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Object-based image analysis: a review of developments and future directions of automated feature detection in landscape archaeology

Dylan S. Davis 🆔

Department of Anthropology, The Pennsylvania State University, University Park, PA, USA

Correspondence
Dylan S. Davis, Department of Anthropology, The Pennsylvania State University, University Park, PA 16802, USA.
Email: dsd40@psu.edu

Abstract

Object-based image analysis (OBIA) is a method of assessing remote sensing data that uses morphometric and spectral parameters simultaneously to identify features in remote sensing imagery. Over the past 10–15 years, OBIA methods have been introduced to detect archaeological features. Improvements in accuracy have been attained by using a greater number of morphometric variables and multiple scales of analysis. This article highlights the developments that have occurred in the application of OBIA within archaeology and argues that OBIA is both a useful and necessary tool for archaeological research. Additionally, I discuss future research paths using this method. Some of the suggestions put forth here include: pushing for multifaceted research designs utilizing OBIA and manual interpretation, using OBIA methods for directly studying landscape settlement patterns, and increasing data sharing of methods between researchers.

KEYWORDS

automated feature extraction, landscape analysis, machine learning, object-based image analysis, pattern recognition, remote sensing

1 | INTRODUCTION

Researchers in many fields – including computer science and geography – have adopted machine learning algorithms to process remote sensing imagery (see Mountrakis, Im, & Ogole, 2011). In the late 1990s and early 2000s, a form of machine learning known as object-based image analysis (OBIA) was developed (Blaschke, 2010), but only recently have archaeologists utilized these methods (e.g. De Laet, Paulissen, & Waelkens, 2007; Menze, Ur, & Sherratt, 2006). In the last ~15 years, archaeologists have used a variety of OBIA techniques that are highly successful in extracting features of interest from large-scale datasets at faster rates and lower costs than manual processing (Bennett, Cowley, & De Laet, 2014, 897). Yet, there is much more that these methods can do to advance our understanding of the human past.

Today, there have been a number of significant studies using OBIA methods within archaeological contexts, but these studies are not evenly distributed geographically (see Table 1). Many focus on European localities, but fewer focus on the Americas, Asia, Africa, or island regions. Furthermore, most archaeological publications using OBIA methods are identifying potential sites, but they are not addressing potential settlement patterns that emerge from their results. This is important because future research should use these methods to answer archaeological questions concerning populations, socio-political organization, and past peoples at large.

This article serves as a review of object-based machine learning methods that archaeologists have applied in landscape-scale remote sensing analysis – including aerial and spaceborne data. I will detail the progress that has been made with these techniques as well as the avenues archaeologists are yet to travel. I begin by reviewing the basic concepts of OBIA and how it operates. I follow with a comprehensive summary of archaeological work that has been conducted using OBIA, paying particular attention to the successes and shortcomings of these studies. Then, I discuss possible future directions of OBIA and computational archaeology. I illustrate that

TABLE 1 Archaeological studies using object-based image analysis (OBIA) by geographic region

Region	OBIA studies
Europe	Bescoby, 2006; Cerrillo-Cuenca, 2017; D'Orazio, Palumbo, & Guaragnella, 2012; Guyot et al., 2018; Magnini et al., 2017; Schneider et al., 2015; Sevara, Pregesbauer, Doneus, Verhoeven, & Trinks, 2016; Traviglia & Torsello, 2017; Trier & Pilø, 2012; Trier et al., 2009; Trier et al., 2015; Verhagen & Drăguţ, 2012; Zingman, Saupe, Penatti, & Lambers, 2016
North America	Davis et al., In Press; Davis et al., 2018; Johnson & Ouimet, 2014; Kvamme, 2013; Riley, 2009; Witharana et al., 2018
South America	Lasaponara & Masini, 2018
Asia	De Laet et al., 2007, 2008; De Laet, Paulissen, Meuleman, & Waelkens, 2009; Harrower, Schuetter, McCorriston, Goel, & Senn, 2013; Jahjah et al., 2007; Lasaponara & Masini, 2018; Menze et al., 2006; Menze, Mühl, & Sherratt, 2007; Menze & Ur, 2012; Schuetter, et al., 2013; Van Ess et al., 2006; Wang et al., 2017
Pacific Islands	Freeland et al., 2016

while archaeologists have just begun to apply OBIA to research questions, the method offers unparalleled advantages that should be fully taken advantage of by future archaeological research.

2 | OBJECT-BASED IMAGE ANALYSIS (OBIA)

OBIA began to rise in popularity in the early twenty-first century, and since that time, uses of these methods have sharply increased (Blaschke, 2010). Blaschke (2010) attributes this rise to the development of a software called eCognition (Trimble, 2016). In addition to eCognition, several open-source platforms have been developed for OBIA analysis [e.g. GEODMA (Körting, Garcia Fonseca, & Câmara, 2013), InterIMAGE (InterIMAGE, 2009), Grass GIS (GRASS Development Team, 2018), also see Knoth & Nüst, 2017].

In its most basic definition, object-based analysis encompasses 'image-processing techniques that when applied either result in the segmentation (i.e. partitioning) of an image into discrete non-overlapping units based on specific criteria, or are applied to define specific multiscale characteristics—from which segmentation may then be based' (Hay, Castilla, Wulder, & Ruiz, 2005, 340). Recently, remote sensing literature has used the term GEOBIA to refer to those applications of OBIA to Earth remote sensing imagery (Blaschke et al., 2014; Hay & Castilla, 2008). GEOBIA therefore constitutes a majority of OBIA applications within archaeology.

In a discussion of automated extraction methods used within archaeology, one cannot ignore the multitude of studies that have used pixel-based classification (e.g. Bennett, Welham, Hill, & Ford, 2012; Campbell, 1981; Custer, Eveleigh, Klemas, & Wells, 1986; Drager, 1983; Kirk, Thompson, & Lippitt, 2016; Lasaponara, Leucci, Masini, & Persico, 2014; Lasaponara & Masini, 2007; Meredith-Williams et al., 2014; also see Lambers, 2018, for a review of remote

sensing analysis in archaeology). Pixel-based approaches deal with the classification of individual pixels in an image into different categories corresponding to unique landscape features. Researchers have used these methods within many fields for a variety of purposes including: land cover and vegetation classification, mapping urban expansion, and measuring surface temperatures (see Jensen, 2007). As such, pixel-based classification is quite useful. However, when compared to object-based approaches, OBIA methods are more accurate for detecting archaeological features (see De Laet et al., 2007; De Laet, Music, Paulissen, & Waelkens, 2008; Sevara & Pregesbauer, 2014).

OBIA methods, in contrast to pixel-based methods, identify features using multiple variables. These include pixel value, object shape, textural information, neighbourhood analysis, and geographic context (Blaschke, 2010, 3; Blaschke et al., 2014). By utilizing multiple parameters simultaneously, OBIA is well suited for identifying features that are small, structurally homogeneous, and display differences with local topography (Davis, Sanger, & Lipo, 2018). OBIA builds on longstanding practices of remote sensing analysis including segmentation, edge detection, and classification (Blaschke, 2010, 3; see Kumar, Raj Kumar, & Reddy, 2014; Weng, 2010, for reviews of different types of segmentation and classification). As such, some have considered OBIA to be one of the greatest achievements in image processing of the twenty-first century (Arvor, Durieux, Andrés, & Laporte, 2013). One limitation of OBIA is that it requires very high-resolution datasets to work effectively (Blaschke et al., 2014, 181). However, as the spatial resolutions of remotely sensed data have improved, the accuracy and use of OBIA techniques have also increased (Hay et al., 2005).

3 | OBIA AND MACHINE LEARNING IN ARCHAEOLOGY

Object-based analysis of remote sensing data has only been extensively utilized by archaeologists for about 15 years. The number of peer reviewed publications using these methods within archaeological contexts is small (< 40) but growing (see Table 2). Additionally, a great deal of work has been presented on the use of OBIA at archaeological conferences.

Beginning in the first decade of the twenty-first century, researchers began to implement object-based computer algorithms to detect archaeological features in a systematic fashion. The first archaeological research implementing OBIA was primarily concerned with identifying large-scale linear features. For example, Bescoby (2006) used a mathematical function known as a Radon transform (which can determine the most common alignment and orientation of features within an image) and segmentation procedures to detect linear Roman structures in satellite imagery. Within a few years, more publications began to emerge using OBIA methods (e.g. De Laet et al., 2007; Jahjah, Ulivieri, Invernizzi, & Parapetti, 2007; Van Ess et al., 2006). All of these studies focus primarily on the detection of archaeological deposits, but Jahjah et al. (2007) also look at how OBIA techniques can monitor sites, document their preservation levels (also see Van Ess et al., 2006), and enhance the digitization of archaeological data acquired from remote sensing sources. As the resolution of

TABLE 2 Outline of developments of object-based image analysis (OBIA) as a method in archaeology from 2000 to the present

Time period	Advances	Limitations

2000–2010	• Segmentation and mathematical algorithms (Bescoby, 2006)
	• Edge detection for roadway identification (De Laet et al., 2007)
	• Morphometric variables used for classification include:
	  • Shape (De Laet et al., 2007; Menze et al., 2006)
	  • Compactness and smoothness (De Laet et al., 2007)
	  • Colour/pixel value (Jahjah et al., 2007)
	  • Neighbourhood analysis (De Laet et al., 2007, 2008, 2009)
	  • Elevation (Menze et al., 2006)
	• Pattern recognition (template matching) is implemented as an automatic detection method (Trier et al., 2009)
		• Most studies use two-dimensional (2D) aerial and satellite imagery, not three-dimensional (3D) topographic datasets such as LiDAR (Menze et al., 2006 is the exception). This limits the variables that can be used to identify features.
		• Low number of morphometric criteria were inefficient at capturing morphological diversity of certain feature types
		• High number of false-positive and false-negative results (e.g. De Laet et al., 2007, 2008, 2009; Menze et al., 2006, 2007; Trier et al., 2009)

2010–2015	• Use of LiDAR and 3D datasets becomes prevalent
	• Morphometric variables used for classification include:
	  • Elevation, slope, and curvature (Schneider et al., 2015; Verhagen & Drăguţ, 2012)
	  • Nearest neighbour analysis, size, shape, and circularity (Harrower et al., 2013; Scheutter et al., 2013)
	  • Hillshade and topographic position index (Schneider et al., 2015)
	  • Principle component analysis (Chen, Comer, Priebe, Sussman, & Tilton, 2013)
	  • Orientation and topographic contours (D'Orazio et al., 2012; Figorito & Tarantino, 2014)
	  • Eccentricity (Figorito & Tarantino, 2014)
	  • Volume (Menze & Ur, 2012)
	• Pattern recognition (template matching) continues to be utilized (Kvamme, 2013; Schneider et al., 2015; Trier et al., 2015; Trier & Pilø, 2012)
	• Increased accuracy achieved by:
	  • Use of statistical classifiers (Chen et al., 2013; Trier et al., 2015)
	  • Using multiple datasets to cross-reference automated results from different sources (Trier et al., 2015)
	  • Using multitemporal datasets to account for possible seasonal lapses in visibility in remotely sensed imagery (Menze & Ur, 2012)
		• Spatial resolution of remote sensing data (> 1 m) sometimes prevent accurate detection of small deposits (Verhagen & Drăguţ, 2012)
		• Many of these methods have significant issues with false-positive and false-negative results (e.g. Kvamme, 2013; Harrower et al., 2013; Scheutter et al., 2013; Schneider et al., 2015; Trier & Pilø, 2012; Trier et al., 2015)
		• Some methods cannot detect features (or present false positives) that are located in close proximity to certain types of topographic anomalies (e.g. D'Orazio et al., 2012; Trier et al., 2015; Trier & Pilø, 2012)

2015–2018	• Co-opting of hydrological depression analyses for mound detection (Davis et al., In Press; Freeland et al., 2016)
	• Morphological variables used for classification include:
	  • Circularity (Davis et al., 2018; Freeland et al., 2016; Witharana et al., 2018)
	  • Rectangularity (Zingman et al., 2016)
	  • Area (Davis et al., 2018; Magnini et al., 2017; Witharana et al., 2018)
	  • Length and width (Magnini et al., 2017; Toumazet, Vautier, Roussel, & Dousteyssier, 2017)
	  • Size (Cerrillo-Cuenca, 2017; Davis et al., 2018; Zingman et al., 2016)
	  • Curvature (Cerrillo-Cuenca, 2017)
	  • Edge detection (Traviglia & Torsello, 2017; Witharana et al., 2018; Zingman et al., 2016)
	  • Elevation (Davis et al., 2018; Guyot et al., 2018)
	• Multiscalar analysis with multiple datasets are incorporated to cross-validate results at small-to-large scales (Guyot et al., 2018; Witharana et al., 2018)
	• Pattern analysis continues to be used (Davis et al., 2018; Trier et al., 2015; Wang et al., 2017)
		• False-positive and false-negative results (Freeland et al., 2016; Schneider et al., 2015; Trier et al., 2015; Witharana et al., 2018)
		• Lack of temporal control during feature detection (Traviglia & Torsello, 2017)
		• Small sample sizes for pattern recognition (Davis et al., 2018; Wang et al., 2017; Zingman et al., 2016)

remote sensing data improved, smaller features were soon the subject of detection via automated processes (e.g. Magnini, Bettineschi, & De Guio, 2017; Wang, Hu, Wang, Ai, & Zhong, 2017; also see Beck, Philip, Abdulkarim, & Donoghue, 2007).

The research conducted prior to 2010 illustrates the first attempts at defining archaeological deposits as objects in a manner that computers can understand and replicate via segmentation and classification procedures. Variables including shape, compactness, texture, and colour are all implemented as parameters for detecting likely archaeological features (De Laet et al., 2007; Jahjah et al., 2007; see Table 2). However, most of these studies use only two-dimensional (2D) satellite imagery, and three-dimensional (3D) topographic data [such as LiDAR (light detection and ranging)] is not analysed using OBIA [Menze et al. (2006) is one exception]. Furthermore, these early studies suffer from high rates of false-positive identifications, which is a result of the quality of the data used and the variables incorporated. Implementing OBIA with a greater number of variables (including multiple scales of analysis) and using higher-resolution datasets improves accuracy for archaeological prospection (e.g. Guyot, Hubert-Moy, & Lorho, 2018; Sevara & Pregesbauer, 2014, 142; Witharana, Ouimet, & Johnson, 2018).

By the beginning of the 2010s there is an increase in archaeological studies analysing LiDAR and topographic datasets – in addition to 2D satellite and aerial imagery – using OBIA procedures (e.g. Trier & Pilø, 2012; Verhagen & Drăguţ, 2012). By incorporating 3D data, the detection of archaeological features becomes easier, as researchers can now incorporate topographic information in multiple dimensions. For example, Verhagen and Drăguţ (2012) use elevation, slope, and curvature as parameters for segmentation and classification of landforms. Although their method is not perfectly accurate – a large part of which is due to the resolution of the datasets used (5 m) and the number of variables included in the segmentation procedure – Verhagen and Drăguţ (2012) illustrate how incorporating 3D morphological and morphometric variables, in addition to 2D profiles, can greatly enhance our ability to detect above-ground archaeological structures.

Trier and Pilø (2012) show how pattern recognition via template matching can incorporate many of these morphometric properties into the classification of topographic data (e.g. LiDAR). The procedure involves the creation of samples of known features of interest (i.e. templates) from digital elevation models (DEMs) using different scales and resolutions. The template matching algorithm is then conducted on each DEM and the computer extracts identifications that overlap between the different scales – thereby acting as a cross-check between each iteration of the algorithm. The method assesses each feature for its degree of statistical similarity to the templates and assigns a corresponding confidence interval. The final results are then field-tested by archaeologists. This procedure – which several researchers have used in different variations (e.g. Kvamme, 2013; Schneider, Takla, Nicolay, Raab, & Raab, 2015; Trier, Larsen, & Solberg, 2009; Trier, Zortea, & Tonning, 2015) proves successful in the identification of previously detected and undetected archaeological structures. As with earlier studies, however, template matching is limited by its number of false-positive and false-negative results.

Subsequent research has implemented a slew of new variables including topographic measurements such as hillshade, slope, and topographic openness (see Table 2). The results of these studies indicate a positive correlation between the number of factors accounted for during OBIA procedures and accuracy. However, if the parameters chosen do not match the features that are being sought after then the algorithm will not work. As such, an expert knowledge of the study area is an essential prerequisite for using automated detection methods.

The increase in studies post-2010 sees a slight diversification in the use of OBIA methods, but as Table 3 shows, most studies use it for the sole purpose of automating the detection of archaeological features (e.g. Davis et al., 2018; Sevara & Pregesbauer, 2014; Trier et al., 2015; Trier & Pilø, 2012; Verhagen & Drăguţ, 2012). Some

TABLE 3 Publications using object-based image analysis (OBIA) as a primary method organized by their research goals

Research goal	Number of publications	References
Identification	28	Bescoby, 2006; Cerrillo-Cuenca, 2017; Chen et al., 2013; D'Orazio et al., 2012; Davis et al., 2018, in press; De Laet et al., 2007, 2008, 2009; Figorito & Tarantino, 2014; Freeland et al., 2016; Guyot et al., 2018; Harrower et al., 2013; Jahjah et al., 2007; Kvamme, 2013; Menze et al., 2006, 2007; Schneider et al., 2015; Schuetter et al., 2013; Sevara & Pregesbauer, 2014; Sevara & Pregesbauer, 2014; Toumazet et al., 2017; Traviglia & Torsello, 2017; Trier et al., 2009, 2015; Verhagen & Drăguţ, 2012; Witharana et al., 2018; Zingman et al., 2016
Preservation/monitoring	6	Lasaponara & Masini, 2018; Magnini et al., 2017; Sevara & Pregesbauer, 2014; Trier & Pilø, 2012; Van Ess et al., 2006; Wang et al., 2017
Mapping/digitization of archaeological features	3	Lasaponara & Masini, 2018; Sevara & Pregesbauer, 2014; Witharana et al., 2018;
Analysis of populations, social organization, settlement patterns, etc.	4	Cerrillo-Cuenca, 2017; Cordero Ruiz et al., 2017; Freeland et al., 2016; Menze & Ur, 2012

Notes: Some publications fall into multiple categories, and as such are listed multiple times. There is a total of 35 sources that have been included in this table.

researchers, however, are using OBIA to protect and monitor sites at risk of destruction (e.g. Lasapopara & Masini, 2018; Magnini et al., 2017; Schneider et al., 2015; Trier & Pilø, 2012; Wang et al., 2017) and to develop more complete maps of archaeological activity to conduct further analysis of settlement patterning and sociopolitical organization (e.g. Cerrillo-Cuenca, 2017; Cordero Ruiz, Cerrillo Cuenca, & Pereira, 2017; Freeland, Heung, Burley, Clark, & Knudby, 2016).

The most recent archaeological uses of OBIA and machine learning yield highly accurate results (Freeland et al., 2016; Guyot et al., 2018; Lasapopara & Masini, 2018; Wang et al., 2017). Freeland et al. (2016) demonstrate the first use of hydrological depression algorithms for archaeological mound detection. In this instance, an inversed DEM was created and processed through an algorithm that looks for topographic depressions, effectively identifying and mapping mound features (also see Davis, Lipo, & Sanger, in press). The work of Guyot et al. (2018) is a strong case for the use of automated object extraction methods within archaeology, as their multiscalar algorithm successfully identified over 2000 Neolithic burial mounds, while false positives ($n = 41$) and false negatives ($n = 46$) were minimal. The lesson from this latest research are simple: landscape level archaeological prospection algorithms must be *multiscalar*. Furthermore, topographic data are invaluable for the automated identification of archaeological deposits. With very-high resolution datasets and the accuracy improvements acquired in recent research, OBIA shows promise for highly accurate automated prospection.[1]

3.1 | Limitations and criticisms

Despite the many successes of OBIA methods within archaeology, there are many who are skeptical of the feasibility of automated detection algorithms – specifically for large-scale landscape analysis (e.g. Casana, 2014; Hanson, 2010; Parcak, 2009). Parcak (2009, 110) claims that automated archaeological site detection is impossible because every archaeological project is dependent on local variables. But local variables are precisely what OBIA can take into consideration when analysing remote sensing data, and regionally specific algorithms are essential for the success of automated prospection (see Davis et al., 2018). Parcak (2009,110) goes on to state that computers cannot pick up on the same subtleties in remotely sensed data as humans can by eye. However, the very fact that recent studies using automated means have detected sites that manual analysis has overlooked directly challenges this claim (e.g. Davis et al., 2018; Witharana et al., 2018).

In discussing the latest state of remote sensing research within archaeology, Opitz and Herrmann (2018) devote some of their attention to the methods involving automated detection of archaeological

features. Part of their discussion revolves around a distrust of these methods, and they state:

> The reluctance to adopt automated feature extraction … is motivated by a combination of technological and social factors. On the technological side, machine learning approaches to automation remain in their infancy. Automatic feature extraction for archaeological materials is still developing and has yet to match the efficiency of automatic feature extraction for targets with consistent appearance or for features in uniform environments. (Opitz & Herrmann, 2018, 30)

The claim that these methods are still new and evolving is very much true, as this article indicates. Regardless, the infancy of the method is not a reason to stop developing and improving its ability to discern information of archaeological significance. OBIA and similar methods are imperfect and cannot replace manual evaluation completely, but at the same time, biases in knowledge by data analysts limit the accuracy of manual procedures and can lead to omission error (Bennett et al., 2014; Gheyle et al., 2018). It can never be our goal to completely automate the archaeological process, and to attempt such a feat would be a fool's errand. Nevertheless, improving automated methods to assist in the detection of archaeological deposits is not only an exciting avenue for future research, but also a necessary task.

Coastal and island regions that are under threat of destruction by climate change and rising sea levels cannot ever be fully surveyed using traditional means before their records are severely damaged. It is therefore imperative to document as much of these areas as we can before they are lost. By using OBIA and similar methods, we can conduct systematic surveys of entire areas and document landscapes efficiently. Thus, it is essential to utilize these techniques to study the archaeological record in a relatively complete form rather than limiting ourselves to small sample sizes of information.

Despite the benefits offered by OBIA, it is still far more common for archaeologists to use manual interpretation methods rather than semi-automatic means (Quintus, Day, & Smith, 2017, 352; also see Casana, 2014). Many researchers echo the earlier sentiments of Parcak (2009) by claiming that automated methods cannot account for the wide range of variability in the archaeological record. However, who is to say that one should only use one single automated method to scan an entire study area? Why not use a multitude of different algorithms to search for different parts of the record and then go through all the results by hand to fill in things that OBIA missed (*sensu* Bennett et al., 2014)? By using automated detection first, we can be sure that the entire study area is surveyed systematically without any lapses. Then by conducting a manual analysis, expert knowledge can assess the results and potentially identify nearby features that the automated method overlooked.

Casana (2014) uses 'brute force', or manual extraction methods to survey an area covering 300 000 km^2. This process took approximately 3–4 years. Using automated methods [which Casana (2014) attempted and stated to be successful], this process could have been sped up considerably. Quitnus et al. (2017) also illustrate the importance of manual evaluation, but highlight the fact that manual processing is imperfect, as there are still many false-positive and false-

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[1]Although this article has focused exclusively on the use of OBIA for large-scale remote sensing data such as satellite imagery and LiDAR (GEOBIA), this method has also been used for other types of image analysis in archaeology. OBIA has been successful in classifying artefacts and features into statistically significant types (e.g. Lamotte & Masson, 2016; Ozawa, 1978), studying site formation processes (e.g. Sanger, 2015), testing the mineralogical classification of artefacts (e. g. Aprile et al., 2014; Hein et al., 2018; Hofmann et al., 2013), and researchers have used it to investigate ground-based remote sensing data (e.g. Pregesbauer, Trinks, & Neubauer, 2014). As such, there is much to gain from OBIA methods within archaeology that goes beyond landscape-level analysis.

negative identifications present using this approach. In the span of two weeks, Quintus et al. (2017) evaluated LiDAR covering approximately 5–10 km^2, whereas semi-automated OBIA methods have allowed for the systematic evaluation of LiDAR datasets covering thousands of square kilometres in the same amount of time (e.g. Davis et al., 2018).

One thing that is certain is that ground-testing and manual analysis following automated detection algorithms is an essential step (Ainsworth, Oswald, & Went, 2013; Freeland et al., 2016, 72; Quintus, Clark, Day, & Schwert, 2015). Without ground-surveys, we cannot confirm the results of remotely sensed analysis and our knowledge cannot pass beyond a theoretical level. Although in some instances automated survey may be inappropriate, we must remember that ground-survey, manual evaluation, and automated detection algorithms are all useful tools for archaeologists, and all possess their own benefits and drawbacks. As such, archaeologists must not exclude any of these methods outright (sensu Hacıgüzeller, 2012).

4 | FUTURE DIRECTIONS

Where do we go from here? Are OBIA and automated object extraction valuable methods for archaeologists? The answer is a resounding yes. For areas at risk of development, destruction, or other disturbance, OBIA provides an efficient way to survey entire landscapes with reasonable accuracy. As such, OBIA methods can serve in a capacity to stop the development and destruction of areas containing cultural deposits and better understand the spatial distribution of human settlements.

Additionally, the use of OBIA allows for the re-visitation of areas and requires far less time and money than a pedestrian style ground survey (e.g. Bennett et al., 2014, 897; Davis et al., 2018). This is not to say that OBIA can detect everything there is to find in any given area; not even manual evaluation can do that. Rather, OBIA can provide a baseline by which to assess the probability of cultural features being present and set in motion a series of intensive ground surveys to validate these conclusions.

Even if researchers are reluctant to use these methods for the detection of features, OBIA can still be useful in an archival sense. Segmentation procedures can digitize archaeological deposits automatically with spatial and morphological accuracy. Archaeologists have done this with artefacts for statistical and morphometric analyses (e.g. Aprile, Castellano, & Eramo, 2014; Hein, Rojas-Domínguez, Ornelas, D'Ercole, & Peloschek, 2018; Hofmann, Marschallinger, Unterwurzacher, & Zobl, 2013; Lamotte & Masson, 2016) and have used similar methods to study site formation processes (e.g. Sanger, 2015). There is a lot to gain from OBIA, especially in terms of understanding landscape-level archaeological patterns. However, there are certain avenues of research where these methods are yet to be fully invested:

- First and foremost, the use of OBIA methods must be expanded into new geographic areas where they have been under-utilized or where they are yet to be introduced (e.g. North America, South America, Africa, coastal islands, etc., see Table 1). This is especially important for areas at risk of destruction from sea-level rises or currently experiencing violent conflict where cultural heritage is at risk.

- Second, we must continue developing new approaches that combine automated analysis with manual evaluation and subsequent field-testing to create a comprehensive landscape survey procedure. Each of these levels are essential for understanding the archaeological record. By combining them together, we can study landscape patterns at multiple scales, which is a vital component of landscape level archaeological research (e.g. Crumley, 1979; Millican, 2012; Robinson, 2010).

- Third, future work with OBIA should seek to compare different methods of automated feature detection (e.g. Davis et al., in review). By comparing different methods, researchers can best determine which methods are most appropriate for specific purposes and thereby adopt the successes and avoid the failures and setbacks of prior studies.

- Fourth, to improve the ability of OBIA to detect archaeological features, researchers must share their datasets – this includes new algorithms, computer code, processing steps, and training data. By sharing this information, archaeologists around the world can contribute to and access different methods and necessary training data, thereby increasing and improving the use of OBIA for archaeological problems. By making code and data available to all, even the non-specialist can utilize some of these methods and contribute to the use of automated object detection.

- Finally, archaeologists should use OBIA for studies beyond the mere detection of features. Researchers can use detected objects to discuss broader spatial patterns of the archaeological record (e.g. Freeland et al., 2016). Although the discovery of new features is important, it is equally important to begin analysing this newly generated information to further our understanding of the human past.

5 | CONCLUSIONS

This article has sought to demonstrate the important advances that have occurred in applications of OBIA methods within landscape archaeology. It has also traced some possible paths for the future of these methods within the discipline. A lot of progress has been made, and yet there is still a great deal of untapped potential for OBIA to expand our understanding of the archaeological record. In the future, we should seek to incorporate (semi-)automated algorithms with manual analysis to ensure the broadest range of data is acquired. The importance of systematic documentation is vital in a world that suffers from cultural site destruction on a daily basis. OBIA is one method that can help to record, preserve, protect, and study the record of our collective human history.

DECLARATION OF CONFLICTS OF INTEREST

The author does not have any conflicts to declare, financial or otherwise.

ORCID

Dylan S. Davis ![ORCID] https://orcid.org/0000-0002-5783-3578

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