Integrating Older Survey Data into Modern Research Paradigms

Identifying and Correcting Spatial Error in "Legacy" Datasets

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ABSTRACT

The data from older archaeological surveys are incredibly important resources, often containing our only information about sites that have been destroyed or that are now inaccessible. These surveys occurred before the advent of GPS technology, however, so their spatial accuracy is often uncertain. Many types of locational errors accumulate in such "legacy" datasets, so using them in modern GIS-based spatial analyses is frequently problematic. Many of the sources of error can be identified and quantified, however, and systematic and random errors (derived mainly from Cartesian, rounding, and human error) can largely be mitigated by scanning the original field maps, georectifying the maps to trusted imagery, and then digitizing sites directly. The remaining "mislocation" errors derive from difficulty identifying locations in the field. The original survey notes may contain clues about mislocation error, but it is impossible to mitigate these errors without re-recording site locations with more accurate survey instruments. Instead, I advocate the use of GIS-based models to estimate the influence of specific surveying practices on site location accuracy. These models can provide a standardized, quantifiable measure of mislocation error in a legacy dataset, which can help guide its use in modern GIS analyses that require accurate site locations.

Los datos de prospecciones arqueológicas antiguas son recursos de una enorme importancia, pues contienen a menudo la única información disponible sobre yacimientos que han sido destruidos, o que resultan inaccesibles en la actualidad. Sin embargo, estas prospecciones tuvieron lugar antes de la llegada de la tecnología GPS, por lo que su precisión espacial es a menudo incierta. Los tipos de errores de localización que se acumulan en este tipo de datos "heredados" son numerosos, por lo que su uso en análisis espaciales modernos basados en SIG es, con frecuencia, problemático. No obstante, muchas de las causas de estos errores pueden ser identificadas y cuantificadas y, tanto los errores sistemáticos como aleatorios (derivados principalmente del Cartesiano, el redondeo y los errores humanos), pueden ser mitigados en gran medida por medio del escaneo de los mapas de campo originales, su georrectificado a partir de imágenes de confianza, y la posterior digitalización de los sitios. Los restantes "errores de ubicación" tienen su origen en la dificultad a la hora de situar los puntos en el campo. Los diarios y anotaciones originales de las prospecciones pueden contener pistas sobre dichos errores de ubicación, pero resulta imposible mitigar su efecto sin volver a registrar las ubicaciones de los yacimientos con instrumentos más precisos. En su lugar, yo abogo por el uso de modelos basados en SIG para estimar la influencia de determinados métodos específicos de exploración en la precisión de la localización de los sitios. Estos modelos pueden proporcionar una medida estandarizada, cuantificable de los errores de ubicación en un conjunto de datos heredado, lo que puede ayudar a guiar su uso en los análisis modernos de SIG, que requieren ubicaciones exactas de los yacimientos.

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The ability to locate a site in the field easily, accurately, and precisely is taken for granted in modern archaeological survey. Global Positioning System (GPS) site location data allow for high-resolution spatial analyses with Geographic Information System (GIS) software, enabling research on settlement patterns, predictive modeling, and human interaction with (and through) the environment (e.g., Barton et al. 2010; Llobera 2003; Ullah 2011; White and Surface-Evans 2012). However, these analyses require that site location data be *accurate* and reasonably *precise* in order to produce meaningful results. It is important to note that accuracy and precision are not the same thing. The accuracy of a site location measurement is the degree to which recorded coordinates *actually match* the location of the surveyor when they were recorded (Goodchild 1993; Goodchild and Gopal 1989). The precision of a site location measurement is the *range of error* induced from the method of recording site coordinates (Goodchild 1993). It is important to note that a survey dataset can contain individually imprecise site locations, but still be quite accurate on the whole, and vice versa.

There is a large body of knowledge about the effects of error in certain types of base GIS data used in archaeological research, such as rasterized elevation models (Goodchild and Gopal 1989; Stanislawski et al. 1996) or categorical types of vectorized data (Goodchild et al. 1992). Also well-studied are the effects of algorithmic error in specific GIS procedures used by archaeologists, such as viewshed analysis (Maloy and Dean 2001) or vector buffer-generation (Shi et al. 2003). There is not, however, a comprehensive treatment of the propagation of error from the way the spatial record of archaeological survey data is collected. However, Ullah and Bergin (2012) have shown that small differences in site location can lead to widely different outcomes in least-cost path analyses in a GIS. The same is likely true of visibility analyses, site catchment analysis, and a host of other GIS-based analyses commonly used by archaeologists (see Wheatley and Gillings 2002).

The availability of highly accurate GPS coordinates for archaeological sites is a recent phenomenon. Although the United States (U.S.) government opened up the military's "Navstar-GPS" system to civilian use in 1993, it intentionally scrambled that GPS signal until May 2, 2000 (Bray 2014; Theiss et al. 2005).[1] Prior to this date, site coordinates were recorded in the field from topographic maps and aerial photographs. Their accuracy was subject to the abilities of field surveyors to visually correlate landmarks between the real world and their representations on these media.[2] Doing so, however, is a non-automated mental operation that involves the use of basic surveying tools and a knowledge of geometry, as well as intuition and experience (Golledge 1999). It combines mathematical measurement with the experience of being in a landscape, and site locations recorded in this manner are products of this convolution. Despite the (not insignificant) level of technical expertise possessed by early archaeological surveyors, site coordinates recorded in the pre-GPS era are subject to a host of errors beyond their control. Complicating matters further, older, inherited datasets are typically manipulated, reorganized, and transformed by every archaeologist who uses them. As the datasets pass through generations of archaeologists, knowledge of previous manipulation can be lost—especially after they are (digitally) archived. Thus, in the form that they are typically inherited, legacy spatial datasets can be unreliable for use in research requiring accurate spatial information.

It may be tempting to simply write off legacy datasets, but in many cases older surveys may contain the only existing record for sites that have since been destroyed or obscured by subsequent human or natural disturbance (Holtorf 2001; Witcher 2008). Or, due to political or environmental conditions, it may now be impossible or impractical to revisit the survey region to re-record site locations with modern techniques (e.g., Galaty and Watkinson 2004; Stone and Zimansky 1992). Even if a revisit is possible, budgetary constraints might restrict the amount of re-recording that can be accomplished. Thus, we may have no other choice *but* to use legacy datasets in many parts of the world.

The purpose of this paper is to discuss how error was introduced into spatial records from pre-GPS archaeological survey, to discuss methods of correcting some of these errors, and to introduce a method for modeling the amount of error that may remain in the corrected data. The procedures laid out herein are designed to bring legacy survey data into modern GIS-based spatial research to the fullest extent possible, while remaining explicitly mindful of their limitations. I focus on pedestrian surveys and less obtrusive sites, mainly from the prehistoric periods. I do not discuss issues of survey goals, sampling methodology, biases in identification of certain types of sites, or survey methodology unrelated to the gathering of site coordinates, as these issues have been dealt with elsewhere (e.g., Athanassopoulos and Wandsnider 2004; Banning 1996; Rosen 1992; Wilkinson 2004; Witcher 2008). Issues of data-mining or integrating the non-spatial portions of legacy data are likewise dealt with by other authors (e.g., Atici et al. 2013; Witcher 2008). Finally, although I do not focus on the curation of legacy datasets in online or other digital repositories, there are several projects that are actively doing so, such as the Comparative Archaeology Database (Drennan et al. 2014), Open Context (Kansa 2010), the Digital Archaeological Record (Kintigh 2006), and the Digital Index of North American Archaeology (Wells et al. 2014), among others.

Legacy Survey Data from Central Jordan

Throughout the paper, I will reference several "legacy" survey datasets from central Jordan, including the Archaeological

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Survey of the Kerak Plateau (ASKP) (Miller 1991), the Southern Ghors and Northeast Arabah Survey (SGNAS) (MacDonald and Amr 1992; MacDonald et al. 1988), the Tafila-Busayra Archaeological Survey (TBAS) (MacDonald et al. 2000; MacDonald et al. 2004; MacDonald et al. 2001),[3] the Archaeological Survey of Central Moab (ASCM) (Miller 1979), and the Southeastern Expedition to the Dead Sea Plain (SEEDSP) (Rast et al. 1980; Rast and Schaub 1981; Schaub and Rast 1984) (Figure 1). I pay particular attention to survey data from the Wadi al-Hasa in central Jordan (Figure 2), which I use as a more detailed case study to exemplify the proposed methodology. Wadi al-Hasa is an excellent example because it was intensively surveyed in the pre-GPS era by two separate teams, and the data has been used by several subsequent researchers. The first intensive pedestrian surveys in Wadi al-Hasa were carried out by a team of archaeologists in the Wadi el Hasa Archaeological Survey (WHS) led by Burton MacDonald in the 1978, 1981, and 1982 field seasons (MacDonald 1982, 1988; MacDonald et al. 1980), which covered much of the southern bank of the Wadi and associated uplands. Further survey was carried out by Geoffrey A. Clark and colleagues on the northern bank of the Wadi during the Wadi Hasa North Bank Survey (WHNBS) in 1992 and 1993 (Clark et al. 1992; Clark et al. 1994), as part of the larger Wadi Hasa Paleolithic Project. Many of the publications related to these projects were gathered together into a two-volume set by Nancy Coinman (Coinman 1998; Coinman 2000), and the data have been used by several subsequent researchers (e.g., Arıkan 2009, 2012; Hill 2002, 2004, 2006; Olszewski and Coinman 1998; Schuldenrein and Clark 1994, 2003). In fact, this paper was in part inspired by difficulties I encountered during my own fieldwork in Wadi al-Hasa, where I attempted to relocate several potential Neolithic sites located by the earlier surveys during the Wadi al-Hasa Ancient Pastoralism Project (WHAPP) (Ullah et al. 2008).

I planned the 2008 pilot season of the WHAPP using a digital database of the WHS and WHNBS survey data that I had inherited through connections at Arizona State University (ASU). The database had been originally compiled by J. Brett Hill for his own dissertation work (Hill 2002). Hill had painstakingly digitized all of information from the original site forms of the two surveys, including site type, likely time periods of occupation, landscape features, notes on artifact collection, and general notes about the site and its location. Importantly, the database included site coordinates in the Universal Transverse Mercator (UTM) Coordinate Reference System (CRS), which, I believed, would make it easy to relocate sites with a hand-held GPS unit.

The goal of the WHAPP survey was to better understand the pastoralist-landscape interactions east of the Jordan Rift during the Neolithic and Chalcolithic periods using high-resolution GIS analysis and Agent-Based modeling. The research plan of the WHAPP required integrating the existing survey data from Wadi al-Hasa with new survey to be conducted in the desert east of the Hasa drainage. In the summer of 2008, I undertook a short, two-week pilot season focused on relocation and reinvestigation of 16 of the previously discovered potential Neolithic pastoralist sites. I exported the UTM coordinates for these 16 sites from the database into a consumer-grade GPS unit (a Garmin eTrex Summit®), which I brought into the field. Expecting some degree of inaccuracy in the coordinates, I also brought the survey notes and high-resolution satellite imagery into the field. Despite these preparations, I was able to "relocate" only eight sites in two weeks of intensive fieldwork. Later analysis would show that, in reality, only *one* of those eight sites was actually a site from my list. Of the remainder, five were other sites identified by the WHS or WHNBS, and two were previously unknown. The issue was four-fold: (1) the coordinates from the database were clearly inaccurate; (2) I did not know the amount of error to expect prior to entering in the field; (3) the topography of some parts of the region is fairly uniform, making landmark reference difficult; and (4) the density of sites in some parts of the region made it very difficult to know that a *specific* site had been (re)located.

The difficulties experienced during the pilot season made it clear that a primary preliminary goal of the WHAPP must be to assess the accuracy of the inherited spatial dataset for the region, apply any possible corrections to this data, and ascertain the degree to which even the corrected data could be used for high-resolution research. The spatial record of the Wadi al-Hasa surveys are therefore good case studies with which to exemplify the best practices of addressing spatial error in any legacy dataset. The original spatial records of these surveys are available from the data portal for the Middle Eastern Geodatabase for Antiquities (MEGA), Jordan (Getty Conservation Institute 2015).

THE PROCESS OF PRE-GPS COORDINATE GATHERING

Determining a discovered site's geographic coordinates in the pre-GPS era was a non-automated, manual, and mental process that relied on the accuracy of the surveyor's measurements, the quality of the available maps and imagery, and the surveyor's ability to read and interpret the maps and imagery (Golledge 1999). Thus the process was both quantitative and qualitative at the same time, which exposed it to multiple sources of error.

Quantitative measurements were collected with manual methods of varying accuracy and precision. Typically, a coordinate fix was achieved by triangulating the bearings to two or more distant landmarks through a handheld transit or sighting compass. The bearings were subject to sighting error and magnetic anomalies, which introduce typical errors of about .5 to 3 compass degrees (Lovallo et al. 1994). More accurate tripod-mounted transit theodolites or an alidade and plane table were sometimes used for triangulation during pedestrian survey, but these were more often used only during limited "high intensity" surveys in the vicinity of long-term excavation projects. For example, the SEEDSP used a theodolite to map sites in the vicinity of the major sites of Bab edh-Drah, Numeira, and es-Safi (Schaub, personal communication 2014). Single bearing and distance measurements from one landmark or previously identified site were used when not enough triangulation points were available. Distance measurements introduced still more error, as they were typically measured by counting paces, with survey chains or long tape measures, or via rod-height triangulation (Compton 1985).

Surveyors were aware of the limited accuracy of typical field measurement techniques, and coordinate fixing was aided through qualitative correlations between the surveyor's senses (e.g., their view of the local topography and landcover) and the representation of features on maps or remotely sensed images (Meilinger et al. 2007; Ottosson 1988). In other words, contour

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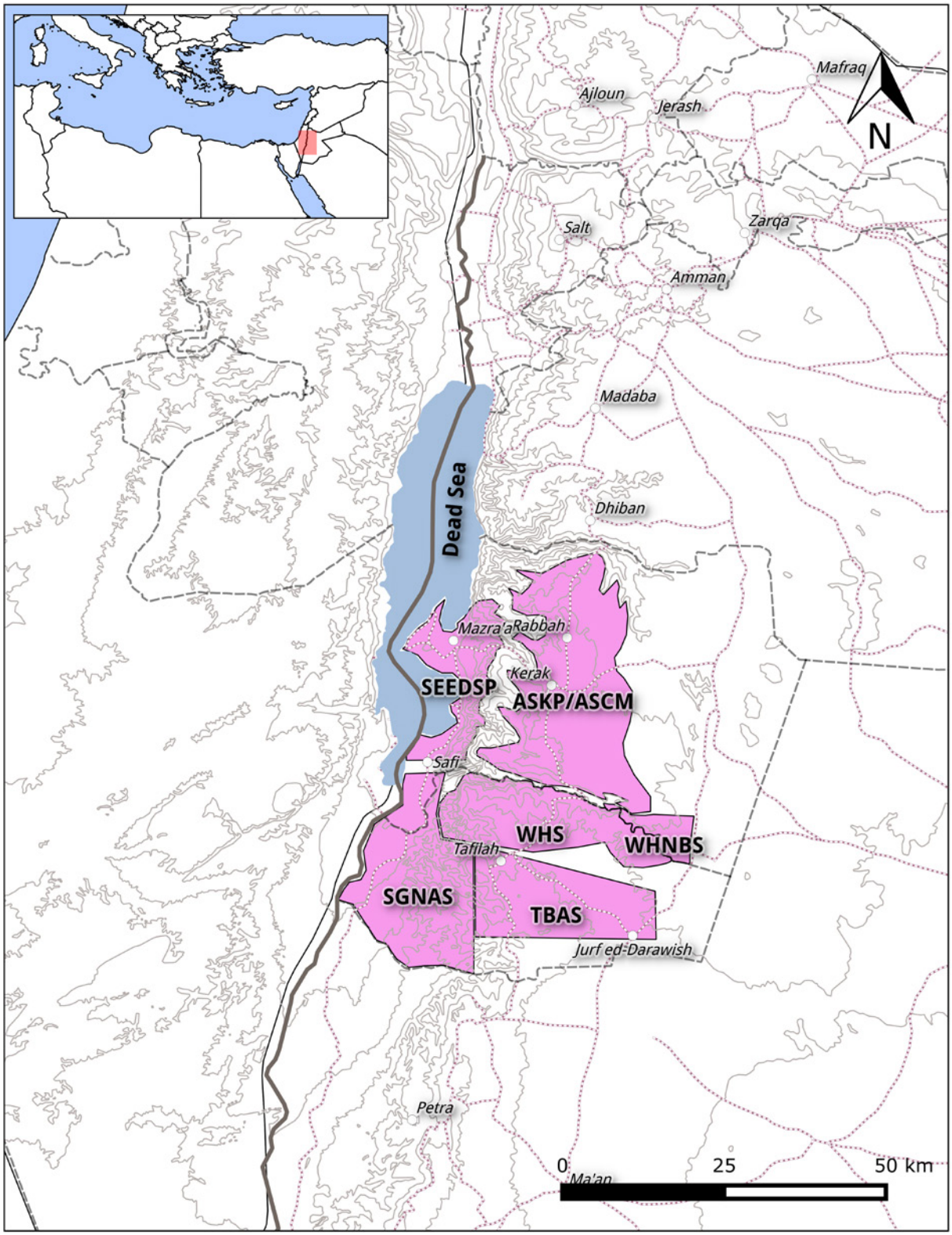


FIGURE 1. Map of central Jordan, showing the approximate boundaries of several archaeological survey projects conducted in the pre-GPS era. SEEDSP = Southeast Expedition to the Dead Sea Plain, ASKP/ASCM = Archaeological Survey of the Kerak Plateau/Archaeological Survey of Central Moab, WHS = Wadi Hasa Survey, WHNBS = Wadi Hasa North Bank Survey, SGNAS = Southern Gohrs and Northern Arabah Survey, TBAS = Tafileh-Busayra Survey. See text for citations about these projects. Inset shows location of larger map.

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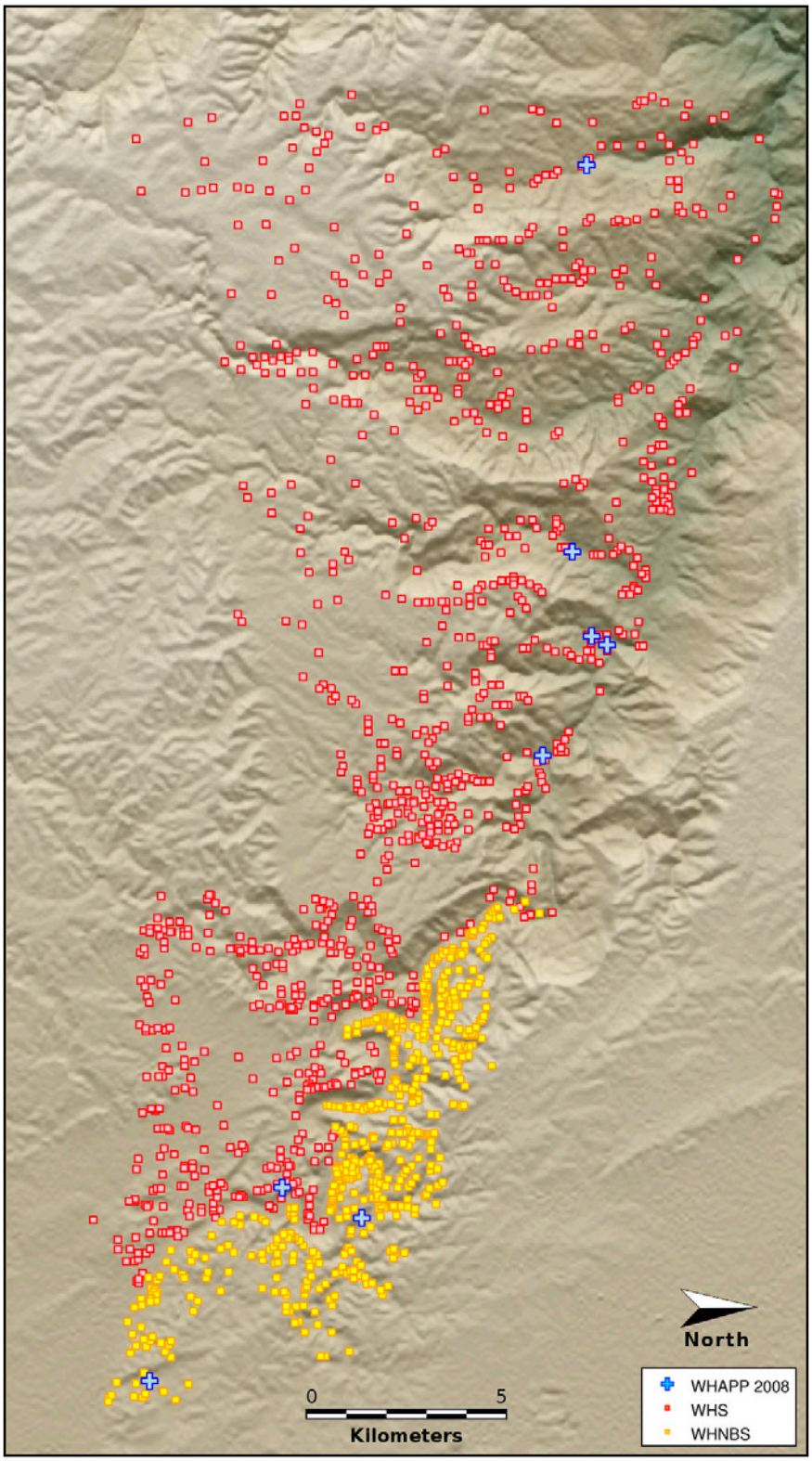


FIGURE 2. Map of the Wadi al-Hasa region, showing sites discovered during the Wadi Hasa Survey (WHS), Wadi Hasa North Bank Survey (WHNBS), and the Wadi Hasa Ancient Pastoralism Project (WHAPP).

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lines, map symbols, place names, or shades of gray had to be intuited into real landscape features using mental models, and these models then had to be translated to a surveyor's visual perception of the environment via pattern matching (Blades and Spencer 1987, 1990; Ottosson 1988). These models—such as the "rule of V's" (Miller and Westerback 1989), estimations of slope from contour densities, recognition of the distinctiveness of local landscape features such as peaks (localized topographic high points), spurs (sloping ridges extending orthogonally from the main topographic trend), and saddles (the topographic low between two adjoining peaks), and interpretation of shadows and textures on imagery—were individually cultivated through pedagogic and actual-use experience and so often varied considerably in their application between researchers (Chang et al. 1985; Gilhooly et al. 1988; Hegarty et al. 2006; Ishikawa and Kastens 2005; Ishikawa and Montello 2006; Kozlowski and Bryant 1977; Liben and Downs 1993; Pick Jr. and Thompson 1991;Thorndyke and Stasz 1993). Both quantitative and qualitative locational information were influenced by the experience of walking in a landscape (Thorndyke and Hayes-Roth 1982). Factors such as the amount of landscape visible from a particular location, the experienced changes in scale of various landscape features during a traverse, changes in lighting conditions throughout the day, vegetation, weather conditions, or even fatigue from walking uphill can all affect or influence a survey measurement or the mental processes of pattern matching (Ishikawa and Montello 2006; Meilinger et al. 2007). Although their *application* would differ from surveyor to surveyor, such qualitative survey assessments would still be conducted using similar *cognitive processes*, which, importantly, are modelable (Hegarty et al. 2006; Ishikawa and Montello 2006; Thorndyke and Stasz 1980). This is important because it offers a way to use quantifiable data (maps, map symbols, landscape features) to understand error associated with different cognitive mapping processes. If such models are encoded in a set of GIS procedures, they can produce standardized outputs that can be compared against each other to assess the relative magnitude of error that might derive from a particular cognitive mapping process for different sites in a landscape.

A final aspect of non-digital site-location recording was the recording of coordinates in a particular CRS (e.g., Latitude/Longitude or UTM) in a site record or site-location log. Once a location was plotted on a map, coordinates were read from CRS markings on the margins of the map, typically using handheld rules to line up site points with CRS grid markings (Compton 1985). This was often complicated by (1) torn, clipped, or otherwise modified field maps; (2) maps with text and numbers written in alphabets foreign to the survey team; (3) use of unfamiliar or highly localized CRS and units of measurement; and (4) projection and/or alignment issues between different map series. Surveyors knew this was an imprecise, inconsistent technique, and so they often rounded coordinates in an effort to provide a minimum of consistency between measurements. While this technically increased the *average* accuracy of the site coordinate database, it did so at the expense of its precision, and the potential accuracy of the individual measurements. Because of this, unless sites were very large or obtrusive, surveyors often recorded only the estimated center point of the site, together with an approximation of the site size. Finally, after the fieldwork was completed (and often many years later), paper records had to be converted to digital. This is most typically achieved by manual data entry, which can lead to considerable error due to typos, transpositions, or misreadings of coordinates.

This discussion makes clear that there are many potential sources of error in the spatial record of legacy survey data. Some of this error is relatively easy to identify and can be corrected through basic data-cleaning protocols. The error that remains can be modeled so that we can understand how it may propagate into spatial analyses of the legacy data. To achieve these things, however, we need to understand how particular errors enter into the data.

CORRECTABLE ERRORS

Sources of Correctable Errors

There are two types of errors that are generally correctable if the original paper survey records and metadata are still available. The first of these are *systematic mapping errors*, which derive from phenomena that affect coordinates in a regular way. Common sources of systematic mapping errors include shifted coordinate reference systems in base maps, errors introduced by rounding the coordinates, and errors in subsequent reprojection of the coordinates. These errors can be common if base maps in a region are in a highly localized coordinate system (e.g., the Palestine Grid of the Southern Levant), if base maps are themselves shifted, if the wrong geographic datum was used in reprojection, or if the scale of base maps is too coarse.

The second type of correctable errors are *random recording errors*, which generally derive from human errors introduced during the reading of site coordinates from survey maps into site records or during manual data entry of coordinates into electronic databases. Random recording errors can derive from rules held nonparallel to the coordinate grid, misreads of coordinates on map margins, errors in communication between readers and recorders, transposition (e.g., of "easting" with "northing"), dyslexia, and typographical errors in the data entered into electronic formats. Random recording errors will generally be found in any pre-GPS survey dataset, but could be particularly pervasive if (1) numbers are written in numeral systems unfamiliar to surveyors (e.g., in the Near East, maps often use Eastern Arabic numerals); (2) if field teams are multi-lingual; (3) if reading and recording of coordinates from maps were conducted by multiple fieldworkers (i.e., many different people were involved in the collection of the coordinates); (4) if the maps contained markings for more than one CRS; or (5) if the base map scale is too large for the project area., thereby making it more difficult to read the coordinates correctly.

Mitigating Correctable Errors

Mitigation of the potentially correctable errors is dependent on the availability of the original survey records and ancillary information about the survey team and methodology. This is important because much of this information is never published. Methods sections are often very brief and generalized. For example, authors will describe the sampling frame of the survey, but not the mapping techniques. This is compounded by the fact that many publications, at best, only perfunctorily address sources or potential magnitude of error in the data. For example, sometimes references to the source of base maps or

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aerial photographs are not published, as was the case with the ASKP and SEEDSP projects, which did not publish map references. The WHS, WHNBS, SGNAS, TBAS, and ASCM, however, did publish this important information. In another example, it was common practice for archaeological surveyors to round site coordinates to the nearest 10 or 100 m, but this fact was very rarely reported in survey publications. For example, among our case studies, ASKP reported that they rounded their coordinates, but WHNBS, WHS, SGNAS, TBAS, ASCM, and SEEDSP did not report whether rounding occurred.

Much of this information can be learned or inferred from what Witcher (2008) calls the "metadata" of the survey—the unpublished notes, records, and memories of surveyors. However, legacy datasets have typically been manipulated by perhaps several generations of researchers, and may be inherited without this metadata. For example, subsequent reprojection of coordinates that were initially recorded as rounded values would mask the fact that they were rounded. Quite typically, legacy datasets are inherited in a form that seems accurate (e.g., as an electronic database with precise-looking coordinates), and locational errors become apparent only after site coordinates are compared to more accurate spatial data (e.g., well-rectified high-resolution imagery, GPS-gathered site location data, etc.).

As an example of this, prior examination of the preliminary survey reports of the WHS and WHNBS (Clark et al. 1992, Clark et al. 1994; MacDonald 1988; MacDonald et al. 1980) had not made clear to me that the surveyors had originally recorded all coordinates in the Palestine Grid (PalGrid) CRS, which is a localized CRS commonly used on mid-twentieth-century maps of the region. The coordinates had clearly been reprojected to the UTM CRS that I had used while planning the WHAPP. I discovered this only after I obtained the copies of the original survey forms and maps, which were curated at ASU in the personal archive of Geoff Clark. Once I obtained these records, the scope of the potential source of errors became clear. The maps were composed of several smaller quads that had been physically cut and taped together and so were missing a significant amount of marginalia such as coordinate markings and map reference information. Some of the maps were in English, and some were in Arabic, including the numerical notation system (Eastern Arabic numerals). Most of the quads had both Latitude/Longitude and PalGrid CRS lines. However, without the marginalia, it was difficult to discern them. Complicating things further, it was also clear that the WHS quads were of a different map series than the WHNBS maps. In the WHS survey report (MacDonald 1988; MacDonald et al. 1980), MacDonald cites the use of the 1:25,000 scale maps prepared by the Ministry of Economy and U.S.A. Operations Mission to Jordan (1955) from 1953 stereo aerial imagery for all but the extreme western edge of the survey region, for which he used the 1:50,000 scale Series K737 maps from the United States Army Map Service (1961). In the WHNBS survey report (Clark et al. 1992; Clark et al. 1994), Clark cites the 1989-series 1:25,000 scale maps prepared by the Royal Geographical Society of Jordan (1989). Discussions with some of the original survey team members and examination of the original survey paper records also made it clear that different recording strategies were employed in the two surveys. A key piece of information that emerged from this investigation was that the surveyors rounded coordinates, greatly reducing their precision and, often, their accuracy.

In the case study example above, going back to the original survey records made it clear that significant amounts of locational errors had been introduced between the time of the original location fixing on field maps and the encoding of the digital database I had inherited. Thus, the first course of action that should be taken to mitigate correctable error is to obtain as many primary sources of information as possible, including all available preliminary reports, original survey records and maps, and, if possible, personal communication with members of the original survey team. Because correctable errors enter into the data during reading or transcription of site coordinates from CRS markings on field maps, it is particularly important to obtain the original maps used during survey.[4] These errors can be *fully mitigated* by digitizing site coordinates directly from a georectified scan of the original field map. I should stress, however, that the scanned maps should *not* be rectified using the CRS reference marks or grids of the maps themselves, given that the CRS markings themselves may be a significant source of error because the CRS grid may be flawed, warped, or misaligned. Maps should therefore be rectified to high-resolution imagery or topographic data via feature matching, using landmarks that are not likely to have moved in the intervening time between the creation of the map and the referencing dataset (e.g., avoid using highly active stream channels or ephemeral trails as landmarks).

To illustrate the types and numbers of correctable spatial errors that may typically be expected in uncorrected legacy survey data, I have made available a spatially corrected set of the WHS/WHNBS survey data in an online repository (Ullah 2015a). This new data set was made by extracting corrected coordinates for the WHS and WHNBS sites following the methodology laid out above. I scanned and georectified all of the original survey maps to LandSat imagery (United States Geological Survey [USGS] 2003). With the help of two work-study students, all of the sites marked on the maps were digitized. The students kept notes on potential misreads and other sources of error in the digitization process. Figures 3a and 4a show example portions of the rectified WHS and WHNBS survey maps, respectively, with newly digitized site points compared to the points from the inherited database. To understand the nature of these correctable errors in each dataset, I undertook a directional analysis of the offset between the original and corrected points. Directional analysis of the WHS data (Figure 3b) shows little consistency between sites, indicating a dominance of random recording errors in the original database. A slight preferential offset to the north and northeast indicates that some systematic mapping errors were also present. The WHNBS dataset, however, shows a very consistent eastward offset (Figure 4b), indicating that systematic errors were most prevalent in the original database. I also undertook an analysis of the offset distances, which also showed differences between the two surveys (Figures 3c and 4c). The offsets were consistently larger in the WHS data, indicating that coordinates were likely rounded to fewer significant digits in the WHS (e.g., the nearest 100 m), whereas the WHNBS team either attempted not to round the data or rounded only to the nearest 10 m.

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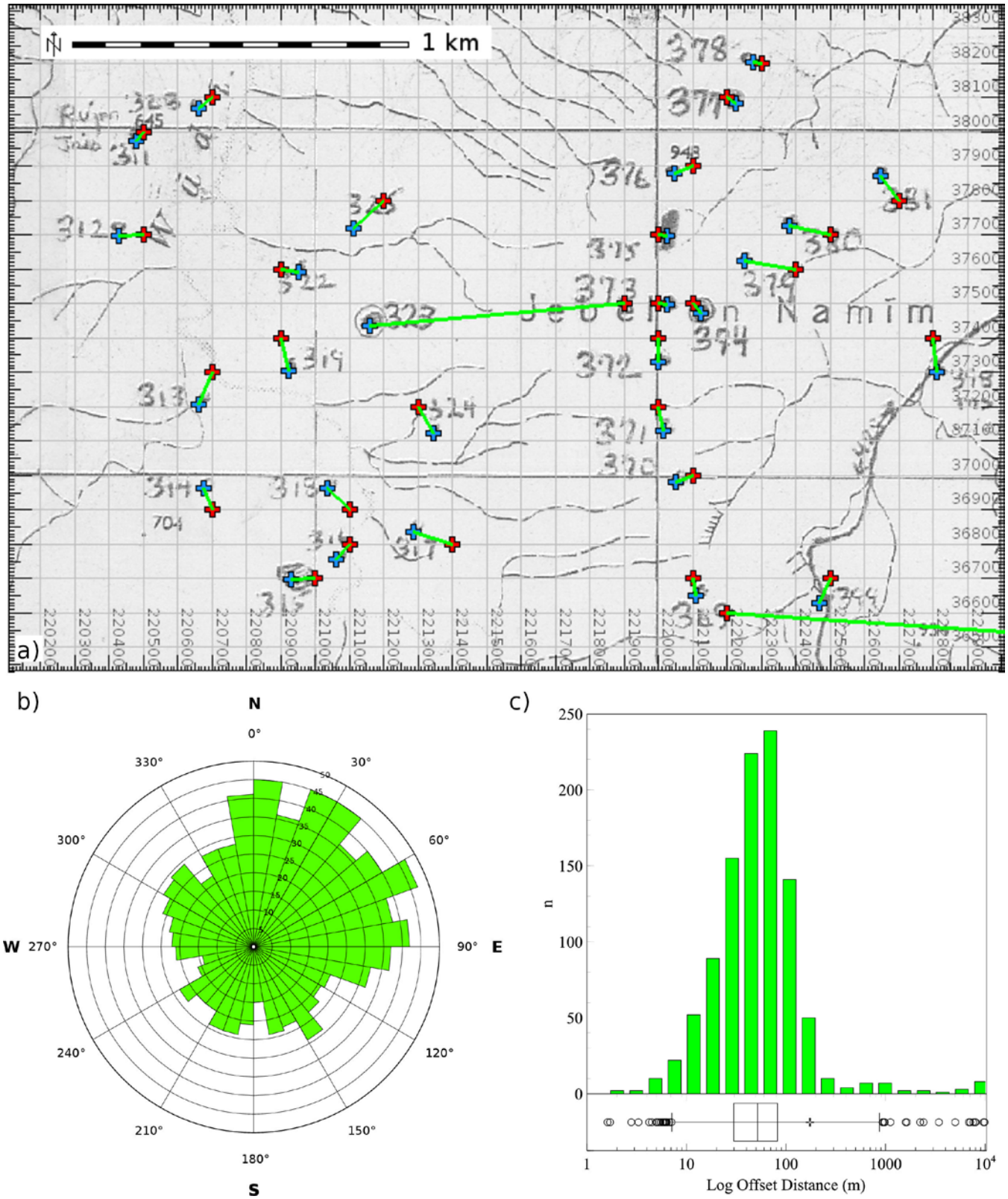


FIGURE 3. Analysis of offset between the original site locations in the WHS database and the site locations newly digitized from the original field map: (a) a portion of the scanned field map, showing the offset (green lines) between database points (red) and the newly digitized points (blue); (b) a rose diagram showing the frequency of different angles of offset between the two sets of points; (c) a histogram showing the frequency of different distances of offset between the two sets of points.

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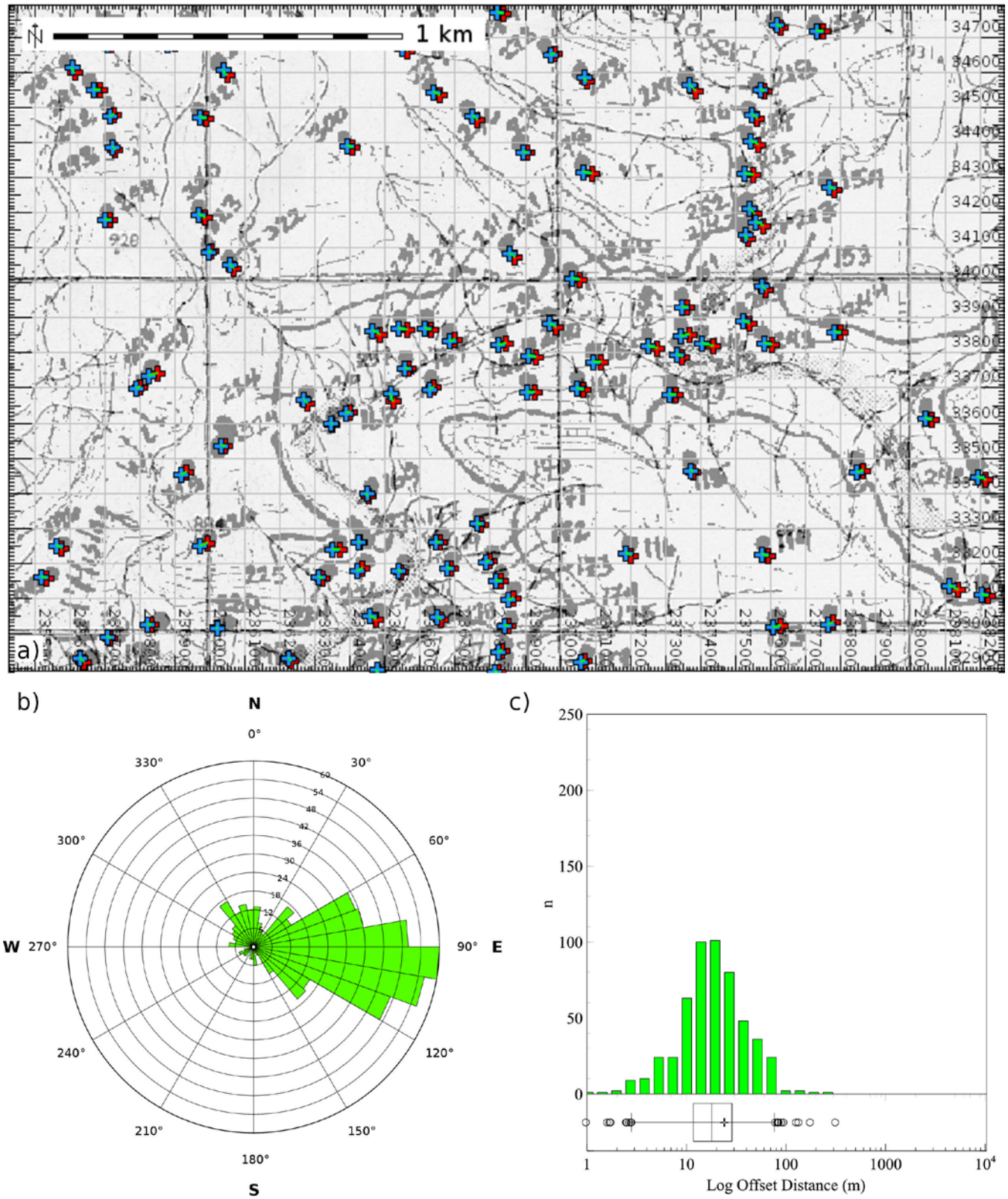


FIGURE 4. Analysis of offset between the original site locations in the WHNBS database and the site locations newly digitized from the original field map: (a) a portion of the scanned field map, showing the offset (green lines) between database points (red) and the newly digitized points (blue); (b) a rose diagram showing the frequency of different angles of offset between the two sets of points; (c) a histogram showing the frequency of different distances of offset between the two sets of points.

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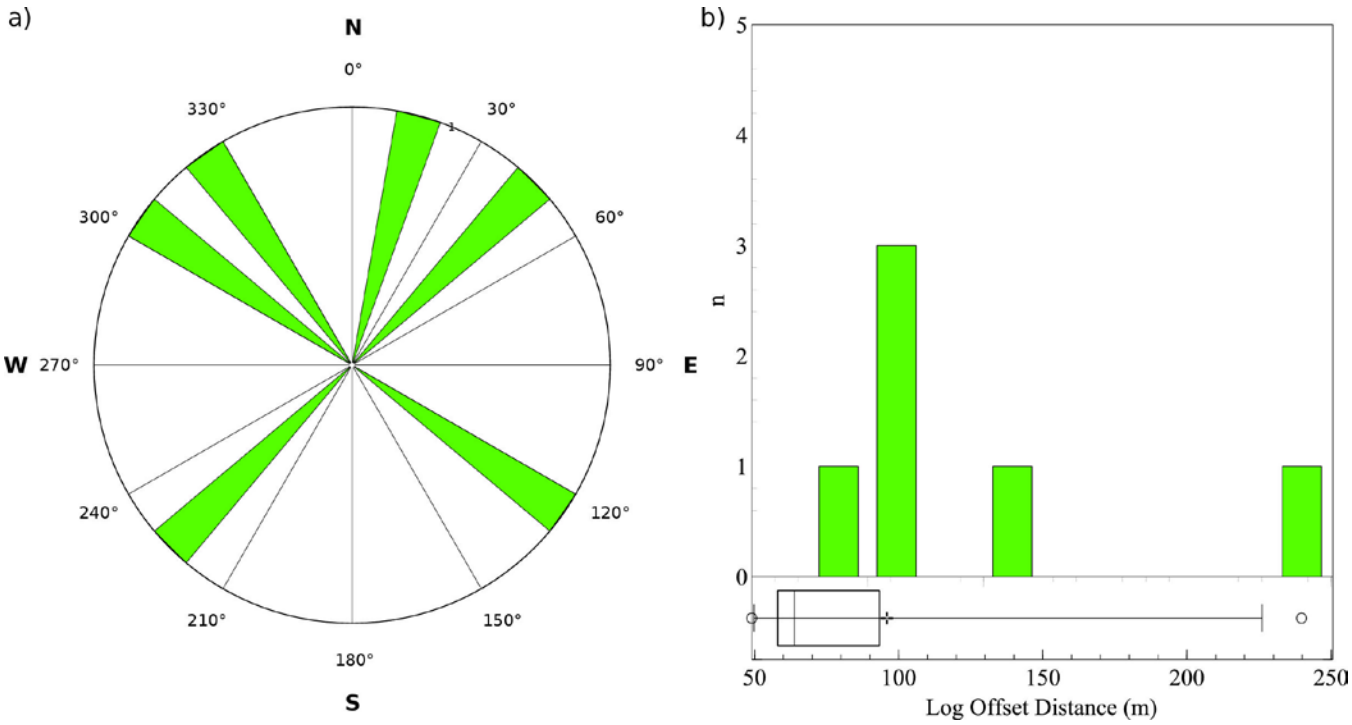


FIGURE 5. Analysis of offset between the GPS coordinates of six WHAPP sites and their coordinates as digitized from the original field map: (a) a rose diagram showing the frequency of different angles of offset between the two sets of points; (b) a histogram showing the frequency of different distances of offset between the two sets of points.

INHERENT ERRORS

Once the correctable errors are removed, the spatial record of the legacy survey dataset will be as accurate as it possibly can be. However, there may still remain significant locational errors that cannot be corrected because they are inherent to the data itself. These errors will propagate through any spatial analyses, and so must be understood and reported.

Sources of Inherent Errors

Inherent errors are the errors that remain after systematic mapping errors and random recording errors are corrected, and they enter into the data during the process of fixing a location to plot on a map or imagery. This can occur as *mismeasurement* with survey tools. Mismeasurement can derive from survey devices if they are inherently low precision (e.g., hand-held transits) or low accuracy (e.g., pacing) tools, or if they are improperly calibrated (e.g., an incorrect declination setting on a compass). They can also derive from misuse of the tools (e.g., improper orientation of compass to map) or other human error (e.g., reading bearings incorrectly). Inherent errors also stem from *landform misidentification*, which is an incorrect correlation between a real landform and a pattern map or image. Misidentification is more likely to occur when local topography is indistinct, highly repetitive, or uniform and when few distant landmarks are visible. This is exacerbated by unclear or distorted maps or images, or when the map scale is too large to show distinctive landscape features. The likelihood of a misidentification is also increased if vegetative cover obscures the view of the surrounding landscape, or if a surveyor is fatigued or inexperienced in reading topographic maps or interpreting imagery. Importantly, these factors may also increase the potential for human errors of mismeasurement as well.

The inherent spatial error of a legacy survey dataset can be directly measured only in comparison to a more accurate control dataset (e.g., GPS waypoints). This is a problem, however, as researchers are often using a legacy dataset precisely *because* they cannot obtain newer, more accurate spatial records for a study area. Even in the case where it is possible for a researcher to gather a set of comparative GPS locations, that sample may be too small or may be spatially or temporally biased. For example, the comparative GPS sample gathered during the WHAPP provides only six locations with which to assess the spatial error that remains in the combined sample of over 1,500 WHS and WHNBS sites after digitization. Analysis of the angular and distance offset between the GPS coordinates and the digitized map locations of the six WHAPP sites shows no consistency (Figure 5), but the sample is too small (and biased towards Neolithic sites) to represent the range locational errors that may remain. This is likely to be true for most legacy survey datasets, so it is important to find alternative methods of estimating or modeling the amount of locational errors remaining in the dataset.

Modeling Inherent Error in Legacy Datasets

A general qualitative estimation of the inherent error in the dataset may be obtained through an assessment of those aspects of the survey metadata relating to surveying conditions—especially any information about survey conditions, surveyor mentality and

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experience, and surveyor familiarity with the landscape. This type of general information about the survey can help provide an overview of the general reliability of locations recorded by the survey project, but does little to help differentiate the amount of spatial error contained in any specific coordinate gathered by the survey team. Conscientious surveyors recorded possible mislocation errors in their unpublished field notes. Classification of descriptive phrases from these notes (e.g., "This site is a small lithic scatter on a large flat terrace") might be used to generate a qualitative typology of mislocation error. The typology could, for example, qualify such characteristics as vagueness of landform identification or obtrusiveness of the site according to a categorical scale. These categorical scores could be combined with quantitative data from the survey notes, such as site size, or number of referenced landmarks, to come up with a general estimation of site location "reliability." Often, however, these types of survey data and metadata are incomplete, were never recorded, or are no longer helpful. For example, many of the notes included with the WHS were referenced to other sites found during the survey (e.g., "This site is 100 m east of site 421"), and so are useful only if the real location of the referenced site is known. Moreover, in very large datasets, such as with the over 1500 combined WHS/WHNBS sites, the effort of manually coding these types of indices may not be commensurate to the information gained. At the very least, however, a general read of the survey metadata and unpublished notes provides a gestalt understanding of the types of error that might remain.

A more efficient, standardizable way to assess inherent errors is to use external models derived from theory about human way-finding, mental processes of orientation in landscapes, and map-reading. This theory is discussed in the "Process of Pre-GPS Coordinate Gathering" section, above. I advocate that models of these processes be encoded as a series of GIS procedures to assess mislocation error in a systematized and largely automated manner. By using GIS tools to quantify theory-derived expectations of how the sources and amplitudes of mislocation error change over space, expectations about the effect of this kind of error are encoded as a series of digital maps, which can be combined and inter-compared. This provides a spatially explicit "reliability index" for all parts of a survey area, and these values, uploaded to the site database, provide a standardized estimate of the relative reliability of recorded site locations. Similar methods have been used to understand the error in other types of GIS data (e.g., Hunter and Goodchild 1995).

To operationalize this method, we need to create abstract, simplified, digital representations of the mental models surveyors used to locate sites and the actual experience of surveying. Here, I present GIS workflows to model four different aspects of the pre-GPS survey experience. Necessarily, these GIS models cannot depict the entire experience of surveying, but they nevertheless provide a standardized approximation of the effect of particular types of mislocation errors. In the spirit of the open data movement that champions the creative reuse of extant archaeological data (Beale 2012; Beck and Neylon 2012; Kansa 2012; Morgan and Eve 2012), I have elected to create these models with the free and open-source GRASS GIS suite (GRASS Development Team 2015). Using open software like GRASS allows the methodology to be more completely tailored (i.e., from the source code up), promotes intellectual equality by removing financial obstacles, allows full transparency, and encourages critique and enhancement of the methods and tools (Ducke 2012). I deploy the four models in the context of the Wadi al-Hasa case study by using the freely available, void-filled, 90-m resolution topographic data for the Wadi al-Hasa region from the Shuttle Radar Topography Mission (SRTM) (USGS 2012) to show example results. The horizontal resolution of the data was interpolated in GRASS to 15 m via regularized spline-tension interpolation (Mitasova and Hofierka 1993; Mitasova and Mitas 1993) before subsequent analysis.

The first workflow models the way surveyors interpret the *spacing* of contour lines on the original survey map. The density of contour lines on topographic maps depicts the steepness of the earth's surface; the more dense the spacing of contour lines, the steeper the actual topography should be. The model approximates a portion of the implicit mental filtering process at work when a surveyor looks to match contour lines on a map to actual topography of a landform (Gilhooly et al. 1988). Specifically, the model assumes that denser contour lines relate to more easily identifiable landforms, because more morphological information is available to the surveyor. This allows them to more confidently identify a particular point on a particular landform. In other words, the model predicts that a point on very steep or rugged topography is easier to accurately identify on a map than is a point on flat topography. The model is operationalized by extracting vector contour lines from elevation data (e.g., the SRTM elevation raster for the Wadi al-Hasa region) at the same interval as the original survey map (e.g., 10 m) using the GRASS module *r.contour*. Points are sampled evenly along the contour lines using the GRASS module *r.to.points*. The points are then used to create a kernel density map with the *v.kernel* tool. This creates a digital map that quantifies the relative density of contours on the original survey map (Figure 6a).

The second workflow models the way surveyors orient themselves to landmarks when obtaining quantitative location fixes for places on the landscape. This is operationalized though cumulative viewshed analysis (CVA), which produces a map of inter-visibility between many viewpoints and all the other pixels on a map (Lake et al. 1998; Llobera 2003; O'Sullivan and Turner 2001; Tabik et al. 2013; Wheatley 1995). When applied to archaeological sites as the originating viewpoints, CVA is useful for modeling how ancient people may have understood and used a landscape. This workflow, however, uses CVA in a different application. During survey, sites locations are triangulated using a small number of distinct landmarks (e.g., local topographic peaks). CVA can be used to model the inter-visibility between these landmarks and all other points on the landscape, which provides an estimation of the surveyor's ability to triangulate a position at all points on the landscape. To operationalize this, points are digitized for all peaks marked on the original survey map. These points, and the rasterized topography (e.g., SRTM data), are used as input for a CVA using a custom GRASS add-on module called *r.viewshed.cva*. I created the *r.viewshed.cva* module with a structure that facilitates this type of analysis, and it can be freely downloaded from the GRASS add-on repository (Ullah 2015b). The module calculates individual viewsheds for each input point (e.g., peak), and then cross-tabulates each viewshed so that the resultant map encodes the number of peaks that can be seen from each pixel (Figure 6b). Areas with few visible landmarks would be harder to triangulate on a topographic map.

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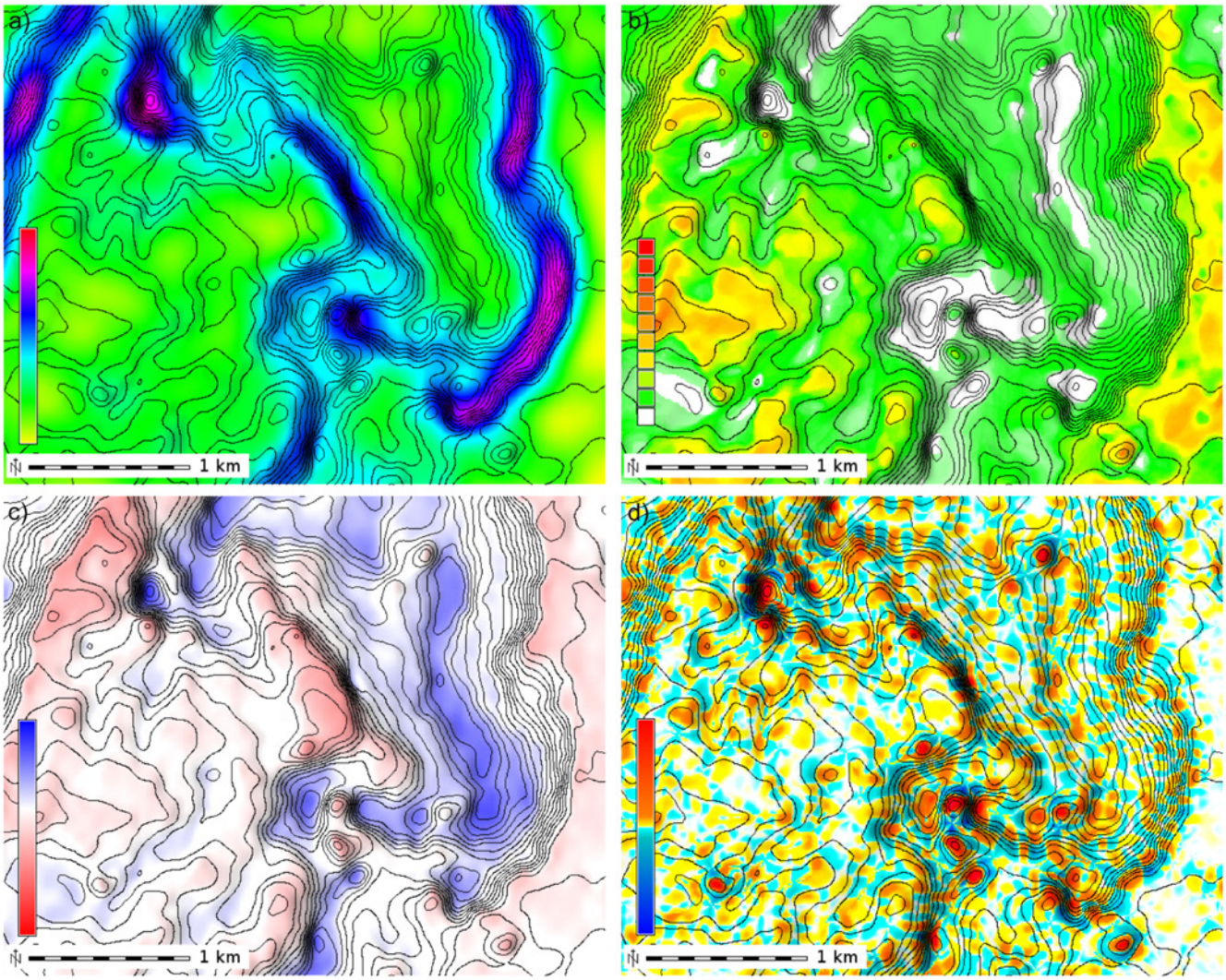


FIGURE 6. Example output for the Wadi al-Hasa area of the four GIS-based models of the cognitive process of fixing locations in the pre-GPS era: (a) output from a model based on contour-line density; (b) output from a model based on the number of visible landmarks; (c) output from a model based on the average topographic prominence; (d) output from a model based on average landform curvatures. For clarity, only a small portion of the entire Wadi al-Hasa region is shown.

The next workflow models the way surveyors experience the landscape as they move through it. The experience of movement in a landscape is important to the way an individual forms a cognitive map of a region, and so plays an important role in human wayfinding and orientation (Fitzjohn 2007; Hegarty et al. 2006; Thorndyke and Hayes-Roth 1982). It can be modeled through analysis of topographic prominence, which is a measure of localized changes in topography at different horizontal scales (Christopherson 2003; Llobera 2001). Prominence studies have been used in archaeological studies that seek to understand and model how the morphological character of a landscape could have influenced the way ancient peoples experienced and moved through it. This idea is directly applicable to the experience of surveyors traversing transects. Highly prominent features are likely to be noticed by a surveyor and, thus, are potentially more likely to be identified on a map. The workflow operationalizes this by calculating the average elevation in different sizes of moving window neighborhoods using the GRASS module *r.neighbors*. This creates a series of elevation maps averaged at different horizontal scales, which are each subtracted from original elevation (e.g., the Wadi al-Hasa SRTM data) using the raster map calculator, *r.mapcalc*. The "Average Prominence" is then calculated in using the *r.series* module to calculate the average of those maps (Figure 6c).

The final workflow models the way surveyors match landforms to the *shape* of contour-line patterns on topographic maps. The horizontal shape of contour-lines represents the curvature of landscape features over space. Surveyors interpret these patterns through a cognitive process called *representational correspondence* (Liben and Downs 1993), which helps them match particular contour-line shapes to specific topographic features. Landforms that are composed of rapidly changing slopes (e.g., peaks, spurs, or saddles) create unique, compact, contour-line shapes when represented on topographic maps, and so are easier to identify than other landforms. The workflow operation-

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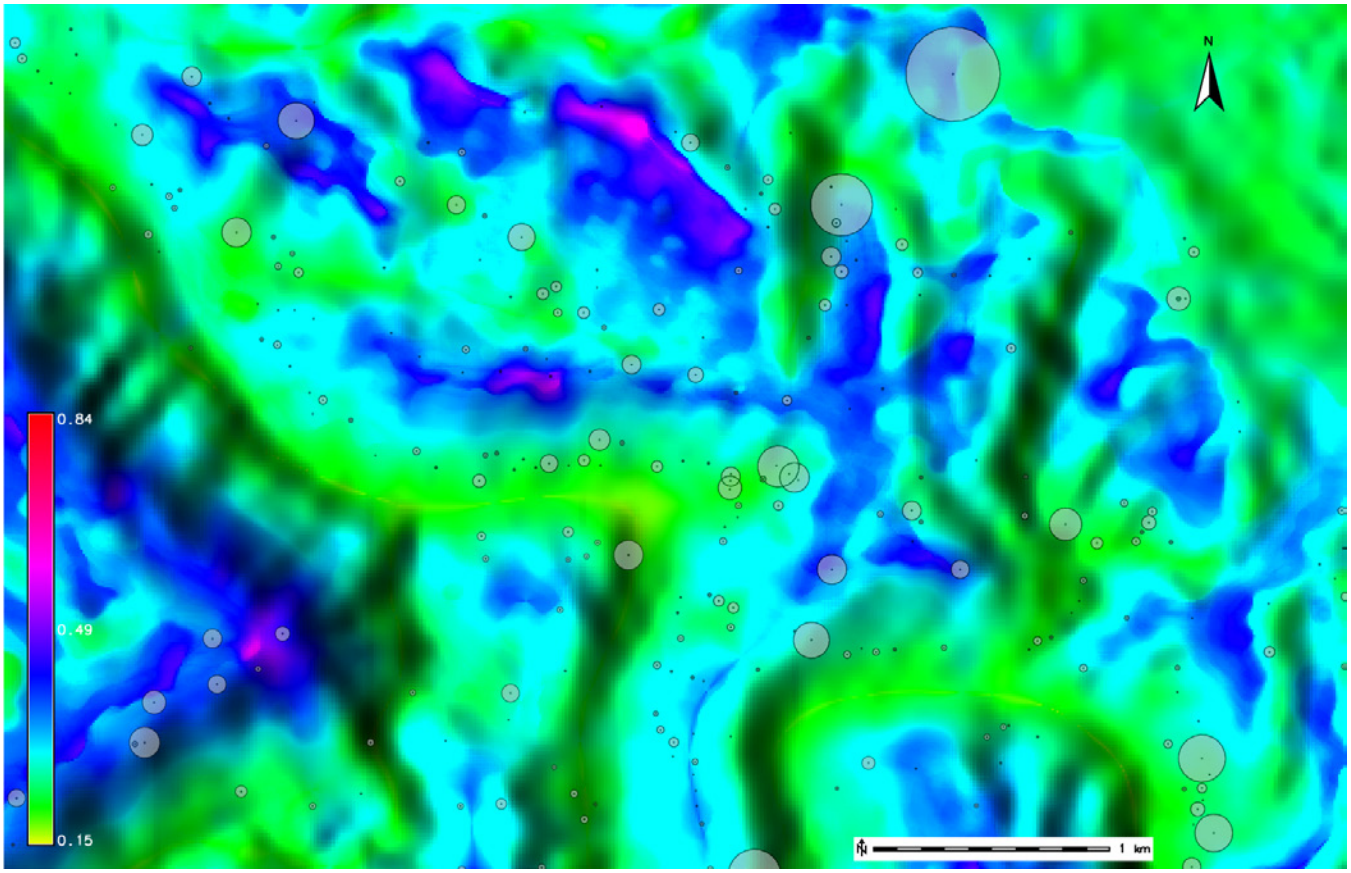


FIGURE 7. A sample Reliability Index map for the Wadi al-Hasa case study, created as the standardized average of the maps shown in Figure 6. Sites from the WHS and WHNBS surveys are shown, with sampling radii based on the reported site sizes. For clarity, this figure shows only a portion of the entire Wadi al-Hasa region.

alizes this idea by measuring topographic curvatures (change in slope) with the GRASS module *r.slope.aspect*. The module calculates the curvatures of the landscape in the direction of steepest slope ("principle" or "profile" curvature) and in the direction perpendicular to the direction of steepest slope along the horizontal plane ("secondary" or "tangential" curvature). Multiplying the two curvatures together creates a map in which high values denote the parts of the landscape where landform shape changes rapidly in both the vertical and horizontal dimensions (Figure 6d). Rapid change of both types of curvature generally translates to distinct, easily identifiable patterning of contour lines on a topographic map.

While each of the individual models produces interesting results on its own (Figures 6a-d), it is more useful to combine them as a holistic "reliability index" for each pixel of the digitized landscape. The most straightforward way to achieve this is to standardize the output from each individual model to a common scale (in the cases here, I chose a scale of 0–1) and then to calculate the average of all the measures across the survey region. The workflow achieves this using a simple averaging formula in the GRASS raster math module, *r.mapcalc*. Figure 7 shows the map of reliability index as calculated for the Wadi al-Hasa region from the four surveying models described above. This particular map was created as a simple unweighted average, but any of the input models could be weighted more heavily than the others if there is reasonable justification to do so. The survey metadata and the unpublished survey notes are the appropriate sources of information about potential weightings of the different factors (e.g., if there were many notes mentioning the difficulty of determining locations on flat areas, then the contour density model might be weighted more heavily than the others).

Finally, I note that although the four models described in this section should be generally applicable to most legacy survey datasets, they are not the only possible ones that could be employed. For example, modeling the density of vegetation might be important for how it obstructs views of landmarks, or a combination of vegetation density and surface roughness could model ground visibility and how that affects the identification of site boundaries. Modeling variation in surface albedo might simulate the recognizability of landscape patches on aerial photographs. A model derived from the proximity of recorded site locations to roads or trails might be useful for surveys that were non-systematic or vehicular. The effect of these particular additional factors appears to be minimal in the Wadi al-Hasa case study (for example, Wadi al-Hasa is very sparsely vegetated), but if these kinds of additional factors are deemed important for a particular survey, then care should be taken to ensure that they are modeled in a way that matches the conditions of the original survey as closely as possible. As an example, if the density of vegetation is thought to be important, then the digital represen-

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TABLE 1. Univariate Statistics Describing the Range of Reliability Index Values for All Pixels of the Wadi al-Hasa DEM, All Sites Discovered by the WHS, and All Sites Discovered by the WHNBS

	All Pixels	WHS Sites	WHNBS Sites
Mean	.283	.288	.269
Median	.268	.277	.258
Variance	.003	.003	.002
Standard deviation	.055	.052	.044
Range	.686	.321	.283
Minimum	.150	.200	.201
Maximum	.836	.521	.484
n	6089320	980	484

Note: Reliability index values for sites were sampled in a radius around the corrected site coordinate. These radii corresponded to the reported size of each site.

tation should be classified based on remotely sensed imagery dating to the period of the original survey. Thus in a survey done in the early 1980s, coarser Landsat MSS data would be preferred over finer, but more recent Landsat TM or ETM+ data (Haack et al. 1987).

Applying the Reliability Index to Legacy Datasets

The location reliability map created with the workflow presented in the preceding section should inform subsequent analyses of the spatial data. To do so, we must first upload reliability values for each site to a field in the site database. If sites were digitized as vector point locations, then a sampling radius (e.g., relative to site size) should be employed in this process. A sampling buffer can be created in GRASS with the *v.buffer* module, using a vector point map of site locations, with a column of average site dimensions to determine the size of the sampling radii for each site (e.g., Figure 7). If the site locations were originally digitized as polygons, they can be used directly. In either case, an average index value should be calculated within the sampling radius or polygon, using the GRASS module *v.rast.stats*. Doing so corrects for issues of scale related to site size and raster resolution and ensures that a reasonable estimate is uploaded for all sites.

Once the values have been uploaded, it is useful to compare them to the spread of all possible values in the Reliability Index raster map. As an example, the Reliability Index values for the corrected WHS/WHNBS sites are made available in the new online repository of these data (Ullah 2015b). Table 1 presents univariate statistics about the range of reliability index values for all pixels of the Wadi al-Hasa SRTM and compares them to the range of reliability index values for all WHS and WHNBS sites. These data show that the average reliability score in the project area is only about 34 percent of the maximum possible score. The average reliability score of the WHS sites matches this, but the average score of the WHNBS sites are slightly lower at about 32 percent of the maximum possible score. These summary statistics also provide a measure with which to assess the score of any individual site, or subset of sites when conducting spatial analyses with the dataset. When accurate, highly precise site locations are needed, the analysis should be constrained to a sample of sites with relatively high reliability index values.

DOING SPATIAL ANALYSIS WITH LEGACY DATASETS

The techniques described in this paper provide what I believe are "best practices" to obtain the highest possible quality spatial records from older archaeological survey work, so that they can be used in modern spatial research. I present here an example of using legacy data in a modern spatial analysis procedure—a cumulative viewshed analysis—that benefits from accurate, precise site coordinates.

Before beginning the analysis, it is important to understand the beginning impact of inherent errors on the output of the routine. I queried the WHS site-database to extract all Neolithic-period lithic scatters to use as input for the CVA analysis. This resulted in a sample of 30 sites, with an average reliability index score of .282 (± .073) at the corrected site locations. This score is similar both to that of the greater WHS database as a whole and to that of the rest of the landscape. Thus, although likely subject to some inherent error, the corrected spatial record of this subsample of sites is not highly suspect. However, the median site size of these Neolithic lithic scatters is fairly small (about 850 m^2), and so it is still possible that any remaining locational error will propagate into the results of the CVA.

To understand better the effect of locational errors on the results of the CVA, I conducted four separate CVA routines. The first CVA used the original, uncorrected coordinates from the inherited WHS database. This point set contains all the correctable errors that had entered into the data. The second used site coordinates as digitized from the scanned, georectified survey maps. This point set is spatially corrected, but likely still contains some inherent error. The third routine used a perturbation of the corrected coordinates that randomly shifted the coordinates by an amount drawn from a uniform-random distribution with a maximum offset of 50 m. This point set contains induced error, roughly equivalent to what might be expected by rounding coordinates to the nearest 100 m. The final routine used a set of 30 new points randomly chosen from within the WHS survey boundaries. This point set acts as a comparative "control" sample.

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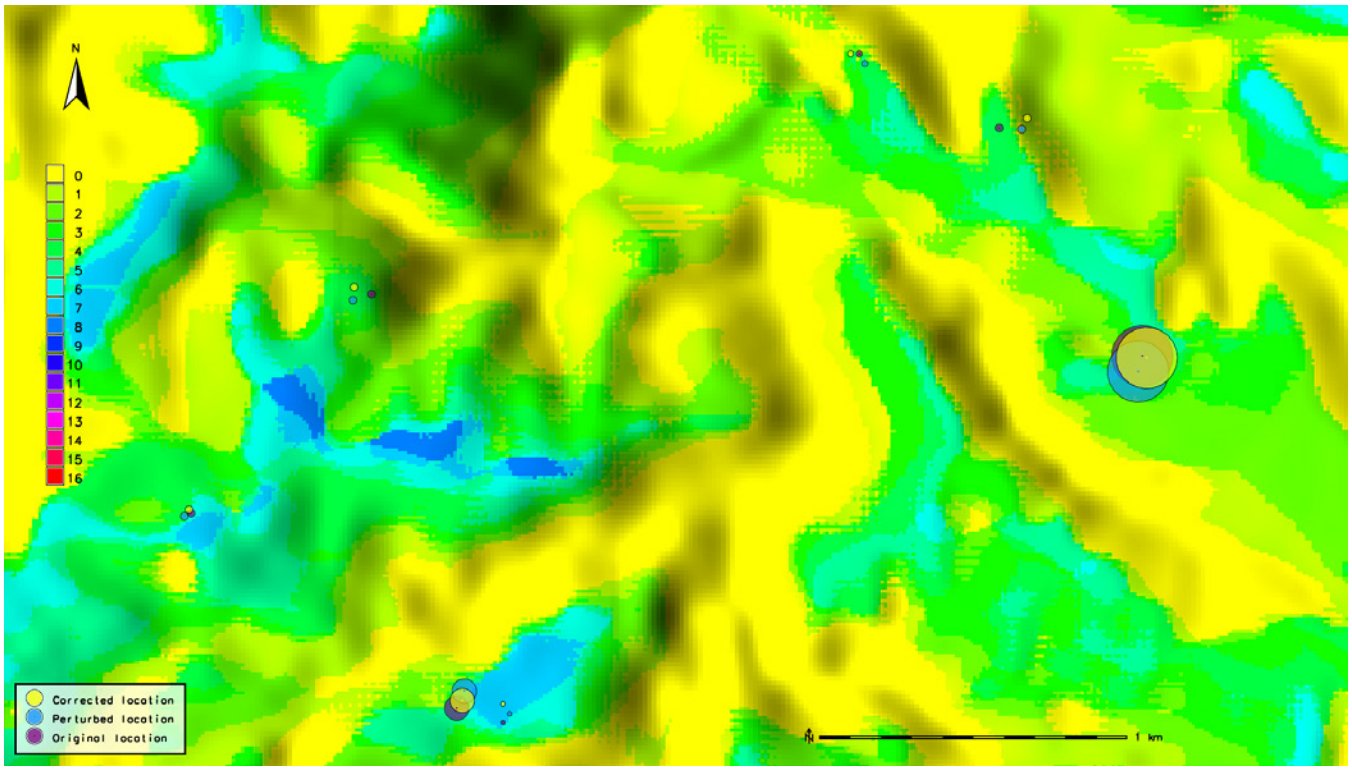


FIGURE 8. A sample output of a Cumulative Viewshed Analysis undertaken with a small sample of the WHS sites. The location and sampling radii of sites are indicated. The purple dots are the original uncorrected site locations, the yellow dots are the corrected site locations, and the blue dots are the perturbed versions of the corrected site locations. The underlaying CVA map was generated from the corrected site locations. For clarity, this figure shows only a portion of the entire Wadi al-Hasa region.

Using each of the four point sets as viewing locations, the four CVA routines returned maps of the number of sites that can see each pixel of the input DEM (Figure 8). I used the site-size radii described in the previous section to upload these values at each site location for each point set. Univariate statistics for the CVA values for each point set are shown in Table 2. Firstly, CVA undertaken with the random "control" point set produced radically different values than the other three point sets. This indicates that even the uncorrected data produced results that are archaeologically significant. However, CVA undertaken with the uncorrected and perturbed point sets overpredicts the average amount of inter-visibility between sites. Correlation statistics (Table 3) show that these differences are systemic, and not due to one or two large differences. Thus, the correction procedure improves the results of the CVA, but we also know that some inherent spatial error may remain that affects the total accuracy of the CVA routine.

CONCLUSIONS AND FUTURE DIRECTIONS

If archaeology has become a largely digital endeavor (Zubrow 2006), where does that leave data gathered in the pre-digital era? These older datasets grow ever more important as damage to the archaeological record accumulates and as access to field sites becomes more and more restricted. Digital geospatial technologies have radically changed the scale of spatial analyses that are possible within the budgets of typical archaeological research projects. For example, Lin and colleagues (2014) leveraged on-the-ground survey with GPS and crowd-sourced digital survey with high-resolution satellite imagery to find and accurately digitize over 2.3 million archaeological features in a region of over 6,000 km^2 in Mongolia. Modern technologies, such as smartphones and tablets, are putting customized, GPS-enabled software literally in the palms of modern archaeologists while they conduct fieldwork (e.g., Austin 2014; Cascalheira et al. 2014; Goodale et al. 2013; and see Harris 2012 for an excellent discussion of challenges and opportunities arising from use of these technologies). Advanced GIS analyses, such as GIS-based site catchment modeling (Pullar and Springer 2000; Ullah 2011), construction of ancient "visualscapes" (Llobera 2003; Wheatley 1995), and construction/evaluation of various predictive models (Graves McEwan 2012; Ladefoged et al. 2009), are now common in landscape archaeology, but are predicated on an accurate spatial record. This study has raised significant concerns about the spatial record of older survey data in the form that they are typically received. In the case of the WHS and WHNBS survey data, digitizing the original survey maps identifies and mitigates many of the spatial errors that had accumulated in the inherited survey database, and this is likely true for most pre-GPS survey data. The accuracy of the corrected data are, however, largely dependent upon the scale and quality of the original base maps, the style of survey and measurement, the relative distinctness of

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TABLE 2. Table of Univariate Statistics for CVA Analyses of Neolithic Lithic Scatters from the WHS.

	Original	Corrected	Perturbed	Random
Mean	2.983	2.687	2.712	1.546
Median	2.321	2.000	2.000	1.107
Variance	4.242	3.391	3.647	.580
Standard deviation	2.060	1.842	1.910	.761
Range	6.529	6.140	5.211	2.487
Minimum	.471	.860	.789	.513
Maximum	7.000	7.000	6.000	3.000
n	30	30	30	30

Note: Statistics are reported for CVA undertaken with the original, uncorrected dataset, the spatially corrected dataset, and a 50-m uniform-random perturbation of the corrected dataset (simulates rounding errors). Statistics are also reported for a randomly generated "control" point set. CVA results are reported as the number of other sites that can be seen from each site.

TABLE 3. Correlation Matrix Comparing the CVA Results for CVA Analyses of WHS Neolithic Lithic Scatters.

	Original	Corrected	Perturbed	Random
Original	1.000			
Corrected	.884	1.000		
Perturbed	.887	.942	1.000	
Random	-.214	-.293	-.370	1.000

Note: Compared are the results for the original, uncorrected dataset, the spatially corrected dataset, a 50-m uniform-random perturbation of the corrected dataset (simulates rounding errors), and a randomly generated "control" point set.

landscape features on which sites are located, the number and quality of easily identifiable nearby landmarks in the survey area, and other physical attributes of the landscape that enhance or impede the process of archaeological survey. Returning to the original "survey metadata" and the unpublished notes and maps is an essential step in identifying remaining errors, but it is often made difficult by missing or inadequate records. I have presented an alternative approach to assessing the amount of error that may remain. Using GIS-based models to estimate the severity of these inherent spatial errors allows a standardized, comparable, and quantifiable measure of confidence in the applicability of spatially corrected legacy survey datasets in analyses that require spatial accuracy. Hopefully, the procedures discussed in this paper will encourage archaeologists to make fuller use of "legacy" data in ongoing research programs and to be more aware of the limitations and benefits of these older datasets for modern archaeological research methods.

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Data Availability Statement. Topographic data used in this paper derive from SRTM scenes SRTM3N31E035V2, SRTM3N31E035V2 (USGS 2012). The survey maps were georectified to LandSat ETM+ scene: LE71740392003006EDC03 (USGS 2003). These data are made freely available by the USGS. The custom GRASS GIS modules developed in the course of this research are available as free add-ons for GRASS GIS (GRASS Development Team 2015), and sourcecode is available at: https://svn.osgeo.org/grass/grass-addons/. They are published there under the GNU license (free for all types of use, modification, and distribution, as long as credit is given and source code remains open). The original WHS and WHSNBS survey data are available through the Middle Eastern Geodatabase for Antiquities (MEGA), Jordan, data portal (Getty Conservation Institute 2015). The corrected WHS and WHSNBS survey data are available at http://dx.doi.org/10.6084/m9.figshare.1404216, under the creative commons license (free to use and modify for any purpose, as long as credit is given).

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NOTES

1. The intentional scrambling of civilian GPS signals by an executive order signed in 1996 by President Clinton was officially ended on May 2, 2000. All civilian GPS signals had a maximum spatial accuracy of ± 100 m up to the May 2000 date. The intentional randomization of the civilian GPS signal was called "selective availability" and is not the same as the error induced by atmospheric aberrations that are removed in "differential" GPS systems that receive external radio-broadcast corrections to these aberrations.
2. From 1993–2000, it was at least possible use a handheld GPS unit to help orient oneself and to get a rough estimate of the site location prior to the manual process of coordinate identification.
3. Of the surveys listed here, only the TBAS occurred in the GPS era, but its first season occurred before the end of "selective availability" for consumer GPS units, and so was subject to the ± 100 m error of early civilian GPS signals.
4. Note that, in some cases, it may be impossible to find the original field maps. In these cases, it may be possible to use "publication" maps that accompany reports, articles, or manuscripts related to the fieldwork, especially if these are large-format "pull-out" maps (e.g., like those that accompany the ASKAP and WHS monographs). In any case, because they are "cleaned" prior to publication, such maps will be less detailed than original field maps and will mask clues to other sources of error.

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