Regional-Scale Archaeological Remote Sensing in the Age of Big Data

Automated Site Discovery vs. Brute Force Methods

Jesse Casana

Over the past decade, the quantity of high-resolution aerial and satellite imagery available to archaeologists has been expanding exponentially, and these resources offer enormous possibilities for the discovery of previously unknown archaeological sites and features. Commercially-acquired submeter resolution satellite imagery with spectral coverage in the visible and near infrared is available across the globe, with archived data increasingly easy to access, offering a wealth of opportunity for site prospection (e.g., Kennedy and Bishop 2011; Lasaponara and Masini 2007, 2011; Salvi et al. 2011; Stone 2008). Very-high-resolution topographic datasets derived from airborne LiDAR are increasingly being used by archaeologists (e.g., Chase et al. 2011; Opitz and Cowley 2013), while 12-m or better satellite-acquired synthetic aperture radar data will soon be available globally

ABSTRACT

With the ever expanding quantity of high-resolution aerial and satellite imagery available to archaeologists, numerous researchers have sought to address this "big data" challenge by developing automated methods to aid in the discovery and mapping of archaeological sites and features. This paper reviews several notable efforts to create automated discovery tools, including both spectral and object-based approaches, and highlights the difficulties these projects have encountered. Arguing instead for the critically important role of a human analyst in archaeological discovery, I illustrate interim results of an ongoing project that utilizes CORONA satellite imagery to document previously unknown sites in a 300,000 km^2 study area in the northern Fertile Crescent. The project is based on what I term "brute force" methods, relying on systematic exploration of imagery by trained analysts, and has now successfully created a database of more than 14,000 sites, some 10,000 of which are previously undocumented. Results of the project highlight the need for human intervention to make any archaeological discovery meaningful, suggesting that imagery analysis, like any act of archaeological investigation, requires an engaged, thoughtful and creative scholar.

Desde la última década, la cantidad de imágenes aéreas y satelitales de alta resolución disponible a los arqueólogos ha crecido exponencialmente, y estos recursos ofrecen posibilidades enormes para el descubrimiento de elementos y sitios arqueológicos. La gran cantidad de datos aéreos y de satélite ya disponible a los arqueólogos puede ser abrumador, y esto ha causado que unos de nosotros busquemos herramientas automatizadas para poder manejar nuestra propia versión de "datos grandes." Yo argumento que el análisis de imágenes aéreas y satelitales para encontrar evidencia de actividades culturales pasadas es tanto un arte hábil como ciencia. Es un proceso que requiere un arqueólogo empeñado, con un entendimiento de la historia del asentamiento local y las practicas de uso de terreno locales, y que pueda explorar imágenes creativamente para encontrar e interpretar elementos de posible importancia. Este es un trabajo que no puede ser automatizado, ni debería de ser, como sería la construcción de robots autónomos de excavación que hicieran nuestras propias excavaciones para nosotros. Ilustro este punto con un estudio de caso, utilizando imágenes satelitales CORONA en un esfuerzo para documentar sitios previamente no conocidos en un área de estudio de 300,000 km cuadrados en el norte de la Creciente Fértil. La base de datos resultante contiene 14,000+ sitios.

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and will have similar archaeological applications (e.g., Linck et al. 2013). The same photogrammetric software packages that have been transforming archaeological documentation at the level of sites, excavations, and artifacts (De Reu et al. 2013), can now be used to very efficiently process hundreds of historic aerial photos, producing highly accurate digital surface models and submeter orthoimagery over vast areas (Bitely 2013). Finally, the growing sophistication and reliability of small unmanned aerial vehicles now enable archaeologists to acquire custom imagery at centimeter resolution across a variety of light spectra at low cost (Casana et al. 2014; Hill 2013).

With these ever expanding datasets, we face a challenge of how best to deploy them in our research programs. In Europe (e.g., Cowley et al. 2010; Crawford and Kieller 1928; Wilson 1982) and the Near East (e.g., Poidebard 1934; Van Liere and Lauffray 1954–1955; Wilkinson 2003), historic aerial photography and other airborne and satellite imagery has been regularly employed for nearly a century to aid in discovery and documentation of archaeological sites but mostly on a relatively small scale (e.g., at the level of an individual site or small study area). In North America and other parts of the world, there has been comparatively much less research into understanding how to directly detect archaeological sites and features on aerial and satellite imagery (Giardino and Haley 2006; Kvamme 2005:28–29).

Faced with the growing deluge of aerial and satellite data, many archaeologists, often in collaboration with remote sensing scientists, have attempted automate the process of site discovery. Building on a long history of imagery being used in archaeological predictive modeling (e.g., Westcott and Brandon 2000), much effort is now being devoted to finding better methods for direct detection of sites, often with the goal of creating an algorithm or machine learning method to automatically search through the imagery to reveal the locations of sites or cultural features. This "Holy Grail" of archaeological remote sensing remains largely elusive however, and even the most impressive efforts have only limited applicability.

In this discussion, I first highlight the variable degrees of success archaeologists have had in their efforts to automate the process of site discovery and outline some of the problems with an automated approach in general. I then illustrate the results of a project undertaken by my research team that uses a large database of high-resolution, Cold War-era CORONA satellite imagery to document archaeological sites and features in the Near East. In this project, we use what might be considered a more conventional method of imagery analysis, but we do so in a systematic and rigorous way over a very large study area of around 300,000 km^2. Our results produce a rich dataset that contains tens of thousands of observations and analyses that could not be reproduced by an automated search process, and highlights the need for continued investment in developing our abilities as archaeologists to interpret imagery, even while employing ever more powerful methods to acquire, process, and display these data.

AUTOMATED SITE DISCOVERY

Dating back at least to the 1980s, when multispectral classification tools became available, archaeologists have hypothesized that sites may possess unique spectral signatures that would enable them to be identified in multispectral satellite imagery such as Landsat (e.g., Custer et al. 1986; Limp 1989). Some attempts to employ this approach have seen success, including Saturno and colleagues' (2007) efforts to map major Maya centers below tree canopy and Altaweel's (2005) use of Aster imagery to recognize mounded sites in northern Iraq. In general, however, many projects have found little consistency in the spectral signature of sites (e.g., Beck et al. 2007; Cavalli et al. 2007; De Laet et al. 2007; Sarris et al. 2009; Wilkinson et al. 2006), while other investigators have been unable to recognize cultural features whatsoever (e.g., Pryce and Abrams 2010). The difficulty in using classic spectral classification methods to identify archaeological sites is related in part to the fact that a "site" itself is very much an archaeological construct. What a site is, how one is identified, and indeed whether the term should be used at all remain contested questions within archaeology (e.g., Banning 2002:11–25; Dunnell 1992; Kantner 2008). Moreover the soil types, ground cover, and response to seasonal changes across sites within even a small region are highly idiosyncratic, controlled by a host of localized and largely unknown variables.

More recently, other researchers have sought to use object-based methods for detection of sites and features, adapting approaches that are increasingly popular in remote sensing science (e.g., Tansey et al. 2009). Object-based detection methods generally rely on both the spectral characteristics and the shape of a training sample of archaeological sites to identify similar clusters or features within imagery. There have been some notable successes in using the technique, as in Du Trier and colleagues' (2009) effort to detect circular crop marks, possibly burial mounds, in Norway, De Laet and colleagues' (2007) extraction of linear archaeological features on Iron Age sites in Turkey from high-resolution multispectral satellite imagery, and Bescoby's (2006) research to detect centuriated Roman field boundaries using historic aerial photographs.

One of the most successful recent attempts to use an object-based approach grew out of a multidisciplinary project to map the distribution of ancient stone-built tombs and monuments in highland Yemen (Harrower et al. 2013; Schuetter et al. 2013). The study region contains thousands of small, usually circular stone tombs, but recording them using conventional methods was very challenging as they are often located in remote regions difficult to access on foot. To automate detection of these features across the vast study area, the research team developed an approach in which each pixel within a multispectral high-resolution QuickBird satellite image is evaluated within a moving window to see if it is surrounded by a cluster of pixels whose shape, size and reflectance is suggestive of the presence of a circular tomb. Passing each window through a series of filters, pixel clusters are gradually eliminated, ultimately leaving only features that may be circular tombs. The strength of the approach over

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more traditional spectral classification methods is that it is able to identify features that are roughly circular and of an expected size, but that may have highly variable spectral characteristics. The approach developed by Schuetter and colleagues (2013) is very useful for finding features that are extremely regular in their size, shape, and appearance but would not work on the archaeological record as a whole, which contains a huge diversity of material traces of cultural activity. For example, the method inevitably excludes all tombs or burials that are unusual (e.g., square or oval, especially big or small), and does not find any other cultural landscape features such as sites, field systems, or irrigation networks that have been documented in the region (Harrower 2010), even if they would be obvious to a human analyst.

In contrast to the methods discussed above, which identify only features of very regular size and shape, Menze and Ur's (2012) recent project has more success in automating site discovery across a wide range of site types. They cleverly use spectral signatures across a series of Aster images to identify probable anthrosols, which are typical of sites in their study region of northern Mesopotamia. The researchers report impressive results, with a 90 percent detection rate for known sites in the two largest survey areas around Tell Brak and Tell Leilan, and somewhat lower rates of 73–87 percent in two other survey areas around Tell Beydar and Hamoukar. However, the two surveys for which the best results were achieved, those around Tell Brak (Wright et al. 2006–07) and Tell Leilan (Ristvet 2005), have only been partially published and, thus, the known sample of sites from both areas is heavily skewed toward large mounded sites. In the more intensively surveyed regions around Tell Beydar (Ur and Wilkinson 2008) and Hamoukar (Ur 2010), the probability map omits more than 20 percent of known sites. Moreover, across the entire study area, the probability map of sites in the region includes a large number of false positives, perhaps as much as 30–40 percent. These false positives are generated not only by modern villages but also by alluvial sediments along seasonal streams and other natural features. Thus, although certainly impressive, the probability map includes a large but unknown percentage of objects that are not archaeological sites while missing a significant but also unknown percentage of objects that are archaeological sites. The authors state that, "in most cases … 'false positive' modern villages can be recognized through visual inspection of standard high-resolution imagery" (Menze and Ur 2012:E782)) essentially meaning that to employ the probability map in an archaeological settlement analysis or regional survey, one would need to visually inspect all positive features to determine whether they are indeed sites, as well as to visually investigate all nonsite areas to determine how many sites were missed in them.

The results of Menze and Ur's (2012) automated detection effort can be contrasted to the results of coauthor Ur's (2003, 2010; Ur and Wilkinson 2008) previous research using more conventional analysis of CORONA imagery in the same region. Ur has spent many years carefully studying archaeological landscape features on satellite imagery and is an adept analyst in this regard. In his survey around Hamoukar (Ur 2010), he reports a nearly 100 percent discovery rate, in which intensive pedestrian surveys were unable to discover any significant archaeological sites that he had not already identified on CORONA imagery. His success in site identification is in part a product of the exceptional preservation and visibility of archaeological landscape features in the northern Mesopotamian plains. This semiarid, largely treeless region has been comparatively stable in geomorphic terms over much of the Holocene and has experienced long periods with little permanent settlement, reducing the impact of anthropogenic transformations. The vast majority of sites in these plains are the remains of long-lived sedentary occupations, are often mounded, and nearly always possess anthrosols that are distinct from natural background soils. All these factors in combination make archaeological sites in the northern Mesopotamian plains among the easiest in the world to recognize on satellite imagery, and, thus, it may not be surprising that this is also the place where the automated detection methods work best. However, the more conventional approach taken by Ur (2010) produces even better results, with a higher site detection rate and a much lower rate of false positives, in addition to the added benefit of identifying other key landscape features such as radial route systems that surround some sites (Casana 2013; Ur 2003, 2013).

CORONA-BASED ARCHAEOLOGICAL PROSPECTION IN THE NEAR EAST

As exemplified by Ur's (2010) research discussed above, declassified CORONA satellite imagery, collected as part of the world's first spy satellite mission from 1960 to 1972 (Day et al. 1998), has proven to be of immense value to archaeological prospection, particularly in the Near East where historic aerial photography is generally unavailable or inaccessible to researchers (e.g., Beck et al. 2007; Casana and Cothren 2008; Casana et al. 2012; Challis et al. 2002–04; Kennedy 1998; Kouchoukos 2001; Philip et al. 2002; Ur 2003, 2013; Wilkinson et al. 2006). Modern commercial satellite imagery now offers superior spatial and spectral resolution when compared to the 2–5-m resolution black-and-white CORONA photographs. However, because CORONA was collected more than 40 years ago, it preserves a picture of archaeological sites and features that have often been obscured or completely destroyed by modern development. In recent decades, the rapid growth of cities, the industrialization of agriculture, and the widespread construction of dams and reservoirs has severely impacted the archaeological landscape, such that even the highest-resolution modern imagery reveals only a fraction of the sites and features visible on CORONA (Casana et al. 2012). CORONA preserves a picture of a landscape that by and large no longer exists and, thus, constitutes a unique resource for archaeological investigations. Furthermore, in the Near East where much CORONA-based archaeological research has been undertaken, many archaeological sites are mounded, and CORONA, collected in the late afternoon to highlight topographic expression, reveals sites particularly well.

Despite the proven value of CORONA to archaeological investigations, most research to date has focused on studies of individual sites or relatively small survey areas, in large part because of the difficulties inherent in orthorectifying CORONA imagery. CORONA was collected by an unusual panoramic camera that was designed to offer very high spatial resolution over very large areas, but in doing so sacrificed spatial fidelity. The spatial distortions in the imagery, particularly on the edges of the long film strips the satellite produced, are so extreme that even the

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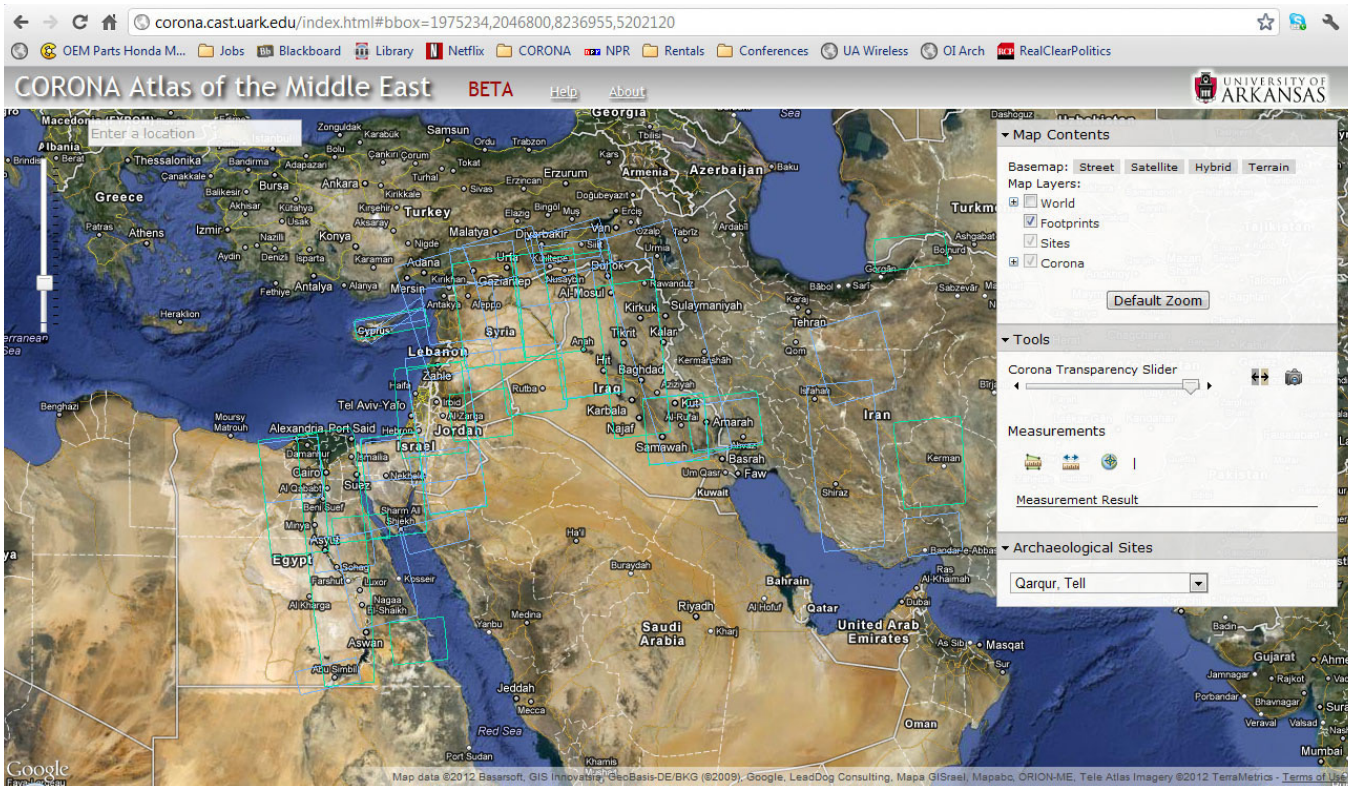

FIGURE 1. Screenshot from the CORONA Atlas of the Middle East (available at corona.cast.uark.edu).

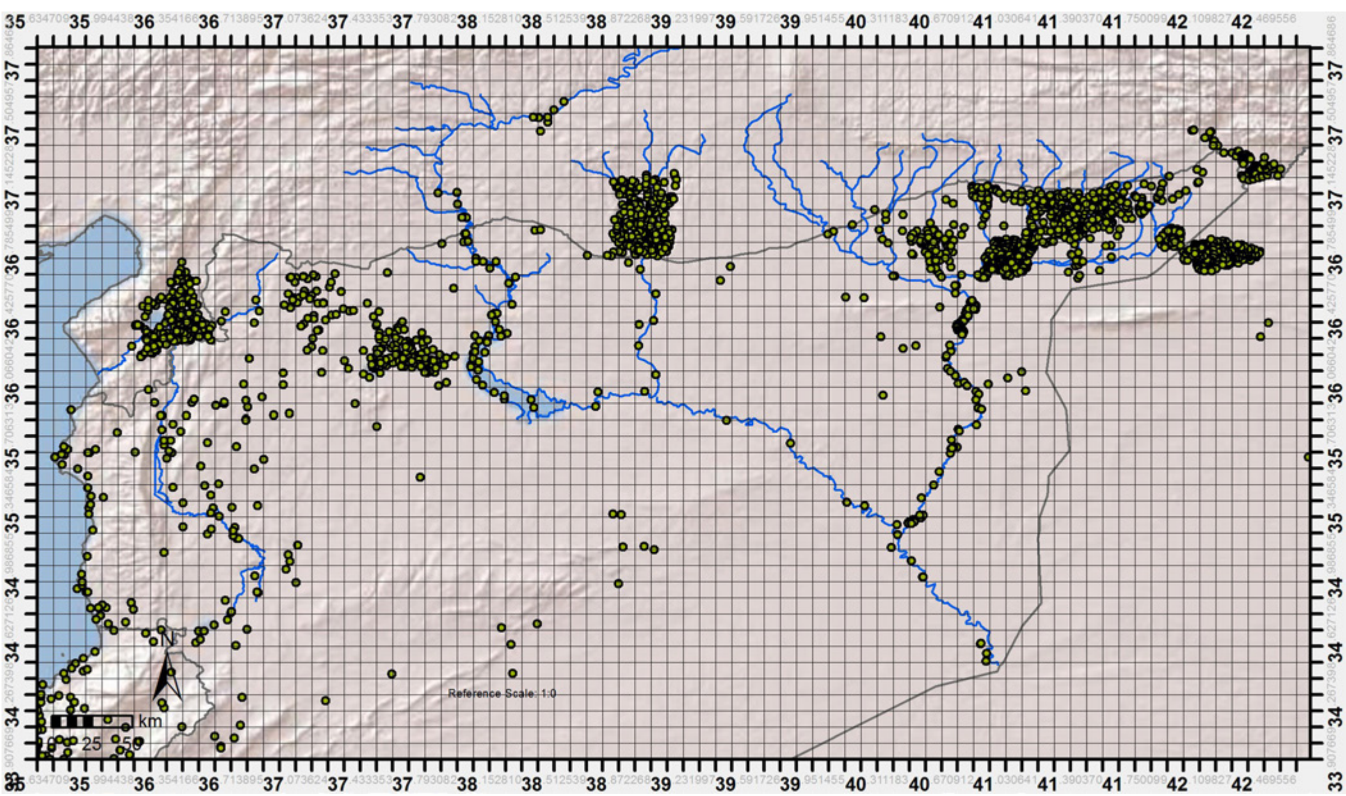

FIGURE 2. All previously published archaeological sites (c. 4500) within the study area of the Northern Fertile Crescent. A 10×10-km search grid is overlaid and was used to systematically search through CORONA satellite imagery.

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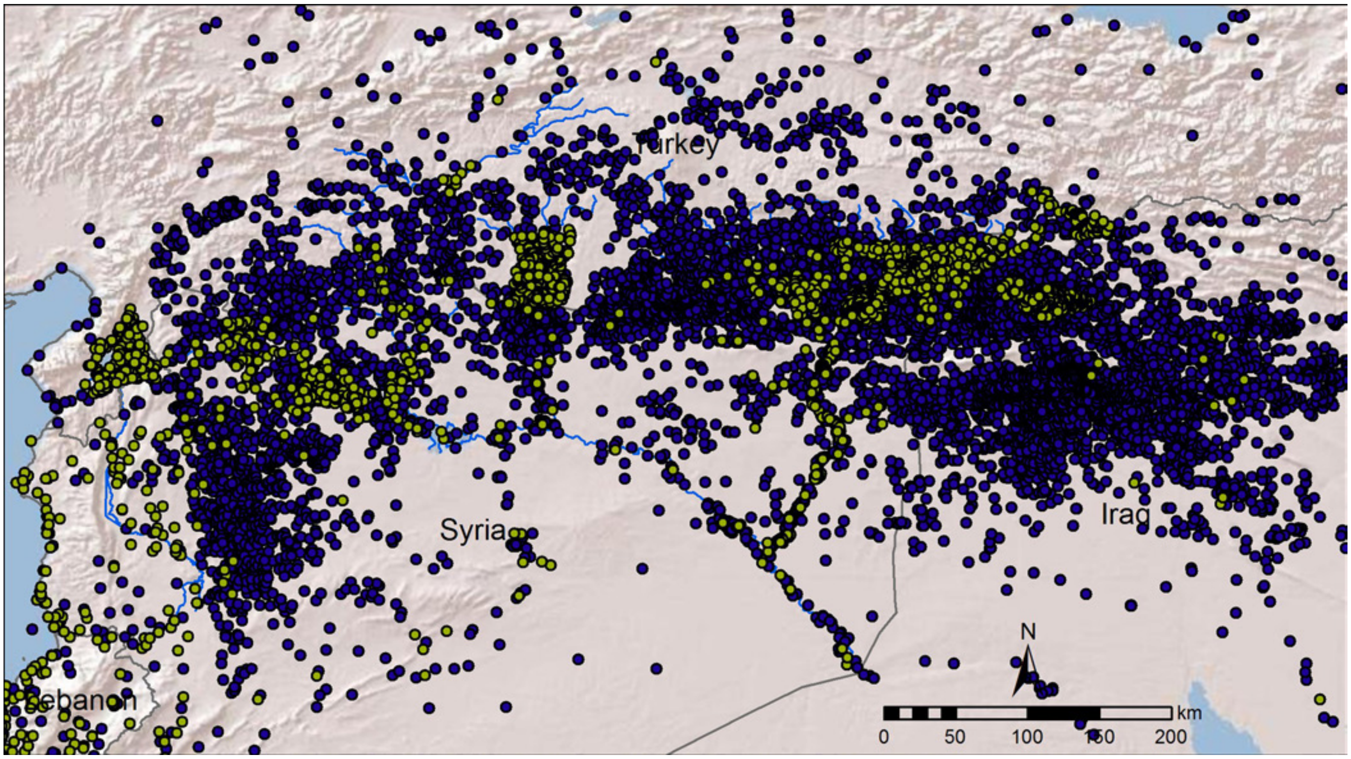

FIGURE 3. All sites currently known from both survey and imagery analysis, totaling more than 14,000. Low site density in the western edge of the study area reflects the incomplete state of database construction.

CIA analysts who originally used the imagery to search for Soviet military installations had no means of mapping from the imagery directly, instead having to reference a lower resolution frame camera image to locate features of interest. Most archaeologists and other researchers who have used CORONA have used rather simple methods offered in off-the-shelf GIS software packages to "rubber-sheet" small segments of imagery. This process is highly labor intensive and results in images with large amounts of error while also impairing use of the imagery in stereo viewing or DEM extraction. Even more critically, the inefficiency of nonrigorous correction methods make it impractical to employ imagery over a large area, and thus most CORONA-based archaeological research has remained relatively small in scale. It is ironic that archaeologists have not taken advantage of the enormous regional coverage that CORONA provides, because this was in fact its primary strategic advantage during the 1960s, offering analysts the ability to search for military installations across the entire globe (Day et al. 1998).

For the past several years, our research team at the Center for Advanced Spatial Technologies at the University of Arkansas has worked to develop new methods for more efficient and accurate orthorectification of CORONA imagery (Casana and Cothren 2013). Our approach, discussed in detail elsewhere (Casana et al. 2012), has now been used to orthorectify nearly 2,000 of the highest-resolution CORONA images, each covering approximately 188×14 km, providing 2-m resolution historic imagery for most of the Near East and surrounding regions (Figure 1). All imagery is now freely available to researchers and the general public in a user-friendly online imagery database through which spatially corrected CORONA can be viewed, searched, and downloaded. In our ongoing work on the CORONA Atlas Project, we are correcting imagery from elsewhere in the world including China, South and Central Asia, Eastern Europe, and the African Sahel, as well as building tools to enable other researchers to correct imagery using our processes and servers.

With corrected CORONA imagery now available at a much larger scale than previously was practical, we began in 2010 a project to systematically document all visible archaeological sites in a 300,000-km^2 study area in the northern Fertile Crescent. Extending from the eastern Mediterranean littoral to the highlands of northern Iraq, our study area encompasses an extremely rich archaeological landscape and one where past research has shown to be particularly amenable to CORONA-based site discovery. We initially planned to use an automated search methodology, and we experimented early on in the project with an object-based method for site identification using eCognition. Although we had some success in identifying many sites using this technique, I quickly came to see the archaeological record of the region as far too heterogeneous to permit such an automated approach, for all the same reasons discussed above. We instead turned to a method that I now call "brute force." Although the term would usually refer to a computer-based search strategy that simply tries every possible solution to a problem until it finds an answer, in our case, we rely on skilled analysts to simply look in every place to see what we find.

To use this approach systematically, we began by assembling all previously published and documented archaeological sites in the region as a training sample (Figure 2). We included 40 published archaeological surveys, along with all sites recorded in several major atlas and gazetteer projects including the Digital Atlas of the Holy Land, the Pleiades Project, and others. In total

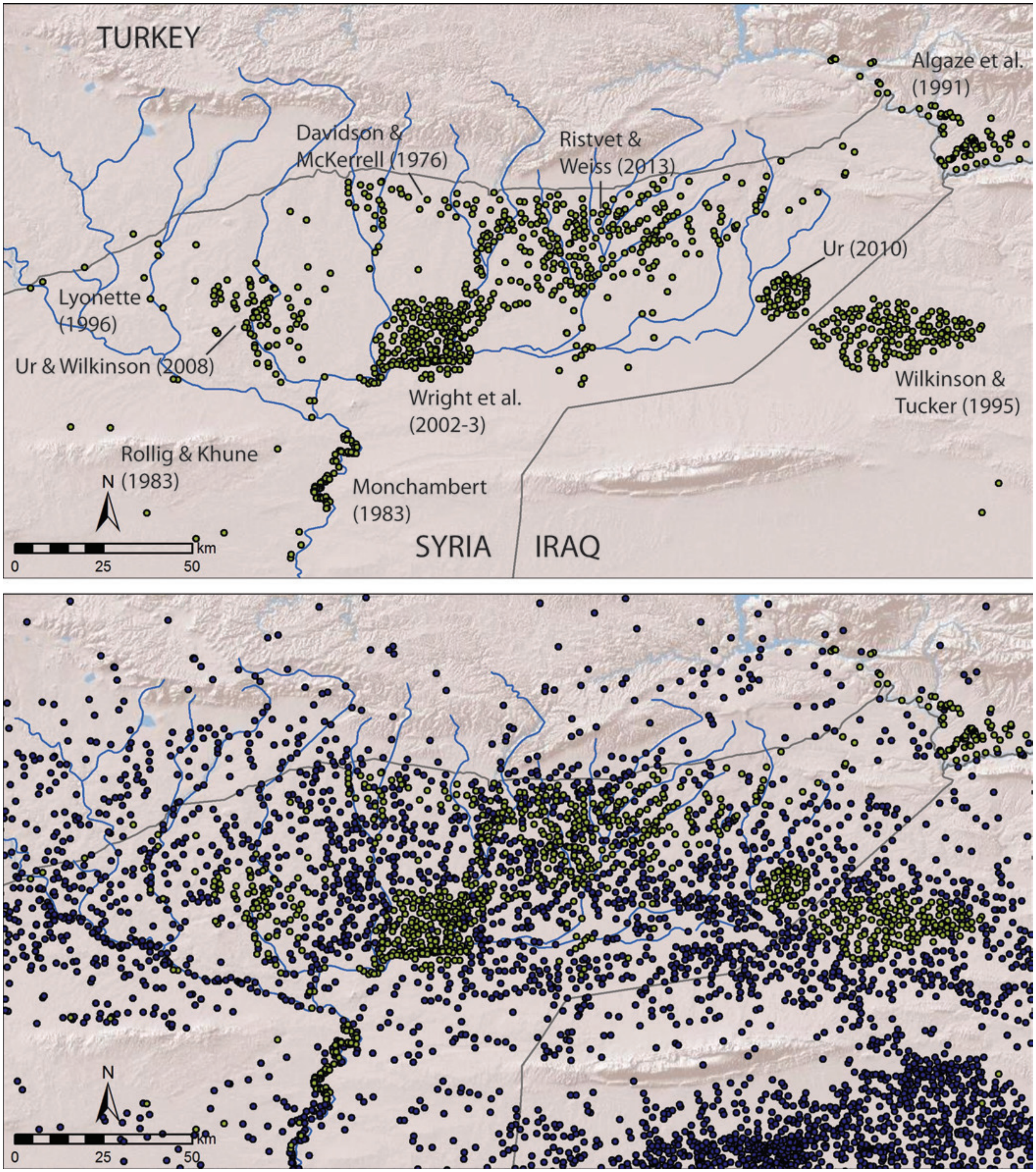

FIGURE 4. Close-up of the northern Mesopotamian plains of eastern Syria, southern Turkey, and northern Iraq, comparing all sites documented by archaeological surveys versus sites found through imagery analysis.

FIGURE 5. Araban Hoyuk in southern Turkey (left) and Tilecib Tepe in northern Syria (right). These still-unpublished sites can be deduced to have been major Bronze Age cities (third or second millennia B.C.).

this produced a dataset of approximately 4,500 sites with some published record, although varying a great deal in the level of detail, comprehensiveness, and reliability.

We then set to the task of systematically mapping all other sites and sitelike features within the study area that we could identify on CORONA imagery. To accomplish this, we divided the area into a series of 10×10-km grids (Figure 2) and employed four part-time students, each trained over a period of several weeks in site and feature identification, to map and record new features. Each newly discovered site was first given a confidence ranking (definite, probably, or possibly), describing how certain the analyst is that the feature is an ancient occupation. Then each site was classified and described according to a set of morphological criteria including the presence and shape of mounding, visible rectilinear architecture, and the presence and severity of erosional gullies and off-site features such as ancient roadways, canals, or field systems.

To date, our research team has documented more than 10,000 previously undiscovered archaeological sites or sitelike features, more than 90 percent of which have a confidence ranking of definite or probably (Figure 3). Figure 4 illustrates a close-up of the northern Mesopotamian plains discussed above, comparing all previously published archaeological sites in which individual survey projects are clearly evident. The differing density of sites across these surveys makes clear the sampling biases inherent in the datasets as most areas north of the Turkish border appear completely blank. Our satellite-based prospection however fills the gaps within surveys and extends our knowledge of site distribution across national borders. Moreover, unlike the results produced by an automated search tool, our dataset already includes the critical element of skilled human analysis, such that all sites in our database have information attached to them about their shape, size, character, and related features. These morphological variables are significant traits, being the product of distinct cultural traditions in the organization of built environments, differing settlement histories, and unique environmental settings (Casana 2012). Our dataset is, thus, not simply one that might be used to aid in archaeological prospection; it is an enormously rich dataset in its own right, which can be queried and explored to search for spatial and temporal patterns in the distribution of morphological types.

These results would not have been possible using an automated search tool, primarily because the nature of the archaeological remains we have documented are so nonuniform. They range from ephemeral smears of anthropogenic soils to patterns of shadows cast by standing architectural ruins to settlement mounds covered by modern villages, and they incorporate a huge range of off-site features in the form of ancient field systems, canal networks, and roadways. Moreover, in conducting this research, analysts are not simply following a rote set of rigid criteria for what constitutes a "site"; they are instead engaging in a discursive, analytic process, thinking creatively about features we see. This means that analysts are also good at identifying unique or unusual features, something that no automated tool can possibly achieve, and it is often the case that these unique discoveries are among the most transformational.

In fact, many of the most interesting things we've discovered in our study are very unlikely to have been recognized by any automated approach, and even if they had been, their significance would have been missed. For example, our analysis discovered a number of very large sites that possess a high, flat-topped central citadel surrounded by an expansive lower town, such as the

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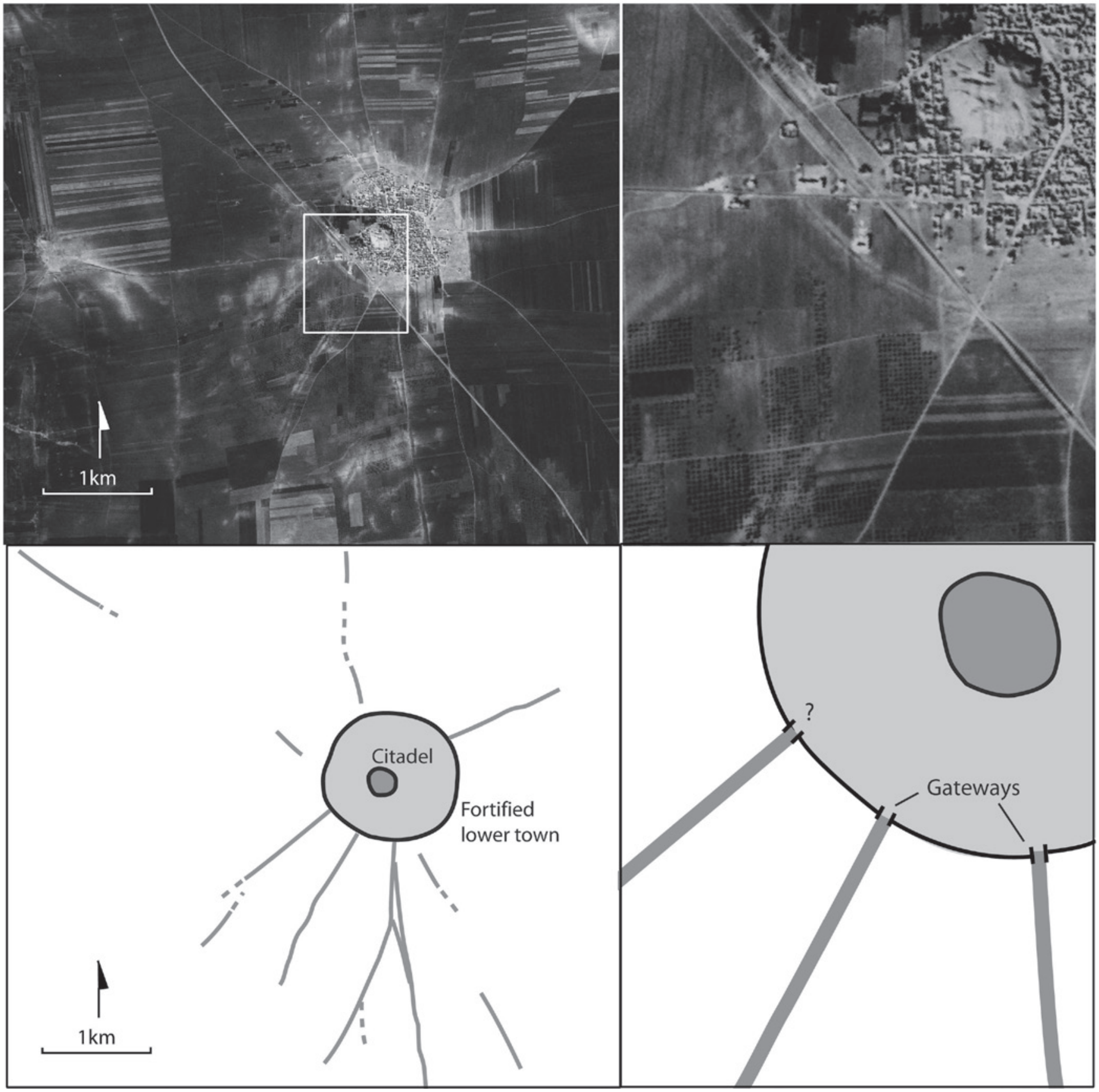

FIGURE 6. Tell Rifa'at in northwest Syria, the Iron Age (early first millennium B.C.) capital of Arpad. Excavations in the 1960s focused on the high central mound, but a massive 120-ha fortified lower city, now completely obscured by the modern town, is visible on CORONA. Radial route systems exiting gateways in the wall can also be traced on the imagery.

two examples illustrated in Figure 5. The distinctive morphology of these sites indicates they are almost certainly Bronze Age cities, and their size, at 50–60 ha, suggests they must have been key urban centers during that period. An automated approach might have discovered such sites, but would not have recognized their significance. Similarly, the large mounded site of Tell Rifa'at would likely have been discovered through an automated approach, as the central mound rises some 30 m above the surrounding plain, making it among the most conspicuous sites in the region (Figure 6). But the subtle traces of the expansive 120-ha lower town, enclosed within the remains of an almost perfectly circular fortification system would likely have been missed. The even more ephemeral radial road systems that surround the mound and their linkage to the fortification wall (Casana 2013) would certainly require a human analyst to recognize. Likewise, in the Mardin Plain of south central Turkey, an automated search tool might have identified the prominent mound we call Akziyaret Tepe (Figure 7). This still-unpublished site appears

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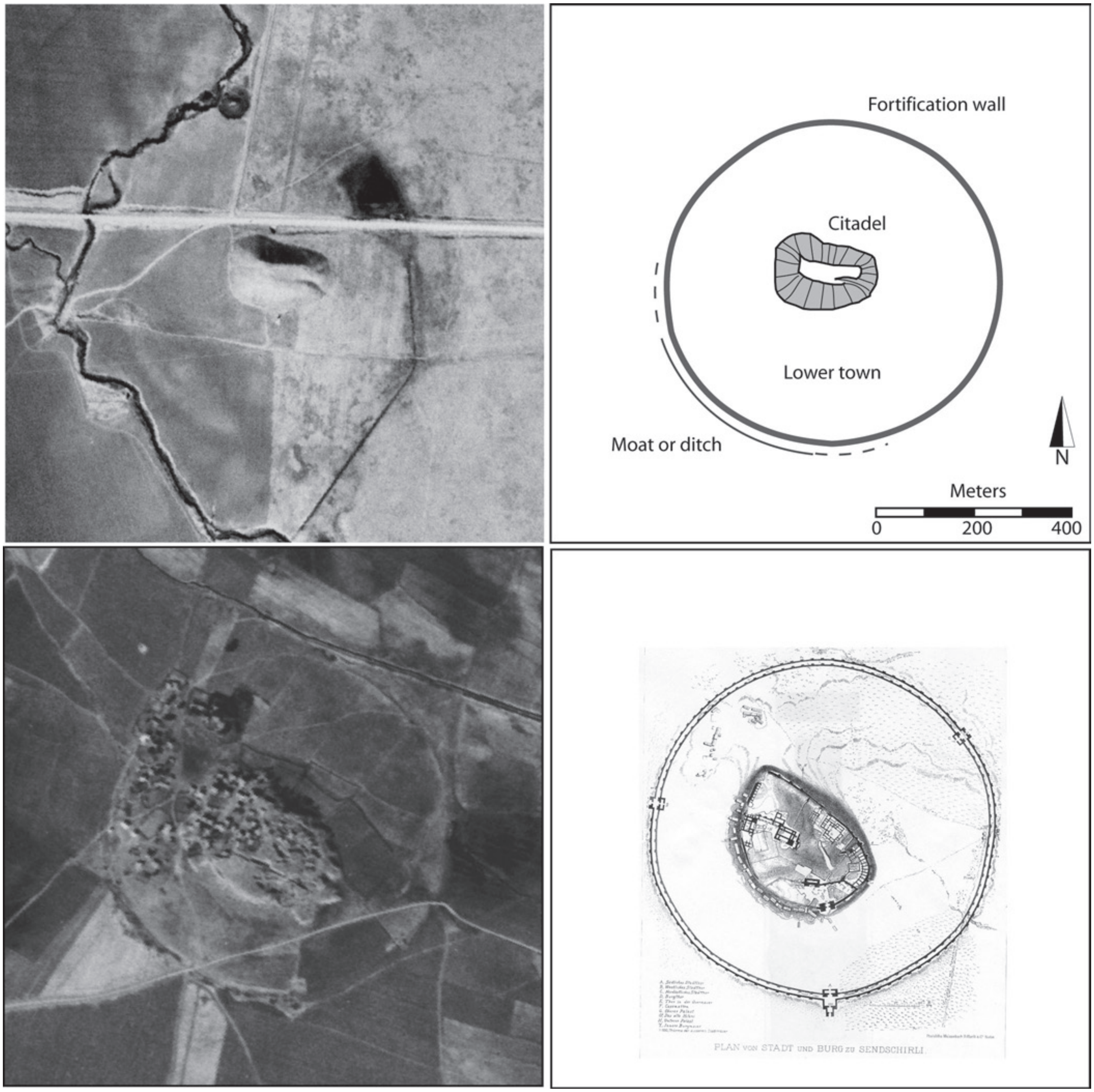

FIGURE 7. Akziyaret Tepe in the Mardin Plain (top), a previously undocumented site. The ephemeral outline of a perfectly circular 40 ha lower town is just visible on the CORONA image, making it a close parallel to the well-known Iron Age (early first millennium B.C.) site of Zincirli Hoyuk (bottom).

quite clearly on CORONA and other imagery, but only a keenly trained eye would recognize the faint outline of a perfectly circular fortification wall surrounding it. The close similarity of the site to the well-known Iron Age site of Zincirli Hoyuk in southern Turkey (Casana and Herrmann 2010) suggests that the two sites are contemporary. Unlike automated approaches that simply identify possible areas of cultural remains, an archaeological analyst who careful scrutinizes imagery can begin to build theories about features and to consider questions to investigate moving forward, such as how widespread such features are, their probable date, and their function.

CONCLUSIONS

The broader point that I hope to illustrate in this article is that analysis of aerial and satellite imagery to look for evidence of past cultural activities is a process that requires an engaged archaeologist, with an understanding of local settlement history and land-use practices, who can creatively explore imagery to find and interpret features of potential significance. This is a job that cannot be automated, nor should it be, any more than we should be trying to create autonomous excavating robots to do our digging for us. Just because this particular act of archaeological discovery takes place on a computer screen, rather than at the bottom of a sweaty trench, does not make it a lesser act of investigation that can be outsourced to an algorithm, or as our research team learned the hard way, to an untrained undergraduate.

The vast quantity of aerial and satellite data now available to archaeologists can seem overwhelming, and this has led some of us to search for automated tools to cope with our version of "big data." Our CORONA research project in the Near East illustrates, however, that in many cases, our data are not so big as to make the traditional "brute force" approach that I advocate here impractical. In our study, the 14,000-plus site database we generated was created over a two-year period with the part-time effort of myself and a few graduate students, and as such is really of the same magnitude, in terms of time and effort, as many archaeological research projects. Like most investigations, it simply requires a little bit of training, some creative engagement with the raw data, and a lot of elbow grease to achieve good results.

There are certainly ways in which the approach advocated here could be further developed and refined, perhaps borrowing from studies in other fields such as medical science where researchers are faced with a similar problem of visually interpreting vast numbers of images. Some studies have worked to develop methods to assess the accuracy of visual observations of human analysts as well as to improve recognition of features by pooling observations from several analysts (e.g., Warfield et al. 2008). We plan to implement a strategy moving forward in which multiple analysts will perform classifications on each site within our database, offering more accurate results and enabling a statistical analysis of rater variance in our project.

I recognize that some of this discussion may have a reactionary ring to it, and I do not intend to discount the potential value of automated search methods as a complement to more traditional visual investigations. The imagery acquisition platforms and computational power we now have are amazing tools, and there are many aspects of the processes involved in preparing and analyzing these data that can and should be automated. However, if we believe in archaeology as a discipline then there must be a moment that necessitates human intervention, and it my contention that the discovery and interpretation of archaeological remains, whether digital or otherwise, is that moment. To confront the deluge of aerial and satellite imagery increasingly before us, we should first and foremost invest in training humans to interpret and understand these data.

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Data Availability Statement

All orthorectified CORONA imagery used in this study is freely available to view and download through the CORONA Atlas of the Middle East (http://corona.cast.uark.edu), hosted by the Center for Advanced Spatial Technologies at the University of Arkansas. The CORONA Atlas also includes an archaeological site database, enabling users to query locations of all major sites discussed in the text.

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