Adapting LiDAR data for regional variation in the tropics: a case study from the Northern Maya
Lowlands.

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14 Abstract

15 Archaeologists have used Light Detection and Ranging (LiDAR) as a remote sensing technique
16 for creating high resolution and high accuracy elevation models of the earth's surface in
17 forested areas. In the Maya area, LiDAR allows archaeologists to conduct full-coverage regional
18 surveys for the first time. Yet due to variation across space in the characteristics of vegetation,
19 topography, and the kinds of archaeological features that archaeologists seek to locate, the use
20 of LiDAR in the tropics will not meet the same level of success in every case study. Such
21 variation in vegetation, topography, and archaeological features also creates opportunities for
22 archaeologists to explore methodological adjustments that can maximize the usefulness of
23 LiDAR data for a particular forested area. Using a case study from Northern Yucatan, Mexico,
24 this paper explores a variety of techniques for visually rendering LiDAR data in an attempt to
25 determine which technique works best for identifying low stone residential platforms given the
26 local topography and vegetation. The most successful technique, a color-classified DEM, was
27 then used to locate hundreds of previously undocumented platforms in the area of LiDAR
28 coverage. Conducting a rapid vegetation survey showed that more features can be found in
29 forested areas when there is less vegetation close to the ground. Vegetation surveys permit the
30 calculation of vegetation-specific correction factors to be used in conclusions derived from
31 LiDAR imagery.

32

33 Key words

34 LiDAR, Settlement Patterns, Ancient Maya, Ground truthing, Political dynamics, Vegetation
35 survey

1. Introduction

Articles highlighting the ability of Light Detection and Ranging (LiDAR, also called Airborne Laser Scanning (ALS)) to penetrate tree cover and render precise topographic maps appeared in flagship archaeology journals as early as a decade ago (Bewley et al. 2005; Challis et al. 2008; Crutchley 2006; Devereaux 2005; Harmon et al. 2006). In the tropics, LiDAR caught fire more recently with the publication of groundbreaking results from the jungle-covered ruins of Caracol, Belize (Chase et al. 2011) and Angkor Wat, Cambodia (Evans et al. 2013). In the Americas, regional surveys covering hundreds and even thousands of square kilometers had only been possible in dry areas where vegetation does not significantly inhibit rapid, systematic pedestrian surveys (Blanton et al. 1982; Bauer and Covey 2002; Sanders et al. 1979; Wilson 1983). In tropical lowlands without modern agriculture, however, dense vegetation often makes regional-scale systematic pedestrian survey prohibitive in terms of cost and time. LiDAR has changed this situation, making it possible to identify residential platforms, agricultural terraces, and other features otherwise hidden by forest cover (Chase et al. 2014a; Rosenswig et al. 2013; 2014; for other successful remote sensing techniques in the Maya area, see Garrison 2010; Garrison et al. 2011). Yet LiDAR has only been used by a handful of archaeology projects in the tropics thus far. Since vegetation and topography affect processing and interpretation of LiDAR data and vary significantly both between and within tropical regions, methods deployed in one area may require refinement when transferred to other areas.

The Maya area (figure 1), which encompasses Guatemala, Belize, eastern Mexico, western Honduras and western El Salvador, contains a great diversity of ecosystems and

58 physiographic regions. The current study uses LiDAR on the coastal plains of northern Yucatan
59 (see also Hare et al. 2014). The vegetation and topography of this region differ significantly
60 from other Maya areas where LiDAR has been used, including the Vaca Plateau at Caracol,
61 Belize (Chase et al. 2011), the Maya Mountains at Uxbenka, Belize (Prufer 2014), the Belize
62 River Valley (Chase et al. 2014a), the Calakmul Biosphere Reserve at Yaxnocah, Mexico (Reese
63 Taylor et al. 2014), and the Soconusco area at Izapa, Mexico (Rosenswig et al. 2013).

Figure 1: Map of the Maya area showing the location of sites mentioned in the text

In this paper I consider three methodological concerns in working with LiDAR data from the coastal plains of Yucatan, gathered as part of the Ucí-Cansahcab Regional Integration Project (UCRIP). The first topic concerns visualization techniques for presenting LiDAR data. I

compare six different visualization techniques to see how well they make pre-Hispanic architecture visible. Second, I discuss criteria for differentiating natural features from artificial constructions using LiDAR imagery from the UCRIP area. The third topic pertains to the way in which height of vegetation, type of vegetation, and ground return density affect the success of using LiDAR imagery for locating ancient architecture. I make the case that vegetation has important effects on the visibility of ancient features on LiDAR imagery, thus justifying a rapid pedestrian vegetation survey in areas with LiDAR coverage.

Figure 2: Map showing the Ucí-Cansahcab causeway, the four major ruins along the causeway, and the areas covered by LiDAR and by pedestrian survey

2. Background

2.1 Geology and ancient architecture of the UCRIP area

The UCRIP study area consists of a series of ruins located in the vicinity of an 18km long causeway that connects the ruins of Ucí, Kancab, Ucanha, and Cansahcab (figure 2). The

86 geology of the northern plains of Yucatan presents both advantages and disadvantages for
87 using LiDAR to locate built features. The causeway between Ucí and Cansahcab lies on a 100km
88 wide swath of low-relief, karstic plain between a range of hills (the Sierrita de Ticul) to the
89 south and the coast to the north (figure 1) (Isphording and Wilson 1973). Figure 3 shows a
90 sample of the terrain at the site of Ucanha and in the figure, the only substantial rises are
91 artificial pyramids, which reach elevations of 10m above the natural ground surface. Fragments
92 of the causeway between Ucí and Cansahcab are also visible in figure 3, not to mention low
93 platforms (see below). Solution features and fractures in the carbonate surface create low
94 bedrock outcrops and depressions. In the vicinity of Ucí, the largest depressions are 5m deep,
95 cover less than half a hectare, and are rare; the depressions visible in figure 3 are the only ones
96 of their kind in the entire 26km² of LiDAR coverage.

Figure 3: Hillshaded image showing natural and artificial features at the archaeological site of Ucanha, Yucatan, Mexico. There are several modern roads and pathways in the image, though only one is labeled. The arrows point to ancient causeways. The arrows at the far left and right point to fragments of the 18km long causeway that connecting Ucí and Cansahcab. Most quadrangular bumps are ancient platforms. The black box contains the terrain displayed in figures 7, 8, and 9.

Bedrock outcrops decrease in elevation from about 5m high on the south edge of the plains, at the base of the Sierrita de Ticul, to less than 1m high as one nears the Gulf of Mexico (Beach 1998:764; Dahlin et al. 2005:235). Unfortunately, these small bedrock outcrops have the same height range and horizontal dimensions as artificial platforms. Figure 3 shows over one hundred platforms. Platforms are raised stone surfaces that support other structures such as houses, shrines, storage structures and kitchens. Typically these other structures are made mostly of materials—wood, thatch, daub—that are no longer preserved. In the Ucí-Cansahcab area, previous research shows that most platforms are generally lower than 2m with surface areas ranging from 25 to 650m² (Hutson and Welch 2014). Section 4.2 discusses techniques for distinguishing artificial platforms from natural outcrops that also show up as “bumps” in LiDAR imagery.

2.2 Vegetation of the UCRIP area

Over 80% of the land where LiDAR data were collected is covered in scrub forest that has not been significantly altered by humans in over a decade. Locals call this *monte*, and the most common tree species are Chukum (*Phitecolobium albicans*), Catzin (*Senegalia gaumeri*), Huaxin (*Leucaena leucocephala*), Chakah (*Bursera simaruba*), Habin (*Piscidia piscipula*), and Dzidzilche (*Gymnopodium antigonoides*). Canopy height is approximately 6m high and underbrush is thick. The area receives an average of 1000mm of precipitation per year. The rest of the terrain features a mosaic of different types of vegetation resulting from recent land use, including pasture, plots burnt for farming (*milpa*) at various times before data collection (see also Prufer et al. 2015), and more (see below). The vegetation in the UCRIP region differs

markedly from other areas with intensive LiDAR data. For example, the Caracol area/Vaca Plateau of Belize, where the potential of LiDAR in the Maya area was first demonstrated, has 20m high canopies with less underbrush (Fernandez et al. 2014: 9972). This difference in vegetation affects the success of algorithms that classify returns into ground versus non-ground points (Fernandez et al, 2014:9980). Specifically, such algorithms work better in higher forests where there is little vegetation between the canopy and ground. They work less well in areas with dense understory (Crow et al. 2007:246; Doneus et al. 2008:883) such as the extremely lush (4000mm precipitation per year) area around Uxbenka (figure 1) explored with LiDAR by Prufer and colleagues (2015).

3. Methods

3.1 LiDAR data collection

The National Center for Airborne Laser Mapping (NCALM), based at the University of Houston and the University of California, Berkeley, collected 26km² of LiDAR data for UCRIP (figure 2) (Fernandez et al. 2014). NCALM used a Gemini 167Khz LiDAR system configured with the following specifications: collection speed of 125 kHz, scan angle of 20°, beam divergence of 0.8 milliradians, and shot density of 7.9 shots per m². The LiDAR system was mounted on a Cessna 337 inline twin engine aircraft flying 600m above the ground at an approximate speed of 100mph. The aircraft flew swaths that were 400m wide. Each new swath overlapped the previous one by 200m, so that each part of the ground was shot twice, yielding an average density of 15 shots per m². The actual number of XYZ points returned per m² was higher. The

following explanation for this phenomenon may help familiarize non-specialists with how LiDAR works (see also Fernandez et al. 2014). As the beam of laser light (a shot) travels from the airplane to the ground and back, sometimes vegetation or the ground itself reflects the entire beam back to the airplane. The first and only return, or point, from such a shot therefore records the precise location of the feature (leaf, branch, rock, etc.) that blocked the shot. Often, however, vegetation reflects only part of the beam, allowing the rest of it to be reflected back to the airplane by something else. In this case, the sensor on the plane picks up two or more returns from the same shot. Each return has its own XYZ coordinate. For UCRIP, the sensor picked up 1.45 returns per shot, yielding about 22 returns per m^2 . For classifying the point cloud into ground returns and other types of returns, NCALM used the “classify as ground” routine within the Terrasolid Terrascan LiDAR processing software. This classification algorithm was developed by Axelsson (2000). NCALM delivered the classified point cloud in $1km^2$ tiles in the .las file format. Such files were converted into las datasets in ArcMAP in order to create bare earth digital elevation models (DEMs, also called digital surface models [DSM] and digital terrain models [DTM]) with a 0.5m resolution (each cell measures $0.25m^2$).

This Axelsson algorithm proved highly successful at Caracol, Belize, where NCALM performed the first LiDAR data collection focusing on a Maya ruin (Chase et al. 2011). In the UCRIP area, which has thick, low, ground cover, filtering out vegetation points from ground points poses greater difficulty (see also Prufer et al. 2015): there is a higher possibility of false positives (returns classified as ground returns but which are actually vegetation returns). A full waveform system, which records the entire return signal, may be preferable to the discrete return results presented in this study (Doneus et al. 2008; Fernandez et al. 2014; Lasaponara et

al. 2011). NCALM has full waveform data for UCRIP but has not been able to analyze it. NCALM collected the data on May 12th 2014. Early May is usually the end of the dry season in Northern Yucatan, the point in the year with the least amount of vegetation. Such conditions favor maximal ground returns but in 2014 the dry season was wetter than normal which meant more green growth that could block/reflect shots. A drier year would permit a slightly higher proportion of ground returns.

3.2 LiDAR data display

Archaeologists have a variety of visualization techniques available for rendering LiDAR point clouds. Like any tool set, certain techniques work best for some tasks, other techniques work better for other tasks. A technique that successfully finds one kind of feature at one particular scale in one kind of terrain may fail to find other kinds of features at that same scale, or may fail to find the same kind of features in terrain that is more (or less) rugged (Challis et al. 2011; Stular et al 2012). Mesoamericanists have used hillshading, stretched shading of DEMs, slope rasters, and, to a lesser extent, Principal Components Analysis (PCA; Prufer 2015:11) and Max Slope Anomaly (Hare et al 2014:9072). This paper compares hillshades, PCA, DEMs with stretched and classified shading, slope rasters, and Sky-View Factor in order to assess which technique works best for detecting low platforms in the relatively flat topography of the northern Maya lowlands. This particular comparison follows that of Challis et al. (2011), who compared five of these six techniques for both low-relief and high-relief areas, but Challis et al.'s comparison comes from temperate Europe as opposed to the tropical Americas.

Hillshading is easily accessible in GIS software and renders topographic relief in a way that is easily and intuitively grasped. For this and other reasons, hillshading has become the most common visualization technique found in publications of LiDAR DEMs, not just in Meosamerica but also in Europe and Southeast Asia (Challis et al. 2011; Chase et al. 2011, 2014b; Imhof 2007; Rosenswig et al. 2013, 2014; Stular et al. 2012:3355). Figure 3 shows a hillshade of the site of Ucanha, highlighting the main features of the site (causeways, high pyramids, low platforms). Challis et al. (2011) demonstrate that many other visualization techniques improve upon hillshades. One inconvenience of hillshading is that some features may not be visible when the light source comes from a particular azimuth or a particular altitude, thus necessitating observation of multiple different hillshades. Nevertheless, there are strong correlations between different hillshaded images of the same DEM and, following the logic that two or three principal components could capture most of the variation in a much larger set of hillshaded images, Devereaux et al (2008) introduced PCA to the analysis of DEMs, which can produce a single image.

Stretched and classified shading differ from hillshading in that each cell of the DEM raster acquires a color/shade from a color ramp based on the elevation value of that cell as opposed to how a light source would illuminate (or not illuminate) that cell. Stretched and classified shading work well for detecting small changes in elevation (such as a 1m high platform) in generally flat areas like that of UCRIP (Challis et al. 2011:286). Stretch-shaded DEMs are often combined with hillshades. Classified shading, also called color classification, differs from stretched shading in that it groups elevation values for the different cells of the DEM raster into a smaller number of color classes (or grey scale class if using a grey-scale color

ramp) so that the user sees distinct color changes from one elevation class to the next and can easily note the mean elevation represented by each color class. Users can also exclude elevation ranges from the classification. With the exception of rare depressions, the elevation of the natural ground surface in the UCRIP area varies by only 3m and artificial platforms rarely exceed 2m in height. Excluding the bare earth raster cells that fall outside of a 6m elevation window therefore maximizes the visibility of artificial platforms. Using the ArcMAP maximum of 32 classes, the top of a 1m high mound occupies a color class that is five or more color grades (depending on the classification technique) different from the color class associated with the natural ground surface.

A slope raster is a transformation of the DEM such that each cell is shaded according to its slope as opposed to elevation (McCoy et al. 2011). Slope rasters can be generated from the spatial analyst toolbox in ArcMAP. Since ancient Maya platforms are generally flat on top and sloped at the sides, a slope raster will highlight the edges of platforms in the UCRIP region. The Sky-View Factor (SVF) visualization technique assigns a value to each cell of the DEM based on the portion of the sky visible from that cell. Kokalj et al. (2011:271) and Zaksek et al. (2011) show that it is an effective means for the interpretation of past cultural landscapes. In particular, whereas hillshading works well for representing sharp edges, SVF is optimal for gradual elevation anomalies. I performed SVF using a free download of Relief Visualization Toolbox (<http://iaps.zrc-sazu.si/en/svf#v>). Section 4.1 presents a controlled test of the six visualization techniques (hillshades, stretched DEM, color-classified DEM, PCA, slope raster, and SCF) to see which one makes visible the highest number of platforms in an area where all platform locations are already known from pedestrian survey.

236

237 3.3 Ground truthing

238 Ground truthing is standard for any use of LiDAR data (Devereux et al. 2005; Doneus et

239 al. 2008). One cannot know whether or not a topographic anomaly visible on a LiDAR imagery

240 represents a cultural feature until an archaeologist has inspected a number of such anomalies

241 in the field. Ground truthing has particular value in the UCRIP area because, as discussed in

242 section 2.1, the topography in the UCRIP area is packed with natural bedrock outcrops that

243 mimic artificial platforms. The current study made use of two kinds of ground truthing: pre-

244 LiDAR and post-LiDAR. Pre-LiDAR ground truthing consisted of systematic, full coverage,

245 pedestrian survey in which teams walked across the landscape with 10m spacing between each

246 team member and recorded every visible feature with GPS, tape, and compass (see Puleston

247 1974 for additional details on this method of survey). Using this method, UCRIP systematically

248 surveyed 13.84km² prior to the LiDAR flight (figure 2); 2.23km² of this area fall within the LiDAR

249 data collection area. Maps of architectural features from the pedestrian survey were overlaid

250 on top of LiDAR imagery to see how these features look using the different visualization

251 techniques and to assess which visualization techniques work best in this context (see section

252 4.1).

253 Post-LiDAR ground truthing involved selecting potential ancient features visible on

254 LiDAR imagery from areas with no pedestrian survey, locating the features in the field with

255 handheld GPS, examining them visually, and determining whether or not they were actual

256 human constructions. I visited 59 potential features suggested by LiDAR imagery.

The pre-LiDAR and post-LiDAR ground truthing facilitated the enumeration of six criteria that characterize the visual signature of Pre-Hispanic platforms in bare earth DEMs (see section 4.2). These criteria were then used to identify new platforms with the LiDAR imagery alone in the vast area that lacks pedestrian survey.

3.4 Vegetation survey

Vegetation impacts the ability to use LiDAR data to detect ancient features (Crow et al. 2007; Rosenswig et al. 2014). Among other things, LiDAR data enable easy classification of vegetation cover according to the vegetation's height above ground (HAG). I created the HAG raster (figure 4) by using ArcMAP's raster calculator tool to subtract the elevation values of the 1m^2 cells of a 1m^2 resolution bare earth DEM raster from the elevation values of the corresponding 1m^2 cells in a DEM raster created entirely from the first returns from each laser shot. In areas where there is vegetation, subtracting ground returns from first returns yields the height of the top of the vegetation. The HAG raster in figure 4 assigns each 1m^2 cell to one of six color-coded height ranges (0-0.5m, 0.5 to 1.5m, 1.5 to 2.5m, 2.5 to 4.5m, 4.5 to 7m, and 7m and above). This raster showed that vegetation in different plots of land generally conformed to four broad categories of vegetation height: minimal (fields burnt for farming), low (weedy fields and areas with low pasture), medium (high pasture and overgrown plots farmed in previous years), and high (scrub forest). Rosenswig et al. (2014) conclude that height above ground in coastal Chiapas, Mexico, does not bias the capacity for detecting mounds.

Figure 4: Height Above Ground raster

Yet, as Crow et al. (2007) demonstrate, the *kind* of vegetation cover could be more important than the *height* of the vegetation when assessing the results of LiDAR analysis. For example, canopies of the same height may have different porosities depending on the nature of the dominant tree species. Furthermore, HAG rasters reveal nothing about low-lying vegetation underneath the canopy. Understanding the nature of such low-lying vegetation is critical because the discrete return system (as opposed to a waveform system) used in this study presents difficulties in generating an accurate bare earth DEMs when low, non-canopy ground cover is dense (Crow et al. 2007:251; Doneus et al. 2008; Lasaponara et al. 2011; Fernandez et al. 2014:9973-5).

For these reasons, Crow et al. (2007) argue that a rapid vegetation survey must go hand-in-hand with LiDAR prospecting in vegetated environments (a systematic survey negates the cost-saving benefits of LiDAR). The vegetation survey categorizes land parcels into an array of vegetation types established on the basis of both canopy and understory. The distinction between grazed and ungrazed scrub forest highlights how vegetation type (as opposed to

294 height) may influence LiDAR results in the UCRIP area. In scrub forest, cattle do not reduce the
295 HAG but they do eliminate some of the vegetation close to the ground. Thus, although grazed
296 scrub forest has the same HAG as ungrazed scrub forest, the total volume of vegetation is lower
297 in the grazed scrub forest (figure 5), which means that laser shots have a better chance of
298 hitting the ground. Furthermore, even in patches of grazed scrub forest where the ground
299 return density is similar to that of ungrazed scrub forest, the Axelsson algorithm for filtering
300 ground points from vegetation points may also work better since cows have grazed away more
301 of the vegetation close to the ground, thus making a clearer separation between points that
302 reflect vegetation in the canopy and points that represent the ground (Crow et al. 2007:246;
303 Doneus et al. 2008:883; Fernandez et al. 2014: 9971-2).

304

305 Figure 5: Two kinds of scrub forest: ungrazed (top) and grazed (bottom).

306

307 Since there is reason to suspect that the type of vegetation, not just height of
308 vegetation, impacts the extrapolation of a bare earth DEM from the point cloud and since the
309 reliability of the DEM is not solely a function of ground return density, I implemented a rapid
310 vegetation survey to see how the different vegetation types affect ground return density and
311 what effect vegetation type has on the visibility of ancient architecture on LiDAR imagery. Crow

et al. (2007) and Prufer et al. (2015) present similar studies – the former in England, the latter in tropical Central America, though in an area of Belize that receives approximately four times as much rain as northern Yucatan. The Belize study assigned vegetation to one of five categories. In this survey, which took approximately four days, I walked most paths, roads, and fencelines to the west of Cansahcab and to the east of Kancab, assigning tracts of land to one of the following 13 types (figure 6): burnt farm plot, farm plot with low weeds, overgrown farm plot, overgrown farm plot with trees, henequen/agave fields, low pasture, high pasture, high pasture with trees, scrub forest, low scrub forest, scrub forest with agave, grazed scrub forest, and patchy grazed scrub forest. A total of 12.29km² of the 26km² of terrain covered by LiDAR was classified into a vegetation type based on the pedestrian vegetation survey. Inspection of the HAG raster and Google Earth images suggests that the vegetation in the rest of the terrain is scrub forest, but since grazed versus ungrazed scrub forest cannot be discriminated from these images I left this terrain unclassified.

Using the point cloud statistics extractor in the LP360 software package from QCoherent Software, I calculated ground return densities for each different vegetation type. After tallying the number of pre-Hispanic buildings mapped by pedestrian survey in each vegetation type, I calculated a “LiDAR identification percentage” for each vegetation type. This percentage is simply the number of built features in the vegetation type visible in LiDAR imagery divided by the total number of built features found by the pedestrian survey in that vegetation type. Section 4.3 presents these results by vegetation type.

Figure 6: Vegetation types identified by the vegetation survey

4. Results

4.1 Visualization techniques

In this section I use the data from the pedestrian survey (pre-LiDAR ground truthing) as a baseline against which the utility of different visualization techniques can be tested. To perform a controlled comparison of the six techniques discussed in section 3.2, I selected a square area south of the Ucanha site core in which pedestrian survey had already located all archaeological features. The goal was to determine which visualization technique (figures 7, 8, 9, 10) made the most features visible. The box in figure 3 shows where this area—called the south Ucanha square—lies in reference to the Ucanha site as a whole. The square is currently in high (5-7m) scrub forest with agave, with a ground return density of 2.79 points per m^2 . Pedestrian survey identified 51 platforms (including two pyramidal platforms) with a surface area of $100m^2$ or more and 23 smaller structures. All of these features are visible as polygons

with black outlines in figure 10d. Nearly all of the smaller structures in the south Ucanha square are invisible in the LiDAR imagery but the six different visualization techniques permit the identification of many of the 51 larger platforms. Table 1 shows how many of the 51 larger platforms are visible using each of these techniques.

Table 1: Number of large platforms (total = 51) visible in the south Ucanha square

Visualization technique	Platforms visible	Percent visible
Hillshade azimuth 45 altitude 22 (figure 7a)	36	70.6
Hillshade azimuth 135 altitude 45 (figure 7d)	28	54.9
Hillshade azimuth 225 altitude 45 (figure 8b)	30	58.8
Hillshade azimuth 315 altitude 22 (figure 8c)	34	66.7
PCA (figure 9a)	44	86.3
Stretched DEM (figure 9b)	44	86.3
Slope raster (figure 9c)	30	58.8
Sky-view Factor (figure 9d)	6	11.8
Classified DEM exclusion (figure 10a)	43	84.3
Classified DEM quantile (figure 10b)	47	92.2
Classified DEM equal interval (figure 10c)	44	86.3
Classified DEM geometrical (figure 10d)	48	94.1

Figures 7 and 8 present hillshaded images of the south Ucanha square using eight different light sources. Since most platforms are quadrangular and usually oriented close to the cardinal directions, light source azimuths of 45°, 135°, 225°, and 315° (each with two separate light source altitudes: 22° and 45°) were used because they have a chance of showing all four sides of a platform: two illuminated, two shaded. These different hillshades make visible between 54.9% and 70.6% of the 51 total platforms (table 1).

Figure 7: Hillshaded images of the terrain contained within the black box in figure 3. A) Azimuth 45, Altitude 22; B) Azimuth 45, Altitude 45; C) Azimuth 135, Altitude 22; D) Azimuth 135, Altitude 45.

Figure 8: Hillshaded images of the terrain contained within the black box in figure 3. A) Azimuth 225, Altitude 22; B) Azimuth 225, Altitude 45; C) Azimuth 315, Altitude 22; D) Azimuth 315, Altitude 45.

Figure 9: Images of the terrain contained within the black box in figure 3, using four different visualization techniques: A) PCA; B) Bare earth DEM; C) Slope raster; and, D) SVF.

Figure 10: Images of the terrain contained within the black box in figure 3, using four different color classifications of the DEM: A) geometrical; B) natural breaks; C) equal interval; and, D) quantile. The black lines in the D represent pre-Hispanic platforms encountered during systematic pedestrian survey.

The PCA technique (figure 9a) successfully synthesized the hillshades into a single image that, as Devereaux et al. (2008) predict, improves upon any lone hillshade. The PCA technique

made visible 86.3% of the 51 platforms in the south Ucanha square. A stretched grey-scale bare earth DEM (figure 9b) performed as well as the PCA (table 1). Slope rasters and SVF (figures 9c and d) make fewer of the platforms visible. Color-classified DEMs perform relatively well. Figure 10 and table 1 show the results of four different color classification techniques: geometrical, natural breaks, equal interval, and quantile. Geometrical and quantile (figures 10a and 10d) were the most successful of the four classification techniques, making 92.2% and 94.1% of the platforms visible, though each of these images led me to misidentify a natural bedrock outcrop as a platform (a false positive).

In sum, the results support Challis et al.'s (2011:286) conclusion that in areas of low natural relief, color-classified DEMs are preferable to the more common hillshading technique. The current study adds the finding that, in the context of low, scrubby, tropical vegetation, color-classified DEMs also show improvement over the other four visualization techniques. The built features most commonly visible in the LiDAR imagery from thick scrub forest are platforms with a surface area of 100m² or more and a height of one meter or more. Even the most successful visualization techniques missed a few platforms with surface areas greater than 200m². The platforms that were missed have heights of between 40 and 60cm. Built features on top of platforms, such as stone footings for walls, are invisible unless they are tall with sharp slopes. Thus, given the technical specifications in section 3.1 and local vegetation conditions, most fine details of ancient architecture are not observable. Facing similar vegetation, Hare et al. (2014) show that with different specifications, such as a doubling of the number of laser shots, more detail can be observed though the data acquisition and processing costs rise significantly.

4.2 Using LiDAR to find new platforms

Since color classification techniques outperformed the other five techniques for identifying platforms already documented by pedestrian survey in the south Ucanha square, I used color-classified imagery to identify previously undocumented platforms in areas with LiDAR coverage but no pedestrian survey. Based on how known platforms appear in the color-classified DEM from the south Ucanha square, six criteria—shape, orientation, size, height, height consistency, and edge slope—help distinguish artificial mounds from natural bedrock outcrops in LiDAR imagery. Stated differently, these criteria help identify features but do not relate to the effectiveness of different visualization techniques. The six criteria derive directly from consistent patterns in the details of architecture recorded during the pedestrian survey. Beginning with shape, most broad platforms are square, though the corners are usually not exactly 90° and some sides are often a few meters longer than others. Regarding orientation, nearly all platforms are oriented within about 20° of the cardinal directions. In other words, a square-like bump whose sides are oriented at 45°/135° invites skepticism as to whether or not it is a pre-Hispanic platform. Regarding size, platforms rarely exceed 25m x 25m (625m²). In terms of height, most of the 51 larger platforms in the south Ucanha square are higher than 0.5m, but often platforms need to be 0.8m or higher to stand out from the vegetation and natural topographic variation. Height uniformity refers to the fact that platform surfaces are either flat or have a consistent and gradual slope across the top. For a color-classified DEM, height uniformity means that the top of a true platform should be rendered with no more than

two colors if the platform surface is flat. For true platforms with gradually sloped tops, the color classes should grade evenly from the high side to the low side. A lack of height uniformity shows up on a color-classified DEM as a rough jumble of multiple colors that do not grade into each other smoothly. Edge slope refers to the steepness of the slope of a platform's edge. Theoretically, a slope raster should emphasize platform edges, but the results from the previous section show that slope rasters perform poorly in identifying platforms in the south Ucanha square. Excavations reveal that the original edges of platforms consisted of nearly vertical stone retaining walls. Today, most retaining walls have slumped or tumbled, so the slope of a typical platform edge is rarely vertical but is also rarely more gentle than 0.5. This means that in the color-classified DEM, the edges of true platforms show up as rather abrupt color changes from the surrounding ground surface to the top of the platform.

Applying these six criteria while visually examining color-classified DEMs allowed potential identifications of 438 previously undocumented platforms. Because these identifications are subjective (another researcher using the same six criteria might identify a different number of platforms), I used post-LiDAR ground truthing (see section 3.3) to inspect 21 of the potential platforms, thus serving as a test of my visual identifications. Ground truthing confirmed that all 21 potential platforms were indeed human built platforms. I therefore consider each of the 438 cases as positive identifications. For several identifications, I did not apply the six criteria nomothetically. In other words, a candidate for an ancient platform could fail to satisfy one of the criteria and still qualify as a positive identification. For example, if a candidate had the correct shape, the correct orientation, the correct height consistency and a plausible size and height, but lacked a sharp slope edge, I registered it as a mound. At the same

time, I weighted some criteria, such as shape and size, more strongly than others. As a justification for weighting the shape criterion strongly, we have never found a crescent-shaped platform, for example, on pedestrian surveys, so a crescent-shaped candidate that satisfied the other five criteria would not be registered as a platform. As a justification for weighting the size criterion strongly, pedestrian survey shows that less than 1% of platforms have a surface area greater than 800m², so candidates that exceeded 800m² were given additional scrutiny.

The six criteria produced 93 ambiguous cases in which a topographic rise on the LiDAR imagery could not be identified as an artificial or natural feature. Most of the post-LiDAR ground truthing—38 of 59 locations visited—focused on these ambiguous cases. Of the 38 locations visited, ten turned out to be artificial platforms, twenty were natural features, four were inaccessible, and four remain ambiguous. Since very few ceramics can be found on the surface of definitively Pre-Hispanic structures in the UCRIP area, the next step in clarifying such ambiguous cases would involve excavation.

4.3 Effects of vegetation on LiDAR interpretation

The vegetation survey combined with pre-LiDAR pedestrian survey shows that vegetation cover affects the use of LiDAR as a prospecting tool in the UCRIP area. For each of the 13 vegetation types presented in section 3.4, Table 2 provides ground return densities, the number of architectural features located on the pedestrian survey, and the number of such features visible in the color-classified LiDAR DEMs. In some vegetation types (such as low scrub forest), very low percentages of known features were visible in the LiDAR imagery. This is likely

a sampling error due to the small amounts of these types of terrain. For example, of the 2600 hectares of LiDAR coverage, only 16 hectares pertain to low scrub forest. Table 3 reduces the thirteen vegetation types into the four vegetation height categories named in section 3.4—minimal, low, medium, and high—and presents the same kinds of data as table 2 for each class.

Table 2: Visibility results for each vegetation type

Vegetation type	General vegetation height	Ground returns per m ²	Total # of architectural features	Number of features visible with LiDAR	Percent of total features visible with LiDAR
Burnt farm plot	very low	5.076	22	19	0.864
Farm plot with low weeds	low	4.318	4	4	1.000
Low pasture	low	5.913	13	4	0.308
Agave	low	na	13	7	0.538
Overgrown farm plot	medium	4.501	28	19	0.679
Overgrown farm plot w/ trees	medium	3.725	0	0	0.000
Low scrub forest	medium	3.089	6	0	0.000
High pasture	medium	4.708	15	11	0.733
Pasture with trees	medium	5.119	1	1	1.000
Scrub forest	high	2.416	358	146	0.408
Grazed scrub forest	high	2.812	69	36	0.522
Grazed patchy scrub forest	high	na	2	0	0.000
Scrub forest with agave	high	2.619	70	44	0.629

Table 3: Visibility results for vegetation height categories

General vegetation height	Ground returns per m ²	Total # of architectural features	Number of features visible with LiDAR	Percent of total features visible with LiDAR
Minimal	5.076	22	19	86.4
Low	4.784	30	15	50.0
Medium	4.012	50	30	60.0
High	2.473	449	227	50.6

Several patterns emerge from the results presented in tables 2 and 3. First, as table 3 shows, higher vegetation results in lower ground return density. Yet, as table 2 shows, this broad pattern conceals noteworthy variation. For example, ground return density is highest in low pasture as opposed to burnt farm plots. This is counter-intuitive given that the density of vegetation in low pasture is higher than in burnt farm plots, where there is essentially no vegetation. Furthermore, as predicted in section 3.4, scrub forest has lower ground return density than grazed scrub forest even though the two types of vegetation have the same height above ground.

Second, the results show, predictably, that features already documented by pedestrian survey were easier to detect in areas with minimal vegetation (86% find rate) than in areas with low, medium, or high vegetation. Oddly, in areas with low vegetation, structures documented with pedestrian survey were just as difficult to locate on LiDAR imagery as in areas with high vegetation. In both vegetation height categories, 50% of the known structures were visible in LiDAR imagery. Furthermore, in medium-height vegetation, 60% of the known structures were visible in LiDAR imagery. These results are difficult to explain because, as table 3 shows, the ground return densities are higher in the low height vegetation category as opposed to the medium or high vegetation categories. There is a weak positive correlation between ground return density and the percentage of total features visible with LiDAR (Pearson's $r = 0.368$, $p = 0.271$).

500 Table 2: Vegetation types and platforms found within types

501 Third, table 2 confirms the suggestion from section 3.4 that within the four vegetation
 502 height categories, vegetation type plays an important role in the ability to identify architectural
 503 features in LiDAR imagery. Though sample sizes in the vegetation types with low and medium
 504 heights are small, three of the scrub forest vegetation types have large enough samples to
 505 illustrate this point. In scrub forest, 40.8% of the known structures were visible with LiDAR
 506 imagery as compared to 52.2% in grazed scrub forest and 62.9% in scrub forest with agave. One
 507 possible explanation for differences in these success rates is that, as noted in section 3.4, the
 508 Axelsson algorithm for filtering ground points may work better in an area where vegetation
 509 close to the ground has been reduced. For example, when compared to ungrazed scrub forest,
 510 grazed scrub forest has less vegetation close to the ground. Indeed, the ground return densities
 511 in table 2 show higher ground point densities in grazed scrub forest as opposed to ungrazed
 512 scrub forest. The difference in success rates between scrub forest and grazed scrub forest is not
 513 an artifact of differing proportions of small structures that elude LiDAR since the percentage of
 514 structures under 1m high in these two areas is nearly identical: 58.5% versus 58.6%. Neither
 515 grazing nor ground return densities succeed in explaining why structures were more likely to be
 516 identified in scrub forest with agave.

517 For the most part, platforms with a height above 1m and a surface area greater than
 518 100m² could be detected regardless of the vegetation type. This suggests that size and height of
 519 platforms are more critical than vegetation cover when attempting to find Pre-Hispanic
 520 features (see also Rosenswig et al. 2014). Nevertheless, the vegetation survey is important
 521 because establishing success rates for different types of vegetation enables the creation of

correction factors for each vegetation type. In other words, if we know that 50% of the terrain in questions is scrub forest and that 40% of the total structures in scrub forest are visible in LiDAR, then we have a decent estimate of how many features remain undetected. Knowing what is missing can improve models of ancient settlement patterns, demographics, and more.

5. Conclusions

As the use of LiDAR data becomes more common, researchers will refine methods of data processing and interpretation based on the exigencies of local vegetation and geography. This paper presents methodological refinements that help adapt the use of LiDAR data to relatively flat, scrubby, tropical areas like the northern plains of Yucatan, Mexico. These refinements include an exploration of techniques for visualizing LiDAR data, criteria for identifying artificial platforms when natural landforms resemble the morphology of such platforms, and implementation of pedestrian vegetation survey.

This paper tested six techniques for visually rendering LiDAR data: hillshading, DEM with stretched shading, DEM with classified shading, slope raster, PCA, and SVF. Of these techniques, PCA, stretched DEM, and color-classified DEMs each work very well for finding platforms that measure between 1m and 2m. In particular, quantile and geometrical classification outperformed all other techniques for the task at hand. Though color classification will not work well for finding similarly low features in areas with extensive topographic relief, a number of geographical areas are suitable for color classification, such as broad river valleys and coastal plains as well as inland basins.

Due to the success of quantile color classification, I used this visualization technique for the next step in this paper: examining LiDAR imagery to locate previously undocumented platforms. In the UCRIP area, the application of six criteria for locating platforms led to the identification of 438 probable platforms. Post-LiDAR ground truthing of a sample of these probable platforms suggests that nearly all are indeed ancient platforms.

Regarding the vegetation survey, earlier results (e.g. Crow et al. 2007) have shown that the kind of vegetation (not just the height) affects the ability to use LiDAR imagery to identify archaeological features. This paper confirmed these results, showing general correlations between vegetation height, ground return density, and the ability to identify archaeological features with LiDAR imagery. Variation in ability to identify features among vegetation types within the same height categories reveals the importance of pairing LiDAR data with a rapid vegetation survey. For example, ancient structures are more easily visible in different forest types even though they have similar ground point densities and vegetation height. To move accurately from structures identified on LiDAR imagery to population estimates, correction factors are necessary. This study shows that different correction factors will need to be used for different vegetation classes, and this presumes the completion of a rapid vegetation survey alongside intensive pedestrian survey of a sample of the LiDAR area.

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712 Figures: THIS IS ALL FROM THE OLD MANUSCRIPT: NEEDS TO BE UPDATED
713 Figure 1: Map of the Maya area showing the location of sites mentioned in the text
714 Figure 2: Map showing the Ucí-Cansahcab causeway, the four major ruins along the causeway,
715 and the areas covered by LiDAR and by pedestrian survey
716 Figure 3: Hillshaded image showing natural and artificial features at the archaeological site of
717 Ucanha, Yucatan, Mexico. There are several modern roads and pathways in the image, though

only one is labeled. The arrows point to ancient causeways. The arrows at the far left and right point to fragments of the 18km long causeway that connecting Ucí and Cansahcab. Most quadrangular bumps are ancient platforms. The black box contains the terrain displayed in figures 7, 8, and 9.

Figure 4: Height Above Ground raster

Figure 5: Two kinds of scrub forest: ungrazed (top) and grazed (bottom).

Figure 6: Vegetation zones identified by the vegetation survey

Figure 7: Hillshaded images of the terrain contained within the black box in figure 3. A) Azimuth 45, Altitude 22; B) Azimuth 45, Altitude 45; C) Azimuth 135, Altitude 22; D) Azimuth 135, Altitude 45.

Figure 8: Hillshaded images of the terrain contained within the black box in figure 3. A) Azimuth 225, Altitude 22; B) Azimuth 225, Altitude 45; C) Azimuth 315, Altitude 22; D) Azimuth 315, Altitude 45.

Figure 9: Images of the terrain contained within the black box in figure 3, using four different visualization techniques: A) PCA; B) Bare earth DEM; C) Slope raster; and, D) SVF.

Figure 10: Images of the terrain contained within the black box in figure 3, using four different color classifications of the DEM: A) geometrical; B) natural breaks; C) equal interval; and, D) quantile. The black lines in the D represent pre-Hispanic platforms encountered during systematic pedestrian survey.

Tables:

Table 1:

740 Table 2: Vegetation types and platforms found within types

741 Table 3:

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