



Aerial and Spaceborne Remote Sensing in African Archaeology: A Review of Current Research and Potential Future Avenues

Dylan S. Davis  · Kristina Douglass

© Springer Science+Business Media, LLC, part of Springer Nature 2020

Abstract Africa represents a vast region where remote sensing technologies have been largely uneven in their archaeological applications. With impending climate-related risks such as increased coastal erosion and rising sea levels, coupled with rapid urban development, gaps in our knowledge of the human history of this continent are in jeopardy of becoming permanent. Spaceborne and aerial remote sensing instruments are powerful tools for producing relatively complete records of archaeological settlement patterns and human behavior at landscape scales. These sensors allow for massive amounts of information to be recorded and analyzed in short spans of time and offer an effective means to increase survey areas and the discovery of new cultural deposits. In this paper, we review various case studies throughout Africa dealing with aerial and satellite remote sensing applications to landscape archaeology in order to highlight recent developments and future research avenues. Specifically, we argue that (semi)automated remote sensing methods stemming from machine learning developments will prove vital to expanding our knowledge base of Africa's archaeological record. This is especially important for coastal and island regions of the continent where climate change threatens the survival of much of

the archaeological record.

Résumé L'Afrique représente une vaste région où les technologies de télédétection ont été largement inégales dans leurs applications archéologiques. Avec les risques imminents liés au changement climatique, tels que la progression de l'érosion côtière et de la montée du niveau de la mer, ainsi que le développement urbain rapide, les lacunes dans nos connaissances sur l'histoire humaine de ce continent risquent de devenir permanentes. Les instruments de télédétection spatiaux et aériens sont des outils puissants pour produire des relevés relativement complets des peuplements archéologiques et du comportement humain à l'échelle du paysage. Ces capteurs permettent d'enregistrer et d'analyser d'énormes quantités d'informations en peu de temps et offrent un moyen efficace d'élargir les zones de prospection et de découvrir de nouveaux dépôts culturels. Dans cet article, nous passons en revue diverses études de cas à travers l'Afrique portant sur les applications de la télédétection aérienne et satellitaire à l'archéologie paysagère afin de souligner les développements récents et les pistes de recherche futures. En particulier, nous soutenons que les méthodes de télédétection (semi)automatisées issues du développement de l'apprentissage automatique s'avéreront vitales pour élargir notre base de connaissances des archives archéologiques de l'Afrique. Cela est particulièrement important pour les régions côtières et insulaires du continent où les changements climatiques menacent la survie d'une grande partie des vestiges archéologiques.

D. S. Davis (✉) · K. Douglass
Department of Anthropology, The Pennsylvania State University,
University Park, PA 16802, USA
e-mail: dsd40@psu.edu

K. Douglass
Institutes of Energy and the Environment, The Pennsylvania State
University, University Park, PA 16802, USA

Keywords Remote sensing · Landscape archaeology · Heritage protection · Africa

Mots-clés Télédétection · Archéologie paysagère · Protection du patrimoine · Protection du paysage · Afrique

Introduction

Remote sensing instruments are powerful tools for producing relatively complete records of archaeological settlement patterns and human behavior at the landscape scale. Literature on aerial and spaceborne technologies (e.g., satellites, LiDAR, aerial photographs) in archaeology has demonstrated that multi- and hyperspectral satellite sensors and aerial platforms such as LiDAR are particularly useful for tackling issues of survey coverage and site identification (e.g., Chase et al. 2012; Lasaponara and Masini 2012; Leisz 2013; Luo et al. 2019; Osicki and Sjogren 2005; Verhoeven 2017). Coupled with machine-learning algorithms, remote sensing offers an effective means to increase survey areas and the discovery of new cultural deposits (Bennett et al. 2014; Davis 2019; Davis et al. 2019b; Trier et al. 2019). Specifically, the use of such technology allows researchers to (1) investigate large geographic scales in a time-efficient (and cost effective) manner; (2) access areas which are difficult to physically visit due to geography, lack of infrastructure, and/or political instability; and (3) achieve enhanced visibility for archaeological survey in environments with dense vegetation or otherwise challenging topography (e.g., LiDAR, SAR). The widespread use of such methods would allow Africanist archaeologists to investigate settlement distributional patterns and landscape use in multiple temporal contexts at extraordinary speeds, as case studies from other areas demonstrate (e.g., Bennett et al. 2014; Davis et al. 2019b; Magnini and Bettineschi 2019).

In this paper, we review landscape-scale remote sensing archaeological research conducted throughout the African continent, focusing primarily on the last two decades (Fig. 1) and how these methods can benefit archaeological research in the face of unprecedented climatic shifts and threats to cultural heritage. Specifically, we look at approaches utilizing aerial and spaceborne remote sensing instruments and avenues of

research that are yet to be fully utilized in this region. We offer several explanations for why remote sensing has been slow to break into the mainstream of Africanist archaeology. Then, we present examples from Africanist research that illustrate why these methods are essential for protecting and recording the archaeological record in the face of climate change and human impacts.

On the African continent, aerial and spaceborne remote sensing approaches have been widely applied, largely utilizing black-and-white aerial photographs to study state formation (Denbow 1979; Evers 1975; Gard and Mauny 1961; Jones 1978; Lampl 1968; Maggs 1976; Mason 1968; Mille 1970; Saumagne 1952; Seddon 1968; Wright 2007). Such studies illustrate the great potential for these approaches to expand our understanding of the archaeological record at the landscape scale and a diversity of social, economic, and political processes. However, these applications have been uneven. Studies by Jones (1978), Maggs (1976), Evers (1975), Mason (1968), and others revolutionized archaeological understanding of Iron Age settlement patterns throughout much of southern Africa. Meanwhile, on African islands, like Madagascar, aerial remote sensing has been much more limited in its archaeological applications (e.g., Fournier 1973; Marchal 1967; Mille 1970). Since the advent of commercial satellite imagery, only two studies (Clark et al. 1998; Davis et al. 2020) have been applied in this region. Such insufficient areal coverage of African islands has severely limited our understanding of their settlement history.

Neglecting to make use of aerial and spaceborne technologies makes it more likely that African archaeological sites and landscapes will soon be permanently lost. Climate change brings with it threats to archaeological deposits, including coastal erosion and sea-level rise (IPCC 2018; Ministère de l'Environnement, des Eaux, et des Forêts 2006; USAID 2016). Some of the sites most vulnerable to climate change contain the earliest traces of human (and early *Homo*) history (Erlandson 2012), while others represent the center of ancient global trading networks and are actively eroding (Radimilahy and Crossland 2015). Many coastal and island sites in Africa are also important for understanding past human adaptation and resilience in the face of climate and other pressures (Douglass and Cooper [in press](#); Turck and Thompson 2016). With today's impending climate crisis, it is imperative to learn all that we can from these sites before they are lost.

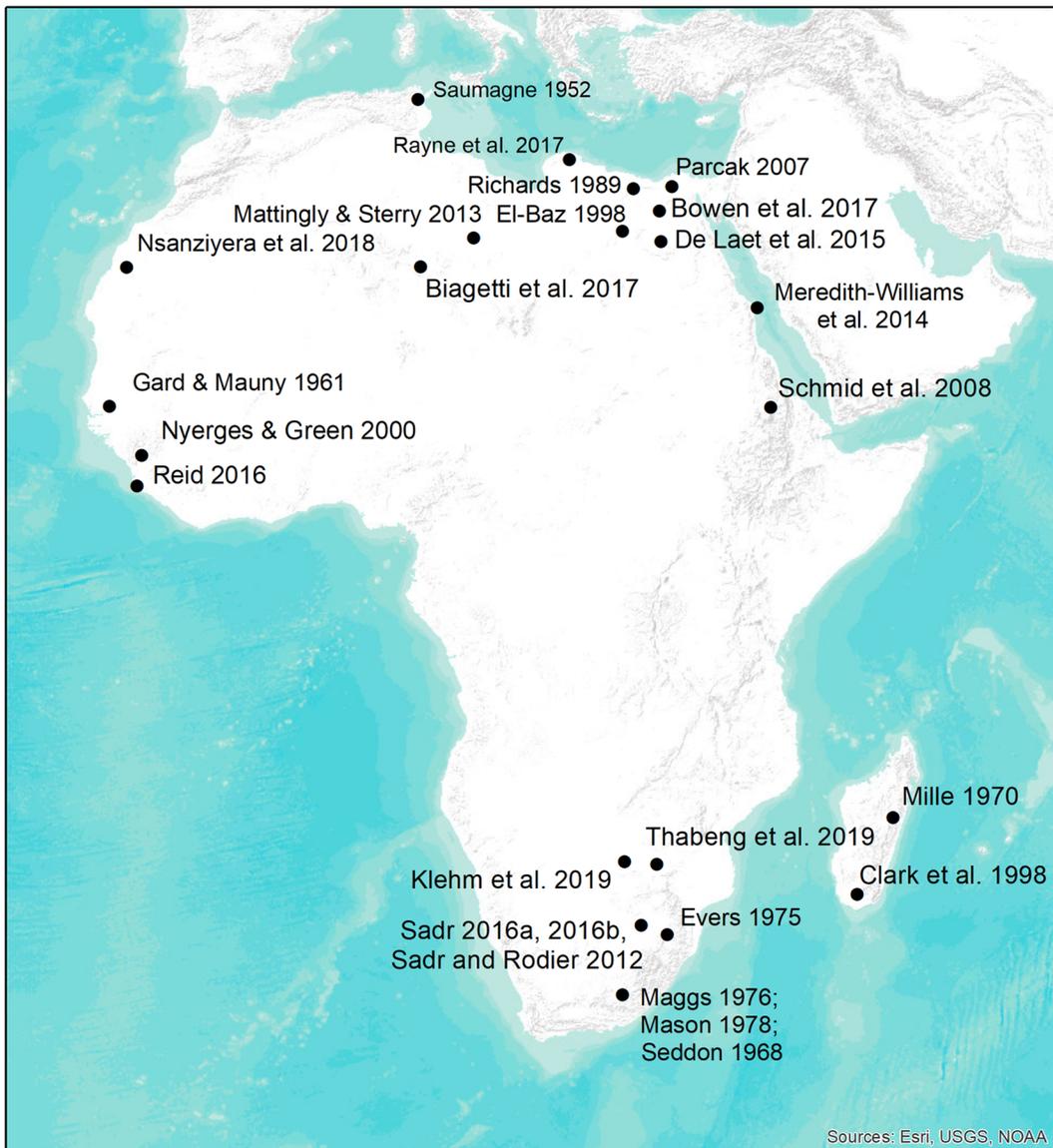


Fig. 1 Map of remote sensing case studies discussed in the text

Further damage occurs from political instability and conflict (e.g., Casana and Laugier 2017; Francioni and Lenzerini 2006; Harmanşah 2015; Pollock 2016) and economic inequality (e.g., Brodie et al. 2006; Parcak et al. 2016). To address anthropological questions concerning demography, the nature of social and political organization in prehistory, and the ecological entanglements of early populations, systematic archaeological investigations are required (e.g., Stahl 2005; also see Verhoeven 2017). Remote sensing instruments provide the ability to survey large geographic areas much faster than

traditional approaches, as has been demonstrated by many studies throughout the world (e.g., Beck et al. 2007; Bescoby 2006; Bini et al. 2018; Biagetti et al. 2017; Borie et al. 2019; Cerrillo-Cuenca 2017; Casana 2014; Davis et al. 2019b; De Laet et al. 2007; Evans et al. 2013; Freeland et al. 2016; Guyot et al. 2018; Harrower et al. 2013; Jahjah et al. 2007; Johnson and Ouimet 2014; Klehm et al. 2019; Krasinski et al. 2016; Lasaponara et al. 2014; Lipo and Hunt 2005; Meyer et al. 2019; Schuetter et al. 2013; Thabeng et al. 2019; Zanni and Rosa 2019). This ability is vital in the face of accelerated rates of

cultural heritage loss, which threatens African communities and livelihoods (Mire 2017).

Remote sensing has rapidly advanced over the past several decades, and the application of some of the more recent innovations in image processing appears underutilized within African contexts. We argue that these latest trends in remote sensing can offer a cost-effective solution for addressing the issue of systematic broadscale survey in Africa by reducing the amount of time required to investigate landscapes, thereby improving our overall understanding of landscape level phenomena throughout the region's history.

Limitations of Recent Remote Sensing Archaeology in Africa

The field of remote sensing and image analysis is constantly expanding, with an explosion of new processing techniques emerging over the past few decades. With such advances come costs, however, and oftentimes these costs prevent their utilization. For example, sensors such as LiDAR permit for the identification of topographic anomalies and have been successfully applied to archaeological prospection around the world (e.g., Cerrillo-Cuenca 2017; Davis et al. 2019a; Evans et al. 2013; Guyot et al. 2018; Lasaponara and Masini 2013; Trier et al. 2019). However, such technologies are infrequently used for archaeology in Africa (one exception being Sadr 2016a) and elsewhere because the cost of LiDAR ranges from the tens-to-hundreds-of-thousands of dollars and is not affordable for most researchers. Commercial satellite imagery, while less expensive (~\$20+ per km²), is still out of the financial reach of some research teams. Thus, while LiDAR and very-high-resolution satellite imagery have been used for archaeological research in other parts of the world, such applications require extensive budgets, and funding for African archaeological research is often limited (Clark 1994; Robertshaw 2012). Other sensors and datasets, however, are available for free (e.g., Landsat, Sentinel-1, and Sentinel-2) and provide similar capabilities.

In addition to new sensors and technologies, there have been advances in image processing methods, which have not yet been widely disseminated through the Africanist archaeology community. Specifically, the emergence of object-based image analysis (OBIA) over the past 15–20 years has seen major improvements in accuracy and identification capabilities for

archaeological objects (see Davis 2019 for a review; also see Blaschke 2010; Magnini and Bettineschi 2019). Such techniques have been used to systematically parse through datasets for archaeological information, successfully producing results with higher accuracy than traditional pixel-based approaches (see Sevara et al. 2016). Automated methods—especially OBIA—help to save time and money on surveying (e.g., Davis et al. 2019b), and this is particularly important in regions where sites are deteriorating due to anthropogenic and other forces.

In addition to OBIA, many advanced classification algorithms—such as random forest, support vector machine, and neural networks—are only just beginning to be utilized by Africanist archaeologists. Such approaches have produced highly accurate results in northern and southern Africa (Biagetti et al. 2017; Thabeng et al. 2019). The recent (and otherwise limited) introduction of such remote sensing techniques in Africanist archaeology may be partially explained by training opportunities for Africanist scholars outside of Africa and opportunities for collaboration between African and foreign scholars.

Archaeological remote sensing training opportunities are offered at a myriad of African universities, museums, and research institutions, with several courses offered by Nigerian, South African, and Ethiopian institutions. For example, Obafemi Awolowo University in Nigeria offers a number of training opportunities in remote sensing and even has a Center for Remote Sensing and GIS (RECTAS). Most opportunities for remote sensing training within Africa appear to be not directly affiliated with archaeology, however. Exceptions include Addis Ababa University in Ethiopia, where the Archaeology and Heritage Management Department offers cartography courses and the University of the Witwatersrand (South Africa), which offers remote sensing courses in the Department of Geography, Archaeology, and Environmental Studies. The results of several workshops and occasional short courses in remote sensing have resulted in training manuals (e.g., Wright 2017). Additionally, the African Association of Remote Sensing of the Environment (AARSE) holds a biannual pan-African conference at which new remote sensing methods are shared among a community of remote sensing experts. It would be useful for Africanist archaeology organizations to establish linkages with AARSE and encourage archaeologists to attend the AARSE conference.

While limited training within Africa cannot alone explain the dearth of archaeological remote sensing

studies in the region, it is a limiting factor for Africanist scholars within Africa to utilize such methods. Because much of the funding for archaeology in Africa comes from outside the continent (Ellison 1996; MacEachern 2010; Robertshaw 2012), and much of the literature pertaining to remote sensing is conducted by scholars outside of Africa, a limit in training opportunities for local archaeologists is certainly a contributing factor for the low number of recent studies when compared to other regions around the world (e.g., Europe). Robertshaw (2012: 98) also emphasizes the structural inequality in funding for African archaeology: “while the number of indigenous African archaeologists has been increasing across the continent in recent years, their access to research funds and logistical support is miniscule compared with that of their overseas colleagues” (also see Arazi 2011; MacEachern 2010).

Another possible reason for a lack of remote sensing stems from the mindset that archaeology requires the highest resolution datasets (which are usually costly to acquire). Most often, remote sensing research in archaeology is focused on directly identifying archaeological deposits in image data, and this requires high spatial resolution (~1 m or less) and spectral resolution (i.e., multispectral, hyperspectral capabilities) (Beck et al. 2007). However, there is also extensive work on *indirect* identification of archaeological deposits, usually using medium-to-course resolution images (e.g., Agapiou et al. 2014; Bennett et al. 2012; Davis et al. 2020; Kirk et al. 2016). Direct investigation utilizes high-resolution data in which archaeological deposits can be visualized and identified. In contrast, indirect investigation—whereby archaeological features are not directly visible—relies on proxies to estimate the likelihood of sites being present in a given area (e.g., Kirk et al. 2016).

Where funding and resources are limited, *indirect* methods are the best option for increasing remote sensing studies on the continent. Using freely available satellite imagery (e.g., Landsat, Sentinel-1, Sentinel-2), researchers can conduct analyses of vegetation patterns to identify likely cultural deposits on large (> 50 km²) geographic scales. Furthermore, the use of explicit theory (e.g., human behavioral ecology models [Charnov 1976; Fretwell and Lucas 1969; MacArthur and Pianka 1966]) can be used in conjunction with remote sensing to improve such predictive modeling approaches (Davis et al. 2020; Verhagen and Whitley 2012).

Given the abundance of freely available remote sensing datasets with coverage for the entirety of the African

continent, as well as many open-source softwares that can be used to process this imagery (see Table 1), it is via an *indirect* approach that remote sensing can be most easily and cost effectively integrated into archaeological research procedures on the continent.

While some of these open-source platforms are well known by archaeologists both within and outside of Africa (e.g., Google Earth), others are less recognized. For example, Google Earth Engine (GEE; Gorelick et al. 2017) is a free platform for educational, research, and nonprofit groups. GEE can be used to access remote sensing imagery and analyze these data with complex image processing algorithms that otherwise require an extensive coding background or potentially costly commercial software. Researchers have demonstrated that Google Earth Engine (GEE) is adept for archaeological prospection, specifically for digitizing archaeological feature boundaries and automating feature detection (Liss et al. 2017). A recent review of GEE indicates that while its use among remote sensing specialists is on the rise, African research has not engaged with this platform in a major way (Luo et al. 2018). Considering the capabilities of GEE—both as a data repository and platform for simple-to-complex analyses—and the fact that it is free to use, there is great potential for Africanist archaeologists to integrate it into their toolkits.

Trends in Remote Sensing Research in African Archaeology

Remote sensing has a long history in archaeology (e.g., Capper 1907; Lindbergh 1929), but the applications of this technology in Africa are more recent and scarcer than in other areas. In a recent special issue of *Geosciences* published on archaeological remote sensing, Africa was only represented by two of 14 articles (Nsanziyera et al. 2018; Oduntan 2019), of which only one (Nsanziyera et al. 2018) was a case study while the other (Oduntan 2019) was a discussion of legal statutes relating to geospatial research on the continent. This example is not an outlier, but represents a trend in recent remote sensing archaeology, where many of the latest developments are focused on other regions, primarily in the northern hemisphere (see Davis 2019). Africa represents over 30 million km², and while numerous studies have employed landscape-level survey since the start of the twenty-first century, vast areas of the continent have not been investigated (Fig. 1). In Madagascar, for

Table 1 List of open-source, freely available data repositories, and software platforms for remote sensing analysis. Although the list is not exhaustive, it summarizes some well-known and lesser known platforms and datasets with have strong capabilities for African regions

Resource name	Operating systems	Notes/capabilities	Reference
QGIS (formerly known as Quantum GIS)	<ul style="list-style-type: none"> • Windows • MacOS • Linux 	<ul style="list-style-type: none"> • Has an extensive number of plugin software, some of which (e.g., GRASS (GRASS Development Team 2018), Orfeo (OTB Development Team 2018)) have significant remote sensing analysis capabilities, including automated and OBIA analyses 	QGIS Development Team (2018)
SAGA	<ul style="list-style-type: none"> • Windows • Linux • FreeBSD • MacOS 	<ul style="list-style-type: none"> • Contains many environmental modeling tools and visualization algorithms 	Conrad et al. (2015)
Google Earth Engine	<ul style="list-style-type: none"> • Internet based. Any operating system will run with internet connection 	<ul style="list-style-type: none"> • Repository of freely accessible image datasets • Cloud-based computer processing allows for extremely fast analysis on large datasets • Ability to conduct automated analysis algorithms 	Gorelick et al. (2017)
R	<ul style="list-style-type: none"> • Windows • MacOS • Linux • Solaris OS 	<ul style="list-style-type: none"> • Coding platform with many remote sensing packages (e.g., raster [Hijmans 2019], RStoolbox [Leutner et al. 2019]) 	R Core Team (2018)
Earth Explorer	<ul style="list-style-type: none"> • Internet based. Any operating system with internet can access 	<ul style="list-style-type: none"> • Remote sensing data repository for the United States Geological Service (USGS). Contains datasets ranging from satellite data to LiDAR and aerial imagery around the globe 	https://earthexplorer.usgs.gov/
Copernicus	<ul style="list-style-type: none"> • Internet based. Any operating system with internet can access 	<ul style="list-style-type: none"> • Remote sensing data repository for the European Space Agency satellites (e.g., Sentinel 1 and 2) 	https://scihub.copernicus.eu/

example, the largest African island consisting of ~ 500,000 km², less than 1% of the island has been systematically investigated using remote sensing techniques. To ensure at-risk archaeological deposits are recorded in a systematic fashion, the latest advances in image processing and automated analysis methods are imperative.

Beginning in the 1950s, Africanist archaeologists took advantage of aerial photographs and identified thousands of archaeological sites from various time periods across the continent (e.g., Denbow 1979; Evers 1975; Jones 1978; Maggs 1976; Mason 1968; Saumagne 1952; Seddon 1968). Saumagne (1952) for example, conducted an aerial survey of archaeological sites in Tunisia. Almost a decade later, Gard and Mauny (1961) used aerial photographs to identify monumental earthen mounds in modern-day Senegal. Following these studies, aerial vantage points were utilized by archaeologists to identify a range of different features.

Denbow (1979), for example, identified hundreds of Iron Age sites in Botswana on the basis of vegetative patterns observed in aerial photographs. Denbow's work led to a better understanding of hilltop settlement dynamics and their connection with surrounding

landscapes. This landscape-level work has also allowed us to test hypotheses about the interactions between different communities of foragers, farmers, and herders in the Bosutswe region. Recent remote sensing studies continue to build on this earlier work but have begun to pay closer attention to subtler and less well-studied components of the archaeological record (e.g., Klehm et al. 2019).

Similarly, work conducted by Maggs (1976) was foundational for Iron Age settlement studies in southern Africa (e.g., Evers 1975; Jones 1978). The information obtained from these aerial surveys allowed for the development of site typologies and the analysis of specific environmental and social contexts that affected settlement choice (Huffman 1986).

On Madagascar, Mille (1970) used aerial photographs to identify and record approximately 16,000 fortified sites in an area encompassing 47,000 km² in the central highlands (Fig. 1). These photographs were systematically investigated to create settlement density maps which were then statistically tested to classify sites into different settlement types (Fournier 1973). Mille's (1970) study transformed archaeologists' understanding of settlement histories of the fifteenth to nineteenth

centuries by unveiling extensive monumental constructions throughout central Madagascar which were previously unrecorded. With this new information, Mille (1970) was able to calculate settlement densities and find connections between political transformation and settlement patterns (Fournier 1973).

While aerial photographs can provide helpful information, the interpretation of (oftentimes) black-and-white images with little-to-no spectral data is inherently limiting. Many early studies that relied on aerial photography identified the largest archaeological sites, while overlooking or under-evaluating more subtle cultural deposits (see Klehm et al. 2019, p. 69–70 for a brief discussion). The identification of cultural deposits via aerial photographs has resulted in the identification of many large structures (e.g., Denbow 1979; Maggs 1978; Mille 1970), but very little in the way of smaller domestic structures. This stems from a combination of resolution issues, lack of multispectral bands, and the limits of human analysts in identifying certain patterns and textures in photographs. The prospection of subtle features of the archaeological record has been enhanced by advances in computer learning and improvements in sensor resolution.

Following the explosion of satellite data in the 1980s and 1990s, remote sensing applications in African archaeology began integrating multispectral sensors into analysis (e.g., Allan and Richards 1983; Clark et al. 1998; Lightfoot and Miller 1996; Richards 1989; Williams and Faure 1980). Much of this work has emerged in the last two decades using both medium- (e.g., Sentinel-1, Sentinel-2, Landsat) and high-resolution (Worldview-2, Worldview-3, Ikonos, etc.) sensors (e.g., Clark et al. 1998; Klehm et al. 2019; Meredith-Williams et al. 2014; Nsanziyera et al. 2018; Nyerges and Green 2000; Reid 2016; Schmid et al. 2008). The application of multispectral satellites has permitted archaeologists to use subtle differences in the electromagnetic spectrum to identify disturbed landscapes and anthropogenic activities.

For example, Clark et al. (1998) illustrate the benefits of multispectral and synthetic aperture radar (SAR) data—an active sensor that can detect moisture content and textural properties of ground surfaces (Chen et al. 2017)—for understanding Madagascar’s settlement history. The researchers focus on several hundred square kilometers of area (Fig. 1) and shed light on the development of land use throughout the region as well as insight into where the oldest archaeological contexts are

located. For example, there have been many recent archaeological discoveries that place cultural contexts in association with ancient megafauna species, including elephant birds (*ratite genera Aepyornis* and *Mullerornis*) (Douglass 2016; Parker Pearson et al. 2010; Radimilahy 2011). In addition, Clark et al. (1998) show how archaeological deposits often produce discernable patterns that are distinct from modern day landscape boundaries. Thus, identification of temporally older cultural features can be made on the basis of their placement in the modern landscape. By so doing, remote sensing provides archaeologists with the capability of monitoring known sites as well as locating new ones.

These advances are not limited to Africanist research and have a long tradition in remote sensing archaeology around the world (Bini et al. 2018; Kirk et al. 2016; Lasaponara et al. 2014; Parcak 2009; Traviglia and Cottica 2011; also see Luo et al. 2019; Opitz and Herrmann 2018; Verhoeven and Sevara 2016). Multispectral sensors have also been used to develop vegetative indices that show the relative health of vegetation and can be used as a proxy of archaeological activity (see Bennett et al. 2012; Klehm et al. 2019; Thabeng et al. 2019), and such indices have proven useful in the detection of archaeological deposits dating to different periods throughout Africa (e.g., Biagetti et al. 2017; Klehm et al. 2019; Reid 2016; Sadr 2016a; Schmid et al. 2008; Thabeng et al. 2019). Additionally, they can be used to monitor the impacts of human activities on cultural materials (Reid 2016; Rütger 2002).

Monitoring anthropogenic impacts on cultural heritage represents one major trend of remote sensing archaeology in Africa (e.g., Casana and Laugier 2017; Lasaponara and Masini 2018; Parcak 2007, 2009; Parcak et al. 2016) and is at the forefront of major projects involving the continent (e.g., EAMENA, <http://eamena.arch.ox.ac.uk/>). The Endangered Archaeology in the Middle East and North Africa (EAMENA) project (Bewley et al. 2016) has created an open-access digital database of aerial images and archaeological data with the goal of rapidly evaluating the status of cultural heritage preservation throughout the Middle East and North African region. The use of these data has resulted in numerous publications on the importance of aerial survey for cultural heritage management (e.g., Fradley and Sheldrick 2017; Hobson 2019; Rayne et al. 2017; Zerbini and Fradley 2018). Additionally, programs like UNITAR’s Operational Satellite Applications Programme (UNOSAT) have

resulted in thorough damage assessments to cultural heritage in Syria (UNOSAT 2014).

A second trend in Africanist archaeological remote sensing literature is the use of vegetative indices for the identification of archaeological materials. For example, Biagetti et al. (2017) studied early Holocene settlements in the Sahara, Schmid et al. (2008) investigated soil properties in anthropogenic environments in Ethiopia, and Reid (2016) investigated settlement patterns in Sierra Leone (Fig. 1). In these projects, scholars calculated relative vegetation health and growth and matched these trends with areas of known anthropogenic activity. These signatures were then used as a basis for understanding the ecological effects of human land use (e.g., Nyerges and Green 2000) and allowed for both the indirect prospection of archaeological materials via geochemical signatures and the monitoring of cultural materials at risk of damage or destruction. Such approaches are particularly useful because they can provide important information using both high- and medium-resolution datasets (Biagetti et al. 2017). In contrast, direct detection of sites via spectral or geometric properties requires higher resolution data (see Beck et al. 2007).

A third trend in African remote sensing archaeology is the focus on mapping geomorphological properties of landscapes and their relationship to ancient settlement patterns. Such studies have successfully identified both archaeological sites and geomorphological features, such as paleolakes in the Sahara (e.g., Biagetti et al. 2017; also see El-Baz 1998) and ancient stone quarries in Egypt (e.g., De Laet et al. 2015). This approach is important, especially for studying human-environmental relationships, as it reveals interconnections between natural resources and human settlement patterns. For example, Clark et al. (1998) illustrate how specific environmental features (i.e., paleodunes) can act as markers of archaeological activity (also see Davis et al. 2020). Geomorphological studies in North Africa have also provided insight into where ancient rivers were located, which holds potential for identifying archaeological sites (El-Baz 1998).

Remote sensing datasets are increasingly analyzed via machine learning classification procedures, and this represents a fourth emerging trend in remote sensing archaeology in Africa, as well as globally. Semiautomated analysis techniques involve the use of statistical classifiers, machine learning algorithms, and/or specialized image processing software to aid in

analyzing remote sensing datasets with greater accuracy and speed. Such methods have been applied increasingly during the past few decades in different areas of the world (see Bennett et al. 2014; Davis 2019; Lambers 2018; Traviglia and Torsello 2017); this includes studies in Africa (Klehm et al. 2019; Reid 2016; Schmid et al. 2008; Thabeng et al. 2019). In the past year, the number of remote sensing studies utilizing automated methods in Africa has increased (e.g., Davis et al. 2020; Klehm et al. 2019; Thabeng et al. 2019), and this trend applies to global archaeology as well (e.g., Davis et al. 2019a, 2019b; Meyer et al. 2019; Trier et al. 2019; Verschoof-van der Vaart and Lambers 2019). In some instances, researchers are using automated methods solely for landscape classification, and the identification of cultural deposits remains a manual task for analysts (e.g., Biagetti et al. 2017). More recently, however, archaeological studies have utilized machine learning algorithms to directly identify archaeological materials.

Automated analysis methods have been implemented in Africa using high-resolution multispectral Worldview-2 imagery. Thabeng et al. (2019) create training data to conduct random-forest and support vector machine classifications to distinguish between anthropogenic and nonanthropogenic land types throughout southern Africa since 900 AD. Their random forest classification uses an iterative predictive modeling approach to select ideal classes for datasets on the basis of popular consensus among the different nodes (Pal 2005). Support vector machine classification then identifies optimal separations between classes and can produce highly accurate results, even with small training datasets (Mountrakis et al. 2011). Advanced classification algorithms can thus help to automate the prospection of archaeological sites on the basis of spectral characteristics with a high rate of accuracy (> 95%). There are some issues of misclassification, however, which can be resolved using object-based image analysis (OBIA) classification methods (Thabeng et al. 2019).

Another recent application of automated remote sensing is by Klehm et al. (2019), who use an unsupervised classification algorithm—wherein a computer divides an image into classes without the input of a human analyst—to identify spectral signatures associated with cultural deposits in Botswana. Klehm et al. (2019) draw attention to hinterland areas with less prominent archaeological features, where the focus of archaeological research was historically on clusters of hilltop settlements (e.g., Denbow 1979). They identify and field test

10 new archaeological sites, of which eight were confirmed to be Iron Age deposits (Klehm et al. 2019). Klehm et al. (2019) demonstrate the benefits of automated survey procedures and the role that these methods can play in improving predictive modeling of archaeological site locations in areas that suffer from lack of funding and survey capabilities. As such, automated remote sensing surveys are vital for increasing our understanding of the archaeological record in areas where survey is difficult or otherwise impeded.

While (semi)automated analysis methods have advantages in terms of processing speed and identification capabilities, programming automated procedures requires training, trial and error, and time, as the processes are often quite complicated and softwares are not always user friendly. There are, however, many online forums and tutorials that can aid researchers in performing specific kinds of tasks (a simple search in YouTube will lead to hundreds of video tutorials using both commercial and open-source software). It should also be mentioned that there are currently no “fully automated” archaeological remote sensing methods: every remote sensing analysis requires validation of results, usually by ground visits or other assessments of accuracy. As such, all automated procedures discussed, here and elsewhere, are truly “semiautomated” procedures.

OBIA represents a recent advancement in automated detection in archaeology (ca. mid-2000s; see Davis 2019). Simply, OBIA is an image-processing technique that segments an image into discrete components on the basis of one or more geometric or textural characteristics. It has been demonstrated that such methods are more accurate than traditional “pixel-based” image analysis methods (see Sevara et al. 2016) and can be used for different scales of analysis ranging from microscopic to global-scale imagery (Magnini and Bettineschi 2019). OBIA has since been followed by neural network analysis and other machine learning techniques (Verschoof-van der Vaart and Lambers 2019). Despite the improvements in the accuracy and reliability of automated detection using OBIA, archaeologists are yet to apply OBIA within African archaeology (Davis 2019), in part due to limited training opportunities (see above) and costs often associated with such processing methods. Use of OBIA can also assist in distinguishing between anthropogenic and nonanthropogenic features (Davis et al. 2019b; Lambers et al. 2019; also see Thabeng et al. 2019).

While automated methods are gaining popularity, plenty of work is still conducted using manual analysis

(e.g., Mattingly and Sterry 2013; Rayne et al. 2017; Sadr 2016a, 2016b). For many researchers, manual analysis can be particularly useful, especially with open-source datasets like Google Earth. The use of manual analysis methods (including ground-testing identified results) is always a necessary component of remote sensing analysis, but complementing these with automated approaches helps to reduce biases and inconsistencies in purely manual results (Bennett et al. 2014; Davis 2019; Verhoeven 2017; also see, for example, Sadr 2016b). While automated analyses introduce their own sets of assumptions and limitations, these biases are explicit and largely reproducible. Manual analysis, however, contains largely implicit biases on the part of the analyst and can introduce confounding assumptions in the analysis of remote sensing data. Part of the slow introduction of automated methods relates to cost, as such software can be exceedingly expensive. Processing capabilities of platforms like Google Earth Engine (Gorelick et al. 2017), however, offer free access to a variety of automated image processing algorithms, as well as the ability to code specifically designed processes for those with coding backgrounds (see Table 1).

Future Directions for Remote Sensing in African Archaeology

Increased integration of remote sensing approaches in African archaeology will provide many avenues for future exploration and discovery. The first step is to expand remote sensing surveys into areas where such methods are largely absent and where cultural heritage is at increased risk (e.g., climate change, political instability). This large-scale effort can be accomplished through a combination of direct and indirect investigations.

Indirect investigations face challenges, however, and require innovative integrations of remote sensing methods with explicit theories and models designed to explain cultural phenomena. Such frameworks are central to disciplines such as anthropology, geography, and history. Currently, one of the fundamental limitations of most archaeological remote sensing studies is their implementation *sans* anthropological theory—with anthropological referring to frameworks mentioned previously (Thompson and Turck 2009). In most remote sensing investigations, identification of patterns or objects in datasets is most commonly conducted using methods and theories exclusively from geosciences and physics.

For example, many researchers have used vegetative indices to predict the locations of cultural deposits (e.g., Biagetti et al. 2017; Kirk et al. 2016; Lasaponara and Masini 2007; Schmid et al. 2008) but most of these studies do not incorporate explicit theoretical models—e.g., ethnography, human behavioral ecology, niche construction—when building indexes of archaeological activity. While these approaches are useful for identifying archaeological sites, they can be limiting in addressing more complex archaeological questions. For this reason, remote sensing archaeology is often published as individual case studies (e.g., Calleja et al. 2018; Davis et al. 2019b; Lasaponara and Masini 2007; Traviglia and Cottica 2011) that demonstrate the usefulness of specific approaches but are rarely developed to address questions of broad anthropological significance.

Much of the recent literature employing new analytical methods for remote sensing is purely experimental and thus is interested solely in developing methods that can be more widely applied by future work. This is inherently useful and should be encouraged. Nonetheless, some researchers have begun incorporating the results of such remote sensing analyses into broader anthropological syntheses, and this should become commonplace in future research (e.g., Borie et al. 2019; Cerrillo-Cuenca and Bueno-Ramírez 2019; Freeland et al. 2016; Inomata et al. 2018; Rutkiewicz et al. 2019).

Because of the disconnect between remote sensing applications and anthropological theory, coarser-resolution imagery is often ignored or avoided by archaeologists because they cannot directly identify deposits, save those that are extraordinarily large (such as fortifications, walls, and roadways) (Beck et al. 2007; Zanni and Rosa 2019). However, there is an abundance of freely downloadable data that is available for nearly every inch of the globe, and despite its lower resolution (~10–30 m or greater), such datasets can be extremely beneficial for archaeological analyses (e.g., Agapiou et al. 2014; Borie et al. 2019; Breeze et al. 2015; Kirk et al. 2016; Zanni and Rosa 2019).

A recent study by Nsanziyera et al. (2018) makes use of anthropological variables in conjunction with geoscience frameworks and freely available remote sensing datasets to predict the locations of archaeological sites in a 1000-km² area in Morocco (Fig. 1). By incorporating anthropological, as well as environmental variables into their model, the authors achieve ~93% accuracy, thereby demonstrating the utility of theoretically driven

analyses and freely available datasets. Africanist archaeologists are well-positioned to lead the way on the integration of anthropological models and theories into applications of remote sensing, given the long tradition of theorizing population movements, the emergence of complex social, political and economic forms, regional interaction, and other landscape-scale behaviors (e.g., Anquandah 1987; Ashley et al. 2016; Breunig et al. 1996; Harlan and Stemler 1976; Stahl 1985; Wynne-Jones and Fleisher 2015).

With the acquisition of remote sensing datasets at higher spatial and spectral resolutions, it is possible to directly identify archaeological deposits, rather than assign general probabilities of where these features are most likely to be located (Calleja et al. 2018; Davis et al. 2019a; De Laet et al. 2007; Klehm et al. 2019; LaRocque et al. 2019; Lasaponara and Masini 2007; Thabeng et al. 2019; Traviglia and Torsello 2017; Trier et al. 2009). While future work should attempt to acquire and analyze high-resolution imagery (e.g., IKONOS, SPOT, Worldview), the immediate priority should be to develop robust theoretical models that can be tested using freely available imagery. This will allow the greatest number of archaeologists—regardless of financial capabilities—to begin utilizing remote sensing technologies.

In addition, future work should seek to analyze satellite imagery using a mix of automated and manual procedures. This will permit researchers to (a) eliminate observer biases that are often abundant in purely manual evaluations of remote sensing data and (b) systematically investigate entire regions in short spans of time. Automated methods, such as OBIA, can also improve our understanding of site dynamics, as these approaches can classify feature shape, size, and other morphometric properties (Davis et al. 2019a).

Conclusions

This paper has reviewed the application of aerial and spaceborne remote sensing methods for landscape analysis in African archaeology. These techniques offer great potential to increase our knowledge of the human past and help to record and protect cultural heritage that is at risk from anthropogenic and natural forces. While Africanist archaeology has a long history of aerial surveys, the most recent advances in aerial and spaceborne technology have

been slow to break into research practices on the continent. Archaeologists need to adopt remote sensing methods that can quickly and accurately record the increasingly threatened archaeological heritage in different parts of Africa.

Climate-related risks are increasing rapidly (IPCC 2018), and much of the African coast is in danger of sea level rise and erosion. Equally problematic for archaeology in other regions of Africa are anthropogenic forces such as urban development and looting. In the case of looting, in particular, researchers have demonstrated the power of remote sensing technologies to identify cultural materials under threat (e.g., Casana and Laugier 2017; Lasaponara and Masini 2018; Lauricella et al. 2017; Parcak et al. 2016; UNOSAT 2014; Xiao et al. 2018). It is therefore necessary to increase the rate at which researchers document the archaeological record, as many African archaeological deposits are rapidly disappearing (Erlandson 2012; Parker Pearson et al. 2010).

Remote sensing can also aid in creating more robust archaeological datasets which can form the basis of large-scale landscape level studies (e.g., Davis et al. 2019b; Freeland et al. 2016; Inomata et al. 2018; Menze and Ur 2012) and improve the speed and accuracy of mapping archaeological deposits (Hesse 2010). The speed and accuracy attainable through remote sensing survey methods are essential for future archaeological research, as datasets continue to expand.

Ultimately, the integration of remote sensing into the mainstream of Africanist archaeology is underway, and as knowledge of cost-effective datasets and processing software increases among Africanists, research using these methods should increase substantially. We emphasize many such platforms above and hope that this article assists researchers in accessing useful analytical tools. However, it is also essential that training in remote sensing techniques become a featured component of archaeology programs throughout Africa and Africanist departments more broadly. Rigorous training is especially critical for the use of techniques involving machine learning and automated analysis.

Scholars in Africa have long made important contributions to the study of landscape change, settlement histories, and spatial analysis. By incorporating remote sensing datasets into future studies, Africanist contributions will be enhanced with more complete datasets and greater geographic coverage of the diversity of Africa's human past.

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval Statement This article does not contain any studies with animals performed by any of the authors.

References

- Agapiou, A., Alexakis, D., Sarris, A., & Hadjimitsis, D. (2014). Evaluating the potentials of Sentinel-2 for archaeological perspective. *Remote Sensing*, 6(3), 2176–2194. <https://doi.org/10.3390/rs6032176>.
- Allan, J. A., & Richards, T. S. (1983). Use of satellite imagery in archaeological surveys. *Libyan Studies*, 14, 4–8.
- Anquandah, J. (1987). The stone circle sites of Komaland, northern Ghana, in West African archaeology. *African Archaeological Review*, 5(1), 171–180.
- Arazi, N. (2011). Safeguarding archaeological cultural resources in Africa—Policies, methods and issues of (non) compliance. *African Archaeological Review*, 28(1), 27–38.
- Ashley, C. Z., Antonites, A., & Fredriksen, P. D. (2016). Mobility and African archaeology: an introduction. *Azania: Archaeological Research in Africa*, 51, 417–434.
- Beck, A., Philip, G., Abdulkarim, M., & Donoghue, D. (2007). Evaluation of Corona and Ikonos high resolution satellite imagery for archaeological prospection in western Syria. *Antiquity*, 81(311), 161–175. <https://doi.org/10.1017/S0003598X00094916>.
- Bennett, R., Cowley, D., & De Laet, V. (2014). The data explosion: Tackling the taboo of automatic feature recognition in airborne survey data. *Antiquity*, 88(341), 896–905. <https://doi.org/10.1017/S0003598X00050766>.
- Bennett, R., Welham, K., Hill, R. A., & Ford, A. L. J. (2012). The application of vegetation indices for the prospection of archaeological features in grass-dominated environments. *Archaeological Prospection*, 19(3), 209–218. <https://doi.org/10.1002/arp.1429>.
- Bescoby, D. J. (2006). Detecting Roman land boundaries in aerial photographs using Radon transforms. *Journal of Archaeological Science*, 33(5), 735–743. <https://doi.org/10.1016/j.jas.2005.10.012>.
- Bewley, R., Wilson, A., Kennedy, D., Mattingly, D., Banks, R., Bishop, M., et al. (2016). Endangered archaeology in the Middle East and North Africa: Introducing the EAMENA project. In *CAA2015. Keep the Revolution Going: Proceedings of the 43rd Annual Conference on Computer Applications and Quantitative Methods in Archaeology* (Vol. 1, p. 919).
- Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65(1), 2–16. <https://doi.org/10.1016/j.isprsjprs.2009.06.004>.
- Biagetti, S., Merlo, S., Adam, E., Lobo, A., Conesa, F. C., Knight, J., ... & Madella, M. (2017). High and medium resolution satellite imagery to evaluate Late Holocene human-environment interactions in Arid Lands: A case study from the Central Sahara. *Remote Sensing*, 9(4), 351. <https://doi.org/10.3390/rs9040351>.

- Bini, M., Isola, I., Zanchetta, G., Ribolini, A., Ciampalini, A., Baneschi, I., et al. (2018). Identification of leveled archaeological mounds (Höyük) in the alluvial plain of the Ceyhan River (Southern Turkey) by satellite remote-sensing analyses. *Remote Sensing*, 10(2), 241. <https://doi.org/10.3390/rs10020241>.
- Borie, C., Parceró-Oubiña, C., Kwon, Y., Salazar, D., Flores, C., Olguín, L., & Andrade, P. (2015). Beyond site detection: The role of satellite remote sensing in analysing archaeological problems. A case study in lithic resource procurement in the Atacama Desert, Northern Chile. *Remote Sensing*, 11(7), 869. <https://doi.org/10.3390/rs11070869>.
- Breeze, P. S., Drake, N. A., Groucutt, H. S., Parton, A., Jennings, R. P., White, T. S., et al. (2015). Remote sensing and GIS techniques for reconstructing Arabian palaeohydrology and identifying archaeological sites. *Quaternary International*, 382, 98–119. <https://doi.org/10.1016/j.quaint.2015.01.022>.
- Breunig, P., Neumann, K., & Van Neer, W. (1996). New research on the Holocene settlement and environment of the Chad Basin in Nigeria. *African Archaeological Review*, 13(2), 111–145.
- Calleja, J. F., Requejo Pagés, O., Díaz-Álvarez, N., Peón, J., Gutiérrez, N., Martín-Hernández, E., Cebada Relea, A., Rubio Melendi, D., & Fernández Álvarez, P. (2018). Detection of buried archaeological remains with the combined use of satellite multispectral data and UAV data. *International Journal of Applied Earth Observation and Geoinformation*, 73, 555–573. <https://doi.org/10.1016/j.jag.2018.07.023>.
- Capper, J. E. (1907). Photographs of Stonehenge as seen from a war balloon. *Archaeologia*, 60, 571.
- Casana, J. (2014). Regional-scale archaeological remote sensing in the age of big data. *Advances in Archaeological Practice*, 2(03), 222–233. <https://doi.org/10.7183/2326-3768.2.3.222>.
- Casana, J., & Laugier, E. J. (2017). Satellite imagery-based monitoring of archaeological site damage in the Syrian civil war. *PLOS ONE*, 12(11), e0188589. <https://doi.org/10.1371/journal.pone.0188589>.
- Cerrillo-Cuenca, E. (2017). An approach to the automatic surveying of prehistoric barrows through LiDAR. *Quaternary International*, 435, 135–145. <https://doi.org/10.1016/j.quaint.2015.12.099>.
- Cerrillo-Cuenca, E., & Bueno-Ramírez, P. (2019). Counting with the invisible record? The role of LiDAR in the interpretation of megalithic landscapes in south-western Iberia (Extremadura, Alentejo and Beira Baixa). *Archaeological Prospection*, 26(3), 251–264. <https://doi.org/10.1002/arp.1738>.
- Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. *Theoretical Population Biology*, 9(2), 129–136.
- Chase, A. F., Chase, D. Z., Fisher, C. T., Leisz, S. J., & Weishampel, J. F. (2012). Geospatial revolution and remote sensing LiDAR in Mesoamerican archaeology. *Proceedings of the National Academy of Sciences*, 109(32), 12916–12921. <https://doi.org/10.1073/pnas.1205198109>.
- Chen, F., Lasaponara, R., & Masini, N. (2017). An overview of satellite synthetic aperture radar remote sensing in archaeology: From site detection to monitoring. *Journal of Cultural Heritage*, 23, 5–11. <https://doi.org/10.1016/j.culher.2015.05.003>.
- Clark, C. D., Garrod, S. M., & Pearson, M. P. (1998). Landscape archaeology and remote sensing in southern Madagascar. *International Journal of Remote Sensing*, 19(8), 1461–1477. <https://doi.org/10.1080/014311698215298>.
- Clark, J. D. (1994). Digging on: A personal record and appraisal of archaeological research in Africa and elsewhere. *Annual Review of Anthropology*, 23, 1–24.
- Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., Wehrg, J., et al. (2015). System for automated geoscientific analyses (SAGA) v. 2.1.4. *Geoscientific Model Development*, 8(7), 1991–2007. <https://doi.org/10.5194/gmd-8-1991-2015>.
- Davis, D. S. (2019). Object-based image analysis: A review of developments and future directions of automated feature detection in landscape archaeology. *Archaeological Prospection*, 26(2), 155–163. <https://doi.org/10.1002/arp.1730>.
- Davis, D. S., Andriankaja, V., Carnat, T. L., Chrisostome, Z. M., Colombe, C., Fenomanana, F., Hubertine, et al. (2020). Satellite-based remote sensing rapidly reveals extensive record of Holocene coastal settlement on Madagascar. *Journal of Archaeological Science*, 115: 105097.
- Davis, D. S., Lipo, C. P., & Sanger, M. C. (2019a). A comparison of automated object extraction methods for mound and shell-ring identification in coastal South Carolina. *Journal of Archaeological Science: Reports*, 23, 166–177. <https://doi.org/10.1016/j.jasrep.2018.10.035>.
- Davis, D. S., Sanger, M. C., & Lipo, C. P. (2019b). Automated mound detection using LiDAR survey in Beaufort County, SC. *Southeastern Archaeology*, 38(1), 23–37. <https://doi.org/10.1080/0734578X.2018.1482186>.
- De Laet, V., Paulissen, E., & Waelkens, M. (2007). Methods for the extraction of archaeological features from very high-resolution Ikonos-2 remote sensing imagery, Hisar (south-west Turkey). *Journal of Archaeological Science*, 34(5), 830–841. <https://doi.org/10.1016/j.jas.2006.09.013>.
- De Laet, V., van Loon, G., Van der Perre, A., Deliever, I., & Willems, H. (2015). Integrated remote sensing investigations of ancient quarries and road systems in the Greater Dayr al-Barshā Region, Middle Egypt: A study of logistics. *Journal of Archaeological Science*, 55, 286–300. <https://doi.org/10.1016/j.jas.2014.10.009>.
- Denbow, J. R. (1979). *Cenchrus ciliaris*: An ecological indicator of Iron Age middens using aerial photography in eastern Botswana. *South African Journal of Science*, 75(9), 405–408.
- Dewar, R. E., & Wright, H. T. (1993). The culture history of Madagascar. *Journal of World Prehistory*, 7(4), 417–466. <https://doi.org/10.1007/BF00997802>.
- Douglass, K. (2016). *An archaeological investigation of settlement and resource exploitation patterns in the Velondriake Marine Protected Area, Southwest Madagascar, ca. 900 BC to AD 1900*. PhD Dissertation, Yale University.
- Douglass, K and J. Cooper. (In Press). Archaeology, environmental justice and climate change on islands of the Caribbean and Western Indian Ocean. *PNAS*.
- El-Baz, F. (1998). Aeolian deposits and palaeo-rivers of the eastern Sahara. *Significance to archaeology and groundwater exploration. Sahara*, 10, 55–66.
- Ellison, J. (1996). The future of African archaeology. *African Archaeological Review*, 13(1), 5–34.
- Erlanson, J. M. (2012). As the world warms: Rising seas, coastal archaeology, and the erosion of maritime history. *Journal of*

- Coastal Conservation*, 16(2), 137–142. <https://doi.org/10.1007/s11852-010-0104-5>.
- Evans, D. H., Fletcher, R. J., Pottier, C., Chevance, J.-B., Soutif, D., Tan, B. S., Im, S., et al. (2013). Uncovering archaeological landscapes at Angkor using lidar. *Proceedings of the National Academy of Sciences*, 110(31), 12595–12600. <https://doi.org/10.1073/pnas.1306539110>.
- Evers, T. M. (1975). Recent iron age research in the eastern Transvaal, South Africa. *South African Archaeological Bulletin*, 30, 71–83.
- Fournier, G. (1973). Villages fortifiés et histoire du peuplement à Madagascar. *Archéologie Médiévale*, 3(1), 432–435. <https://doi.org/10.3406/arcme.1973.1277>.
- Fradley, M., & Sheldrick, N. (2017). Satellite imagery and heritage damage in Egypt: A response to Parcak et al. (2016). *Antiquity*, 91(357), 784–792.
- Francioni, F., & Lenzerini, F. (2006). The obligation to prevent and avoid destruction of cultural heritage: From Bamiyan to Iraq. In B. T. Hoffman (Ed.), *Art and Cultural Heritage: Law, Policy and Practice* (pp. 28–40). Cambridge: Cambridge University Press.
- Freeland, T., Heung, B., Burley, D. V., Clark, G., & Knudby, A. (2016). Automated feature extraction for prospection and analysis of monumental earthworks from aerial LiDAR in the Kingdom of Tonga. *Journal of Archaeological Science*, 69, 64–74. <https://doi.org/10.1016/j.jas.2016.04.011>.
- Fretwell, S. D., & Lucas, H. L. (1969). On territorial behavior and other factors influencing habitat distribution in birds: I. Theoretical development. *Acta Biotheoretica*, 19(1), 16–36. <https://doi.org/10.1007/BF01601953>.
- Gard, J., & Mauny, R. (1961). Découverte de tumulus dans la région de Diourbel (Sénégal). *Notes Africaines*, 89, 10–11.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27.
- GRASS Development Team. (2018). Geographic Resources Analysis Support System (GRASS) Software (Version 7.4). Open Source Geospatial Foundation. <https://grass.osgeo.org>.
- Guyot, A., Hubert-Moy, L., & Lorho, T. (2018). Detecting Neolithic burial mounds from LiDAR-Derived elevation data using a multi-scale approach and machine learning techniques. *Remote Sensing*, 10(2), 225. <https://doi.org/10.3390/rs10020225>.
- Harlan, J., & Stemler, A. B. (1976). The races of sorghum in Africa. In J. Harlan (Ed.), *Origins of African plant domestication* (pp. 465–478). The Hague: Mouton Publishers.
- Harmansah, Ö. (2015). ISIS, heritage, and the spectacles of destruction in the global media. *Near Eastern Archaeology*, 78(3), 170–177.
- Harrower, M. J., Schuetter, J., McCriston, J., Goel, P. K., & Senn, M. J. (2013). Survey, automated detection, and spatial distribution analysis of cairn tombs in Ancient Southern Arabia. In D. C. Comer & M. J. Harrower (Eds.), *Mapping archaeological landscapes from space* (pp. 259–268). New York: Springer. https://doi.org/10.1007/978-1-4614-6074-9_22.
- Hesse, R. (2010). LiDAR-derived local relief models - A new tool for archaeological prospection. *Archaeological Prospection*, 17(2), 67–72. <https://doi.org/10.1002/arp.374>.
- Hijmans, R. J. (2019). raster: Geographic Data Analysis and Modeling. *R package version*, 2, 9–5 <https://CRAN.R-project.org/package=raster>.
- Hobson, M. S. (2019). EAMENA training in the use of satellite remote sensing and digital technologies in heritage management: Libya and Tunisia workshops 2017–2019. *Libyan Studies*, 50, 63–71.
- Huffman, T. N. (1986). Archaeological evidence and conventional explanations of Southern Bantu settlement patterns. *Africa*, 56(3), 280–298.
- IPCC. (2018). *Global Warming of 1.5 °C: An IPCC special report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty (No. SR15)*. Intergovernmental Panel on Climate Change. <https://www.ipcc.ch/report/sr15/>.
- Inomata, T., Triadan, D., Pinzón, F., Burham, M., Ranchos, J. L., Aoyama, K., & Haraguchi, T. (2018). Archaeological application of airborne LiDAR to examine social changes in the Ceibal region of the Maya lowlands. *PLOS ONE*, 13(2), e0191619. <https://doi.org/10.1371/journal.pone.0191619>.
- Jahjah, M., Olivieri, C., Invernizzi, A., & Parapetti, R. (2007). Archaeological remote sensing application pre-post war situation of Babylon archaeological site—Iraq. *Acta Astronautica*, 61(1–6), 121–130. <https://doi.org/10.1016/j.actastro.2007.01.034>.
- Johnson, K. M., & Ouimet, W. B. (2014). Rediscovering the lost archaeological landscape of southern New England using airborne light detection and ranging (LiDAR). *Journal of Archaeological Science*, 43, 9–20. <https://doi.org/10.1016/j.jas.2013.12.004>.
- Jones, P. (1978). An approach to stone settlement typology of the late Iron Age: stone walling on the Klip River 27° 10's 29° 10'e. *African Studies*, 37(1), 83–97.
- Klehm, C., Barnes, A., Follett, F., Simon, K., Kiahtipes, C., & Mothulatshipi, S. (2019). Toward archaeological predictive modeling in the Bosutswe region of Botswana: Utilizing multispectral satellite imagery to conceptualize ancient landscapes. *Journal of Anthropological Archaeology*, 54, 68–83. <https://doi.org/10.1016/j.jaa.2019.02.002>.
- Krasinski, K. E., Wygal, B. T., Wells, J., Martin, R. L., & Seager-Boss, F. (2016). Detecting Late Holocene cultural landscape modifications using LiDAR imagery in the Boreal Forest, Susitna Valley, Southcentral Alaska. *Journal of Field Archaeology*, 41(3), 255–270. <https://doi.org/10.1080/00934690.2016.1174764>.
- Lambers, K. (2018). Airborne and spaceborne remote sensing and digital image analysis in archaeology. In C. Siart, M. Forbriger, & O. Bubenzer (Eds.), *Digital Geoarchaeology* (pp. 109–122). Cham: Springer. https://doi.org/10.1007/978-3-319-25316-9_7.
- Lambers, K., Verschoof-van der Vaart, W., & Bourgeois, Q. (2019). Integrating remote sensing, machine learning, and citizen science in Dutch archaeological prospection. *Remote Sensing*, 11(7), 794. <https://doi.org/10.3390/rs11070794>.
- Lampl, P. (1968). *Cities and planning in the ancient Near East*. New York: George Braziller.
- LaRocque, A., Leblon, B., & Ek, J. (2019). Detection of potential large Maya settlements in the northern Petén area (State of Campeche, Mexico) using optical and radar remote sensing.

- Journal of Archaeological Science: Reports*, 23, 80–97. <https://doi.org/10.1016/j.jasrep.2018.10.020>.
- Lasaponara, R., & Masini, N. (2018). Space-based identification of archaeological illegal excavations and a new automatic method for looting feature extraction in desert areas. *Surveys in Geophysics*, 39(6), 1323–1346. <https://doi.org/10.1007/s10712-018-9480-4>.
- Lasaponara, R., & Masini, N. (2013). Satellite Synthetic Aperture Radar in archaeology and cultural landscape: An overview. *Archaeological Prospection*, 20(2), 71–78. <https://doi.org/10.1002/arp.1452>.
- Lasaponara, R., & Masini, N. (2012). Image enhancement, feature extraction and geospatial analysis in an archaeological perspective. In R. Lasaponara & N. Masini (Eds.), *Satellite remote sensing* (pp. 17–63). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-90-481-8801-7_2.
- Lasaponara, R., & Masini, N. (2007). Detection of archaeological crop marks by using satellite QuickBird multispectral imagery. *Journal of Archaeological Science*, 34(2), 214–221.
- Lasaponara, R., Leucci, G., Masini, N., & Persico, R. (2014). Investigating archaeological looting using satellite images and GEORADAR: The experience in Lambayeque in North Peru. *Journal of Archaeological Science*, 42, 216–230. <https://doi.org/10.1016/j.jas.2013.10.032>.
- Lauricella, A., Cannon, J., Branting, S., & Hammer, E. (2017). Semi-automated detection of looting in Afghanistan using multispectral imagery and principal component analysis. *Antiquity*, 91(359), 1344–1355. <https://doi.org/10.15184/aqy.2017.90>.
- Leisz, S. J. (2013). An overview of the application of remote sensing to archaeology during the twentieth century. In D. C. Comer & M. J. Harrower (Eds.), *Mapping archaeological landscapes from space* (pp. 11–19). New York: Springer. https://doi.org/10.1007/978-1-4614-6074-9_2.
- Leutner, B., Horning, N., & Schwalb-Willmann, J. (2019). RStoolbox: Tools for remote sensing data analysis. R package version 0.2.4. <https://CRAN.R-project.org/package=RStoolbox>.
- Lightfoot, D. R., & Miller, J. A. (1996). Sijilmassa: The rise and fall of a walled oasis in medieval Morocco. *Annals of the Association of American Geographers*, 86(1), 78–101.
- Lindbergh, C. A. (1929). The discovery of the ruined Maya cities. *Science*, 70, 12–13.
- Lipo, C. P., & Hunt, T. L. (2005). Mapping prehistoric statue roads on Easter Island. *Antiquity*, 79(303), 158–168.
- Liss, B., Howland, M. D., & Levy, T. E. (2017). Testing Google Earth Engine for the automatic identification and vectorization of archaeological features: A case study from Faynan, Jordan. *Journal of Archaeological Science: Reports*, 15, 299–304.
- Luo, L., Wang, X., Guo, H., Lasaponara, R., Shi, P., Bachagha, N., Li, L., Yao, Y., Masini, N., Chen, F., Wei, J., Cao, H., Li, C., & Hu, N. (2018). Google Earth as a powerful tool for archaeological and cultural heritage applications: A review. *Remote Sensing*, 10(10), 1558.
- Luo, L., Wang, X., Guo, H., Lasaponara, R., Zong, X., Masini, N., Wang, G., Shi, P., Khatteli, H., Chen, F., Tariq, S., Shao, J., Bachagha, N., Yang, R., & Yao, Y. (2019). Airborne and spaceborne remote sensing for archaeological and cultural heritage applications: A review of the century (1907–2017). *Remote Sensing of Environment*, 232, 111280. <https://doi.org/10.1016/j.rse.2019.111280>.
- MacArthur, R. H., & Pianka, E. R. (1966). On Optimal Use of a Patchy Environment. *The American Naturalist*, 100(916), 603–609. <https://doi.org/10.1086/282454>.
- MacEachern, S. (2010). Seeing like an oil company's CHM programme: Exxon and archaeology on the Chad Export Project. *Journal of Social Archaeology*, 10(3), 347–366.
- Maggs, T. (1976). *Iron Age communities of the southern Highveld (No. 2)*. Pietermaritzburg: Council of the Natal Museum.
- Magnini, L., & Bettineschi, C. (2019). Theory and practice for an object-based approach in archaeological remote sensing. *Journal of Archaeological Science*, 107, 10–22. <https://doi.org/10.1016/j.jas.2019.04.005>.
- Marchal, J. Y. (1967). Contribution à l'étude historique du Vakinankaratra: Évolution du peuplement dans la cuvette d'Ambohimanambola (sous-Préfecture de Betafo). *Bulletin de Madagascar*, 241–280.
- Mason, R. J. (1968). Transvaal and Natal Iron Age settlement revealed by aerial photography and excavation. *African Studies*, 27(4), 167–180.
- Mattingly, D. J., & Sterry, M. (2013). The first towns in the central Sahara. *Antiquity*, 87(336), 503–518.
- Menze, B. H., & Ur, J. A. (2012). Mapping patterns of long-term settlement in Northern Mesopotamia at a large scale. *Proceedings of the National Academy of Sciences*, 109(14), E778–E787. <https://doi.org/10.1073/pnas.1115472109>.
- Meredith-Williams, M. G., Hausmann, N., Bailey, G. N., King, G. C. P., Alsharekh, A., Al Ghamdi, S., & Inglis, R. H. (2014). Mapping, modelling and predicting prehistoric coastal archaeology in the southern Red Sea using new applications of digital-imaging techniques. *World Archaeology*, 46(1), 10–24. <https://doi.org/10.1080/00438243.2014.890913>.
- Meyer, M., Pfeffer, I., & Jürgens, C. (2019). Automated detection of field monuments in digital terrain models of Westphalia using OBIA. *Geosciences*, 9(3), 109. <https://doi.org/10.3390/geosciences9030109>.
- Mille, A. (1970). *Contribution à l'étude des villages fortifiés de l'Imerina ancien (Travaux et Documents II)*. Antananarivo: Musée d'Art et d'Archeologie de l'Université de Tananarive.
- Ministère de l'Environnement, des Eaux, et des Forêts. (2006). *Programme d'action national 'adaptation au changement climatique'*. https://www.preventionweb.net/files/8530_mdg01f.pdf.
- Mire, S. (2017). The role of cultural heritage in the basic needs of East African pastoralists. *African Study Monographs, Supplement*, 5, 147–157.
- Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3), 247–259. <https://doi.org/10.1016/j.isprsjprs.2010.11.001>.
- Nsanziyera, A., Rhinane, H., Oujaa, A., & Mubea, K. (2018). GIS and remote-sensing application in archaeological site mapping in the Awsard Area (Morocco). *Geosciences*, 8(6), 207. <https://doi.org/10.3390/geosciences8060207>.
- Nyerges, A. E., & Green, G. M. (2000). The ethnography of landscape: GIS and remote sensing in the study of forest change in West African Guinea Savanna. *American Anthropologist*, 102(2), 271–289. <https://doi.org/10.1525/aa.2000.102.2.271>.

- Oduntan, G. (2019). Geospatial sciences and space law: Legal aspects of Earth Observation, remote sensing and geoscientific ground investigations in Africa. *Geosciences*, 9(4), 149. <https://doi.org/10.3390/geosciences9040149>.
- Opitz, R., & Herrmann, J. (2018). Recent trends and long-standing problems in archaeological remote sensing. *Journal of Computer Applications in Archaeology*, 1(1), 19–41. <https://doi.org/10.5334/jcaa.11>.
- Osicki, A., & Sjogren, D. (2005). A review of remote sensing application in archaeological research. *Geography*, 795(28), 333.
- Pal, M. (2005). Random forest classifier for remote sensing classification. *International Journal of Remote Sensing*, 26(1), 217–222.
- Parcak, S. (2007). Satellite remote sensing methods for monitoring archaeological tells in the Middle East. *Journal of Field Archaeology*, 32(1), 65–81.
- Parcak, S. H. (2009). *Satellite remote sensing for archaeology*. New York: Routledge.
- Parcak, S., Gathings, D., Childs, C., Mumford, G., & Cline, E. (2016). Satellite evidence of archaeological site looting in Egypt: 2002–2013. *Antiquity*, 90(349), 188–205. <https://doi.org/10.15184/aqy.2016.1>.
- Parker Pearson, M., Godden, K., Ramilisonina, R., Schwenninger, J.-L., Heurtebize, G., Radimilahy, C., & Smith, H. (2010). *Pastoralists, warriors and colonists: The archaeology of Southern Madagascar*. Oxford: Archaeopress.
- Pollock, S. (2016). Archaeology and contemporary warfare. *Annual Review of Anthropology*, 45, 215–231.
- QGIS Development Team. (2018). *QGIS Geographic Information System*. Open Source Geospatial Foundation Project. Retrieved from <http://qgis.osgeo.org>.
- R Core Team. (2018). R: A language and environment for statistical computing (Version 3.5.2). <http://www.R-project.org/>.
- Radimilahy, C. (2011). Contribution à l'archéologie du Sud-ouest de Madagascar. In C. Radimilahy & N. Rajaonarimanana (Eds.), *Civilisations des mondes insulaires: (Madagascar, îles du canal de Mozambique, Mascareignes, Polynésie, Guyanes)* (pp. 825–853). Paris: Karthala.
- Radimilahy, C. M., & Crossland, Z. (2015). Situating Madagascar: Indian Ocean dynamics and archaeological histories. *Azania: Archaeological Research in Africa*, 50(4), 495–518. <https://doi.org/10.1080/0067270X.2015.1102942>.
- Rayne, L., Bradbury, J., Mattingly, D., Philip, G., Bewley, R., & Wilson, A. (2017). From above and on the ground: Geospatial methods for recording endangered archaeology in the Middle East and North Africa. *Geosciences*, 7(4), 100. <https://doi.org/10.3390/geosciences7040100>.
- Reid, S. H. (2016). Satellite remote sensing of archaeological vegetation signatures in Coastal West Africa. *African Archaeological Review*, 33(2), 163–182. <https://doi.org/10.1007/s10437-016-9222-2>.
- Richards, T. S. (1989). Evidence of ancient rainwater concentrating structures in northern Egypt as seen on Landsat MSS imagery. *International Journal of Remote Sensing*, 10(6), 1135–1140.
- Robertshaw, P. (2012). African archaeology, multidisciplinary reconstructions of Africa's recent past, and archaeology's role in future collaborative research. *African Archaeological Review*, 29(2-3), 95–108.
- Rüther, H. (2002). An African heritage database: The virtual preservation of Africa's past. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXIV(Part6/W6), 185–192.
- Rutkiewicz, P., Malik, I., Wistuba, M., & Osika, A. (2019). High concentration of charcoal hearth remains as legacy of historical ferrous metallurgy in southern Poland. *Quaternary International*, S1040618218308371. <https://doi.org/10.1016/j.quaint.2019.04.015>
- Sadr, K. (2016a). A comparison of accuracy and precision in remote sensing stone-walled structures with Google Earth, high resolution aerial photography and LiDAR: A case study from the South African Iron Age. *Archaeological Prospection*, 23(2), 95–104. <https://doi.org/10.1002/arp.1532>.
- Sadr, K. (2016b). The impact of coder reliability on reconstructing archaeological settlement patterns from satellite imagery: A case study from South Africa. *Archaeological Prospection*, 23(1), 45–54. <https://doi.org/10.1002/arp.1515>.
- Saumagne, C. (1952). La photographie aérienne au service de l'archéologie en Tunisie. *Comptes rendus des séances de l'Académie des Inscriptions et Belles-Lettres*, 96(96), 287–301.
- Schuetter, J., Goel, P., McCorriston, J., Park, J., Senn, M., & Harrower, M. (2013). Autodetection of ancient Arabian tombs in high-resolution satellite imagery. *International Journal of Remote Sensing*, 34(19), 6611–6635. <https://doi.org/10.1080/01431161.2013.802054>.
- Schmid, T., Koch, M., DiBlasi, M., & Hagos, M. (2008). Spatial and spectral analysis of soil surface properties for an archaeological area in Aksum, Ethiopia: Applying high and medium resolution data. *CATENA*, 75(1), 93–101. <https://doi.org/10.1016/j.catena.2008.04.008>.
- Seddon, J. D. (1968). An aerial survey of settlement and living patterns in the Transvaal Iron Age: Preliminary report. *African Studies*, 27(4), 189–194.
- Sevara, C., Pregesbauer, M., Doneus, M., Verhoeven, G., & Trinks, I. (2016). Pixel versus object — A comparison of strategies for the semi-automated mapping of archaeological features using airborne laser scanning data. *Journal of Archaeological Science: Reports*, 5, 485–498. <https://doi.org/10.1016/j.jasrep.2015.12.023>.
- Stahl, A. B. (Ed.). (2005). *African archaeology: A critical introduction*. Oxford: Blackwell.
- Stahl, A. B. (1985). Reinvestigation of Kintampo 6 rock shelter, Ghana: Implications for the nature of culture change. *African Archaeological Review*, 3(1), 117–150.
- Thabeng, O. L., Merlo, S., & Adam, E. (2019). High-resolution remote sensing and advanced classification techniques for the prospection of archaeological sites' markers: The case of dung deposits in the Shashi-Limpopo Confluence area (southern Africa). *Journal of Archaeological Science*, 102, 48–60. <https://doi.org/10.1016/j.jas.2018.12.003>.
- Thompson, V. D., & Turk, J. A. (2009). Adaptive Cycles of Coastal Hunter-Gatherers. *American Antiquity*, 74(2), 255–278.
- Traviglia, A., & Cottica, D. (2011). Remote sensing applications and archaeological research in the Northern Lagoon of Venice: The case of the lost settlement of Constanciacus. *Journal of Archaeological Science*, 38(9), 2040–2050. <https://doi.org/10.1016/j.jas.2010.10.024>.

- Traviglia, A., & Torsello, A. (2017). Landscape pattern detection in archaeological remote sensing. *Geosciences*, 7(4), 128. <https://doi.org/10.3390/geosciences7040128>.
- Trier, Ø. D., Cowley, D. C., & Waldeland, A. U. (2019). Using deep neural networks on airborne laser scanning data: Results from a case study of semi-automatic mapping of archaeological topography on Arran, Scotland. *Archaeological Prospection*, 26(2), 165–175. <https://doi.org/10.1002/arp.1731>.
- Trier, Ø. D., Larsen, S. Ø., & Solberg, R. (2009). Automatic detection of circular structures in high-resolution satellite images of agricultural land. *Archaeological Prospection*, 16(1), 1–15. <https://doi.org/10.1002/arp.339>.
- Turck, J. A., & Thompson, V. D. (2016). Revisiting the resilience of Late Archaic hunter-gatherers along the Georgia coast. *Journal of Anthropological Archaeology*, 43, 39–55. <https://doi.org/10.1016/j.jaa.2016.05.006>.
- UNOSAT (2014). Satellite-based damage assessment to cultural heritage sites in Syria. *UNITAR/UNOSAT*. http://unosat.web.cern.ch/unosat/unitar/downloads/chs/FINAL_Syria_WHS.pdf.
- USAID. (2016). *Climate Change Risk Profile: Madagascar*. Retrieved from https://www.climatelinks.org/sites/default/files/asset/document/2016%20CRM%20Factsheet%20Madagascar_use%20this.pdf.
- Verhagen, P., & Whitley, T. G. (2012). Integrating archaeological theory and predictive modeling: A live report from the scene. *Journal of Archaeological Method and Theory*, 19(1), 49–100. <https://doi.org/10.1007/s10816-011-9102-7>.
- Verhoeven, G. (2017). Are we there yet? A review and assessment of archaeological passive airborne optical imaging approaches in the light of landscape archaeology. *Geosciences*, 7(3), 86. <https://doi.org/10.3390/geosciences7030086>.
- Verhoeven, G., & Sevara, C. (2016). Trying to break new ground in aerial archaeology. *Remote Sensing*, 8(11), 918. <https://doi.org/10.3390/rs8110918>.
- Verschoof-van der Vaart, W. B., & Lambers, K. (2019). Learning to look at LiDAR: The use of R-CNN in the automated detection of archaeological objects in LiDAR data from the Netherlands. *Journal of Computer Applications in Archaeology*, 2(1), 31–40. <https://doi.org/10.5334/jcaa.32>.
- Williams, M. A. J., & Faure, H. (1980). *The Sahara and the Nile*. Rotterdam: Balkema.
- Wright, D. (2017). *An introduction to QGIS: National Museums of Kenya training manual (August 2017)*. Seoul: Seoul National University.
- Wright, H. T. (Ed.). (2007). *Early state formation in Central Madagascar: An archaeological survey of Western Avaradrano* (Vol. Vol. 43). Ann Arbor: Museum of Anthropology, University of Michigan.
- Wynne-Jones, S., & Fleisher, J. (Eds.). (2015). *Theory in Africa, Africa in theory: Locating meaning in archaeology*. New York: Routledge.
- Xiao, W., Mills, J., Guidi, G., Rodríguez-González, P., Gonizzi Barsanti, S., & González-Aguilera, D. (2018). Geoinformatics for the conservation and promotion of cultural heritage in support of the UN Sustainable Development Goals. *ISPRS Journal of Photogrammetry and Remote Sensing*, 142, 389–406. <https://doi.org/10.1016/j.isprsjprs.2018.01.001>.
- Zanni, S., & Rosa, A. D. (2019). Remote sensing analyses on Sentinel-2 Images: Looking for Roman Roads in Srem Region (Serbia). *Geosciences*, 9(1), 25. <https://doi.org/10.3390/geosciences9010025>.
- Zerbini, A., & Fradley, M. (2018). Higher resolution satellite imagery of Israel and Palestine: Reassessing the Kyl-Bingaman Amendment. *Journal of Space Policy*, 44–45, 14–28. <https://doi.org/10.1016/j.spacepol.2018.03.002>.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.