Theoretical Repositioning of Automated Remote Sensing Archaeology: Shifting from Features to Ephemeral Landscapes

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ABSTRACT

Automated remote sensing has made substantial breakthroughs for archaeological investigation. Over the past 20 years, the reliability of these methods has vastly improved, and the total number of practitioners has been increasing. Nonetheless, much of the work conducted, to date, focuses almost exclusively on specific topographic features and monumental architecture, ignoring the potential of automation to readily assess more ephemeral components of the archaeological record. Likewise, the emphasis on specific feature types overlooks broader landscape patterns, thus delegating automated remote sensing analysis as a method in and of itself, mostly disconnected from larger archaeological and anthropological investigations. Here, I review recent attempts to rectify this shortcoming by using automated analysis methods to record and explain ephemeral archaeological material distributions. While such research is limited, I argue that the successes achieved in these recent studies offer a pathway forward for automated remote sensing to become more fully integrated with archaeological work beyond the detection of specific topographically distinct features.

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INTRODUCTION

Remote sensing archaeology has a long history and improvements in sensing technologies and data analysis methods have greatly expanded our ability to record archaeological data (Adamopoulos and Rinaudo 2020; Lambers 2018; Luo et al. 2019; Osicki and Sjogren 2005; Verhoeven 2017). One of the most significant methodological advances in archaeological remote sensing, in recent years, has been the development of automated techniques for landscape-level archaeological prospection (Davis 2019; Lambers, Verschoof-van der Vaart and Bourgeois 2019; Traviglia and Torsello 2017). In recent reviews of automated remote sensing in archaeology, a clear pattern emerges within the use of these methods, specifically an intense focus on the detection of *individual features*, oftentimes "monumental" constructions such as mound complexes, large-architectural features, or other topographically distinct remnants of human activity (e.g., charcoal kilns, craters of war, etc.) (e.g., Magnini, Bettineschi and De Guio 2017; Schneider et al. 2015; Trier, Cowley and Waldeland 2019; Wang et al. 2017).

While nearly all published case studies utilizing automated detection are focused on explicitly noticeable landscape modifications, such large-scale features do not comprise most of the archaeological record. Of course, there is a very good reason for why most archaeological applications of AI and automation are restricted to such types of features: they are distinct, unique from surrounding landscapes, and easy to detect. It is also important to note that with the continued struggle by researchers to limit false positive results within archaeology and heritage management, developing and refining automated techniques has required target features that are simpler to detect in terms of their morphology. In addition, the lack of high-resolution data until more recently made detecting anything else largely a dream rather than an achievable reality. Nonetheless, researchers have made great strides in automatically detecting cultural features from remotely sensed data, but research affixed to dominant landscape features can come at the expense of broader understandings of human occupancy and its connection to ecological conditions throughout the world (which remains poor in many regions, see Stephens et al. 2019).

Thus, a pivotal question for researchers focused on automated workflows for archaeological investigations is how useful this niche really is for archaeology if all we can do is locate the largest or most morphologically uniform displays of cultural activity? This echoes a recent sentiment of Palmer (2020, 26) who states that researchers "have been doing the same thing, maybe with different algorithms, for at least 10 years... Show me that [automated detection] works on those sites with 'no shape' and I'll begin to believe [in these methods' usefulness]."

With this sentiment in mind, a shift of automated remote sensing in archaeology beyond individual features to broader and more complex patterns of human activity, cultural niche construction, and landscape modification could greatly enhance the utility of these methods. If we begin to take the knowledge gained by previously successful efforts for automated archaeological prospection and refocus on a multi-scalar landscape perspective attuned to *ephemeral archaeological deposits* and *broader patterns of landscape use* (also see Doneus 2013; Traviglia and Torsello 2017), we may be able to greatly improve our understanding of the true impact that ancient populations had on landscapes.

Recently, there have been attempts to using machine learning for predictive modeling and the detection of subtle archaeological deposits with few – if any – structural remains. Some examples are "indirect" approaches (*sensu* Davis and Douglass 2020; Howey et al. 2020) for locating archaeological materials (e.g., Davis et al. 2020a), while others have successfully detected features like dung deposits and remnants of farming communities where no structures still stand (e.g., Thabeng et al., 2020; Thabeng, Merlo, & Adam, 2019). For these "direct" approaches for archaeological prospection, the use of multi- and hyper-spectral sensors at extremely high spatial resolutions was key to their success. While the use of spaceborne sensing for the detection of such archaeological deposits is still new, it offers an unparalleled ability to reconstruct past settlement patterns and landscape use on a vast geographic scale. Such advancements also offer unique opportunities to better integrate automated remote sensing methods into broader archaeological research agendas beyond prospection. In what follows, I review some of these recent applications and discuss the implications of such methodological breakthroughs on the advancement of anthropological and archaeological theory.

A BRIEF HISTORY OF AUTOMATION IN LANDSCAPE ARCHAEOLOGICAL REMOTE SENSING

Remote sensing archaeologists first began to experiment with automated methods of feature extraction about 20–30 years ago with the development of object-based image analysis (OBIA) and statistical machine learning algorithms for image analysis (Davis 2019; Lambers and Traviglia 2016). However, when considering the use of remote sensing data for the creation of archaeological predictive models, the use of semi-automated remote sensing within archaeology expands several decades earlier (e.g., Custer et al. 1986; Drager 1983; Findlow and Confeld 1980; Jones 1979; Madry and Crumley 1990).

Landscape classification has long been a staple of remote sensing analysis, and archaeologists have used

such methods for the purpose of exploring settlement patterns and expediting survey projects since the 1980s (e.g., Custer et al., 1986); such methods continue to persist today (e.g., Abate et al. 2020; Davis et al. 2020a; Kirk, Thompson and Lippitt 2016; Klehm et al. 2019). Automated methods for direct feature extraction begin in the mid-1990s (Lemmens, Stančić and Verwaal 1993; also see Lambers and Traviglia 2016), at which point there is a gap in publications until the early 21st century, at which point the use of mathematical algorithms begin to gain prominence in locating ancient Roman roadways and mounded architecture in aerial imagery (Bescoby 2006; Menze, Ur and Sherratt 2006). From this point, dozens of case studies assessing various methods were published trying to maximize ways of accurately extracting information relevant for cultural heritage management from remotely sensed data (e.g., De Laet, Paulissen and Waelkens 2007; Jahjah et al. 2007; Magnini, Bettineschi and De Guio 2017; Sevara et al. 2016; Trier, Larsen and Solberg 2009). While some researchers achieved remarkably accurate results (e.g., Caspari and Crespo 2019; Guyot, Hubert-Moy and Lorho 2018), many struggled with issues of false positive and negative errors, leading some researchers to question the efficacy of such methods for archaeological work (e.g., Casana 2014; Hanson 2010; Parcak 2009). With the advent of deep learning models (a branch of machine learning), specifically those based on convolutional neural networks (CNNs) – a model architecture that makes use of multidirectional data analysis for pattern recognition – the issue of accuracy is beginning to diminish, but challenges still remain (e.g., Bonhage et al. 2021; Caspari and Crespo 2019; Garcia-Molsosa et al. 2021; Somrak, Džeroski and Kokalj 2020; Soroush et al.

2020; Trier, Cowley and Waldeland 2019; Verschoof-van der Vaart and Lambers 2019).

Today, there are fewer pushbacks against automation for remote sensing analysis in archaeology (cf. Palmer 2020), as these methods have greatly improved in their reliability. Nonetheless, the standard formula for such studies is simply to develop a method and report results, but never really mention the function of such methodological advances in the face of broader archaeological questions (Davis 2019; Davis and Douglass 2020). Furthermore, many automated remote sensing archaeological case studies focus exclusively on monumental architecture (e.g., mounds, tombs, medieval castles, roadway systems, palaces and urban complexes) or topographically distinct features like charcoal kilns and burning pits (e.g., Bonhage et al. 2021; Caspari and Crespo 2019; Davis, Sanger and Lipo 2019; Guyot, Hubert-Moy and Lorho 2018; Masini et al. 2018; Schneider et al. 2015; Somrak, Džeroski and Kokalj 2020; Trier, Reksten and Løseth 2021). Ultimately, these foci limit the inherent utility of automated approaches to archaeological remote sensing, as this research leaves little direct impact on archaeological inquiry, but rather stays within a niche methodological focus within remote sensing analysis (*Figure 1*). By expanding the use of automated remote sensing to greater portions of the archaeological record, these tools have the potential to become more fully integrated into archaeological research focused on a myriad of important questions.

While a great deal of space can be taken to discuss the many advances of automated methods in archaeology, as others have recently done (see Davis 2019; Lambers, Verschoof-van der Vaart and Bourgeois 2019; Traviglia and Torsello 2017), I will focus exclusively
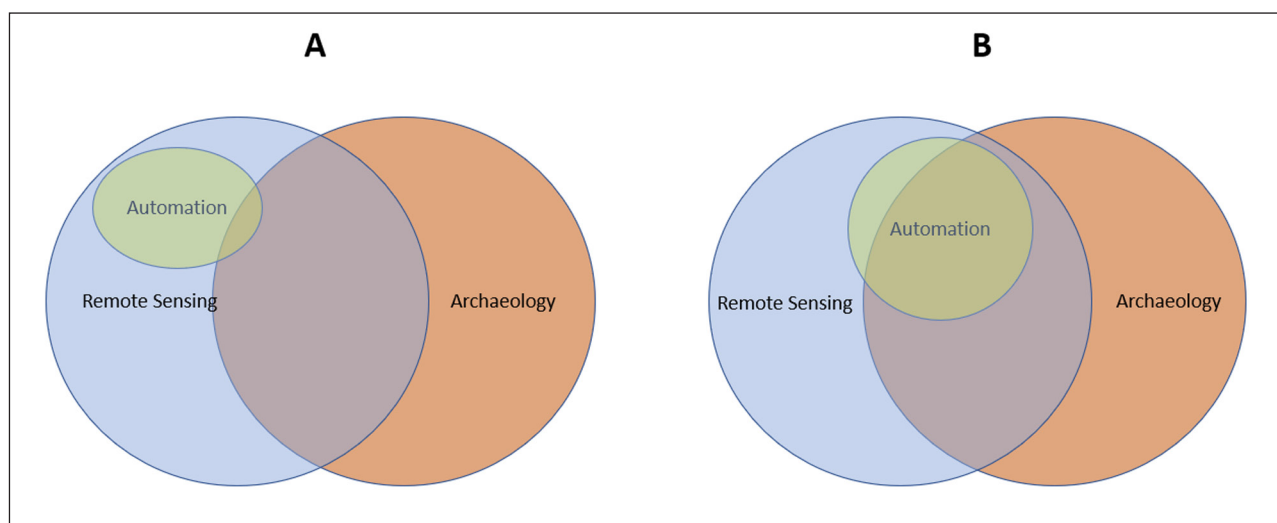

Figure 1 Illustration of how automated methods have integrated within archaeological research. **A:** Current state of automated remote sensing archaeology, where automation makes many methodological contributions to remote sensing, but few direct benefits to archaeological research more generally. **B:** Proposed future of automated approaches in remote sensing archaeology, wherein automated techniques play direct roles in larger archaeological research projects beyond merely technical advances to remote sensing analysis.

on a select subset of applications of machine learning and automation that have received far less attention: the prospection of ephemeral archaeological remains.

A SHIFT TOWARDS THE EPHEMERAL

Archaeological research has long been challenged by taphonomic processes (Schiffer 1983; Schiffer, Sullivan and Klinger 1978; Schon 2002), and even among remote sensing archaeologists this problem has been noted in the strive towards improving automated archaeological analyses (see Magnini and Bettineschi 2019). The loss of history to the sands of time is a problem not easily solved, and the degradation of many traces of past human activity has long limited our understanding of the earliest human societies. For example, foraging societies, whose archaeological traces are often more discrete when compared with agropastoral or industrial populations, make up some of the least well-documented and understood archaeological cultures from a landscape perspective (see Stephens et al. 2019).

AUTOMATION AND SEMANTIC CONSISTENCY

In many ways, issues of taphonomy (e.g., multifinality and equifinality) are not circumventable by any suite of methods. However, we can rethink how to use the tools at our disposal to improve our capacity to recognize those sites that are disappearing (Magnini and Bettineschi 2019). This issue is discussed at length by Magnini and Bettineschi (2019), who discuss the implications of depositional processes on the characteristics of archaeological materials (i.e., equifinality and multifinality). The authors state that:

> …having a clear picture of how an ancient context should have looked like is not enough. One needs to be aware of the possible modifications that occurred during the millennia to develop an efficient conceptualized model that can be translated in machine language and used to maximize the results of a semi-automatic image analysis (Magnini and Bettineschi 2019: 13).

Magnini and Bettineschi (2019) propose the use of Diachronic Semantic Models (DhSMs) to help address questions about the evolution of archaeological materials in the face of taphonomic activities. In brief terms, DhSMs are a type of ontological system (*sensu* Guarino et al., 2009), meaning that it constitutes a formalized model by which we can conceptualize the archaeological record in its many forms. There are numerous sources of bias that can affect data collection and the results of different research agendas, and formalized conceptual frameworks can aid in replicability of research and interoperability of datasets (Nuninger et al. 2020a,

2020b). DhSMs are one form of formalized conceptual framework that are designed to create a link between theoretical notions of taphonomic effects and digital representations of these materials in remote sensing data (Magnini and Bettineschi 2019; also see Arvor et al. 2019). By formalizing our expectations of what modifications may have taken place to cultural materials, we can improve our capacity to predict and identify these features within the modern landscape, as it widens our expectations of the form that these materials may take given changes over time. The same has recently been advocated by Nuninger et al. (2020a, 2020b), who develop conceptual frameworks for identifying and tracing movement via "pathways" in the archaeological record. By formalizing our conceptions of these cultural phenomena, it allows for researchers to improve their interpretations of archaeological data by rethinking the scales at which they investigate certain concepts. As I explain below, such conceptualizations are key for improving automated archaeological remote sensing methods and broadening their impact to archaeology by situating these approaches within explicit archaeological theoretical frameworks.

Uncovering more ephemeral traces of human activities is challenging because the nature of habitat modifications and material remains – often consisting of temporary or semi-permanent living structures that decay shortly after abandonment – are far more subtle when compared with cultural features like monuments. The long-term effects of depositional processes will ultimately reduce such materials into microscale traces that require a multitude of different analytical methods to perceive (Davis, Seeber and Sanger 2020). However, recent successes of automated remote sensing bring a suite of advantages to documenting land-use practices in a systematic and replicable manner, and recently this has included the identification of ephemeral land-use activities (Davis et al. 2020a; Orengo and Garcia-Molsosa 2019; Thabeng, Merlo and Adam 2019, 2020).

MACHINE LEARNING AND THE DIRECT DETECTION OF NON-STRUCTURAL ARCHAEOLOGICAL ELEMENTS

One key example of how automated remote sensing analysis is beginning to allow for the direct documentation of ephemeral archaeological sites is through machine learning and UAV imagery. Orengo and Garcia-Molsosa (2019) demonstrate how drone images can be flown on paths conforming to traditional survey transects to record artifact scatters commonly associated with most archaeological surface investigations. They demonstrate how UAV survey can vastly outperform pedestrian survey strategies and even generate more accurate artifact counts in areas with vegetative obstructions. However, this method is extremely new, and suffers several setbacks including: computational cost, a

steep learning curve to implement, and the impact of light, shadow, and environmental surface conditions on results. Nevertheless, the study is promising for the future development of reliable methods of conducting artifact-level identification using aerial remote sensing instruments.

Another example of automated remote sensing analysis for the detection of ephemeral, complex, and degrading archaeological remains is the use of deep learning models to detect traces of sunken cart-tracks from the post-Medieval period in the Netherlands (Verschoof-van der Vaart and Landauer 2020). As the authors of this study note, archaeological research using deep learning (e.g., convolutional neural networks [CNNs]) and other automated approaches have done very little to investigate complex, large-scale landscape components (e.g., roadways). Using LiDAR data and a new deep learning model architecture, Verschoof-van der Vaart and Landauer (2020) manage to capture a broad network of roadways with promising levels of precision and accuracy. Nevertheless, issues of misclassification are pervasive, as these roadways are often damaged, overlaid with newer streets, and are, overall, much more difficult to discern from other, more pronounced features. The authors also point out that while model performance issues are present, the results of such automated analyses will permit for a more comprehensive understanding of transport networks in the post-Medieval period. Furthermore, it will improve chronological information pertaining to the connectivity of people and places throughout this landscape.

Researchers are also demonstrating how very-high-resolution satellite imagery can be used to record archaeological features typically overlooked by traditional landscape surveys (e.g., Klehm et al. 2019) or otherwise ephemeral archaeological deposits. Thabeng, Merlo, and Adam (2019) use WorldView-2 satellite imagery from Maxar (formerly DigitalGlobe) to locate dung deposits associated with archaeological farming communities in Botswana. Remains of animal stables within this region can be characterized by the presence of dung piles. The researchers use WorldView-2 – which has 1.84 m spatial resolution multispectral data and 0.46 m resolution panchromatic data – in conjunction with random-forest (RF) and support-vector machine (SVM) classifiers to successfully detect these dung piles. Overall, they achieve ~95% accuracy and successfully reidentify ~300 archaeological sites, despite very few surface indicators of archaeological activities.

Thabeng and colleagues further explore the possibilities of detecting these ancient farming sites using hyperspectral analysis (Thabeng et al., 2020; Thabeng, Adam, & Merlo, 2019). They find that collecting hyperspectral measurements of archaeological deposits on the ground can be used to train machine learning algorithms to directly detect these features in

satellites, even those with coarser spatial resolutions (e.g., Sentinel-2, Landsat, etc.). While such feats require extensive fieldwork and laboratory analysis, it is extremely promising for the expansion of survey operations using automated procedures. Furthermore, the ability to detect subtle archaeological deposits in freely available satellite imagery is particularly significant for researchers without access to large pools of funding.

PREDICTIVE MODELING AND THE INDIRECT DETECTION OF EPHEMERAL ARCHAEOLOGICAL DEPOSITS

In this light, work recently conducted on Madagascar is demonstrating how freely available medium-resolution satellite imagery can be used to accurately predict the locations of ephemeral remnants of Holocene era foraging camps (Davis et al. 2020a). Using Sentinel-2 data – which is freely available from the European Space Agency – and SVM classifiers, the team identified culturally significant environmental resources across a 1400km^2 area of the island's southwest coast. Using these data, the researchers created a predictive model that operated under the theoretical assumptions of an ideal free distribution (IFD, Fretwell and Lucas 1969). IFD is a settlement model from population ecology that suggests populations – without any restrictions – will choose to settle areas with the best access to important natural resources. The results of this analysis successfully identified archaeological sites consisting of ephemeral artifact scatters with over 80% accuracy, while simultaneously adding to archaeological knowledge about the nature of settlement distributions in this region over the past several thousand years. Follow-up analyses further improved the model using spatial statistical modeling (Davis, DiNapoli and Douglass 2020).

While there are many instances of similar forms of predictive modeling in archaeology (e.g., Borie et al. 2019; Sonnemann et al. 2017), the explicit framing of the model in theoretical terms is significant for advancing archaeological remote sensing. Despite low data resolution and vegetative cover throughout much of the study region, Davis and colleagues (2020a) were able to reliably locate ephemeral archaeological deposits in record time compared with traditional ground-based survey approaches. Furthermore, the results of these projects led to the collection of enough training data to begin testing machine learning algorithms for the direct detection of these foraging sites (see Davis and Douglass In Review). The results of this continuing work are promising with accuracy metrics exceeding 90% and providing archaeologists with the ability to quantify extant human niche construction and its ecological legacies.

DETECTION OF EPHEMERAL SITES BY PROXY
Apart from these examples, there are some researchers who have focused on the reconstruction

of palaeoecological features (i.e., palaeorivers, lakes, streams, etc.), which in turn can help to pinpoint the locations of early archaeological sites. For example, researchers working in the Arabian Peninsula used a variety of hydrological algorithms and automation procedures to locate palaeohydrological features. Subsequently, these features acted as a proxy for Paleolithic archaeological sites, which successfully identified 19 new archaeological deposits (Breeze et al. 2015). Similarly, Elfadaly et al. (2020) used amplitude radar imagery to locate palaeorivers and drainage systems in the Mediterranean region, which in turn provides important insight to the placement of early Neolithic archaeological sites. While this study was not automated, it demonstrates the potential for using automated methods to locate non-archaeological features that act as proxies for early human settlements.

One of the most significant and widespread detection efforts by proxy involves vegetative signatures (e.g., Agapiou 2020; Bennett et al. 2012; Brooks and Johannes 1990; Lasaponara and Masini 2007). It has been well established that buried archaeological remains tend to affect plant health and growth patterns, and in some instances even change the kinds of plants that occupy areas with associated cultural contexts (Brophy and Cowley 2005; Verhoeven 2012; Wilson 1975). With the advent of mathematical metrics of quantifying vegetation, the use of vegetative indices for archaeological prospection efforts has been a staple of semi-automated analyses for decades (see Bennett et al. 2012). Indeed, such vegetative proxies have been incorporated into many predictive modeling efforts to locate archaeological sites (e.g., Agapiou 2020; Calleja et al. 2018; Davis et al. 2020a; Hegyi et al. 2020; Kirk, Thompson and Lippitt 2016; Yaworsky and Codding 2018). In several instances, vegetative indices have been used in conjunction with other automated remote sensing methods (e.g., Davis et al. 2020a; Kirk, Thompson and Lippitt 2016; Yaworsky et al. 2020).

Despite the successes of studies like those discussed in this section, the vast majority of automation within archaeological remote sensing continues to utilize the most novel methodologies (e.g., machine learning and deep learning) but focus on the same types of large, topographically distinct archaeological objects (e.g., Orengo et al. 2020; Sărăşan et al. 2020; Somrak, Džeroski and Kokalj 2020; Soroush et al. 2020; Trier, Reksten and Løseth 2021). These efforts are important and worthwhile, but so too is broadening the range of questions that can be assessed by such techniques. Using remotely sensed data as proxies for archaeological prospection can aid researchers not only in locating ephemeral archaeological traces (*Figure 2*), but also in linking these studies back to broader archaeological research questions. The concept of archaeological landscapes as a palimpsest (as illustrated in *Figure 2*) is

a fundamental tenet in the development of landscape archaeology as a holistic archaeological discipline. In this context, remote sensing approaches, in combination with other datasets from geology, demography, history, and anthropology provide long-term observations of both visible and ephemeral anthropogenic features.

THE CASE FOR THEORETICAL INTEGRATION AND EXPANSION WITHIN AUTOMATED REMOTE SENSING ANALYSIS

As the previous section highlights, automated remote sensing analyses are beginning to make breakthroughs in documenting subtle traces of the archaeological record that are often overlooked in landscape-scale research. This, in turn, can help to advance archaeological theory, but all too often direct linkages to theoretical frameworks are absent from automated remote sensing approaches (Davis and Douglass 2020; Thompson et al. 2011). When the data used is of high enough resolution it is tempting to simply detect whatever objects can be found, irrespective of broader archaeological frameworks. However, when data is too coarse for such "direct" detection approaches, or the procurement of an unbounded dataset is too costly, theory is invaluable for framing methods of analysis (e.g., Davis et al. 2020a).

Indeed, the detection of ephemeral archaeological sites has been aided by predictive modeling efforts based on environmental information procured from medium-to-coarse-grained satellite imagery. For example, Custer et al. (1986) use Landsat satellite imagery and statistical machine learning to classify environmental landscape types to determine the greatest likelihood for archaeological site locations. While this method is most explicitly rooted in statistical theory, the predictive modeling approach itself is entrenched in cultural ecology approaches that have been part of standard archaeological frameworks for nearly a century (Butzer 1982; Steward 1937, 1955). Very similar approaches persist in archaeology today, many of which rely on at least some remotely sensed environmental information (e.g., Davis, DiNapoli and Douglass 2020; Verhagen and Whitley 2012; Yaworsky et al. 2020).

Perhaps the greatest theoretical advancement offered by the methods discussed here is the reformulation of "site"-based archaeological studies. For decades, researchers have challenged the usefulness of the archaeological unit of "site" and its role in archaeological investigations (Caraher, Nakassis and Pettegrew 2006; Dunnell 1992; Dunnell and Dancey 1983; McCoy 2020). Particularly with the rise of geospatial technologies like remote sensing, the "site" concept has been vastly complicated by new levels of resolution and scale (McCoy 2020: S24; also see Czajlik et al. 2021). Alternatives
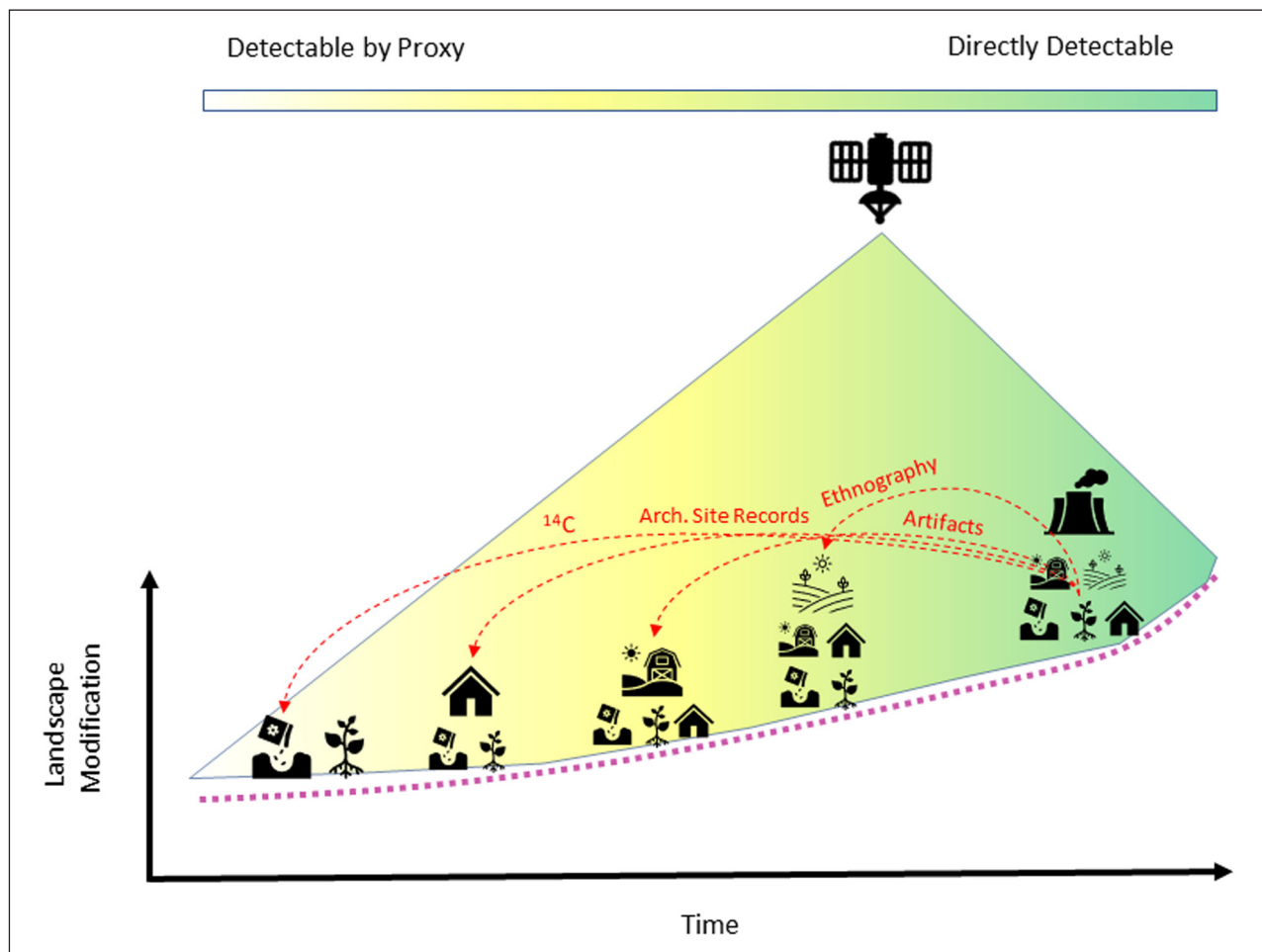
Figure 2 Over time, the degree of landscape modification has increased (purple dotted-line). The modern landscape, which is directly detectable (highlighted in green) by satellite remote sensing, represents a palimpsest of collective human actions, which are each detectable in different ways and to varying degrees. Modern modifications and some older landscape modifications can be directly identified, while other older and subtler activities that leave fewer direct traces can be identified by proxy (highlighted in yellow), wherein we can infer the timing of different changes seen in the present by linking visible differences to known areas of historic/archaeological human presence (red dashed-arrows).

to "site" based investigation have been proposed and include "siteless" surveys (Dunnell and Dancey 1983), landscape surveys, which, rather than assess the archaeological record as a collection of individual "sites", views it as a connected system of different parts (Anschuetz, Wilhusen and Scheick 2001), and in temporal terms (coined *time perspectivism* [Bailey 1981, 2008]), which view the archaeological record as a palimpsest without dissected components. With an ability to record archaeological components at multiple scales and at varying levels of resolution, how we think about and categorize archaeological data requires reformulation. As researchers have argued, it is vital that the term "site" is understood as a result of archaeological observation, and not anything inherent in how things actually are; in other words, we find sites, but sites are not what we actively seek out (Dunnell 1992; McCoy 2020).

As remote sensing studies shift towards documentation of artifacts and anthropogenic niche construction at finer scales, the very nature of remotely detected archaeological data will require adjustment,

as "sites" are no longer an adequate descriptor of the results of these investigations. Rather, remote sensing archaeology can record – to varying degrees of completeness – the very palimpsests and interconnected systems that define the record according to landscape and time perspectivist approaches. Take, for example, recent work utilizing multitemporal image analysis (e.g., Lasaponara, Abate and Masini 2021; Orengo et al. 2020) which takes time-series averages of remote sensing imagery to establish atemporal geophysical profiles of features of interest. In this case, a large portion of time is used to establish a general set of characteristics by which archaeological and anthropogenic activities exist relative to other elements within that geographic space (like a time perspectivist approach [*sensu* Bailey 1981]). Similarly, landscape theoretical perspectives are encapsulated by remote sensing instruments whereby individual features and "sites" are defined in terms of their similarity or difference from surrounding regions based on spectral signature, physical or chemical composition, or orientation within a landscape of connected features.

Another important contribution of automated remote sensing techniques is the capability of characterizing the archaeological record in a uniform and semantically consistent manner (Davis 2020), alleviating one of the major problems with the "site" concept. As McCoy (2020) argues, remotely sensed archaeological data may require new and distinct definitions from traditional "site" based categories. At the same time, it is important not to distance remotely sensed and ground-based data as fundamentally different or incompatible with one another, as this deepens an epistemological divide among researchers with respect to the connection of different data sources to their human roots (Hacıgüzeller 2012; Millican 2012; Thomas 1993).

While not all scholars will agree on the best theoretical approach, remote sensing data can be incorporated into many studies rooted in very different theoretical positions. For example, researchers have used remotely sensed data to assess social questions concerning changes in landscape use (e.g., Chase, Chase and Chase 2017; Inomata et al. 2018; Vining 2018), mobility and connectivity (e.g., Oltean and Fonte 2021; Pawlowicz 2020), socio-political boundaries (e.g., Evans et al. 2013; Harrower and D'Andrea 2014; Inomata et al. 2020), and perceptions and experiences of place (e.g., Fitzjohn 2007; Millican 2012), among others. While not all these approaches necessarily rely on (or require) automated remote sensing analysis, many – if not all – of these questions can benefit from automated remote sensing studies – specifically in the use of data generated by such endeavors. For example, Cerrillo-Cuenca and Bueno-Ramírez (2019) use data collected via automated remote sensing analysis by Cerrillo-Cuenca (2017) to explore the differences in land-use and monument distribution in the Iberian Peninsula. This study revealed new connections between different kinds of archaeological features, indicating a vast landscape of human activity – even in so-called "marginal" locations where prior research had discovered very few archaeological materials. While this example focuses on monumental sites, the same can be shown in cases of ephemeral archaeological patterns discussed above.

In addition to the interpretive advantages of theoretical integration, the incorporation of archaeological theory into automated research can also help alleviate the problem posed by taphonomic processes mentioned earlier. By formalizing our expectations of what modifications to cultural materials may have taken place using ontological systems (see Arvor et al. 2019; Magnini and Bettineschi 2019), we can improve our capacity to predict and identify these features within the modern landscape, as it widens our expectations of the form that these materials may take given changes over time.

Such evolutionary perspectives of the archaeological record are well established, and in relating such theoretical knowledge directly into automated remote sensing

analysis, we can improve the utility of these approaches, as well as their overall impact on archaeological thought. For example, niche construction theory (NCT) – a branch of evolutionary biology – postulates that ecological modifications made by individual organisms result in subsequent environmental changes that impact other cohabiting organisms (Laland and O'Brien 2010; Odling-Smee, Laland and Feldman 2003). The line of thought associated with NCT goes well with Magnini and Bettineschi's (2019) concept of DhSMs discussed previously, as the assumptions of NCT can create hypotheses surrounding the long-term ecological effects of human activity. This, in turn, can inform researchers of possible proxies by which archaeological materials can be identified. In practice, new research is already demonstrating the potential of such an approach for documenting ephemeral foraging sites via satellite remote sensing (Davis and Douglass In Review; also see Vining 2018; Czajlik et al. 2021).

While I advocate for the linkage of archaeological remote sensing with explicit archaeological theory, it is obvious that such a methodological-theoretical marriage is not always warranted depending upon one's research goals. All research is based on some set of theoretical assumptions, and automated remote sensing is no exception: it is tightly intertwined in information theory, statistical and mathematical theory, and geophysical theory, among others. However, the issue that arises when archaeological theory is left out is the delegation of all such methodological achievements as simply a technical report within archaeological literature.

According to a Web of Science search (see Supplemental Materials), automated archaeology research is primarily cited by articles in geoscience and remote sensing journals, followed by interdisciplinary publications and archaeological science publications (*Figure 3*). Medical journals, such as *Statistics in Medicine* and *International Journal of Environmental Research and Public Health* were unexpected sources of citations, and such publications appear primarily concerned with spatial modeling of disease transmission. Further work would be needed to evaluate these trends fully, but this goes beyond the scope of this article.

When evaluating the publications that reference automated remote sensing studies (see Supplementary Materials for more details), the bulk of these citations appear to be methodologically focused where direct contributions to archaeological theoretical questions are of secondary importance, if mentioned at all (Supplementary Materials; Table S1). While many methodological studies are small parts of much larger projects, in such cases, the results of these studies should be used and cited within papers that result from these larger research agendas. However, it appears that such advances are primarily published as methods reports, and are thereafter cited primarily by other methods reports,
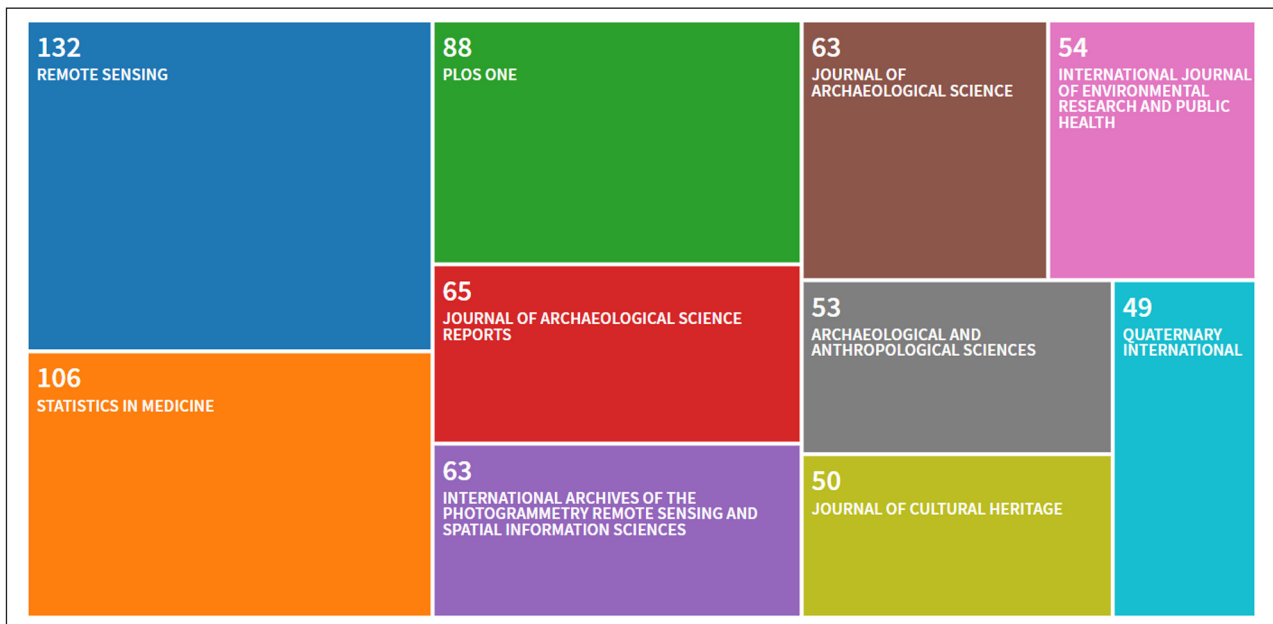
Figure 3 Top 10 publications of articles that cite automated remote sensing archaeology papers (Results from Web of Science search conducted on 2 March 2021).

but rarely by scholars delving into more theoretical research. As such, the abundance of data generated by automated remote sensing archaeologists may never find its way into larger-scale investigations that are the crux of archaeological inquiry. Thus, it is imperative that datasets procured by such work be incorporated into broader, interdisciplinary studies of the archaeological record; and doing so requires an engagement with theoretical frameworks from the social sciences (i.e., anthropology, archaeology, geography, etc.).

SUMMARY

Automated archaeological remote sensing has made incredible strides in the development of algorithms to locate a myriad of feature types from image datasets. The achievements of locating large architectural features can make further advances in archaeological research by helping to locate more ephemeral traces of human activity. In many cases, the detection of monumental structures (or other topographically distinct cultural heritage) can actually lead researchers to discover ephemeral cultural remains (e.g., Davis, Seeber and Sanger 2020; Klehm et al. 2019). The use of larger-scale cultural heritage as a proxy for detecting smaller scale heritage is certainly worthy of further emphasis in future studies. As the above discussion illustrates, researchers are beginning to make great strides in advancing the use of automated remote sensing methods for the documentation of the most difficult components of the archaeological record to identify.

Ultimately, the future of AI, machine learning, and other automation techniques within remote sensing archaeology is contingent upon what it can offer

the discipline beyond data collection. Practitioners of this methodological niche must demonstrate the benefits that such approaches offer to the study and interpretation of the archaeological record, in addition to its documentation power. For example, automated methods can help redefine how archaeologists classify the materials we study. Instead of relying on "site-based" analyses, remote sensing data can be used to better account for multiple scales of anthropogenic activity that push beyond the bounds of "sites" or "features", but rather encompass a myriad of deposits including micro-scale artifact scatters, landscape-level transformations, and multi-temporal anthropogenic modifications that define human activity in a region.

With the ability of computer automation to consistently define units of measurement, these methods can also more concretely define the boundaries of "landscape" archaeology, as opposed to other forms of settlement studies. Kowalewski (2008) criticizes many "landscape" scale approaches to archaeology for their lack of unified organization, serving more as an "umbrella" or "junk-drawer" where virtually everything can be included. He argues that settlement patterns must be viewed as a living system that is bounded by specified scales within a particular place (Kowalewski 2008). Automation may hold a solution to this critique. By standardizing units of measurement and means of archaeological identification, semantic consistency can aid in the explicit defining of landscape boundaries and characteristics, making "landscape" approaches less of a hodgepodge and more explicit in their theoretical assumptions. Furthermore, archaeological research can be replicated by different scholars at multiple scales of analysis because of such standardization. Not only does this improve archaeological research in terms of
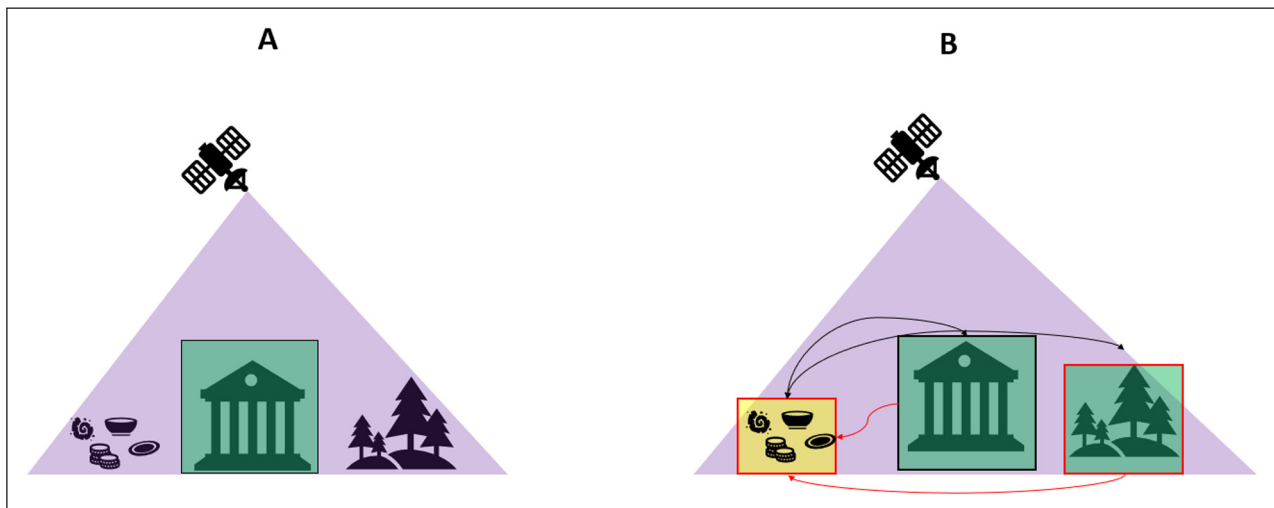
Figure 4 A: Remote sensing usually scans entire regions (purple), but traditional uses of automation in archaeology focus only on directly identifying (green box) large-scale, topographically distinct features. **B:** Shows proposed integrative automated archaeological remote sensing, wherein monuments are still detected, but so too are other environmental features which can be used as proxies (boxes with red outlines) to detect small artifact scatters and non-architectural components of the archaeological record (yellow box). Detections should then form a feedback loop wherein the large- and small-scale features inform archaeologists about each other as parts of a complete system.

study design and reliability of results, but it can also aid in solving the problem of taphonomy, and how we approach components of the archaeological record that have been changed over the course of time.

Nonetheless, publications focused on the development of automated protocols often focus on the methods themselves and offer little concrete discussion of the implications that the method has for understanding important archaeological phenomena (cf., Cerrillo-Cuenca and Bueno-Ramírez 2019; Davis et al. 2020b; Freeland et al. 2016; Klehm et al. 2019). While methods reports are invaluable for advancing the utility of automated procedures, great progress has been made in recent years leading to highly accurate protocols. While improvements can always be made, it is time for the methodological rigor afforded by automation to be applied to a wider set of phenomena than mounds and other large-scale cultural features (*Figure 4*). By integrating automated methods for the study of anthropogenic landscapes as a whole, we can advance our understanding of the archaeological record in a more complete manner by viewing the record as a system of interrelated components that provide information at different scales.

In sum, achievements made by those working on methodologically innovative research like automation should pass beyond methodological significance by directly informing larger research agendas (*Figure 1*). Thus, the advocacy of automated remote sensing to push the boundaries towards ephemeral archaeological deposits is an extension of this argument: by extending the utility of these innovative data collection solutions, this "niche" of archaeological research can begin to impact the discipline's most central questions and longstanding debates by documenting the presence

and impact of underrepresented components of the archaeological record.

ADDITIONAL FILE

The additional file for this article can be found as follows:

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