POSITION PAPER

Recent Trends and Long-standing Problems in Archaeological Remote Sensing

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The variety and sophistication of data sources, sensors, and platforms employed in archaeological remote sensing have increased significantly over the past decade. Projects incorporating data from UAV surveys, regional and research-driven lidar surveys, the uptake of hyperspectral imaging, the launch of high-temporal revisit satellites, the advent of multi-sensor rigs for geophysical survey, and increased use of structure from motion mean that more archaeologists are engaging with remote sensing than ever. These technological advances continue to drive research in the specialist community and provide reasons for optimism about future applications, but many social and technical obstacles to the integration of remote sensing into archaeological research and heritage management remain. This article addresses the challenges of contemporary archaeological remote sensing by briefly reviewing trends and then focusing on providing a critical overview of the main structural problems. The discussion here concentrates on topics that have dominated the discourse in recent archaeological literature and featured prominently in ongoing fieldwork for the past decade across three broad segments of landscape archaeology: data collection in the field, the current state of data access and archives, and processing and interpretation.

Introduction

The past decade has witnessed an explosion in the variety and sophistication of data sources, sensors, and platforms employed in archaeological remote sensing (ARS). The proliferation of UAVs, regional and research-driven lidar surveys, the uptake of hyperspectral imaging, the launch of high-temporal revisit satellites, the advent of multi-sensor rigs for geophysical survey, and the explosion of use of structure from motion (SfM) mean that more archaeologists are engaging with remote sensing than ever. Improvements in data quality and coverage make the techniques broadly available and applicable. At the same time, increased availability of low-cost and open software, creative implementation of non-metric sensors, and public and free data sources have made remote sensing and its applications to archaeology more accessible to non-specialists. Growing awareness of remote sensing methods and their applications has created an environment in which new technologies are applied to a relatively broad set of projects early in their development, with many researchers experimenting in parallel.

This positive momentum is reflected in both university level teaching and the literature. The broad definition

and basic applications of archaeological remote sensing, including the use of aerial photographs, satellite imagery, geophysical prospection, and topographic data to investigate past landscapes, are now introduced at a basic level at universities in the Anglophone world and beyond, albeit with uneven depth of coverage and frequency (Aitchison 2017; Cowley & Palmer 2009; CIfA 2014; but see the absence of ARS in the 2015 special issue of *The Historic Environment: Policy & Practice* on *Training and Teaching in the Historic Environment*). The breadth of interest in remote sensing in archaeology is reflected in recent volumes including Comer and Harrower's (2013) *Mapping Archaeological Landscapes from Space* or Kamermans, Gojda and Posluschny (2014) *A sense of the past: studies in current archaeological applications of remote sensing and non-invasive prospection methods*, McKinnon and Haley's (2017) *Archaeological Remote Sensing in North America*, and in metric surveys of trends in archaeological literature e.g. by Agapiou and Lysandrou (2015) who show the increase in citations and the variety of venues in which they appear.

While the discipline has gained momentum and technological advances continue to drive research in the specialist community, providing reasons for optimism that we will see increasingly sophisticated research and heritage management applications forthcoming, many long-standing problems remain unresolved. Central are the need to broaden access to task-appropriate

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high-quality data to reach regions and sub-disciplines where remote sensing is underutilized, the need to cultivate the necessary theoretical and methodological expertise to engage with increasingly complex data and tools, and the development of frameworks to contextualize remote sensing applications within the process of archaeological interpretation. Why, we may ask, are these problems so persistent if they are readily named and widely recognized? In this article we suggest that while technological obstacles have been progressively overcome, these challenges stem predominantly from the discipline's intellectual history and orientation. In this light, this article aims to contextualize these problems, drawing on reviews on various specialist topics (e.g. Colomina & Molina 2014, Comer & Harrower 2013, Thompson et al. 2011, Verhoeven & Sevara 2016, Verhoeven 2017), reports on individual fieldwork projects, and on analytical projects across three broad segments of landscape archaeology: data collection in the field, the current state of data access and archives, and processing and interpretation. In bringing these threads together, we endeavour to encourage reflection on the broad impacts of recent rapid technological progress on the trajectory and roles of remote sensing in archaeological practice.

Data Collection in the Field

While the roster of remote sensing techniques used in archaeology has largely remained static, the mechanics of data collection have improved significantly thanks to technological advances over the past decade. Applications using data collected from UAVs, large area geophysical survey rigs, and high temporal revisit satellites all represent a reworking of the platforms and equipment behind existing techniques already used in archaeology. In each case, marked improvements in spatial and temporal resolution, together with a decrease in cost, have led to a step change and a significant broadening of the application of these technologies. Lidar and SfM in particular, while based on extant technology, were so transformed as to appear on the scene as 'new technologies'. Lidar has been available since the 1960s (McCormick 2005) and SfM has roots in photogrammetry (Carrivick, Smith & Quincey 2016), but technological developments in the early 2000s allowed the collection of dense topographic data at a level of detail previously impractical and, in the case of airborne lidar, allowing the efficient collection of high resolution topographic data in wooded areas, as well as in open fields (Shell & Roughley 2004, Doneus & Briese 2006).

These progressive improvements in spatial resolution and coverage, and the renewed enthusiasm for each technology as the data it provided became more granular for larger areas, highlight the community's preoccupation with detail and feature detection. In the fieldwork culture of archaeological remote sensing, higher resolution, larger areas, and faster data collection are prized. While an improved ability to detect small features of interest is clearly important for many applications, the strong emphasis placed on working with high spatial resolution data may lead to the neglect of the potential for lower resolution data to continue to shed important light

on land use patterns, activity areas, and geological and morphological contexts affecting preservation (see Herrmann 2012 and Howey et al. 2014 for examples of the use of moderate resolution satellite data in the age of high resolution). Further, improved spatial resolution and coverage, the canonical 'more data', may be promoted as a solution to interpretive difficulties or end in itself. Below, we explore the implications of the transformation of the key platforms for aerial and terrestrial remote sensing, considering the impact of the emphasis placed on spatial resolution and extensive collection.

UAVs

The emergence of UAVs as a platform for archaeological prospection is probably the most visible trend in archaeological remote sensing in recent years (e.g. Campana 2017a; Lasaponara & Masini 2016, Mozas-Calvache et al. 2012; Sonnemann, Malatesta & Hofman 2016). The popularity of the platform not only in archaeology, but across industries including construction, agriculture, security, and survey (Nex & Remondino 2014; Valavanis & Vachtsevanos 2015), incited the miniaturisation of a variety of sensors and platforms (Casana et al. 2017; Ludeno et al. 2017; McDaniel et al. 2017; Suomalainen et al. 2014; Yarlequé, Alvarez & Martínez 2017). These include thermal, hyperspectral and lidar instruments, as well as a variety of multispectral sensors, conventional still cameras and video cameras, and the development of relatively user friendly, if black-box, tools for the analysis of the data captured. These broad industry investments, coupled with an active amateur UAV user community, have benefitted archaeology in promoting the availability of relatively low-cost instruments, as well as an active 'UAV survey as a service' market that allows for rental or contracting surveys rather than ownership. In the archaeological context, the greatest effect of this technological watershed has been a democratisation of the collection of small-area remote sensing datasets, a topic taken up in more detail later in this article. The attraction of UAVs for the archaeological community has been twofold: they provide a degree of independence as fully licensed pilots and aircraft are not required, and they can be used to collect very high spatial resolution data. UAV data is typically captured at the trench, site, or site and hinterland scale to support the detailed mapping of remains either on the surface or with some surface expression e.g. sub-surface remains affecting spectral response, or resulting in topographic features. A review of the major journals shows dozens of articles promoting the results of UAV-based surveys (e.g. Fernández-Hernandez, González-Aguilera & Rodríguez-Gonzálvez 2014; Khan, Aragão & Iriarte 2017; Smith et al. 2014), and many other projects are clearly using UAVs to carry out basic tasks such as capturing aerial views of trenches or creating local topographic models, as discussed below under 'Structure from Motion'. Given the energy currently going into UAV surveys in archaeology we must ask: what are the impacts and benefits of these often centimetre scale models and images? Are they used for illustration, as baseline data for monitoring, to explore fine-grained temporal patterns, or integrated into further

analyses and interpretations? What are the archaeological questions we ask at the 5 cm–25 cm scale at the extent of a site, a site and its hinterland, or a small chunk of landscape? Identifying research themes that truly benefit from scaling up the available data is likewise important in the practice of terrestrial geophysical survey, which has undergone its own revolution in platforms over the past decade.

Large Array Geophysics

As Kvamme (2003) demonstrated and Campana (2017b) recently reiterated, geophysical survey can operate as a form of landscape archaeology thanks to the increasing spatial extent of the areas covered by individual surveys. This thinking has been borne out, particularly in open alluvial and plains landscapes where the use of motorized arrays of multiple sensors with integrated with positioning systems have become de rigueur for surveys of entire urban settlements and of landscape blocks, wherever cost, ground cover, and topography permit. It is increasingly common for magnetometer surveys to be carried out with cart-mounted arrays paired with dGPS, RTK GPS, or robotic total stations that can guide sensor orientation and field coverage, allowing for larger areas to be surveyed with considerable speed (**Figure 1**). Coverage with geophysical sensors is not only wider but more detailed. Arrays of multi-frequency GPR antennae arranged at distances shorter than the central antenna frequency wavelength can produce three-dimensional full-waveform maps of the subsurface (Gramuseck et al. 2005). When tracked with precise positioning systems, multi-channel GPR survey, like magnetometry, can reasonably produce data for 5+ hectares per day, far surpassing the density and coverage possible otherwise.

Landmark survey projects including the Stonehenge Hidden Landscapes project (De Smedt et al. 2014; Gaffney et al. 2012) and BREBEMI project (Campana & Dabas 2011) and ongoing work mapping prehistoric landscapes in Ohio (Burks 2014a; Burks 2014b) demonstrate the value of scaling up geophysical survey beyond the site, prompting a reconsideration of approaches to the archaeological countryside. These new approaches to the archaeology of the rural world draw on extensive geophysical survey data that can complement fieldwalking or shovel testing (Thompson et al. 2018), leading to the identification of physical roads and pathways that link sites to points of interest in the wider landscape (Casana & Herrmann 2010: 64), and to the identification of previously undiscovered and archaeological features and sites (Campana 2017b: 1238) that contextualize previously known sites or show activity in formerly quiet areas of the landscape. The implications of larger scale geophysical surveys have also been particularly profound for the study of urban plans and urban development, building on numerous surveys of entire cityscapes (Bossuet et al. 2012; Gaffney & Gaffney 2000; Gaffney et al. 2016; Johnson & Millett 2013; Keay et al. 2000; Keay et al. 2009) and providing a framework for analyses of architectural forms and site organization (Benech 2007), and movement (Branting 2010). In addition to providing growing quantities of new data, as discussed below, the increase in coverage of high spatial resolution geophysical data provides opportunities for a refocus of geophysical survey from feature detection to land use characterisation, increasing the overlap between archaeological prospection and geomorphological approaches to landscape taphonomy and expanding opportunities for basic research in the context of landscape archaeology more broadly.

UAVs and Multi-sensor Arrays Together

One apparent impact of the new resolution and extent of the data provided by UAV and multi-sensor array platforms is a rapprochement between aerial and terrestrial survey. This convergence in scale leads to the potential for an increase in projects integrating aerial and geophysical data productively. This stands in contrast to past circumstances, where aerial photography was available at 20 cm resolution, but most other non RGB-IR aerial data sources remained at 50 cm resolution or coarser, and data at better than 2 m resolution were relatively expensive. These data were collected for extensive areas,

Figure 1: Multi-sensor array geophysics in action. Left: magnetic gradiometry, right: multichannel GPR survey (image courtesy Alexandre Novo and Geostudi Astier).

and generally used to address micro-regional or large landscape questions. Terrestrial geophysics was frequently collected at resolutions ranging from 50 cm to 1 m over small areas, and the limited collection areas oriented research and management applications to the site or feature scale.

Consequently, a divide has persisted between the aerial and geophysical communities, as evidenced by separate professional societies. In Europe, for example, CIfA's GeoSIG (CIfA 2018) and the International Society of Archaeological Prospection (ISAP) (ISAP 2018) primarily focus on terrestrial geophysics and the Aerial Archaeology Research Group (AARG) (AARG 2018) primarily focuses on aerial remote sensing. This divide is also reflected in the delimitation of remits in organizations like Historic England, which maintain separate groups for these areas. With airborne sensing and terrestrial geophysics allied more closely through their scale and extent, closer professional links and intentionally integrated training schemes should be a priority. The ArchaeoLandscapes Europe Project (2010–2015), and the formation of ArcLand International (ArcLand 2018) in 2016, an umbrella organization in which ISAP and AARG serve jointly as leadership organizations, represent important steps in this direction.

Structure from Motion

Topographic study has a long history in archaeology but, we note, has traditionally been more closely connected to the domain of survey than to remote sensing. Manual photogrammetric workflows for aerial imagery from stereo pairs were relatively slow and the use of this approach to create 3D data therefore remained limited, although interpretation and planning from stereo pairs was widely practiced (Brophy & Cowley 2005; Ducke, Score & Reeves 2011; Lambers et al. 2007). Although significant interest in Structure from Motion for 3D modelling is evident from the early 2000s (Pollefeys et al. 2002; Pollefeys et al. 2003), the step change came in the 2010s when, almost concurrent with the wider availability of UAV platforms, significant improvements in algorithms and computational capacity led to a revolution in the generation of 3D models from imagery (e.g. Green, Bevan & Shapland 2014; Remondino et al. 2011; Verhoeven 2011). Together with increasing engagement with lidar, discussed below, the availability of SfM data has led to the study of the shape of landforms and topographic morphology at various scales through 3D models becoming an integral part of archaeological remote sensing. Structure from Motion (SfM), particularly employing aerial imagery, is now an important source of topographic data for small landscape areas and for site-based projects (Fernández-Hernandez et al. 2015; Jorayev et al. 2016; Remondino et al. 2011, Verhoeven 2009; Campana 2017b; Watanabe et al. 2017). Together with the proliferation of UAV use in archaeology, SfM allows the creation of high spatial resolution topographic models over limited areas at relatively low cost. Examples including Mozas et al. (2012) and Wernke, Adams and Hooten (2014) illustrate the clear practical utility of SfM as a way to fulfil a basic archaeological desire – better maps of the area under study and detailed data on local surface topography (**Figure 2**). The creation of terrain models for
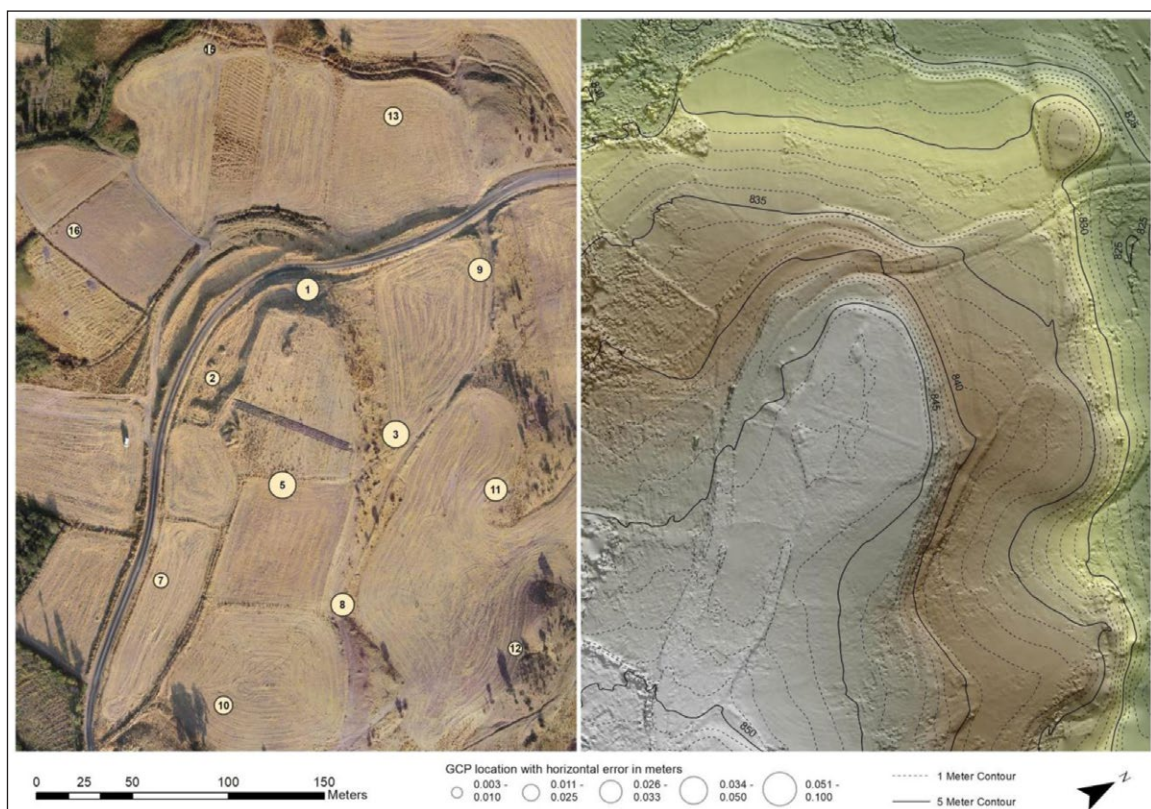

Figure 2: SfM-generated orthomosaic (left) and topographic map (right) of an archaeological site, created from photographic images collected with a UAV. Horizontal error for individual ground control points is displayed on the orthomosaic. Eastern Ḥabur Archaeological Survey.

larger areas by processing historic imagery not collected explicitly with photogrammetric processing in mind, as carried out by Risbøl et al. (2015) and Sevara et al. (2017) demonstrate the potential for SfM to support landscape archaeological research by allowing archaeologists to reconstruct terrains that have since been transformed, and by opening new avenues for tracking landscape change at a higher resolutions and through deeper timelines than satellite imagery will permit.

In addition to reinvigorating topographic study and helping to bring the active use of 3D data to remote sensing, together with UAVs, SfM has played a leading role in spreading the practice of capturing and working with archaeological remote sensing data to a broader community. The use of close-range and mid-range SfM for the recording of stratigraphy during excavations is increasingly common (e.g. Koenig, Willis & Black 2017; Roosevelt et al. 2015), as is the practice of documenting the landscape surrounding an excavation. This shift in recording practice in the context of excavations has democratised the practice of working with 3D models of miniature terrains, and provides a bridge to working with 3D topographic data at the landscape scale.

Lidar
Lidar, also commonly referred to as airborne laser scanning (ALS) has now been in relatively wide use in archaeology for over a decade (Chase et al. 2011; Devereux et al. 2005; Fisher et al. 2017; Harmon et al. 2006; Opitz & Cowley 2012; Doneus et al. 2013; Vinci & Bernadini 2017). The impacts of the increasing availability of this data are clear, including the discovery of large quantities of previously unrecorded sites and features across the landscape, a renewed interest in the study of the topographic context of sites and landscape features, an increased integration of geomorphological studies in archaeological projects, an intensification of interest in woodland landscapes and the archaeology of woodlands and a growing number of projects targeting uplands and other non-agricultural areas that were previously considered prohibitively costly or labour intensive to survey. The broad availability of high spatial resolution topographic data has also precipitated a new generation of projects revisiting path modelling, questions of movement, visibility studies, and other analyses of the experience of landscape (Brady et al. 2012; Corns & Shaw 2009; Primeau & Witt 2017; Schindling & Gibbes 2014) previously widely acknowledged to be hampered by the limited resolution of the available terrain data.

Beyond its impacts in the research community, ALS is now treated as a basic data source to be employed wherever available by commercial projects in the UK, France, the Netherlands, and other European countries with public data available (Barnes 2003; Böfinger & Hesse 2011; Crutchley 2010; Meylemans et al. 2017). Collection of the data in advance of major infrastructure projects to benefit their generally planning and execution continues to benefit archaeology, as the data is often made available for research beyond the mitigation strategy e.g. the LGV Est construction (Georges-Leroy & Villier 2016) and the Tor Top tunnel system (Stichelbaut et al. 2017). Regional

and national collections, generally acquired in the context of flood risk, landslide, or other hazard management, are increasingly being made available to archaeologists, and a continuation of this trend will only further increase the impact of ALS on archaeological research and heritage management. Publicly available and well described data, as discussed below in the sections on data access and archives, is particularly important for broadening the use of archaeological remote sensing data outside the core specialist community, and consequently for its application to new questions and challenges in research and heritage management.

Lidar and SfM together – the landscape in 3D
Measuring and depicting the landscape in 3D and topographic survey are nothing new in archaeology. As with UAV sensors and multi-instrument geophysical surveys, the spatial resolution and extensive coverage of the data available has proved key to transforming the research agenda and, in this case, the interpretive context and process. While reading sparse survey points, contour maps, or hachure plans requires a trained eye, the realistic look and detail of lidar and SfM generated topographic models at least give the impression they are easily understood. While not slowing the pace of projects employing the 3D terrain models to identify sites and features and interrogate taphonomic and geomorphological processes, the ready availability of detailed (20 cm–1 m resolution) 3D data for relatively large areas and the transition to the domain of remote sensing, where earlier topographic data had primarily been collected and interpreted by surveyors, has incited some debate within the community over the interpretation of this data. The interpretation of landscape topography, long inherently tied to the process of carrying out the survey on the ground, no longer requires personal physical engagement with the terrain to be interpreted. This shift in the practice of interpreting terrain data (Opitz & Cowley 2012) is the subject of ongoing debate, and is now linked to an emerging discourse on automation and machine learning (Bennett, Cowley & De Laet 2014). For the surveyor and the remote sensing communities, jointly engaged in the business of studying the landscape, the question is one of situating expertise. Can someone who has never been to the place interpret its topography? Can an algorithm interpret topography? To what extent is the knowledge required to interpret remotely sensed data technical, about the sensors and platforms, and to what extent is it contextual? The answer, we may surmise, is somewhere in the middle as usual, but the implications for the practice of remote sensing as practitioners increasingly engage with a complex interpretive process are important, and we will return to these questions below.

High Temporal Revisit Satellites
While most recent innovations in data collection have focused on improving spatial resolution and coverage, the value of high temporal resolution data merits serious consideration. The launch of high temporal revisit satellites producing publicly accessible data, notably the Sentinel satellites (Showstack 2014), to date has received limited attention in the archaeological literature (but see

Agapiou et al. 2014; Agapiou 2016; Ruciński, Rączkowski & Niedzielko 2015). The limited spatial resolution of these data, too low for the reliable detection and interpretation of many archaeological features, is the primary reason for their relative neglect. However, archaeologists whose interests lie in reconstructing paleoenvironments (El-Baz et al. 2007; Herrmann 2012; Howey et al. 2014), the distribution of anthropogenic soils and landscapes (e.g. Menze & Ur 2012), or in monitoring of changes in overall land use, may find data from Sentinel series and other low- to moderate-resolution satellites useful. In this light, the potential impact of these platforms within archaeological remote sensing, particularly in the context of heritage monitoring and management applications, is great, and will grow as extensive multi-temporal archives are generated (see Giuliani et al. 2017 for a discussion of relevant parallel applications in environmental monitoring and Cuca & Hadjimitsis 2017 for an overview for heritage monitoring). High-temporal revisit platforms, together with detailed local weather data, provide an opportunity to better understand the process of crop and other vegetation development in relation to the presence of archaeological features or changes in land use. Improving our understanding of the cycle of farmed and unmanaged vegetation growth has significant implications for our ability to detect cropmarks and understand their formation or their absence. It also provides further means of engaging in the study of landscape change at a temporal scale often neglected, the short term, season, or event. To date, the focus of many archaeological landscape studies has been long term change, with remote sensing data providing a series of snapshots or a single palimpsest of evidence (see Bailey 2007 and Fairclough 2003 for discussions of temporalities and palimpsest). Pursuing the study of short term change in the landscape will require developing methods and frameworks to take advantage of improved temporal resolution and engaging seriously with theories of the temporal rhythms of landscape change.

These satellites also provide an important resource for monitoring in areas of conflict or rapid development. Recent articles by Parcak et al. (2016) and Fradley and Sheldrick (2017) in *Antiquity*, while in disagreement on some points, highlight the importance of ongoing monitoring and timely data updates to manage heritage in dynamic contexts. Several major efforts now leverage the advantages of serial satellite imaging across the Middle East and North Africa for the purpose of site and landscape monitoring, including the Endangered Archaeology of the Middle East and North Africa project (EAMENA – Bewley et al. 2016), the ASOR Cultural Heritage Initiatives (Casana and Panahipour 2014; Casana 2015; Danti et al. 2017) and the Afghan Heritage Mapping Project (Stein 2015). Now that these projects have been operating for three years or more, they are able to move beyond data collection and examine the how and why of looting and destruction through development. For example, analysis of the timing and location of looting patterns over the duration of the Syrian civil war through WorldView series satellites has helped to untangle the complex social and political forces that drive threats to cultural heritage (Casana &

Laugier 2017). Parallel efforts are using satellite imagery to monitor looting and its effects in South America (Lasaponara et al. 2014; Contreras 2010) and Asia (Chen et al. 2017; Lasaponara & Masini 2013; Thomas & Kidd 2017). These projects can be viewed as a foray into dealing with the event temporal scale, and conversations among different areas of the community, between heritage monitoring and research practitioners, will be essential to translate these experiences into a landscape research context.

Access, Archives and Standards
While technologies for data collection have advanced significantly, the archaeological community continues to struggle with the uneven availability of these technologies and the data produced through them, and with our ability to manage, maintain and make useful that data once it has been collected. These challenges are not unique to remote sensing within archaeology, but the scale, variability and complexity of the data involved make them acute. This section synthesizes and reflects on the wide-ranging discourse surrounding access, archiving and standards for archaeological remote sensing data, as well as the question 'what constitutes good data?'

Access to data and 'good data'
While it is widely acknowledged that the availability of satellite and aerial data has improved significantly overall, because much archaeological work is location specific, most archaeological users wish to know if data, and if 'good data' is available for *their area*. In spite of the general improvement, the availability of data, or coverage, varies widely. While some satellite data sources have global coverage, airborne and terrestrial data are collected on a national, regional or ad hoc basis. Over the past decade, national and regional airborne datasets have become increasingly important to archaeologists, as lidar, conventional high resolution aerial photography, and some multispectral data are collected at these levels, and frequently made available at no cost to researchers. Examples of national and regional (e.g. state, province, department) data made freely available, at least to in country researchers, include lidar data from Denmark, Spain, the USA, Australia, and the UK (Denmark: Styrelsen for Dataforsyning og Effektivisering 2018; Spain: Centro de Descargas 2018; USA: Office for Coastal Management NOAA 2018; Australia: Australian Government 2018; UK: Government Digital Service 2018). In short, it is unusual to work somewhere for which no data is available, but the increasing availability of relatively high resolution data, with which much of the research community is enamoured, means that it is difficult to engage in the current research discourse on the basis of what may be viewed as sub-par data. The consequence of this is a relative lack of engagement with researchers working in less data-rich regions. Variability in coverage (**Figure 3**), in this sense, is a structural problem in itself, and often the divide is along the lines of more and less wealthy or developed nations or regions. The Amazon region provides a case in point. This region has seen significant international
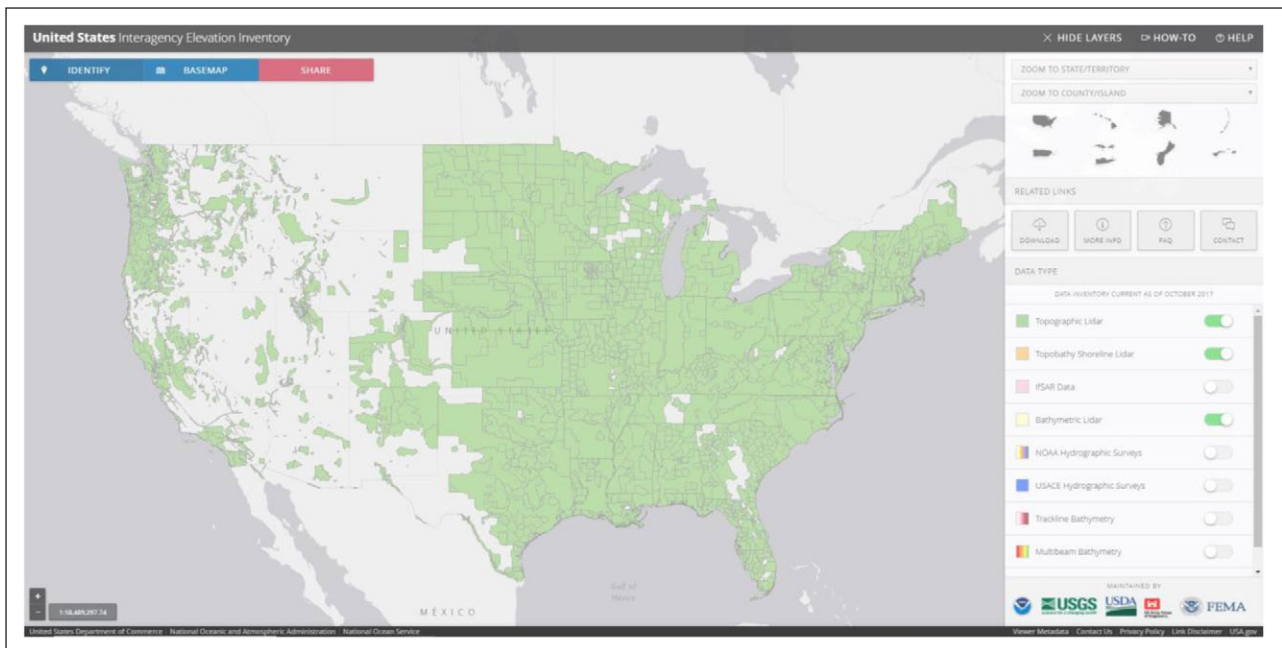
Figure 3: lidar coverage in the USA is partial, as seen on the *United States Interagency Elevation Inventory* map provided by NOAA (accessed 13 December 2017). Partial coverage is typical of national and regional datasets. In addition to areas without available data, the quality and spatial resolution of the data will vary.

investment in remote sensing through NGOs for purposes of environmental monitoring (e.g. Asner et al. 2010 and 2012) but this data has not been made widely available to the broader research community, nor is it necessarily collected using parameters that would make it most useful for archaeologists, as well as environmental scientists. The regional picture in Central America is rather different. NCALM (NCALM 2018) are active in Central America, collecting data specified for research projects (see Chase & Chase 2017 for a useful summary) and making this data available on an Open Access basis after an embargo period, or immediately if agreed by the project's lead investigators. These data have been instrumental in the rapid uptake of lidar-led landscape and survey projects in this region. The availability of data on an Open Access basis is clearly directly linked to the extensive application of this method across the board, and particularly in less wealthy regions. Appropriate lobbying of international agencies and government organisations may result in some improvements in the availability of high resolution data for research or management, or alterations in data collection strategies.

Closely linked to the problem of coverage in the sense of data vs. no data, is the variable availability of high spatial resolution data (Chase & Chase 2017, Table 1; Rosenswig, López-Torrijos & Antonelli 2015). Spatial and signal resolution, especially spatial resolution, are long-standing problems in archaeological remote sensing (although recall our discussion above for research strands that benefit from lower spatial resolution data). In spite of the availability of very high resolution data from public sources for some areas and the proliferation of UAV surveys, archaeologists working at the landscape scale still regularly make choices between extensive areas and spatial detail. In arguing for a role for lower

spatial resolution data and the need to develop research frameworks and questions to leverage it, it is essential to provide good training in the real, pragmatic relationship between nominal data resolution and the ability to recognize features reliably and run different analyses realistically. The resolution required for both detection of certain feature types and for some analyses is higher than may at first seem apparent.

If you imagine a square feature, how many points are needed, if they are placed on a regular but random grid, to capture the shape? If a shape is curved or irregular, how many points are needed? This simple thought exercise leads to the conclusion that a ground resolution of 20–50 cm is necessary to reliably capture many archaeological features such that they are recognizable. Again, we are faced more with a social problem than a technical one. Too many projects attempt to "get something out of" lower resolution data and start off with unrealistic expectations, resulting in a general frustration with remote sensing as an approach (see comments in Campana 2016; Lasaponara et al. 2017; Linck et al. 2013; Viberg, Trinks & Lidén 2011). As evidenced by many successful projects (see the recent special issue of *Remote Sensing* (Kvamme 2017) for a collection of examples of good practice) when data is collected at a resolution appropriate (Schmidt et al. 2015: 12–16) to the scale of the features, archaeological interpretations can be reached. Given the importance of the availability of high resolution data, and of basic coverage in less well-resourced regions, archival data sources play an important role, and the support of the development of new archives should be a priority. Equally, the reframing of the research agenda to take landscape change at a broader scale into account could be pursued, among other research strands, to provide a means of activating the vast and growing

archive of lower resolution (5–10m) data, opening regions with limited high resolution data to further study.

Archival Responsibilities

Increasing access to high quality data is fundamental to the continued improvement of archaeological remote sensing research and applications. That said, the ability to manage this data is increasingly a prerequisite for access, introducing a new potential barrier. The management and proper archiving of new, often large, archaeological remote sensing datasets remains a persistent problem for academics and professionals, particularly those without strong institutional support who are attempting to comply with grant-driven data management policies (Kintigh et al. 2015; Richards 2017; Richards & Winters 2015). To date it has been relatively unusual to collect large aerial datasets without the involvement of an organisation who would take responsibility for archiving, as amateur flyers working outside an agency or institutional context, collecting data purely for archaeological purposes were few. With the growing popularity of UAV platforms, this situation seems likely to change, and to more closely parallel the experience of the archaeological geophysics community, where many small research teams collect data in support of specific research projects. Good guidance for the archiving of archaeological geophysical survey data, e.g. the ADS Guide to Good Practice (ADS 2018) exists and forms the foundation for many data management plans. That said, the implementation of these plans remains limited, in part because the cost of archiving larger datasets with many files, and the costs of preparing the archive correctly remain beyond the reach of many researchers, and are insufficiently planned for at the budgeting and project planning stage (McKeague, Corns & Shaw 2012). Given the choice between collecting more data and paying for archiving, most archaeologists will choose the former unless forced to do otherwise by funding bodies, or by a creation of the expectation of planning and budgeting for archiving and data management driven by professional societies and the community itself.

The Stacks/Data Recycling

The implicit aim of increased data availability through improved coverage and archival practices is that these archived data will be reused in the pursuit of new research goals, or that the reliability of analyses and interpretations can be interrogated by researchers external to the original project (Atici et al. 2013). The reuse of data and reproducibility in research are closely linked themes, as discussed in Marwick et al.'s (2017) "Open Science in Archaeology". In this context, older archival imagery also serves as a distinct resource, adding crucial time depth to landscape studies. As discussed fully in Hanson and Oltean (2012) and Gojda (2012) archival imagery is widely acknowledged in the aerial archaeology community as an important resource, "These various sets of data have a number of particular advantages over more recent imagery (whether aerial or satellite). First and foremost, they provide a unique insight into the character of the landscape across parts of Europe and beyond as it was

approximately century or more ago before the destructive impact of later twentieth century development, whether from the increasing mechanisation of agriculture, intensive industrialisation or urban expansion" (Hanson and Oltean 2012, p. 6).

Given the potential of the resource, it remains little exploited. In part this is explained by the relative difficulty of accessing the collections, which are scattered geographically, with major collections in the US (NARA), the UK (NCAP), and Italy (Aerofototeca Nazionale) and the majority of which are not digitized. Digitisation work, primarily led by NCAP (NCAP 2018) is ongoing, and continued efforts to bring collections online are essential to increasing the use of these resources (Cowley & Stichelbaut 2012). The inconsistency of finding aids, the documentation provided to locate imagery within collections, as discussed by McKeague and Jones (2013) likewise hampers progress. The ongoing digitisation of finding aids will likewise continue to improve the accessibility of these collections. As is the case in other areas, however, the problem is as much social as it is technical, and the perceived value of the archival work remains an important obstacle. "Survey" is usually equated with flying in a small aircraft or walking across the ground, but probably the most effective means of survey, of discovering previously unrecorded sites and creating a basic record of them, remains existing aerial photographs. Undertaking 'survey' in boxes of aerial photographs or viewing digital images on screen may lack the appeal or glamour of aerial or field survey, but for simple value for money in discovering and recording sites, we contend that it has no equal" (Cowley & Stichelbaut 2012: 20) Perhaps the most good can be done by promoting projects that make use of archival materials, and initiatives such as the CAA Recycle Award (CAA 2018) are well placed to do this.

Considering archiving of new data and the exploitation of extant archives together, the danger of reproducing some of the problems with historic archives, notably the difficulties discovering data and fragmentation among many institutions, in the context of newly created archives is clear. Organisations including DANS, the ADS, tDAR, and OpenContext are working to play centralizing and aggregating roles (Bauer-Clapp & Kirakosian 2017; McManamon et al. 2017; Richards 2017), but complications of remit and obstacles of costing remain in place. While we are not suggesting a single archival solution, there is a role for international professional organisations in maintaining channels of communication between these groups, and providing links out to relevant organisations, which most often operate at the national level. In parallel, there is a need to engage with the disciplinary discourse on open science and open data (**Figure 4**) in archaeology in relation to the use and creation of archival data sets and our interactions with archives and other institutions acting as data repositories.

Analysis and Interpretation

As archaeological remote sensing data collections grow larger and we seek to tap the potential of archived and newly acquired data, the ability to analyse complex
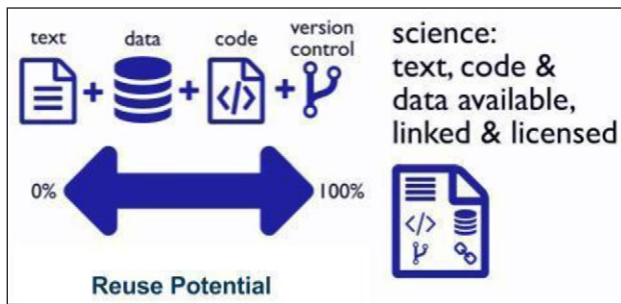
Figure 4: After Marwick et al. 2017. The value of
archives and archival data can be enhanced through
research practices that promote and reward data reuse.
Beyond making the data itself and information on
processing routines available, data reuse is also linked
to the creation of incentives for reproducible research.
Archaeologists working with archival data should be
prepared to engage in the disciplinary discourse around
these issues as applied to remote sensing data sources.

data effectively and to automate routine tasks such as
georeferencing and initial feature detection has become
increasingly important. Image analysis, signal analysis
and multivariate techniques are all well established
in archaeological remote sensing (e.g. Aqdus, Hanson
& Drummond 2012; Cassidy 2009; Challis & Howard
2006; Giardino 2011). More recently, machine learning
and computer vision have seen significant recent
improvements (Barceló 2010; LeCun, Bengio & Hinton
2015; Szeliski 2010; Schmidhuber 2015; van der
Maaten 2006), and have been applied successfully to
archaeological remote sensing projects in the past five
years (Toumazet et al. 2017; Trier & Pilø 2012; Due Trier
et al. 2016). Machine learning, computer vision, and
automation are increasingly seen as instrumental to
mobilizing archaeological remote sensing's 'big data', and
a priority for research. This section reviews the state of the
art in analysis and interpretation, highlighting current
obstacles to progress, and lays out an agenda for future
work.

Obstacles to processing advances

Kvamme (2003) notes, in the context of magnetometry
survey, that data processing is almost as important as
the collection of raw data. He elaborates on various
aspects of data processing that improve the visibility and
coherence of archaeological features in magnetometry
data, including augmentations designed to improve the
appearance of the data as presented in print or on screen.
His article highlights the importance of processing to
the interpretation process. Fundamentally there are two
ways to improve the interpretability of the data, and
consequently the results of an archaeological remote
sensing project. The first means is improvement in the
quality of the data collected, e.g. signal to noise ratio,
spatial and signal resolution and range. The second route
is to pursue improvements in the processing techniques
applied to the data. Is it easier to collect better data or to
improve the processing of less than ideal data? Looking
at the balance of archaeological innovations over the

past decade, it seems the community has come down on
the side of improvements in the quality of the raw data
itself (e.g. Belina et al. 2009; Schmidt 2004; Trinks et
al. 2010; see Jordan 2009; Schmidt & Marshall 1997 for
more general discussion on improvements needed in the
practice of archaeological geophysics). There has been
significant investment in particular in the ability to collect
high spatial resolution data over large areas, perhaps at
least in part because the gains in interpretability and
visual clarity from improved spatial resolution are obvious.
We may further ascribe this emphasis to several factors:
the relative difficulty in applying more sophisticated
techniques, the difficulty selecting the right technique
for a given application, and the fact that sometimes
data simply is not improvable to the point of becoming
interpretable (Traviglia 2006; Schmidt 2004). In spite of
any obstacles, improvements in processing techniques
should, in some cases, be able to improve the legibility of
data as collected (Orlando & Soldovieri 2008; Schmidt &
Tsetskhladze 2013).

Basic improvements in processing techniques will most
likely come from outside archaeology and continued
experimentation to identify those that will be broadly
applicable to archaeological data is needed. Once
major advances in processing have been identified, the
difficulty lies in identifying situations where processing
improvements are significant enough, and the basic data
is good enough, that it is worthwhile to reprocess old
data to achieve more informative or interpretable results.
Areas that have been excavated or otherwise altered or
removed since they were surveyed are likely candidates
for reprocessing, as are areas rendered inaccessible for a
variety of reasons. The reprocessing of Corona imagery
to improve absolute georeferencing and reduce image
distortions (Casana & Cothren 2013) is one such case, as
is the re-processing of archival frame imagery to remove
distortions and improve georeferencing (Verhoeven
et al. 2013). Encouragement of data reuse broadly in
archaeology, which has gained momentum in recent years
(Faniel et al. 2013; Huggett 2015; Kansa & Kansa 2013),
may further encourage the reprocessing of legacy data.

Prioritizing improving data fusion

In addition to improving the quality of data collection
and processing, archaeologists have looked to combined
datasets to aid in interpretability and provide additional
insights. Combining datasets, or data fusion, in theory
allows us to supply the deficiencies of one dataset with
data from another, or bring together information on
different aspects of the surface or substrata as recorded
by a variety of sensors or through multi-temporal surveys.
In practice, data fusion covers a range of techniques
essential for integrating diverse sources of information
(Zhang 2010), which are variably applied in archaeological
contexts. Lasaponara and Masini (2012) usefully outline
four categories of data fusion: signal level fusion, pixel
level fusion, feature level fusion, and decision level fusion.
Signal level fusion is intended to improve signal-to-noise
ratios and creates a new signal by compiling signals from
multiple instruments or multiple measurements taken

with the same instrument. Pixel level fusion is primarily carried out to improve the visibility of features by combining spectral and spatial information at the pixel level, resampling all coarser spatial data to the smallest pixel size. Feature level fusion is an object oriented technique, where information from pixel and signal sources are assigned to a single object. Decision fusion is relevant where rules-based systems of classification or identification are employed using information abstracted from pixel and signal sources. Below, we focus on signal and pixel level fusion, the methods most commonly applied in archaeology.

Pan sharpening techniques combine the spectral data available from coarser resolution multi-spectral imagery with the spectral and spatial information from higher resolution panchromatic or single band imagery, and are widely used in archaeological remote sensing. A review of these techniques illustrates the benefits, but also the limitations, of fusion as currently employed. Many algorithms have been developed (Alparone et al. 2007; Vivone et al. 2015; Zhu & Bamler 2013) to carry out the fusion and pan-sharpening is a standard part of processing multi-spectral satellite imagery from platforms such as GeoEye or Ikonos, and the techniques have been in widespread use since the 1980s (Park & Schowengerdt 1983; Ngan 1986; Tom, Carlotto & Way 1985). The reason for the multiplicity of techniques is that either the spatial or spectral properties of the image are always compromised in the process. "If the [transformation] is perfect, the resulting imagery will have the same sharpness as the original panchromatic image as well as the same colors as the original multispectral image. In practice, however, it is impossible to meet both of these goals and one often trades sharpness for color recovery or vice-versa." (Padwick et al. 2010, p. 1). In spite of the inherent loss in fidelity, where both pan and multi-spectral imagery is captured from the same platform at the same date, the difference between the results of various pan-sharpening algorithms is not significant and the algorithms such as IHS, PC and Brovey available in commonly used GIS or image processing software e.g. QGIS and ArcGIS are suitable (Pesántez-Cobos, Cánovas-García & Alonso-Sarría 2017). Spatial resolution is improved, though usually with a loss in spectral consistency (Klonus & Ehlers 2007). However, the situation is different when pan-sharpening with data from multiple sensors and capture dates. Significant spectral distortions can be introduced when fusing across multiple sensors, particularly where their spectral ranges are not well-aligned, e.g. a fusion of Ikonos and TerraSAR-X data. Mercovich (2015) provides a further comparison of algorithms as implemented in commercial software, noting both spatial and spectral distortions across the board.

The situation with hyperspectral imagery is even more complicated because this imagery's value is primarily derived from its fine spectral resolution and correlations of the spectral values with known reflective properties of materials and, as discussed above, spectral distortion is a common artefact of pan-sharpening algorithms. New approaches are emerging specific to the fusion of hyperspectral imagery e.g. Yi et al. (2017) taking advantage of spectral unmixing as a constraint to spatial resolution enhancement, but these are not yet widely implemented in commercial software.

The case of pan-sharpening illustrates how data fusion remains 'potentially important' while having limited real impact. In cases where it works well as implemented in the available software, the added value is limited, as the spectral enhancement provided by relatively coarse multispectral bands rarely adds features that are not at least partly visible in the panchromatic imagery collected by the same sensor at the same moment. There is usually an improvement but rarely one that takes us from 'invisible' to 'visible'. On the other hand, where features totally invisible in high spatial resolution panchromatic imagery are visible in lower resolution hyperspectral imagery collected with a different sensor at the same moment, the available pan-sharpening techniques introduce considerable noise and distortions and often do not make the imagery more readily interpretable. We have well published examples of hyperspectral imagery showing features invisible in panchromatic imagery (e.g. Bertok, Gati and Bela 2015; Doneus et al. 2014; Masini et al. 2018) and hyperspectral imagery is often collected at a lower resolution e.g. 1–2 m than aerial photography, with a typical resolution of 20–50 cm. Image collections of this nature would benefit greatly from tailored pan-sharpening algorithms, and some progress is being made in this direction (Loncan et al. 2015).

A second important set of applications of data fusion, bringing together data from multiple sensors, surround the topographic correction of signal data or imagery, such as the topographic correction of GPR data (**Figure 5**) (e.g. Piro, Mauriello & Cammarano 2000). These applications combine data from a variety of spectral or geophysical sensors with terrain data generated from satellite sensors like SAR or SRTM, airborne lidar, airborne SfM or terrestrial survey. Topographically corrected GPR, seismic, or resistance tomography data provide examples of how signal-level data fusion directly improves data interpretability. By applying topographic corrections to the signal, the 3D location of sub-surface reflections is moved, significantly reducing spatial distortion of subsurface anomalies (Goodman et al. 2006). Topographic correction of airborne hyperspectral data and spectral data from satellite sensors likewise improves the interpretability of the spectral values and, importantly, facilitates comparisons between areas of a spectral or signal dataset where the landscape has different topographic properties (Agapiou et al. 2011; Hesse 2015; Vanonckelen, Lhermitte & Van Rompaey 2013).

Leisz's (2013) overview of remote sensing in archaeology reflects an ambition to focus further on data fusion that brings together information from very different sensors, going beyond topographic correction. He notes, "in closing, a final point needs to be made regarding the use of remote sensing within the field of archaeology that will remain true no matter how many new tools are added: The most promising aspect of all of these technologies may be how they can be integrated" (p. 18). While we share this
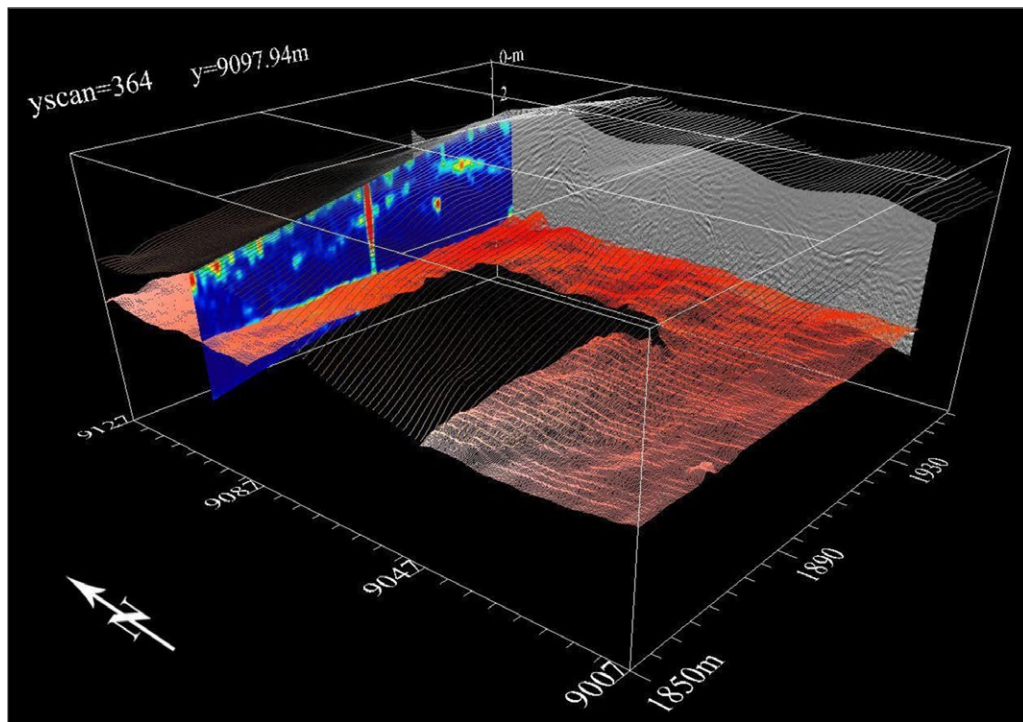
Figure 5: Signal-level fusion of topographic and GPR data. GPR data were shifted vertically based on surface topography collected with at total station. The vertical shift of radar profiles (in grey) permits creation of secondary 3D datasets including vertical slices through radar data (blue) and meshes that represent buried stratigraphic interfaces (red). After Herrmann (2012) and Herrmann (2013).

ambition, we can cite only limited examples of attempts to undertake multi-sensor fusion that go beyond layering in GIS, and note that the authors of these studies report limited success to date e.g. Agapiou et al. (2017), where the authors state that the "proposed regression approach provided acceptable but not completely satisfactory results" (p. 16). Multi-instrument integration where the data types are quite different remains a challenge, and should be an active area for future research.

Future applications of Machine Learning and Computer Vision

Data fusion and image analysis have relatively long histories of application in archaeological remote sensing, and recent years have seen increasing exploration of the potential of newer sets of methods including machine learning, computer vision and automated feature detection. The terms machine learning, deep learning, convolution neural nets, and support vector machines have appeared increasingly in both popular and academic media over the past few years, as significant improvements in a variety of techniques related to computer vision and artificial intelligence continue to be made. Archaeologists working with remote sensing data have been quick to see the potential applications of these techniques, which allow for the automatic detection of a variety of types of archaeological features, and a number of discussion pieces and articles presenting early case studies have appeared (e.g. Leckebusch, Weibel & Bühler 2008; Robin & Sadr 2016; Toumazet et al. 2017; Traviglia, Cowley & Lambers 2016; Trier et al. 2016). The ability to rapidly process large remote sensing datasets and better target the process of

visual interpretation has obvious and broadly positive implications for both research and heritage management. As discussed below, the enthusiasm of many in the archaeological remote sensing community is tempered by concerns over accuracy and contextualisation. In spite of the concerns raised, we can expect studies using machine learning approaches to increase in number and sophistication.

Machine learning techniques have much to contribute to full-waveform processing in remote sensing. In the past, the volume of data from such a survey would make processing and interpretation difficult, however, advances in processing workflows and available hardware have now made multi-channel GPR surveys an option for archaeological research in suitable areas (see *automation* below). This has become increasingly important as larger areas are surveyed at denser resolution (Conyers & Leckebusch 2010: 122).

Distrusting Automation

The potential interest of the automation of feature detection has been widely recognized in the aerial archaeology and heritage management communities, as evidenced by conference sessions e.g. at the Computer Applications in Archaeology (CAA) 2016 meeting and the Aerial Archaeology Research Group (AARG) 2016 meeting devoted to the topic. The growing interest in automation occurs in the context of significant improvements in machine learning, a field that has greatly advanced over the past 5 years, with further significant gains predicted (Abadi et al. 2016; Ioannidou et al. 2017; Temam 2016; Ceze, Hill & Wenisch 2016). The interest in automation

in archaeological remote sensing, as in the broader discipline, is primarily in its ability to improve the rate and consistency of feature identification over large areas when compared with visual interpretation. While more efficient identification of potential archaeological features may seem an obvious good, particularly for those institutions charged with the management of heritage resources, Bennett, Cowley and De Laet (2014) note in an article discussing the status quo of automation in archaeological remote sensing, "The ability of historic environment professionals to engage with large datasets is impeded by an overwhelming adherence to an entirely manual prospection and interpretation approach, as traditionally applied to aerial photographic interpretation" (p. 897).

The reluctance to adopt automated feature extraction, in the authors' opinion, 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 (Verdonck et al. 2017) and has yet to match the efficiency of automatic feature extraction for targets with consistent appearance (Barton and Montagu 2004; Núñez-Nieto et al. 2014) or for features in uniform environments, with accuracy rates generally below 75%. In a 2013 study, Risbøl et al. assessed detection success rates of a variety of feature classes as they appeared in a lidar-derived DTM by four interpreters making visual assessments. This study, while in itself focused on the impact of point density on predictive accuracy, highlighted the variability of detection accuracy from near 100% of charcoal kilns to pitfalls and tar kilns, at 13% and 40% respectively. In a recent study, Due Trier et al. (2016) achieved 85% accuracy detecting charcoal kilns using a machine learning (CNN) approach. For a feature type like charcoal kilns, is the difference between 85% and 97% important enough to justify the greater cost and time required for visual interpretation and the corresponding restriction of the area covered?

The willingness to trade high levels of reliability in detection for the efficiencies gained through automation are obviously dependent on the social and organisational factors surrounding the project. In the context of research projects one must ask: does automated feature detection contribute toward a clear anthropological or historical research objective? In the context of heritage management one might ask: does automated feature detection significantly improve heritage management practices or interpretation for the public? The objective of automated feature detection will vary from case to case, but for most endeavours it will fall into one of two categories, 1) the detection of cultural features for documentation or verification, or 2) feature mapping to model human behaviour using detected features as a proxy. In both instances, the 'scale vs. detail' problem looms large. Put simply, what level of accuracy from an automated system is acceptable for decision making, planning, and research? For cultural heritage projects and hypotheses development, automated feature detection with middling levels of accuracy may be appropriate, since independent verification through field survey or

other means would presumably follow feature detection. Automated detection without independent verification of results, however, may not be appropriate as primary data used to inform explanatory models of human behaviour without external verification, as one runs an even greater than usual risk affirming one's assumptions.

Underlying all of this is the question of value for money or effort. Developing successful machine learning and automated detection systems requires a not insignificant initial investment. This initial investment includes both investment in personnel and access to infrastructure, and in developing effective training datasets that identify a variety of archaeological features in complex datasets and landscape contexts. Further, machine learning systems trained on large, generic image sets e.g. Places205 (Zhou et al. 2017) or SUN2012 (Xiao et al. 2010) are unlikely to be successful on archaeological remote sensing data because the features of interest are too different from those tagged in the current main training datasets. Rather the archaeological record as it appears in remote sensing data must be segmented into different feature classes, which each need their own training set. For example, training datasets must be created for pits, linear earthworks, quadrangular buildings, etc. against a variety of backgrounds, an approach paralleling work in automated detection by Trier et al. (2012) and Trier, Larsen and Solberg (2009) where individual classes of features are targeted. Therefore, for automated feature extraction to work in archaeology, the creation of robust training datasets that teach computers to discriminate between features of interest and background landscapes requires, at the very least, a significant manual investment, as images must be selected and tagged correctly. Given the effort involved, the likelihood of a reasonable level of success and the value of the results in producing new interpretations or knowledge must be demonstrated. Equally, the place of automated routines within the broader process of interpreting remote sensing data must be established.

Interpretation and deskilling
The current debate surrounding the reliability of automated detection and the impact of automation on the interpretive process is embedded in a broader discourse on the practice of interpretation (see Howey & Brouwer Burg 2017; Morgan & Wright 2018; Westin 2014 for related discussions of changes in archaeological practice and their effects on interpretation). Working with archaeological remote sensing data is, at a basic level, easier than it was 20 years ago and this is, on balance, a good thing. In the era of Google Maps, Google Earth, and national geoportals, non-specialists can readily access high resolution RGB satellite imagery, historical imagery, air photos and a variety of cadastral and land cover datasets for visual interpretation with relatively little effort. Today many people spend time navigating and finding shops and restaurants via smartphone or desktop map and this provides a basic level of comfort and familiarity with the top down view and basic aerial image interpretation, arguably a generational shift.

The basic functionality of GIS software has likewise become more accessible. The combination of easier to access data and easier to use software, augmented by an increasing number of projects successfully using community based crowdsourcing to undertake large scale archaeological remote sensing, e.g. Parcak's Global Xplorer (Global Xplorer 2018) or Wernke's GeoPacha (Wernke 2016), has moved part of the archaeological remote sensing skillset from specialist to generalist knowledge (see Earley-Spadoni 2017 for a broader discussion of the de-specialisation of GIS and spatial work in the context of intersections with Digital Humanities). The improvements in popular open source GIS packages, notably QGIS, have made a difference by providing more sophisticated GIS and mapping capabilities while removing the licensing barrier and its associated costs.

A perhaps unexpected consequence of the relative ease of programming and the proliferation of open source software is that selecting the 'right tool' and understanding the implications of that selection has become more difficult. Generally, for any given GIS task there are multiple tools available, and it is often unclear which is the best tool for the job, or what the difference is between two implementations of the same basic analysis. Slope is a classic example of this situation. Conceptually, slope is simply the change in elevation over a given horizontal distance, an idea that does not need specialist training to be grasped. How slope is calculated across a 3D dataset is another matter and a student might be horrified to learn that there are dozens of algorithms. For many analyses, the way slope is calculated will be unimportant, but for some it will have an impact. The process of unpacking the black box around calculations and highlighting that choices are being made become essential tasks.

On this basis, some practitioners have sounded a note of caution in reaction to the current trend toward democratisation, expressing concern that with wider and less informed use inevitably comes misuse and frustration. The widespread availability of evermore powerful personal computers and the growing accessibility and relative user-friendliness of GIS software has led to the notion that anyone can sit down and "teach themselves GIS" in relatively short order. This attitude toward what is a relatively complex technology supported by a substantial theoretical corpus may be directly linked to the apparent dissatisfaction with the technology in some cases, and be responsible for the gap between practical heritage management and research applications of GIS (Brouwer Burg 2017). These concerns about misuse or unsophisticated use leading to frustration and the impression that GIS and RS approaches are inherently flawed, while justified, should not prevent us from benefitting from the broad improvements in the technological status quo.

While one can find poorly motivated or decontextualized applications readily enough in the literature, many projects do encourage archaeologists to consider the role that remote sensing plays in larger research efforts and the discipline itself, with some emphasizing the potential for remote sensing to be the central source of data for answering archaeological and anthropological questions.

Conyers and Leckebusch (2010) point out that spatial analysis of results of remote sensing surveys, in their case GPR surveys, used with complementary archaeological data can identify diagnostic architectural forms or to understand construction sequences and provide a basis for testing cultural historical hypotheses. Thompson et al. (2011) define four explicit categories of spatial analysis of geophysical results that can lead off intensive anthropological and archaeological research: 1) variation in the built environment 2) identifying continuity and discontinuity in the use of space 3) untangling natural and cultural modifications to mapped features and 4) spatial regularities in the built environment at the regional level. Conyers and Leckebusch (2010: 122), however seem more optimistic that future archaeo-geophysical investigations can stand alone as automated feature extraction techniques are refined and the relationships between geophysical signals and specific materials become better understood.

In this context, the aim of the specialist community becomes supporting the broadest possible use while flagging areas of complexity, the necessity of considering the research or management questions posed, and teaching spatial thinking and how to choose the right analytical tools. Providing guidance about technical choices possible at different steps will aid in selecting good analytical tools, but does not address the deeper concern regarding the potential proliferation of under-theorized analyses. This risk seems, to the authors, is one that can be mitigated by making the case loudly and often that any application of GIS or RS must be question driven and the theoretical implications of the spatial analyses well set out, and by reinforcing these arguments through the mechanisms of teaching, peer review, and public discourse.

Conclusions

This article attempts to provide a balanced view of the progress in and obstacles to the contemporary practice of archaeological remote sensing. Specialists in archaeological remote sensing are actively pursuing the opportunities created by technological advances, while recognizing that significant obstacles to the broader integration of these methods into the general toolkit of landscape studies remain. Therefore, while not seeking to detract from the real benefits of recent technological improvements, the discussion here highlights areas where long recognized problems persist: differential availability of high resolution data, inadequate methods for data fusion, the burden of managing archival imagery, outsourcing processing advances, distrust of automation, and the democratisation of aerial imagery interpretation. We must remain aware of impact of these constraints on the potential of emerging technologies and methods, and undertake the serious reflection needed to make progress on these issues, many of which are both social and technical.

In spite of these persistent challenges, archaeological remote sensing has much to contribute to the future of heritage management and archaeological research. The central themes in archaeological remote sensing theory

and practice, including the importance of landscape as a framework, awareness of the highly differential uptake of archaeological remote sensing methods and availability of data in different contexts, the promotion of good practice without creating exclusive research communities, integration with related disciplines, and connections between research and management, continue to be developed. Beyond continuing to contribute within our own domain, the potential to act as an impetus for integration with other domains studying the landscape is great. This integrative role, one archaeological remote sensing already plays as a data source and set of methods in use in a variety of projects, will remain central to its future development.

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