Response to reviewers

Reviewers comments are in black, our responses are in red

Reviewer 1

First, the largest issue I see is still minor. The new LiDAR data in the Guatemalan Biosphere Reserve is given a lot of credit (page 8 lines 114-117). However, that project has yet to produce a peer reviewed article on their dataset. While Inomata works in Guatemala (and is a good reference) he was not part of that LiDAR consortium. The Guatemalan data has made some drastic statements, but until they manage to pass peer review, I might not give them so much credit ... yet. While the data will certainly impact interpretations, it does a disservice to other scholars in the region who have already used LiDAR data to advance our understanding of the Maya (such as Prufer and Thompson already cited later in the paper). I could recommend other citations here as well, but they aren't absolutely necessary to the paper. Instead, on page 8 lines 114-117. Would you consider separating the list of LiDAR study areas? Most of those papers do not cover Guatemalan LiDAR data, so instead I would recommend something along the lines of this in place of "see also", "... as has the past decade of LiDAR use worldwide" followed by the non-Guatemalan LiDAR citations. This will at least highlight the impact of previous research along with the new research out of Guatemala, even if Inomata's article is from a separate LiDAR project.

The project from Guatemala was finally published in October (Canuto et al, 2018) which we have now cited in conjunction with the other references. With the addition of this reference, we have also modified the citations on page 8 with accordance to the suggestions of the reviewer. After citing the Guatemala case study, we include "This is accompanied by a decade of LiDAR studies worldwide" followed by the string of related citations.

As an addition to Evans on page 4 line 62, I would also recommend citing the following reference, which describes LiDAR use in archaeology in a historical context.

We have added the reference to Chase et al. (2017) as suggested by the reviewer.

On page 8 line 118. There are algorithms used for LiDAR analysis that create alternative visualizations. As such, could you change the line to "Two general classes of automated detection algorithms exist ..."

We have rephrased the sentence as suggested by the reviewer.

On page 15, line 255. Could you please provide the specific inputs used for the Focal Statistics tool (shape and size used probably) and include the version of ArcGIS used for this analysis?

The inputs and the version of ArcGIS have been added to the sentence.

On page 26-27, lines 393-403. What is the minimum feature size that you would expect to be able to identify through the four methods provided? How does the quality of the input dataset/DEM affect the size of detectable objects? If this comment is too difficult to answer in text, then absolutely feel free to ignore it.

Our methods and datasets allow us to detect “features as small as a few meters across and about half-a-meter tall” (lines 403-404). The second question regarding quality and its effect on the detection of different sized objects is addressed in the following paragraph on lines 409-410 “Increasing the ability to detect smaller features requires higher resolution dataset: greater the spatial resolution, the smaller the objects that can be detected.”

Reviewer 2

- LINE 26: The Howe,2014 reference may not be the most authoritative source to estimate the number of mounds in the eastern US. Just saying "thousands" get the point across. If you would like to suggest a higher number perhaps some additional citations might bolster this claim.

We have changed the sentence to say “thousands” as suggested by the reviewer and we have added several other sources in addition to Howe (2014).

LINE 61,62: "Active sensors, such as light detecting and ranging (LiDAR), offer maps of topography (Evans et al., 2013)" It's not just the ability to map the terrain, but a non-bias topographic mapping technique, which is substantially different (and much quicker) than traditional total station mapping.

We have rephrased the sentence to include this information. It now reads: “Active sensors, such as light detecting and ranging (LiDAR), provide a mapping technique that permits direct measurements of surface topography that is faster, more systematic, and more accurate than other forms of manual mapping.”

LINE 214: In the section on Template Matching it appears that the target objects are switched to only pre-contact mounds? Are the shell rings and other archaeological features eschewed for this methodology?

We have rephrased the statement to include the fact that rings are included in this template dataset. Both shell rings and earthen/shell mound features in the study areas are included in these templates. The statement now reads as “We created templates using a selection of 29 mound and ring features using characteristics of elevation, slope, focal statistics, and openness.” (lines 218-220).

GENERAL: Standardize formatting in all figures. Legends, scales and text font are not consistent.

The formatting of all legends and fonts has been standardized for all figures. In instances of different scaling for different panels of a figure, multiple scale-bars are used to indicate the difference.

GENERAL: Would be interesting to provide a comparison between the computer algorithmic detection and manual detection for at least one of the areas. Does a human operator provide fewer false positives or would they miss a number of features the algorithms detect?

We added a paragraph to our discussion/conclusion section which briefly goes over some comparisons between manual evaluation and automatic evaluation in this area (lines 419-429). Most of the features used for our template process were identified via manual evaluation in the LiDAR datasets. But within these same areas in Beaufort County the automated algorithms identified many other confirmed sites that were not picked out via manual means.

Highlights

- 4 different automatic detection methods are examined
- Segmentation, inverse depression analysis, template matching, combined method
- Most effective method of mound detection combines segmentation and template matching
- Inverse Depression Analysis is highly effective with several hundred iterations
- Template matching can reduce false positives resulting from natural features
- A previously unknown shell ring is identified using the proposed OBIA approach

A comparison of automated object extraction methods for mound and shell-ring identification in coastal South Carolina

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Abstract

One persistent archaeological challenge is the generation of systematic documentation for the extant archaeological record at the scale of landscapes. Often our information for landscapes is the result of haphazard and patchy surveys that stem from opportunistic and historic efforts. Consequently, overall knowledge of some regions is the product of *ad hoc* survey area delineation, degree of accessibility, effective ground visibility, and the fraction of areas that have survived destruction from development. These factors subsequently contribute unknown biases to our understanding of chronology, settlements patterns, interaction, and exchange. Aerial remote sensing offers one potential solution for improving our knowledge of landscapes. With sensors that include LiDAR, remote sensing can identify archaeological features that are otherwise obscured by vegetation. Object-based image analyses (OBIA) of remote sensing data hold particular promise to facilitate regional analyses thorough the automation of archaeological feature recognition. Here, we explore four OBIA algorithms for artificial mound feature detection using LiDAR from Beaufort County, South Carolina: multiresolution segmentation, inverse depression analysis, template matching, and a newly designed algorithm that combines elements of segmentation and template matching. While no single algorithm proved to be consistently superior to the others, a combination of methods is shown to be the most effective for detecting archaeological features.

Keywords: Object based image analysis, template matching, automatic feature identification, remote sensing, shell rings, LiDAR, American Southeast

1.1 INTRODUCTION

At the time of European arrival into Eastern North America, the archaeological record included thousands of intact earth and shell mound structures (Anderson, 2012; Howe, 2014; Thomas, 1894). Beginning in the 19th century, these deposits became the focus of archaeological research due to their ability to produce artifacts that shed light on cultural affinity and chronology (Lyman et al. 1997; e.g., Claflin, 1931; Fairbanks, 1942; Ford and Willey, 1941; Jones et al., 1933; Moore, 1894a, 1894b, 1899; Moorehead, 1891; Putnam, 1875; Squier and Davis, 1848; Swallow, 1858; Wauchope, 1948; Willey, 1939). Over time, archaeological interest in mounds has grown to include studies of pre-contact technology, diet, social behavior, trade, exchange, interaction, and settlement (e.g., Anderson, 2004; Caldwell, 1952; Calmes, 1967; Claassen, 1986, 1991, 2010; Crusoe and DePratter, 1976; Marquardt, 2010; Matteson, 1960; Russo, 2004, 2006; Thompson et al., 2011; Trinkley, 1985).

Our knowledge of the distribution of mound features, however, tends to be biased towards some areas more than others. These areas may come from regions that have seen a greater number of field studies (e.g., Michie's (1980) survey of the coastal plains of the Port Royal Sound) but also include those that are easier to survey due to a lack of substantial ground cover such as in areas of beaches and shallow intertidal zones (South, 1960) as well as piedmonts and coastal plains (House and Ballinger, 1976). Specifically, environments that are dominated by heavy vegetation (e.g., woodlands, bayous, and coastal marshes) are often missing from our knowledge of the record as they are difficult to evaluate using systematic pedestrian tactics. The most recent example of this lapse in knowledge is the discovery of thousands of monumental complexes in the dense forests of Guatemala (Canuto et al., 2018). Prior to the use of LiDAR survey, these archaeological features were unknown, and their discovery may rewrite the history of this area.

This aspect of past archaeological surveys raises the possibility that our knowledge of the record is biased towards features that appear in the best cleared and most visible landscapes (Banning et al., 2017; Bintliff, 2000; Bintliff et al., 1999; Hirth, 1978; Nance 1979; Stark and Garraty, 2008). The potential for increasing our understanding of the archaeological record is likely greatest in the exploration of areas that have seen little systematic observation. Given that unknown deposits are often least visited and impacted, those that remain hidden in vegetation potentially hold some of the most promising opportunities for new archaeological discovery. To address the challenges of large-scale documentation presented by heavily-vegetated landscapes, and to aid in the study of these poorly studied regions, new kinds of techniques are required.

Remote sensing using computational algorithms for automatic feature detection offers one promising solution. High-resolution aerial imagery provides detailed information about the structure of landscapes. Multispectral imagery expands the wavelengths that can be used for sensing to include bands that are sensitive to vegetation and sediment composition (Jensen, 2007). Active sensors, such as light detecting and ranging (LiDAR), provide a mapping technique that permits direct measurements of surface topography that is faster, more systematic, and more accurate than other forms of manual mapping (Chase et al., 2017; Evans et al., 2013). New computational methods greatly facilitate the use of these many classes of data as they can be configured to automatically identify features of interest (Freeland et al., 2016; Magnini et al., 2016; Sevara et al., 2016; Trier et al., 2015). Object-based image analysis (OBIA) covers a broad array of promising algorithms for archaeological prospection (Sevara et al., 2016). These compositional techniques include shape templates (Kvamme, 2013; Trier et al., 2008), machine learning algorithms (Wu et al., 2015, 2016), and image segmentation (Witharana et al., 2018).

Here, we evaluate an application of four OBIA methods – multiresolution segmentation, inverse depression analysis, template matching, and a method combining segmentation and template matching – as tools for identifying artificial mounds and rings. In our example applications, we make use of LiDAR data from coastal South Carolina. Our goal is to compare the results obtained by implementing these methods on a single shared set of data. In this way, the results can provide suggestions for the best practices in the use of these remote sensing tools for documenting the archaeological record.

1.2 Study Area

The coastal plains of South Carolina contain a rich archaeological record but have been subjected to only limited ground surveys due to the prominence of forests and bayous (Anderson et al., 2017). Beaufort County, South Carolina, in particular, contains one of the largest number of recognized archaeological deposits in the state, a significant number of which are mound features (Frierson, 2000; Stephenson, 1971). A majority of the area, however, is densely vegetated and only limited systematic surface surveys having been conducted (e.g., Michie, 1980; South, 1960, 1976).

The lack of systematic surveys in the region is more than an academic issue. By 2040, warming due to climate change will result in the submergence of 30,000 acres of presently dry land in this area (NOAA, 2015; see also Anderson et al., 2017). The effects of sea-level change, combined with recent urban development and population increases will potentially result in the loss of many archaeological deposits before they can be recognized. In this way, the application of new approaches for rapid assessment of the otherwise hidden landscape of Beaufort County is particularly urgent.

To evaluate the potential of new remote sensing approaches, we chose three study areas in Beaufort County (Figure 1). Areas 1 (Victoria Bluff Heritage Preserve) and 2 (Pinckney Island Wildlife Refuge) consist of a total of 25 km^2 of forested land. Area 3 is composed of 3 km^2 of land on Hilton Head Island. These areas were chosen for evaluation based on the presence of known features, public access, and the availability of high resolution remote sensing data.

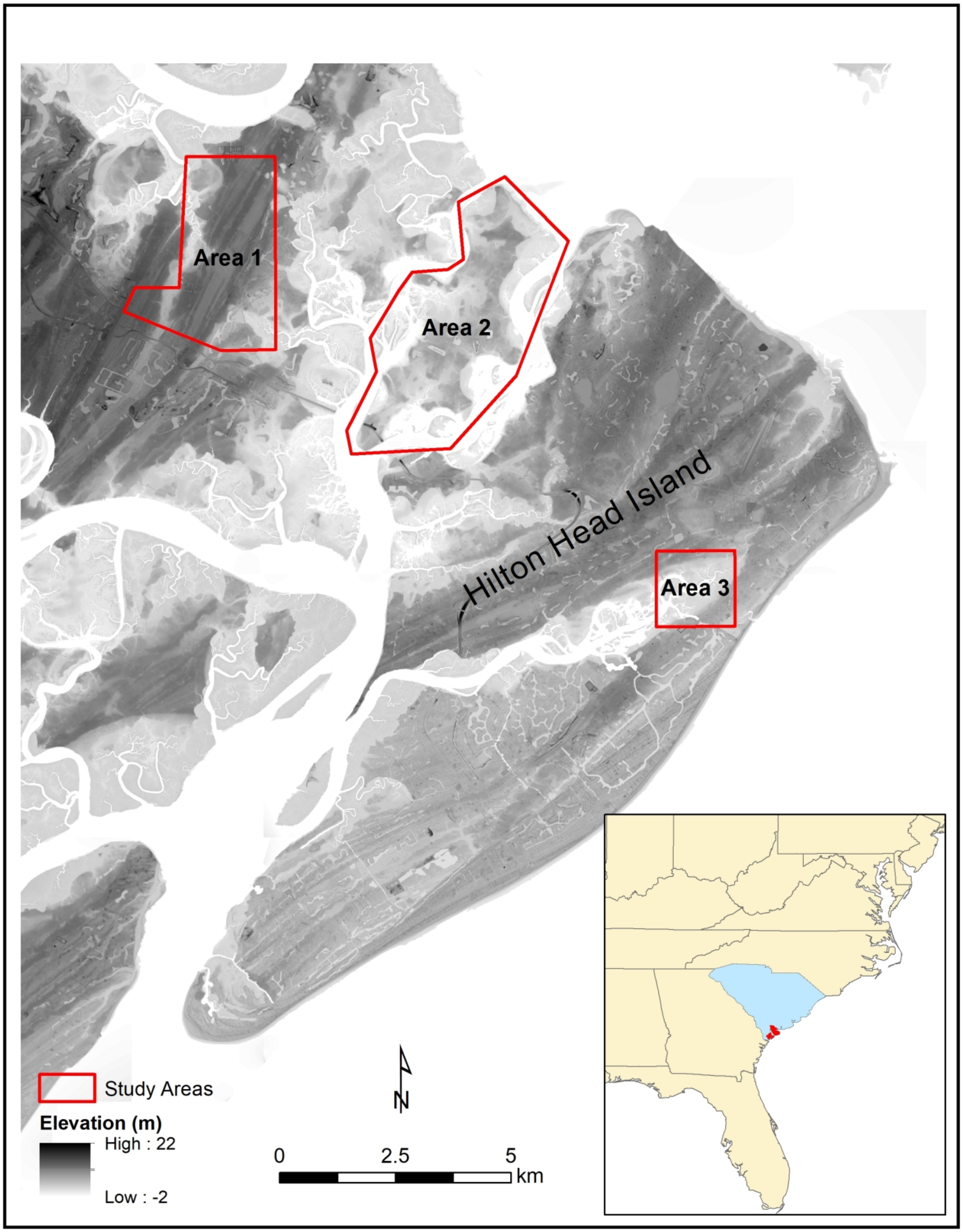

Figure 1: Study Area in Beaufort County, SC (Color online).

2.1 OBJECT-BASED IMAGE ANALYSIS (OBIA)

Aerial imagery has long provided archaeologists a source of information for studying archaeological features across landscapes in an efficient and cost-effective fashion (e.g., Agache, 1968; Bradford, 1956; Buettner-Januch, 1954; Campbell, 1981; Capper, 1907; Drager, 1983; Engelbach, 1929; Harp, 1966; Lindbergh, 1929a, 1929b; Madry and Crumley, 1990; McKinley, 1921; Parrington, 1983; Schaedel, 1951; Williams-Hunt, 1950). While visible light cameras were the first sensors used by archaeologists on aerial platforms, new instruments have expanded the ability of researchers to remotely sense landscapes using wavelengths across the electromagnetic spectrum. These new sensors can be passive – as in the case of multispectral cameras – or active – as in the case of light detecting and ranging (LiDAR) data.

LiDAR data are produced using a laser and sensor that records the return speeds of pulses of light that are reflected off of distant surfaces. LiDAR data often contain responses from multiple surfaces and can therefore provide information about feature elevations that are otherwise obscured by vegetative canopies. Consequently, LiDAR has proven to be particularly useful for detecting architectural structures (Eskew, 2008; Freeland et al., 2016; Johnson and Ouimet, 2014; Krasinski et al., 2016; Magnini et al., 2016; Prufer et al., 2015; Riley, 2009; Thompson and Prufer, 2015; Trier and Pilø, 2012; Trier and Zortea, 2012). Similar to the pioneering work in Guatemala (Canuto et al., 2018), there has been over a decade of productive studies using LiDAR that have taken place around the world (e.g., Inomata et al. 2018; Chase et al., 2014; Evans et al., 2013; Johnson and Oiumet, 2018; Wieshample et al., 2011; Witharana et al., 2018).

Two general classes of automated detection algorithms exist for analyzing remote sensing data: pixel- and object-based approaches. Pixel-based algorithms rely on spectral values encoded in raster data. These approaches identify regions of data that match specific spectral values associated with targets of interest. Object-based image algorithms (OBIA), in contrast, use morphological characteristics such as texture, shape, and size – in addition to spectral values – to divide images into recognizable components with similar qualities. This feature of OBIA allows archaeologists to use attributes for identification that are often distinctive of cultural forms: shape, size, and spatial organization. With this ability, research over the past 15 years has demonstrated the potential of OBIA to efficiently identify anthropogenic structures from remote sensing data (e.g., De Laet et al., 2007; Larsen et al., 2008; Riley, 2009; Trier et al., 2015; Sevara et al., 2016; also see Davis, 2018 for a review of this literature).

2.2 Segmentation

Segmentation is a process that groups pixels into spectrally-similar segments. Software algorithms can then characterize these segments in terms of their geometric and textural properties. In the case of LiDAR data, these objects represent distinct topographic land forms on the ground. There are many forms of segmentation, but one of the most common processes used by archaeologists is multiresolution segmentation. Multiresolution segmentation adds to this process by iteratively dividing data into segments based on additional morphological differences such as shape, size, and texture (Magnini et al., 2016). For this reason, multiresolution segmentation provides greater ability to discriminate features of interest than segmentation methods that rely on just one set of criteria (Mao and Jing, 1992).

2.3 Inverse Depression Analysis

OBIA methods can focus on the use of hydrological depression algorithms (Lindsay and Creed, 2006; Wu et al., 2015, 2016) to identify archaeological mound features (Freeland et al., 2016). This process requires the creation of an “inverse raster” in which a DEM is inverted so that mounds are represented as depressions. Freeland et al. (2016) has demonstrated this method in a study of a landscape in Tonga, revealing thousands of mounded features.

Stochastic depression analysis (SDA) is one algorithm that uses Monte Carlo simulation to map topographic depressions by evaluating morphological uncertainty (Lindsay and Creed, 2006). The method works by estimating the likelihood that a given area contains an elevation change based on variability in topography. The benefit of SDA is that it highlights small elevation changes due to its sensitivity to topographic differences in elevation data. Here, we utilize an inversed version of SDA to identify mounded features in South Carolina. We initially process LiDAR data following Freeland et al. (2016) by creating an inversed DEM. We then apply an SDA algorithm and classify the results using morphological parameters such as compactness and mound size. This approach allows us to co-opt algorithms traditionally reserved for hydrological modeling for the detection of archaeological deposits.

2.4 Template Matching

OBIA methods that employ template matching (TM) use statistical probabilities generated from aggregated examples of features that are characterized by pattern, texture, and shape. These probabilities form templates that are systematically and statistically used as comparisons to sub-sections of image data. Matches with templates are determined by identifying patterns in data that fall within specified statistical limits established by the template.

The archaeological utility of template matching is well-demonstrated (e.g., Kvamme, 2013; Schneider et al., 2015; Trier et al., 2008, 2015; Trier and Zortea, 2012; Trier and Pilø, 2012). One problem with template matching based approaches, however, is its tendency to produce false positive and negative results. Reducing false positives requires careful construction of templates that narrowly define anthropogenic features. However, this step comes at the expense of an increased number of false negatives. The advantage of template matching, however, is that the statistical classifiers provide confidence intervals for detected objects, allowing one to quantitatively assess degrees of matching.

3.1 MATERIALS AND METHODS

In our evaluation of OBIA approaches for detecting mound features in heavily forested regions, we analyzed the same set of LiDAR data for each of the three study areas. These data come from the National Oceanic and Atmospheric Administration (NOAA)[1] and were created to plan for flood control and monitor coastal erosion. The raw data are available as processed Digital Elevation Models (DEMs) that have a spatial resolution of 1.2 meters, a resolution suitable for architecture-scaled feature analysis (see Beck et al., 2005). Using these data, we conducted analyses using (1) multiresolution segmentation, (2) Inverse Depression Analysis (IDA), (3) Template Matching (TM), and (4) a combined segmentation and TM approach. All of our analyses were conducted using a combination of eCognition (Trimble, 2016), WhiteBox GAT (Lindsay, 2016) and ArcGIS (ESRI, 2017).

3.1 Multiresolution Segmentation Analysis

Following Magnini et al. (2016), we utilized a multiresolution segmentation process and selected segments of the LiDAR data that met circularity, asymmetry and compactness criteria stipulated by our summary of known features for the study area (Table 1). Asymmetry is

[1] https://coast.noaa.gov/digitalcoast/data/coastallidar

particularly effective for isolating archaeological features, as it is generally low in anthropogenic structures and high in naturally occurring landforms (Kvamme, 2013:55).

Table 1: Parameters used in multiresolution segmentation of the Beaufort County LiDAR data.

Parameter	*Threshold*
Area	<=150 m^2
Circularity	>= 0.6
Asymmetry	0 – 0.3
Compactness	>= 1.0

To minimize false positive identifications, we compared the location of potential features with United States Geological Survey (USGS) land-use maps[2] and roadway shapefiles produced by the South Carolina Department of Transportation (DOT).[3] We eliminated those locations that appeared on "developed" or "disturbed" areas and within 10-meters of a roadway.[4] Next, we created a raster that represented the differences between local elevation and maximum neighborhood values calculated as focal statistics. Focal statistics help to highlight local elevation changes that would signify a mound feature. We then restricted our results to those features have a local positive elevation difference of half a meter or greater. Based on a review of known features in the area, topographic rises that are less than half-a-meter of relief are rarely associated with anthropogenic mounds or rings (Russo, 2006). Our process resulted in the identification of 2,490 potential features. Among these detections was a previously undocumented shell ring and earthen mound.

3.2 Inverse Stochastic Depression Analysis (IDA)

[2] Downloaded from the South Carolina Department of Natural Resources website (http://www.dnr.sc.gov)
[3] Downloaded from http://www.gis.sc.gov/
[4] We chose the buffer sizes based on standard road widths in the U.S.: 4-meters for single lane roads, 8-meters for two-lane, and 16-meters for 4-lane highways. For the buffers, we used 2 additional meters to serve as a buffer from the edges of the roads.

Here, we followed a strategy developed by Freeland et al. (2016) who demonstrated that depression analysis combined with morphometric criteria (size, shape, area, elevation and neighborhood) is effective in isolating mound structures. We created an inverse DEM using the equation

$$Inverse = ((r - Z_{max}) \times (-1)) + Z_{min}$$

where r = DEM raster, Z_{max} = maximum elevation, and Z_{min} = minimum elevation. The results of the SDA analyses depend on the number of iterations that are used to process the data. In each iteration the assumption for topographic uncertainty is changed slightly to produce slightly different outcomes, and as the number of iterations increases, the algorithm produces more refined and consistent results. Using the SDA tool in Whitebox GAT (Lindsay, 2016) we compared the results of our analyses using 100, 200, and 300 iterations.[5] We filtered the result by then selecting only those features that were greater than 15m and less than 250m in diameter, the range known for rings and mounds in the region (Gibson, 1994; Russo, 2006; Walker, 2016). Finally, we excluded features that appeared on USGS land-use maps in areas that were designated as "disturbed", "developed", or "open water", and those that were within 10-meters of a roadway and 20-meters of a major highway. This process produced 5,422 potential features.

3.3 Template Matching (TM)

In our evaluation of template matching we followed steps in Figure 2. We created templates using a selection of 29 mound and ring features using characteristics of elevation, slope, focal statistics, and openness. Slope has been shown to be one of the most effective

[5] The number of iterations used for analysis impacts the amount of time required and depends on the processing capabilities of the computers used for data processing. Using 100 iterations for the analysis of our study areas required 36 hours. 1000 iterations would have taken at least a month of processing.

methods for identifying mound features as it shows a strong contrast between flat and uneven surfaces, highlighting the outlines of mounds (e.g., Larson et al., 2017; Podobnikar, 2012; Prufer et al., 2015; Riley, 2009; Thompson and Prufer, 2015). We used focal statistics to highlight major changes in elevation that suggest the presence of topographic anomalies, similarly to the processes mentioned above. Openness is a parameter that measures "topographic dominance" of landforms (Yokoyama et al., 2002) and provides shade-free visualization for smaller topographic anomalies.[6] Openness comes in two forms: positive and negative. Positive openness measures the degree of concavity and negative openness measures the degree of convexity of a feature on a landscape.

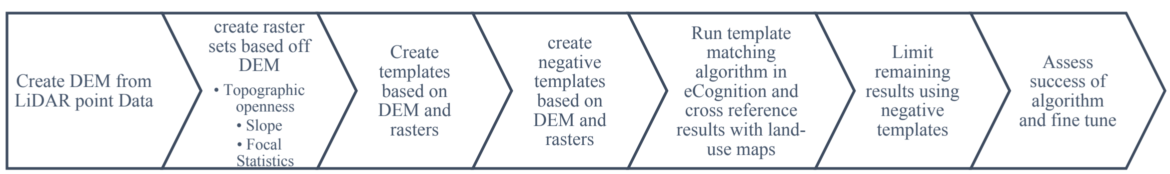

Figure 2: Steps involved in the use of template matching for the identification of mound features.

To create the templates, we used a sample of six known mound features that are recorded in the South Carolina Archaeological Archives and 23 suspected features that were identified manually using existing LiDAR data. These examples served as the basis for setting the statistical limits for each of our templates.[7] Our use of multiple classes of data (elevation, slope, openness, and focal statistics) to create templates enables us to compare results using different characteristics. Following this process, we created 15 templates.[8]

[6] We calculated topographic openness using SAGA (Conrad et al., 2015)
[7] The templates are available from the Open Repository at Binghamton University (https://orb.binghamton.edu/anthro_data/3)
[8] We used the Template Editor tool in eCognition to create all of the templates

We also created 20 negative templates to represent those features that are topographically distinct but are not pre-contact mounds. Recent land disturbance, for example, might produce topographic features that could be confused as a prehistoric mound. To create these negative templates, we used 393 topographically distinct features that are not archaeological in their origin (e.g., linear contemporary features, building imprints, and river boundaries).

Once created, we used eCognition to apply the templates to the LiDAR data. This step produced over 10,000 potential identifications. Like the other two algorithms, we eliminated results that fell on land identified by USGS land-use maps as "developed" or "disturbed", those that were located within waterbodies, and those that fell within 10-meters of roadways and 20 meters of major highways. We also rejected all results that the algorithm calculated as at least 75% likely to be a false positive based on their similarity to our negative templates. The final results included only those detections that were calculated by the algorithm to be at least 60% "most statistically likely." The final template matching process produced 10 potential features.

3.4: Combined TM and Segmentation Method

In order to evaluate the degree to which the strengths of each OBIA method can be combined to produce superior results, we also developed a multidimensional algorithm that includes segmentation and template matching steps (see Davis et al., 2018). This algorithm begins with template matching to create correlation-coefficient maps of potential features. Then, we used multiresolution segmentation on these results. We subsequently isolated those features that had a local elevation difference of between 0.5 and 5 meters from the surrounding area (Russo, 2006). We calculated neighborhood changes in elevation using the focal statistics tool (shape = circle, height and width = 5) in ArcMap 10.5 (ESRI 2017). We rejected all results that occur on developed land, that are located in areas close to roadways, and that have slopes that are less than five or greater than 50 degrees.

Next, we superimposed the remaining results with the correlation rasters that we produced during the template matching process. As the templates are used to iteratively scan sections of the LiDAR data, each section examined is assigned a positive and negative correlation coefficient value that corresponds to the overall match of a location to the positive and negative templates. We used the negative correlation raster to eliminate results that were identified as at least 75% likely to be false positives. Lastly, we created a new raster by subtracting the negative correlation coefficient from the positive correlation coefficient. Areas of this raster containing negative values indicate strong likelihoods of false identifications, as they closely correlate with non-mound features in the negative template. As such, we rejected any results that overlap a portion of this raster containing negative values. This process left 10 potential features.

3.5 Ground Survey

Following our OBIA analyses, we chose 22 locations to visit on the ground to evaluate the degree to which the algorithmic detection correctly identified anthropogenic features (Figure 3). All of these features are located on public land and were accessible for pedestrian survey.

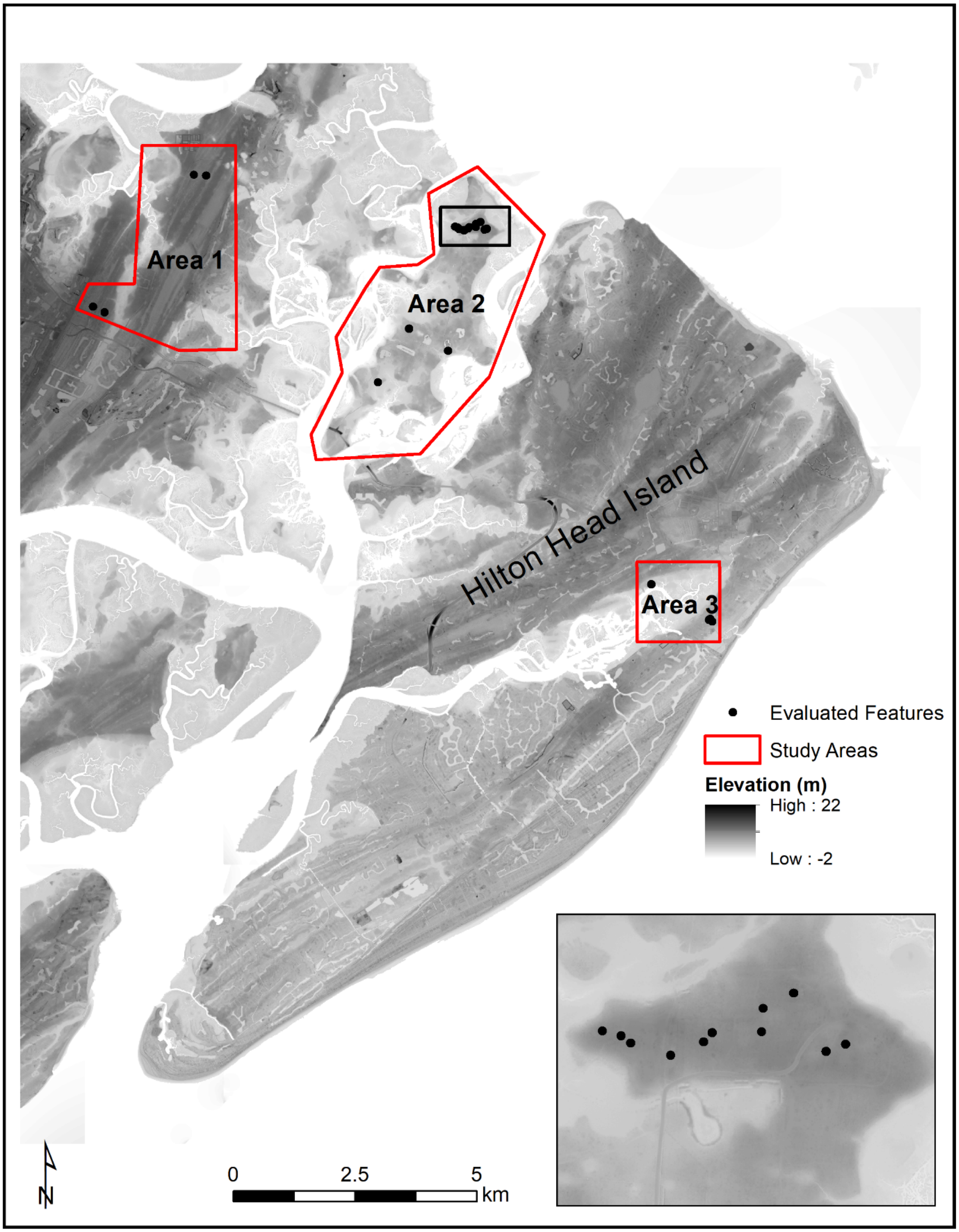

Figure 3: Features evaluated during ground surveys. The inset provides detail of an area of Study Area 2 (marked by the black box) where a number of features were found in close proximity (Color online).

4.1 RESULTS

The results of each OBIA analysis shows that there are distinct differences in the yield of potential features depending on the approach used (Tables 2 and 3). Areas 1 and 2 (see Figure 1) provide useful environments within which to test each OBIA method. Within Area 2, the combined method did not identify any features, indicating that it cannot identify midden structures effectively, as many archaeological middens are present on Pinckney Island (Charles, 1984; Kanaski, 1997; Trinkley, 1981). Area 3 (Figure 1) encompasses publicly available land on Hilton Head Island, some of which is highly developed. The number of features identified is substantial given its small size (~3 km^2) and indicates a high level of false positive identifications in developed locations. The template matching and combined approaches only identify a handful of potential sites, suggesting their capability of reducing false identifications.

Table 2: Total detections made by each OBIA technique.

OBIA Method	Total Detections Study Area 1	Total Detections Study Area 2	Total Detections Study Area 3
Segmentation	1,399	1,091	380
IDA (100 iterations)	3,332	1,677	413
IDA (200 iterations)	1,582	1,829	807
IDA (300 iterations)	1,093	2,485	817
Template Matching	6	3	3
Combined	7	0	3

The segmentation approach was particularly effective in identifying mounds, yet also produced many results that are likely false positives (Figure 4). Using shapefiles provided by the

South Carolina SHPO, we determined that 384 detections made by segmentation are located on 84 previously surveyed archaeological sites on Pinckney Island (Supplemental Table 1). Significantly, the segmentation analysis identified a new mound feature that is previously unrecorded (this feature was also identified by TM and IDA but was missed by the combined method).

Table 3: OBIA Method Results from Field Survey

OBIA Method	Sites Surveyed	Accurate identifications determined by field survey	False Positives determined by field survey	Rate of positive identification/false positives based on field survey	Total Detections in Study Areas	Potential new mound features
Segmentation Classification	12	6	6*	1:1	2,490	1,245
IDA (100 iterations)	14	5	9**	5:9	5,422	3,012
TM	6	3	3	1:1	10	5
Combined (segmentation and TM)	4	4	0	1:0	10	10

* Two sites were inconclusive
** One site was inconclusive

IDA proved successful in identifying pre-contact mounds, including shell rings (Figure 5). Nonetheless, a common issue with this method is the plethora of false positive results that occur due to natural topographic changes. Some of the limitations of IDA in feature detection, however, are likely due to resolution limits of the LiDAR DEM that we used, and the number of iterations performed on the analysis. Using higher-resolution LiDAR as well as greater processing hardware may improve the relative effectiveness of IDA in detecting features.

To evaluate the degree to which the amount of processing can improve our results, we conducted our IDA analyses with 200, and 300 iterations. In all instances, the increase in iterations correlates with an improvement in archaeological feature detection (Tables 4 and 5). In all three study areas, false positive results identified using 100 iterations and surveyed were not reidentified using 300 iterations (Table 5).

Looking at Area 2 (Pinckney Island), we compared identified results to known archaeological sites in this area in order to gauge the accuracy of IDA in identifying previously detected archaeological deposits (Table 4; also see Supplemental Table 1). We chose this area because of its history of extensive archaeological surveys. In addition to increased iterations, it is possible that with higher resolution DEMs better discrimination of topographic features can be obtained (Vaze et al., 2010).

Table 4: Change in detection accuracy for known archaeological deposits in Area 2 using increasing numbers of iterations. As the number of iterations increases, so too does the number of identified archaeological deposits.

Number of Iterations	**Number of Identified Archaeological Deposits**
100	40
200	59
300	60

Table 5: Overall accuracy for IDA using increasing numbers of iterations. As the number of iterations increases, the number of false positive detections decreases, and the overall accuracy increases.

Number of Iterations	**True Positive Identifications (Determined by ground-survey)**	**False Positive Identifications (Determined by ground-survey)**	**Total Detections**	**Overall Accuracy**
100	5	9	5,422	35.71%
200	3	3	4,218	50.00%
300	5	2	4,395	71.43%

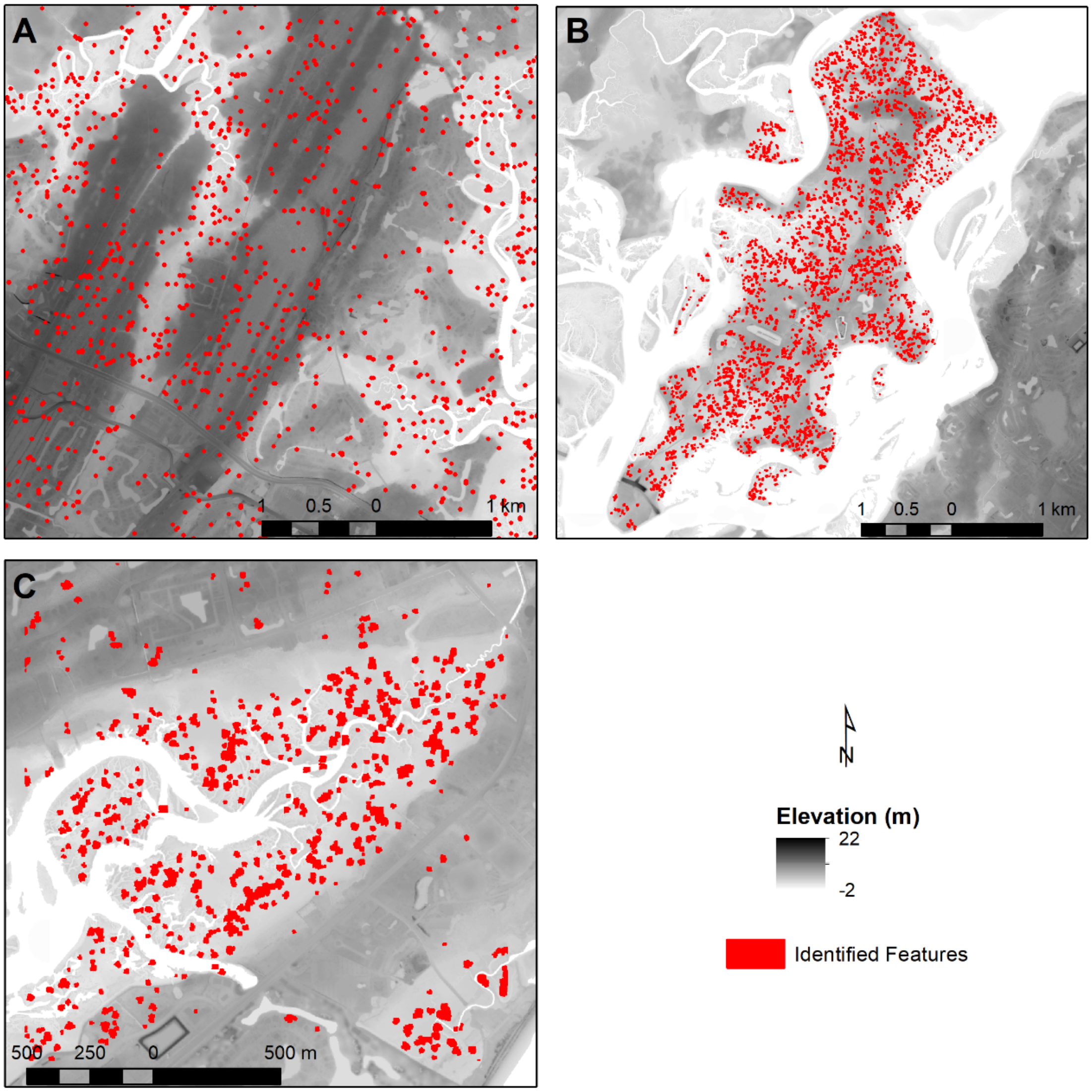

Figure 4: Segmentation results. A: Study Area 1 results. The majority of the identifications are false positives caused by natural phenomena. B: Study Area 2 results. C: Study Area 3 results. The majority of identifications are explained as natural levee features that line the bayous. Several other identifications in this scene are housing footprints or other recent landscape disturbances. Highly developed areas tend to show numerous false positive results (Color online).

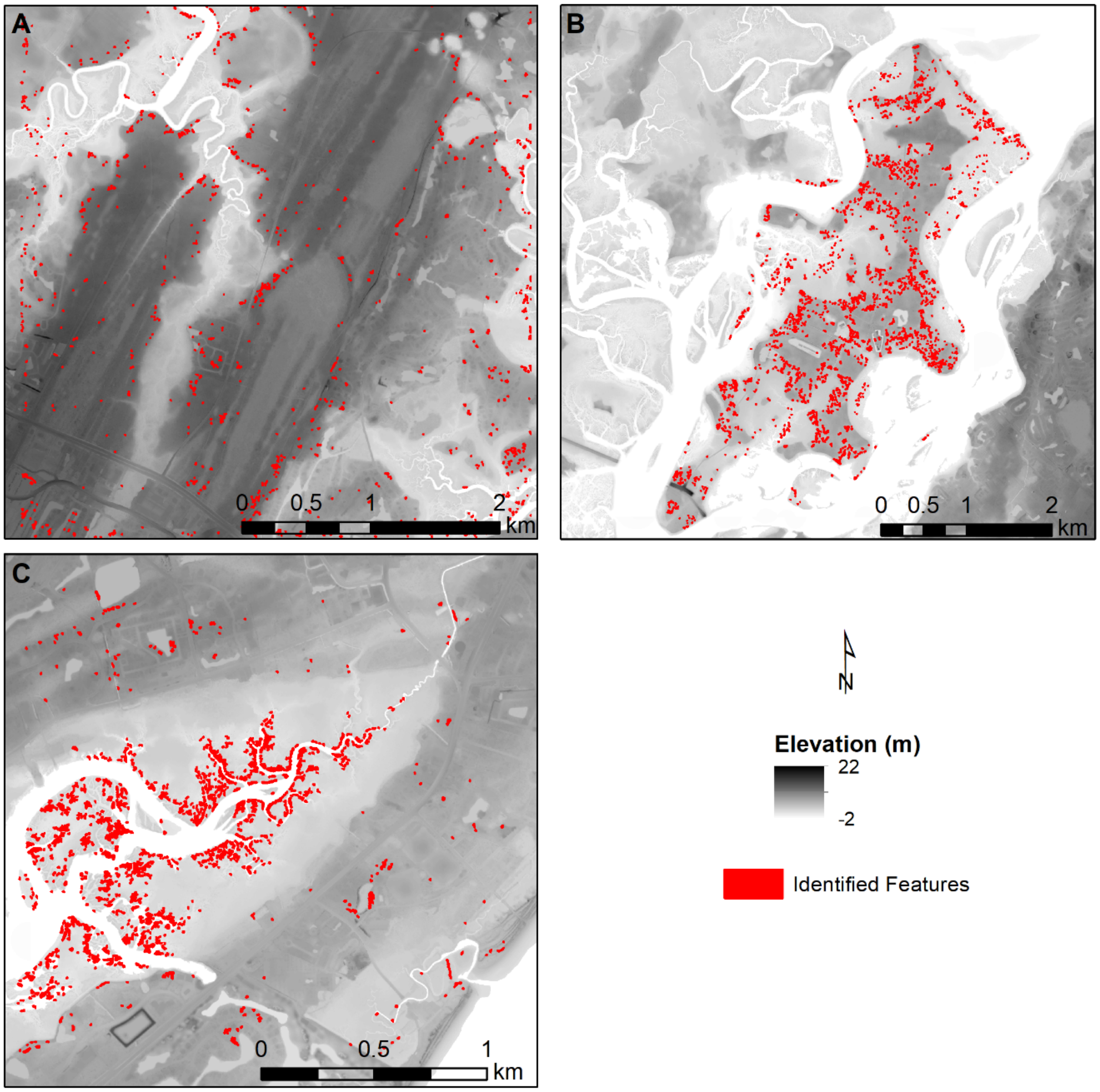

Figure 5: Results of IDA analysis using 300 iterations. A: Study Area 1 results. In addition to several mounds, IDA also identified a new shell ring site in this area. B: Study Area 2 results. C: Study Area 3 results. Many results in all areas are the result of natural topographic changes and/or modern disturbance (Color online).

In contrast to segmentation and IDA, template matching *only* identified features that were anthropogenic in origin, though the method missed a shell-ring that was located by segmentation (Figures 6). Finally, our combined approach that includes template matching and segmentation improved on all of these results by retaining only the positively identified features (see Figure 7).

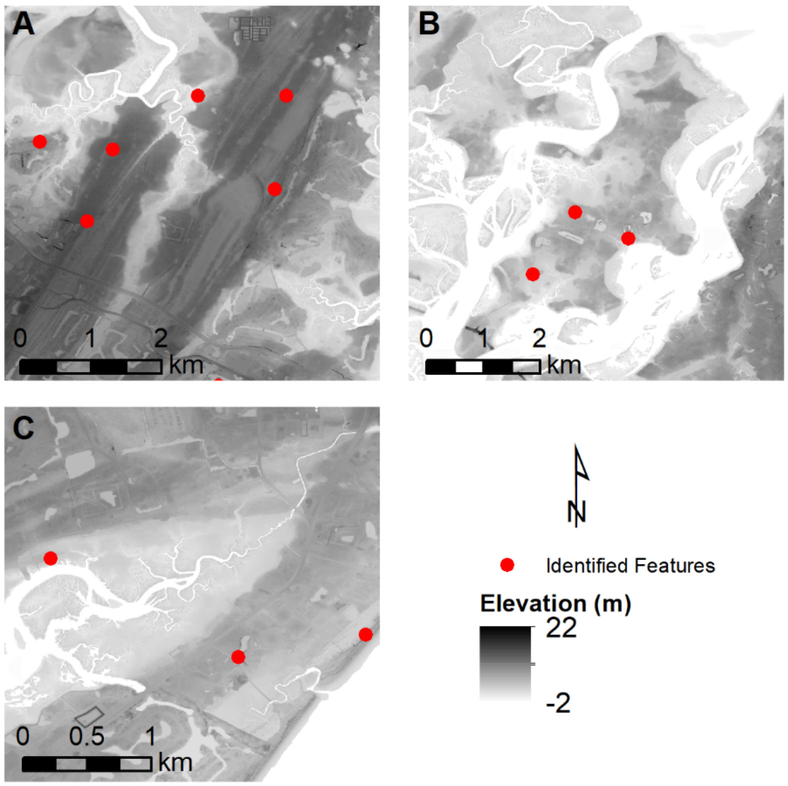

Figure 6: Results of the template matching algorithm on the three study areas. A: Study Area 1 results. The algorithm failed to identify the shell ring site (indicated by arrow). B: Study Area 2 results. All identified locations are anthropogenic. Two of the three have archaeological contexts. C: Study Area 3 results. Two of the three features were surveyed and were both anthropogenic. Neither one was archaeological in context. White areas represent water and coastline (Color online).

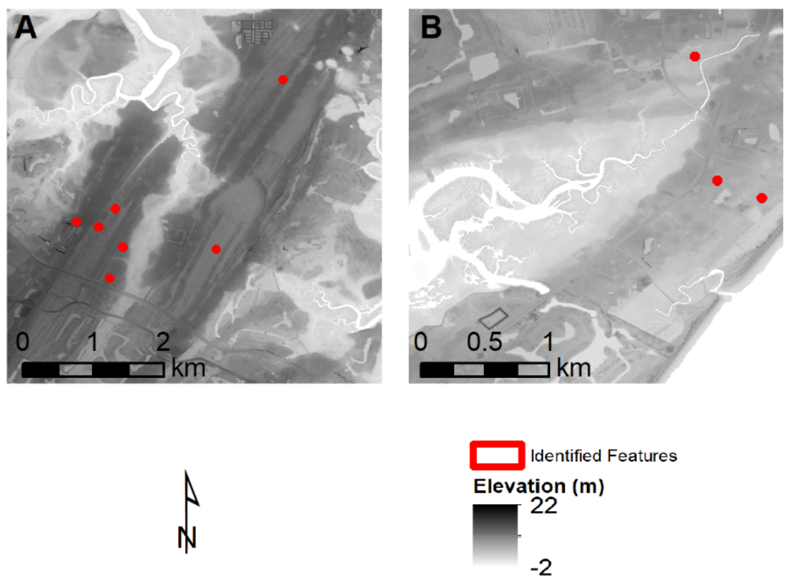

Figure 7: Results of the combined segmentation and template matching algorithm. A: Study Area 1 results. B: Study Area 3 results. In comparison to the segmentation and IDA methods (see Figures 4 and 5) the combined method provides fewer false positives (Color online).

4.4 Method Results and Comparisons

Study Area 3 proved to be problematic for the detection of archaeological deposits due to the extensive recent land disturbance activity. In general, any use of automated techniques such as OBIA is going to be hampered in areas that have been subject to development. One can expect considerably more manual labor will be required to filter false positives from total results. The combined approach, however, was the most effective in these conditions and did not falsely identify the hundreds of features that were identified by the other methods (Figure 7). This result further emphasizes the benefits of using a combined approach for archaeological prospection.

Numerically, segmentation and IDA were the most successful OBIA methods for identifying mounded features, as they detected the most archaeological sites compared to the other methods (Table 2). They yield, however, the highest number of false positives. Using a greater number of iterations appears to alleviate this issue and makes IDA far more successful than a pure segmentation procedure. The use of template matching produced no false positives related to natural phenomena but failed to discriminate between prehistoric and historic features. Our new combined approach that includes template matching and segmentation provided the greatest consistency in correctly identifying archaeological features (also see Davis et al., 2018) (Table 6).

Table 6: Archaeological utility of OBIA methods. Topographic discrimination refers to each method's ability to distinguish between natural and anthropogenic features. Archaeological detection accuracy refers to the ratio of positive detections to false ones. Overall utility is the average of the topographic discrimination and archaeological detection accuracies.

METHOD	Segmentation	IDA (100 iterations)	IDA (200 iterations)	IDA (300 iterations)	TM	Combined
Topographic Discrimination Accuracy	50%	57.14%	66.67%	85.71%	100%	100%
Archaeological Detection Accuracy	50%	35.71%	50%	71.43%	50%	100%
Overall Utility (average of accuracies)	**50%**	**46.43%**	**58.34%**	**78.57%**	**75%**	**100%**

5.1 DISCUSSION AND CONCLUSION

While each OBIA method that we evaluated yields positive identifications, our results show that a combination of approaches produces the most reliable information for archaeological prospection. Of course, some of the differences we note in our analyses depend on the quality of the data we used: the effectiveness of methods depends to some degree on the resolution and quality of the data. The difference between segmentation and IDA in our study of Beaufort County, for example, was likely due to the limits of the resolution of our LiDAR data. Improved resolution of the LiDAR data will address the deficiency observed in this study. By tripling the number of iterations, IDA yielded more accurate results than segmentation, as opposed to slightly less accurate results using only 100 iterations. The processing requirements, however, make IDA less useful for large-scale landscape studies, as the amount of computing power required makes the process extremely time consuming.

The results here are promising but it should be noted that a single universal algorithm is unlikely to be developed. In the case of OBIA, the analyst must always establish the definition for classes of objects to be identified in advance. These definitions must be based on specific hypotheses about the necessary and sufficient conditions needed for the algorithm to identify a feature of interest. The parameters for these conditions can be derived using regionally-specific parameters, but doing so means that the conditions will be contingency-bound generalizations and will be incapable of detecting previously unknown features with morphologies other than those described in reference samples. For this reason, analyses must be repeated by varying the parameters to test new hypotheses and as new knowledge of the local archaeological is developed.

Ultimately, the identification of new aspects of the archaeological record in the American Southeast will permit for researchers to re-evaluate our current notions about pre-contact settlement patterns, as well as the significance of features like shell rings. The shell ring identified by this study (also see Davis et al., 2018) is significantly smaller than most known shell rings in this area. The methods and datasets used here permit for the detection of features as small as a few meters across and about half-a-meter tall. The average diameter of known ring plazas in South Carolina is 32 meters (Russo 2006:25). The ring discovered here has a plaza diameter of approximately 16 meters, half that of the size of known rings. Additionally, the maximum diameter of the ring is only 36 meters. Compared to the average in South Carolina of 64 meters (Russo 2006:25), this ring is considerably smaller than those previously studied. As such, new discoveries may reveal new information about the range of feature structure and composition, challenging previous notions of prehistoric activity (e.g., Russo, 2004; Saunders, 2004; Trinkley, 1985).

This substantial difference in size of this new ring feature compared to previously surveyed rings in this area also speaks to a bias in archaeological knowledge towards monumental structures compared to smaller ones. This requires high resolution datasets, as the higher the spatial resolution, the smaller the objects that are detectable. A future avenue of research must focus on the potential for remote sensing surveys in alleviating human error in traditional surveying, where visibility becomes a considerable issue in detection in heavily vegetated environments (Hirth 1978; Nance 1979; Schiffer et al. 1978).

The results of our new approach show several new features that were undetected by previous manual surveys (see Davis et al., 2018). These features include previously unrecorded deposits such the new shell ring in Study Area 1 and a pre-contact mound in Study Area 2. As such, the use of automated methods is successful in picking out features that manual approaches overlook, and ensures full, systematic coverage of areas being surveyed. Nevertheless, it should be stressed that manual evaluation is also an essential step in analyzing remote sensing data, as it often provides the first step in building robust datasets that can be used as training data for more complex automated methods.

Urbanization and climate related sea level changes pose imminent threats to cultural resources in areas such as Beaufort County, but also across the American Southeast. The use of remote sensing technologies such as LiDAR and computational algorithms offer new means for addressing existing deficiencies in our knowledge of the archaeological record. While no single algorithm offers a universal solution, the use of LiDAR data and OBIA can yield accurate identifications of mound features that lay under tree canopies and across large areas. While preliminary, this study demonstrates the potential for OBIA and remote sensing to greatly assist in archaeological landscape survey efforts. Given the urgency to document our extant archaeological record before it is lost, such an approach promises to greatly contribute to our knowledge of the archaeological record.

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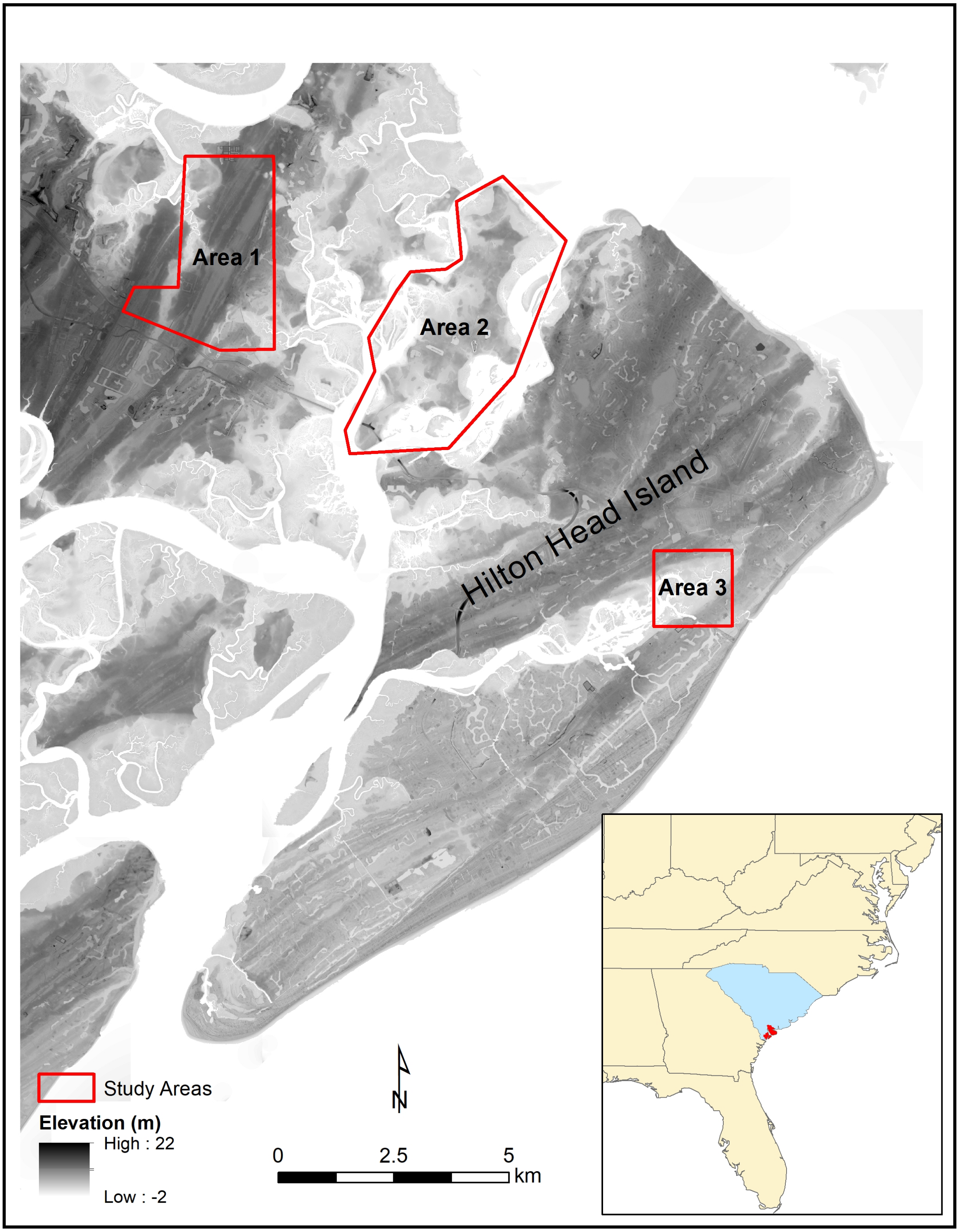

Area 1
Area 2
Area 3
Hilton Head Island
Study Areas
Elevation (m)
High : 22
Low : -2
0
2.5
5
km
N

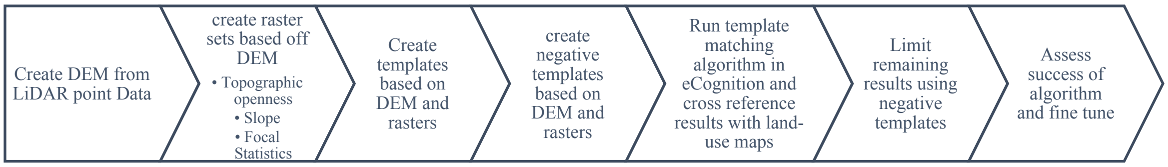
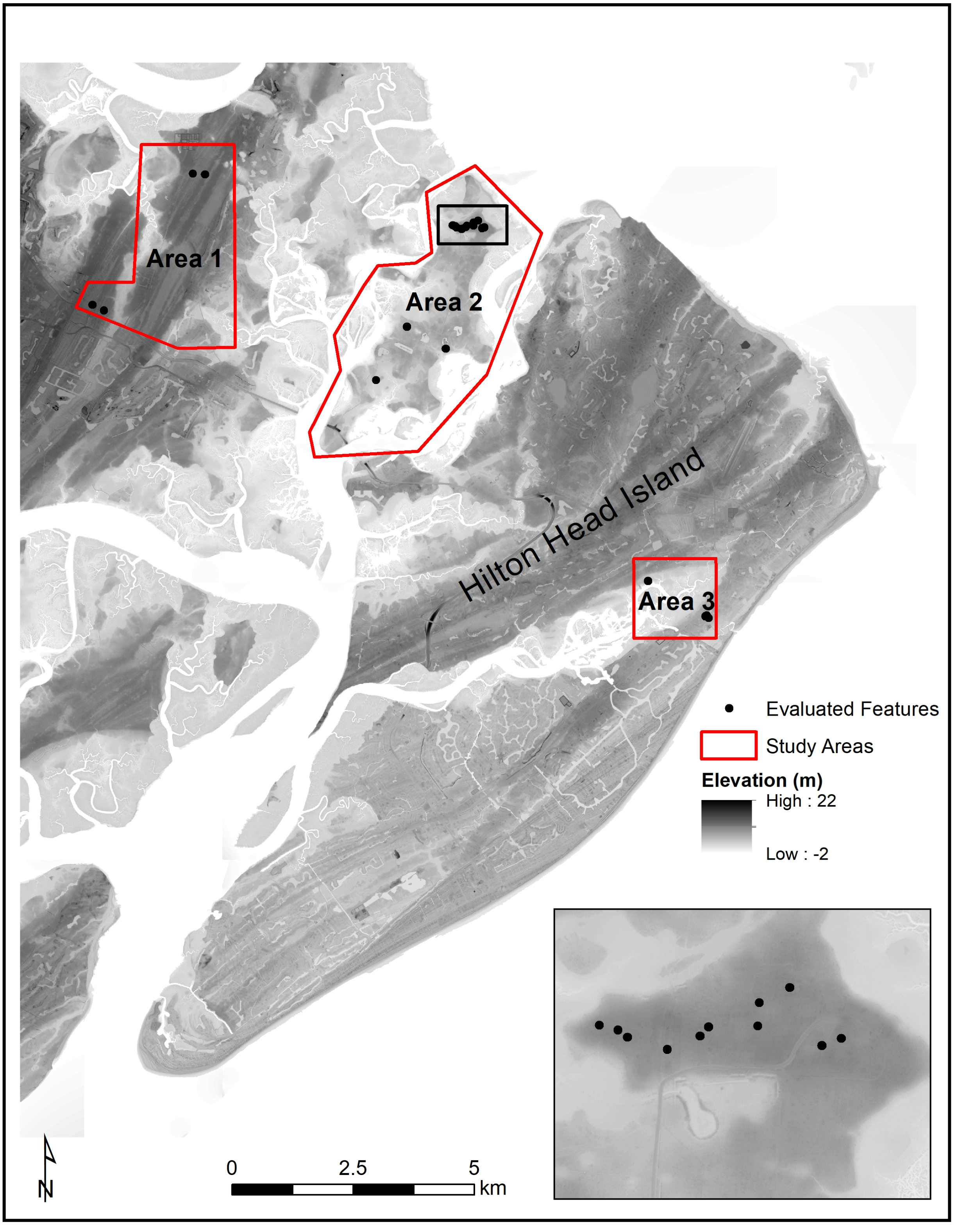
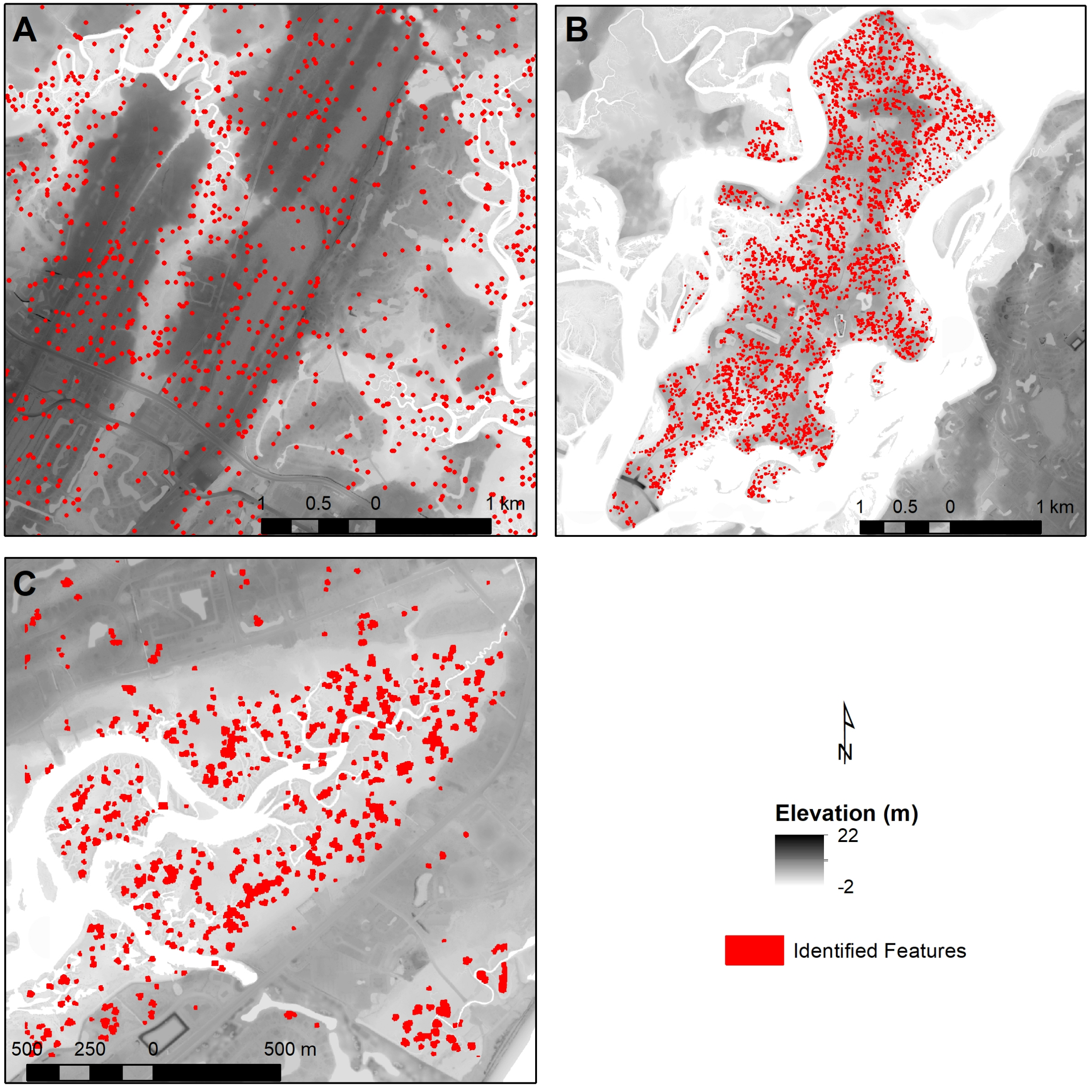
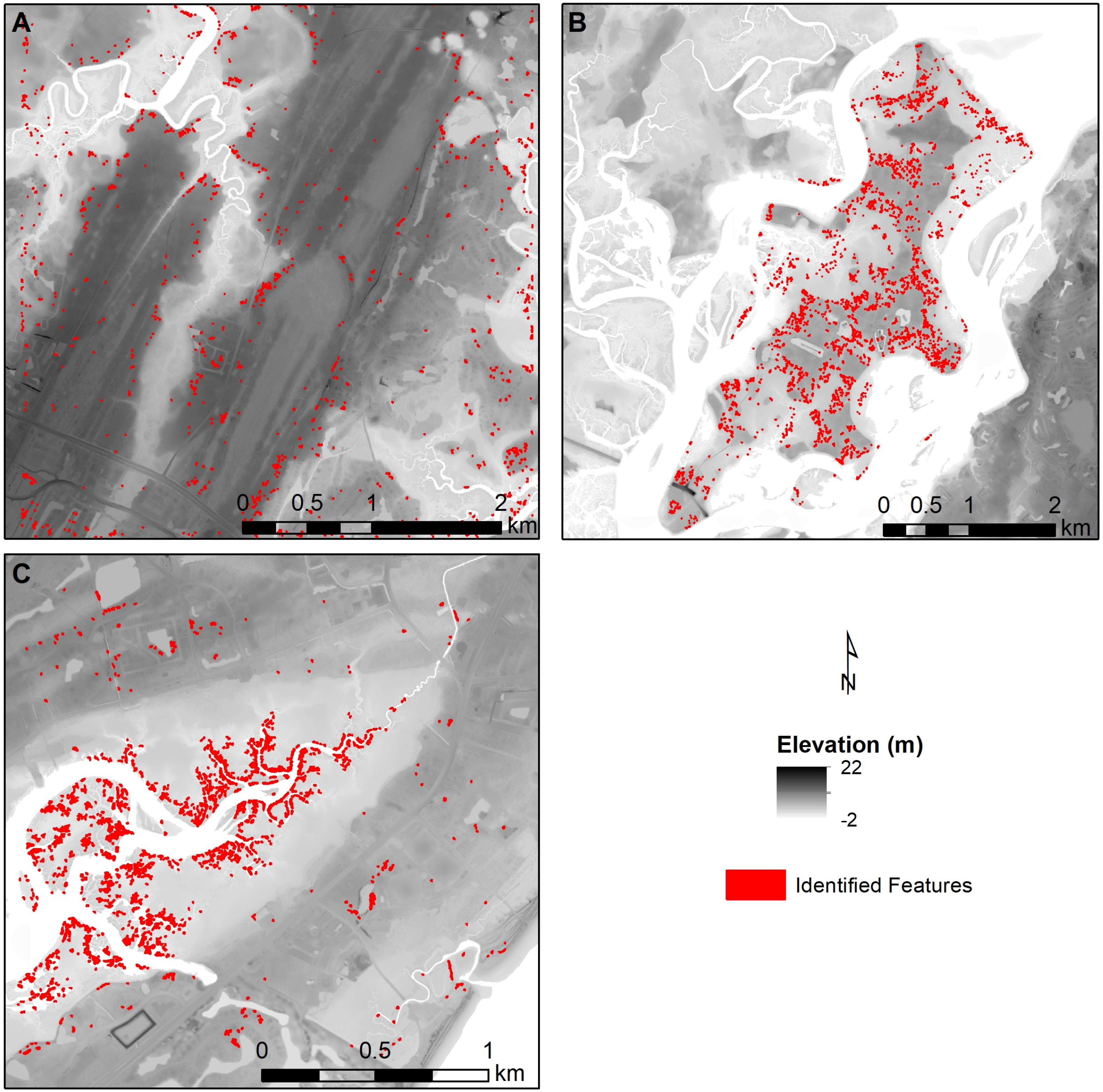


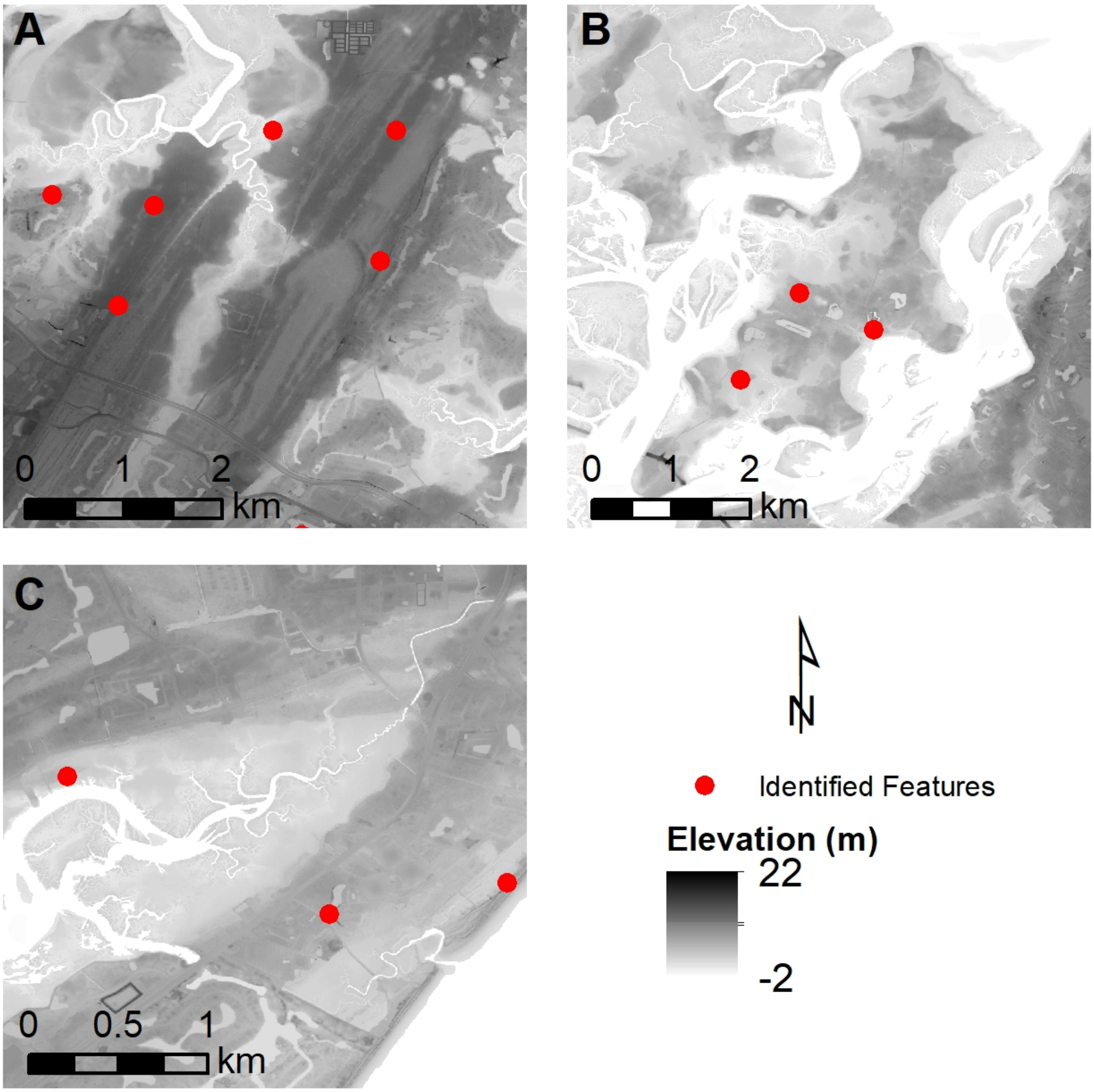
Figure 2: Steps involved in the use of template matching for the identification of mound features.

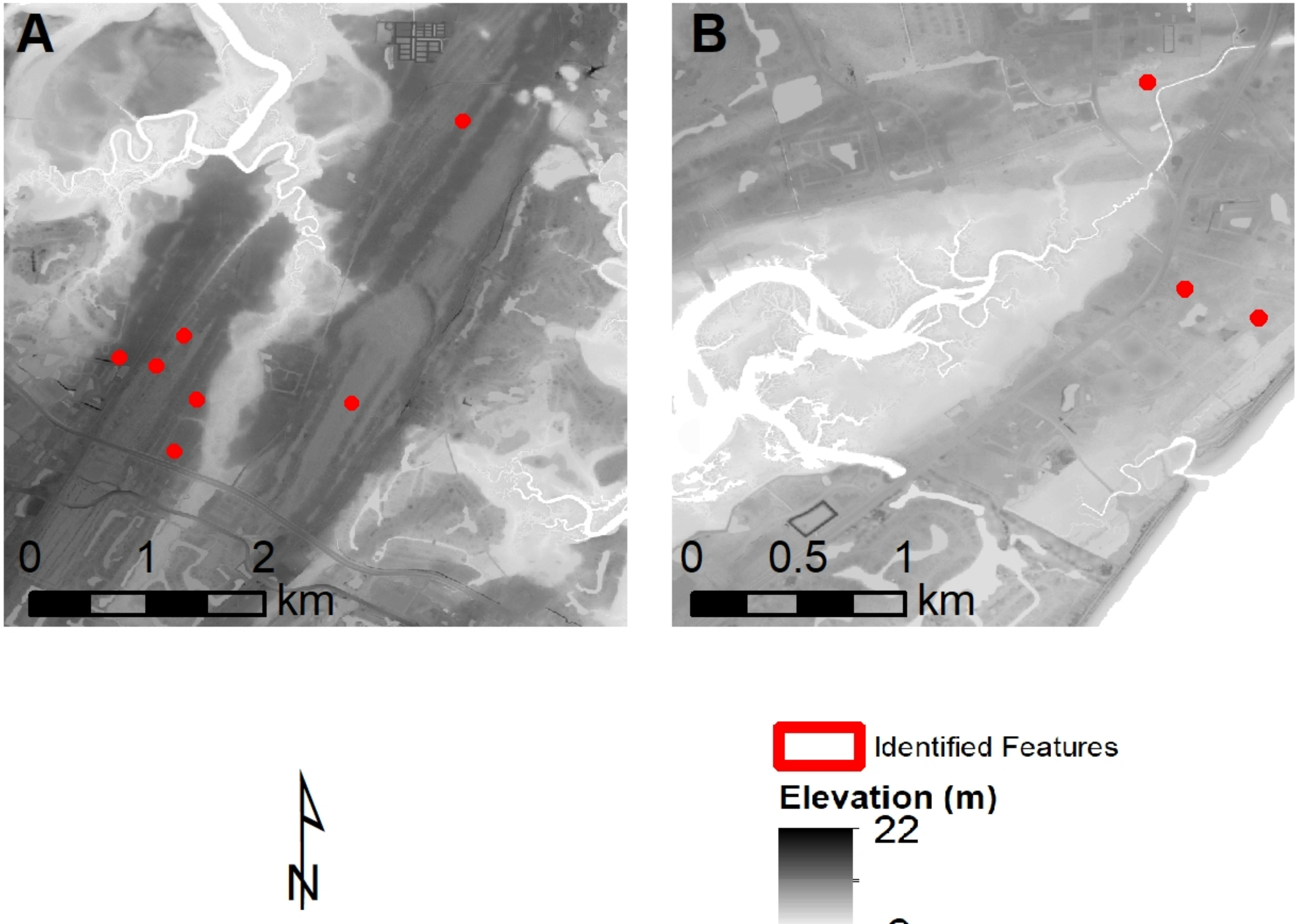

Area 1
Area 2
Area 3
Hilton Head Island
Evaluated Features
Study Areas
Elevation (m)
High : 22
Low : -2
N
0
2.5
5
km


A
1 0.5 0 1 km
B
1 0.5 0 1 km
C
500 250 0 500 m
N
Elevation (m)
22
-2
Identified Features



A
0
0.5
1
2
km
B
0
0.5
1
2
km
C
0
0.5
1
km
N
Elevation (m)
22
-2
Identified Features


A
0
1
2
km
B
0
1
2
km
C
0
0.5
1
km
N
Identified Features
Elevation (m)
22
-2



A
0
1
2
km
B
0
0.5
1
km
Identified Features
Elevation (m)
22
-2
N

Table 1: Parameters used in multiresolution segmentation of the Beaufort County LiDAR data.

Parameter	*Threshold*
Area	<=150 m^2
Circularity	>= 0.6
Asymmetry	0 – 0.3
Compactness	>= 1.0

Table 2: Total detections made by each OBIA technique.

OBIA Method	Total Detections Study Area 1	Total Detections Study Area 2	Total Detections Study Area 3
Segmentation	1,399	1,091	380
IDA (100 iterations)	3,332	1,677	413
IDA (200 iterations)	1,582	1,829	807
IDA (300 iterations)	1,093	2,485	817
Template Matching	6	3	3
Combined	7	0	3

Table 3: OBIA Method Results from Field Survey

OBIA Method	Sites Surveyed	Accurate identifications determined by field survey	False Positives determined by field survey	Rate of positive identification/false positives based on field survey	Total Detections in Study Areas	Potential new mound features
Segmentation Classification	12	6	6*	1:1	2,490	1,245
IDA (100 iterations)	14	5	9**	5:9	5,422	3,012
TM	6	3	3	1:1	10	5
Combined (segmentation and TM)	4	4	0	1:0	10	10

* Two sites were inconclusive
** One site was inconclusive

Table 4: Change in detection accuracy for known archaeological deposits in Area 2 using increasing numbers of iterations. As the number of iterations increases, so too does the number of identified archaeological deposits.

Number of Iterations	Number of Identified Archaeological Deposits
100	40
200	59
300	60

Table 5: Overall accuracy for IDA using increasing numbers of iterations. As the number of iterations increases, the number of false positive detections decreases, and the overall accuracy increases.

Number of Iterations	True Positive Identifications (Determined by ground-survey)	False Positive Identifications (Determined by ground-survey)	Total Detections	Overall Accuracy
100	5	9	5,422	35.71%
200	3	3	4,218	50.00%
300	5	2	4,395	71.43%

Table 6: Archaeological utility of OBIA methods. Topographic discrimination refers to each method's ability to distinguish between natural and anthropogenic features. Archaeological detection accuracy refers to the ratio of positive detections to false ones. Overall utility is the average of the topographic discrimination and archaeological detection accuracies.

METHOD	Segmentation	IDA (100 iterations)	IDA (200 iterations)	IDA (300 iterations)	TM	Combined
Topographic Discrimination Accuracy	50%	57.14%	66.67%	85.71%	100%	100%
Archaeological Detection Accuracy	50%	35.71%	50%	71.43%	50%	100%
Overall Utility (average of accuracies)	**50%**	**46.43%**	**58.34%**	**78.57%**	**75%**	**100%**

Supplemental Table 1: List of Sites on Pinckney Island (Study Area 2) identified by IDA and Segmentation. Template matching and the combined method did not identify any pre-identified archaeological deposits. An *I* indicates that the method identified that site. If a method did not identify a site, the column is left blank.

SITEID	IDA (100 Iterations)	IDA (200 Iterations)	IDA (300 Iterations)	Segmentation
38BU0092		*I*		*I*
38BU0653		*I*	*I*	*I*
38BU0092		*I*		*I*
38BU0092		*I*	*I*	*I*
38BU0093	*I*	*I*	*I*	*I*
38BU0094	*I*	*I*	*I*	
38BU0095	*I*		*I*	*I*
38BU0066	*I*	*I*	*I*	*I*
38BU0067	*I*	*I*	*I*	
38BU0068		*I*		*I*
38BU0069		*I*		*I*
38BU0193	*I*	*I*	*I*	*I*
38BU0193	*I*	*I*	*I*	*I*
38BU0069	*I*	*I*	*I*	*I*
38BU0069	*I*	*I*	*I*	*I*
38BU0166				*I*
38BU0168	*I*	*I*	*I*	*I*
38BU0169	*I*		*I*	*I*
38BU0170	*I*			
38BU0172				*I*
38BU0173	*I*	*I*	*I*	
38BU0174	*I*		*I*	*I*
38BU0175		*I*		
38BU0176	*I*	*I*	*I*	*I*
38BU0177		*I*	*I*	*I*
38BU0180	*I*		*I*	
38BU0181	*I*	*I*	*I*	*I*
38BU0182	*I*	*I*		*I*
38BU0183	*I*	*I*	*I*	*I*
38BU0185	*I*	*I*		*I*
38BU0186				*I*
38BU0187	*I*	*I*	*I*	*I*
38BU0188	*I*		*I*	
38BU0191	*I*		*I*	*I*
38BU0192	*I*			*I*
38BU0194				*I*
38BU0195	*I*	*I*	*I*	*I*
38BU0198				*I*
38BU0199	*I*		*I*	*I*

38BU0201	/			/
38BU0202				/
38BU0203		/		/
38BU0204		/	/	/
38BU0205	/	/	/	/
38BU0206	/	/	/	/
38BU0208	/	/	/	/
38BU0209		/	/	/
38BU0210		/	/	/
38BU0211		/		
38BU0212		/	/	/
38BU0213	/	/	/	/
38BU0214				/
38BU0215			/	/
38BU0216		/		
38BU0217		/		/
38BU0368				/
38BU0664	/		/	
38BU0665	/		/	/
38BU0668				/
38BU0669				/
38BU0670				/
38BU0672		/		
38BU0673	/			/
38BU0674				/
38BU0470				/
38BU0471		/	/	/
38BU0694		/	/	/
38BU0694		/	/	/
38BU0471		/	/	/
38BU0472	/	/	/	/
38BU0473	/	/	/	/
38BU0474	/	/	/	/
38BU0650		/	/	/
38BU0651	/	/	/	/
38BU0652	/	/	/	/
38BU0654	/		/	/
38BU0656	/	/	/	/
38BU0657				/
38BU0658			/	/
38BU0661			/	/
38BU0662	/	/	/	/
38BU0675	/	/	/	/
38BU0676		/	/	/

38BU0677			/	/
38BU0678				/
38BU0693	/		/	/
38BU0696		/		/
38BU0699				/
38BU0700	/		/	
38BU0702	/	/	/	/
38BU0703	/	/	/	/
38BU0704				/
38BU0705	/	/	/	/
38BU0706		/		/
38BU0707	/	/	/	/
38BU0710		/		/
38BU1215		/		
TOTAL	**49**	**59**	**60**	**84**