protocol to help (semi)automatic photointerpretation and data analysis, capable of simultaneously operating on multiple layers for the classification of archaeo-objects. It also grants the opportunity to speed up the process of image analysis and object recognition when working at landscape level or with huge amount of data thanks to the exportability of the rule-sets. Finally, it is a powerful tool for protecting the archaeological record as a multi-temporal, multi-level, (semi)automatic monitoring system. In detail, object-based image analysis is an instrument of exceptional potential for the time-series diagnostics of the degradation processes both at landscape and item level. In this sense, it is also an effective means to identify and prevent illegal excavations and looting actions in the perspective of an ‘Applied Archaeology’ (Downum, Price, 1999). Furthermore, the method can be used to monitor processes of destruction (voluntary or accidental) of cultural heritage areas impacted by military conflicts or natural hazards, that are essentially inaccessible for direct interventions on the field (as seen in Lasaponara, Masini, 2018 using automatic feature extraction). Another possible direction is the application of ArchaeOBIA to Unmanned Aerial Vehicles (UAV)-derived data. After the success and capillary diffusion in the archaeological practice of aerial platforms equipped with a variety of sensors (from optical to multi/hyper-spectral and LiDAR) (Bosco et al., 2015; Stek, 2016; De Reu et al., 2016; Campana, 2017; Colombatti et al., 2017) it is just a matter of time before OBIA will start to be employed in the post-processing of data from UAV surveys.

Future research is expected to further expand the role of OBIA in archaeology. Although this is only the beginning of a long-term process, we anticipate that the proposed ArchaeOBIA approach will be able to enhance the interoperability of the rule-sets and disclose new possibilities towards an explicit method for extracting archaeological information from RS imagery. Building from this preliminary discussion, we hope that the archaeologists will become more and more aware of their fundamental value in the (semi)automatic recognition of archaeo-objects. As their knowledge and mental models will be systematically integrated in DhSM, translated in machine-readable language and used as a reference for OPSR, the overall accuracy of the results will hopefully reach new standards.

Author contributions

Conceptualization, L.M. and C.B.; methodology, L.M. and C.B.; software, L.M.; validation, C.B. and L.M.; investigation, L.M.; data curation, L.M.; writing—original draft preparation, C.B.; writing—review and editing, L.M.; visualization, C.B.; project administration, L.M.

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Conflicts of interest

The authors declare no conflict of interest.

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