THE USE OF LIDAR DATA TO IDENTIFY ANCIENT AND MODERN
STRUCTURES IN THE TEOTIHUACAN VALLEY

by

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A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at George Mason University.

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DEDICATION

This is dedicated to my family.
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ABSTRACT

THE USE OF LIDAR DATA TO IDENTIFY ANCIENT AND MODERN STRUCTURES IN THE TEOTIHUACAN VALLEY

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George Mason University, 2018

Thesis Director: Dr. Sven Fuhrmann

Archaeologists spend considerable time and effort manually identifying landscape features on maps. This thesis explores the analysis of lidar data by developing and applying automated methods of feature identification and classification, which could ease and hasten the current process. Lidar data of an approximately 170 km² area of the Teotihuacan Valley, northeast of Mexico City, Mexico, were used. Features for identification were field system terrace edges, springs, and structures. Spatial analysis and filtering of the lidar imagery was pursued predominantly using ArcGIS and Matlab. The automated identification of the feature types was inconclusive because of the complexities of the landscapes and the limitations of the available methodologies. Current methodologies remain suitable for enhancing the manual classification of landscapes using remote sensing data.
CHAPTER ONE: INTRODUCTION

1.1 Introduction

Teotihuacan, located outside Mexico City in the Basin of Mexico, was a large polity centered around its namesake city that thrived between approximately the beginning of the first century BCE to around the seventh century CE (Cowgill 2015, 1). The city, with a population of up to 125,000 at its height (Cowgill 2015, 140–142), was one of the largest and most complex early urban centers in the Americas and regularly traded and interacted with the Mayan territories to its south (Houston & Inomata 2009, 106–108). Teotihuacan may have controlled as many as a half-million people, while interacting less directly with many more (Cowgill 2015, 247). While other polities in other places and times have certainly been larger and more complex, Teotihuacan still faced many challenges common to modern urban centers, needing to provide its inhabitants with food, water, religion, homes, etc. Understanding how this ancient city supplied its people with their needs, and understanding how it collapsed, adds to our cultural history and also apprises us of many situations urban states can encounter.

Teotihuacan has been studied by a number of different groups over the periods since its collapse, from the Aztecs in the fifteenth century, to the Conquistadors in the sixteenth and seventeenth centuries, and to a series of antiquarians and archaeologists from the nineteenth century onwards (Cowgill 2015, 14–15). The initial interests of
researchers were in the city's art and monumental pyramids, with research on the lower status areas following (Cowgill 2015, 17–18). In the 1950s and 1960s, chronological sequences were relatively secure and two large projects commenced: the Teotihuacan Mapping Project directed by René Millon and the regional settlement pattern survey directed by William Sanders (Millon et al 1975; Sanders et al 1979). Subsequent research has resulted in individual excavation maps and in detailed maps and scans of the civil-ceremonial center and protected archaeological zone (Cowgill 2015, 23). More recently, near-infrared and multispectral imagery has been used to analyze the Tlajinga Canals (Nichols 1988; Mejía Ramón 2016). Only recently, new landscape-scale mapping was incorporated into research programs, involving the lidar collection used in this project and related efforts.

The collection of lidar data that covers hundreds of hectares across the surrounding landscape of Teotihuacan should allow features to be defined more rapidly and spatial and other statistical analyses to be calculated more efficiently than from the analog maps of the past. This combination of geographical methods and archaeological data should assist further archaeological studies through the computational identification of features, which should require significantly less human effort and fewer excavations.

1.2 Research Questions

This research project will approach three types of archaeological landscape features — field system terraces, springs, and building structures — and attempt to identify their locations and character without extensive field work through the automated processing of lidar data, using conventional image processing operations.
This can be summarized in three main research questions.

1. Can archaeological terraced field systems on a mountain be identified using lidar data?

   If so, can the terraces created by modern mechanical technologies be differentiated from fields created by non-mechanical techniques?

   Can their identification be expanded to other mountain systems? to the Teotihuacan Valley?

   To what degree is the identification accurate, and can it be quantified and compared to ground truthed field systems?

2. Can springs be identified in the lidar data?

   If so, can other springs be found across the Valley?

   How accurate are these identifications?

   If springs are found, are they likely to substantially change the understanding of water resources around Teotihuacan?

3. Can building structures be identified as modern or archaeological?

   With what accuracy?

1.3 Outline

This thesis is separated into six chapters, with some supporting material in subsequent appendixes. This first chapter contains an introduction to the thesis and states the research questions.

Chapter two contains the literature review, which introduces the field and summarizes current research using lidar data in both archaeology and geography.

Chapter three discusses the methodology of the research, as well as the validity of
the methods and their accuracy. In addition, chapter three communicates some of the weaknesses of the research.

Chapter four summarizes the results for each of the three main research questions. Here, specific details of the analyses are explained and initial outcomes shown.

Chapter five discusses the results for each research question in further detail. The results are compared to similar research in the Teotihuacan Valley, as well as further afield. The significance of the results and their strengths and weaknesses are also considered. Finally, it examines possible directions of further studies.

Chapter six reviews all of the evidence and concludes the thesis. It answers the research questions and places the research project in a wider context.
CHAPTER TWO: LITERATURE REVIEW

This research project combines two fields — archaeology and geography — and, thus, must communicate in each. Here are three sections summarizing the previous research: one covering research on Teotihuacan, especially its field systems, springs, and urban planning; a second relating the basics of lidar and how processing of lidar works to extract classified features; and a third describing how archaeology has used lidar data in the past.

2.1 Archaeological Background

Terraces

Agricultural practices around the city produced the majority of the food that supported it. As demonstrated in a mix of ethnographic, historic, and archaeological sources, it is likely that Teotihuacanos used a combination of types of field systems (Sanders et al 1979, 241–242). Temporal agriculture, primarily rain fed, is and likely was historically used in locations with deep soils across the valley and on mild slopes with thinner soils and less intensive agricultural use (Sanders et al 1979, 243). Terrace agriculture is and was used where the topography has a significant slope and erosion must be stopped by wall structures. The terracing does affect under-soil structures, which can be seen even after total soil erosion from the surface (Sanders et al 1979, 249). This means that, with excavation (if not with simpler field walking), it is possible to identify
locations of terracing even after full surface erosion, although not necessarily the date of the terracing (unless datable evidence pertaining to the formation of the terrace is found). Both of these types of field systems historically would have used hoe cultivation, rather than plow (Sanders et al 1979, 241). If the fields have not been used since the era of Teotihuacan, then these hoe marks and terracing would be eroded but possibly identifiable. However, modern plows (horse pulled and then mechanized) have obliterated some of the landscape features, while modern terracing and continued agricultural use of the same fields muddles the determination of specific usage time periods (Sanders et al 1979, 412).

**Springs**

Teotihuacan and the surrounding Valley are in a region with irregular rainfall, which would have required water management systems to irrigate the fields and produce enough crops to feed the population (Cowgill 2015, 30). Rainfall is seasonal, with rain coming between June and October and averaging around 600 millimeters (mm) per year in the Valley. However, that amount varies significantly year to year and can come with damaging storms. In some years and some regions, the Basin of Mexico receives enough water to grow corn (maize) without irrigation (Cowgill 2015, 31). However, it is not reliable enough for regular agriculture, and so some form of irrigation is required. In the Teotihuacan Valley, there are also two streams, the Río San Juan and the Río San Lorenzo, which are small and have highly variable, rainfall-dominated flows (Cowgill 2015, 34). These rivers were canalized and re-routed during an early reorganization of the city (Nichols, Frederick, et al 2006). A series of year-round springs existed to the east
of the confluence of the two rivers near the San Juan Teotihuacán parish church (Cowgill 2015, 32; Evans 2016). Sanders, Parsons, & Santley find that the springs could irrigate 36.5 square kilometers (km²) of the Valley (out of approximately 500 km²) in 1954 with an average flow of 590 liters per second (L/s) (Sanders et al 1979, 258). However, they also find that the springs were failing due to a falling water table, as the average flow in 1922 was approximately twice that (around 1200 L/s), and by 1975 it was only 382 L/s (Sanders et al 1979, 256–258). A second set of springs near Texcoco (with a map of their locations) was also involved in irrigation systems (Sanders et al 1979, 274). From the springs and the irrigation systems known, Sanders, Parsons, & Santley calculate agricultural carrying capacities of various regions, but the values are estimates, as the flow rates and exact details of the irrigation systems are unclear (Sanders et al 1979).

Nichols et al. and Evans & Nichols discuss how these springs and their related irrigation systems may have functioned politically and ideologically, and suggest that water and its flow is a highly important landscape feature (Nichols, Frederick, et al 2006; Evans & Nichols 2016).

Structures

One of the most famous and interesting details about the city of Teotihuacan is its alignment, at 15.5° east of true north, which is observed in the civil-ceremonial core, the residential blocks, roads leading from (or to) the city, and roads stretching out into the surrounding valley (Cowgill 2015, 125). This alignment, for whatever reason, was followed in the city from around the turn of the first century CE (before then, an alignment of about 11° off north was followed), and is still followed in some roads and
blocks built subsequently and aligned to previous structures and roads (Cowgill 2015, 69).

Residential structures in Teotihuacan were made of two successive building materials: adobe during the earliest periods and concrete later (Cowgill 2015, 124). These concrete buildings, which replaced the earlier adobe, had floors of concrete over tepetate subfloors, of cobble, or of earth. Walls had rubble centers with thin layers of concrete on each exterior, which was then topped with plaster. The arrangement of residential buildings and compounds was relatively standardized in orientation and structure, with an approximately square central courtyard surrounded by apartments (Cowgill 2015, 157 & 154). The size of the courtyards or apartments, however, are not very consistent, suggesting differences in status among the city's inhabitants.

Despite the overall size variations, Teotihuacan was likely to have a unit of distance measurement that does not conform to the modern Metric system in use in Mexico today. That measure is theorized to be equivalent to 83 centimeters (cm) (Sugiyama 2010). While modifications of buildings and re-construction complicate measurements, it is likely that many structures have dimensions that are multiples of this length. This dimensional clue may help identify buildings dating to the Teotihuacan period. The identification of structures of that period by these combined characteristics could focus archaeological investigations and excavations, providing new insights on the agricultural, rural portions of Teotihuacano society.

2.2 Lidar

Lidar, light detection and ranging, is an active remote sensing system that uses
near infrared (for topographic mapping) laser pulses to measure the distance between the laser pulse — generally emitted from an aircraft — and the ground (ArcGIS i). In combination with global positioning system (GPS) data and the aircraft's inertial navigation system (INS), the laser responses provide detailed, accurate locational data about the ground surfaces. Emitted laser pulses can reflect back to the aircraft off of multiple surfaces, which are referred to as multiple returns; these are rarely collected beyond the first five. The first response is associated with the highest point on the landscape at that position, and could be the top of a tree, a building, or, if nothing is above it, the bare ground (in which case the first response is also the last). The last pulse is often assumed to be the ground; however, in a thickly vegetated area with many thick branches, the laser pulse may not reach all the way to the ground and the last response may be above ground level. This is especially true if fewer responses are collected. Excepting errors in analysis (or bathymetric lidar), responses will not have elevations below the ground surface.

Directly after lidar's development, lidar data were usually shared in ASCII format. However, due to the large quantity of data, the LAS format, a binary format, was defined by American Society for Photogrammetry and Remote Sensing (ASPRS) (ArcGIS i). This format allows more information to be read more efficiently during processing and use. Post-processed lidar returns may be assigned 'point classifications,' which define the type of object the pulse was reflected from (ArcGIS e). These classifications are also defined by ASPRS as part of the LAS file system (ASPRS).

There is some confusion within the community of lidar users about the definitions
of "Bare Earth Models," Digital Elevation Models (DEM), Digital Terrain Models (DTM), and Digital Surface Models (DSM). DTMs are often understood to be digital models of the ground surface (especially those of natural features), and DSMs the highest point of the ground and everything on it (Li et al 2005, 7–8). However, whether those models are gridded rasters or Triangulated Irregular Networks (TINs) in a vector form is up to the provider. The USGS defines a DEM as a gridded file with regularly spaced elevation data and defines a DTM as a 3D representation of that data (USGS). This research will use "bare earth model" as the synonym for this type of DEM, where the model only uses data from its original data source (the lidar data) and in a '2.5D' raster format.

Bare earth models can be created from lidar data in a variety of ways. If the research uses ArcGIS, .las files are first turned into a LAS Dataset (ArcGIS l). Then, to process the dataset out of its point cloud form, there are three options: a raster mosaic dataset (which cannot use breaklines), a raster directly from a LAS dataset (which can incorporate breaklines, but is limited in data management tools), or a terrain dataset (a TIN geodatabase, which can include breaklines and has advanced data management functions, but can be unwieldy) (ArcGIS c). Once they are in a raster format with elevation values in each pixel (in this research's case, a bare earth model), these values can be treated like image intensity values, and the lidar images can be treated like grayscale images — although the elevation values are not likely to be positive integers scaled to a specific bit per pixel size like in grey scale images. The images can also be treated like grayscale images for their analysis, locating discontinuities, adjacencies and
2.3 Lidar Data in Archaeology

Lidar is a method of getting surface elevation data of very fine spatial resolution rapidly, and archaeology has been quite happy to have that information, despite the expense. The predominant use of lidar data in archaeology is as a simple DTM, where it might be used as a colored background on maps or to calculate visibility information. Sometimes lidar has been used to find and classify features, although often with complications from non-archaeological uses. In archaeology, however, research is often focused on what is under, if not just under, the surface of the earth, limiting the ease of use of the surface data. Many other fields care about the surface of the earth, about the vegetation on the surface of the earth, or about structures built on the surface of the earth. When archaeology is looking for standing structures, methods from other fields work well, especially in locations with little substantial re-use of the landscape (e.g. in the Mayan lowlands, see Chase, Chase, et al 2010). When archaeology is searching for standing buildings mixed among modern buildings or for ruined buildings underneath and around the footings of modern buildings, lidar analyses have been less conclusive.

The most common use of lidar in archaeology is where the lidar data are used as a fine scale, very detailed image of the region, and studies have worked to determine the best methods for human visualization of archaeological features (Challis, Forlin, & Kincey 2011). In an example of using lidar as a detailed image, Thompson uses lidar to analyze four anthropogenic islands in Florida (Thompson 2017).
is entirely visual and descriptive, as he manually, visually identifies and labels canals, causeways, axes, and linear features on the islands (Thompson 2017, 133, 134, 136). The comparison of identified features is the entire scope of his discussion, and the generation of the very-fine scaled data simply provided an easier method for data acquisition than visiting each of the islands and manually mapping them to the necessary scale.

Ladefoged et al. perform an analysis of a Hawaiian field system with their lidar data (Ladefoged, McCoy, et al 2011). This study takes the base lidar data and turns it into a DEM, and then hillshades the DEM data (Ladefoged, McCoy, et al 2011, 3610–3611). After this point, the authors manually digitize the agricultural fields made visible by the hillshading. Finally, they calculate the densities of the field alignments, which is a proxy for infrastructural intensification (Ladefoged, McCoy, et al 2011, 3608–3609). These quantitative calculations are entirely based on the lidar data having much finer-scale evidence of human activity, which was not previously visible in any other format. So, as with Thompson's research, the analysis could have been done without lidar, but the data were less accessible.

In a related study, McCoy, Anser, & Graves look at the same Hawaiian field system, but use slope contrast mapping with the lidar data to identify and classify specific types of land (McCoy, Asner, & Graves 2011). Here, slope contrast mapping calculates the slope across all neighboring points on a DEM and then classifies them in a raster as flat, low, or high (McCoy, Asner, & Graves 2011, 2141). The raster is "vectorized into polygons representing micro-topographical regions," which can then be used to differentiate between natural and human-built landscape features (in this study, defining
terraces and tableland) (McCoy, Asner, & Graves 2011, 2141). This use of lidar data goes a step further than the previous ones, as it uses algorithmically defined areas to identify specific classes of features in the landscape, but it is not fully automated and the raster areas are not separated into different features or objects for further classification or analysis.

Risbøl et al. test detection rates and accuracy of cultural features of varying size and shapes from a DTM (Risbøl, Bollandsås, et al 2013). Here, the DTM is fed into a program called "Quick Terrain Modeller," and archaeologists then use the program to manually identify and classify features (Risbøl, Bollandsås, et al 2013, 4689 & 4693). They find that larger features with distinctly geometric shapes are classified better by the combination of human and program, while smaller and less clearly geometrically shaped features are less likely to be correctly classified (Risbøl, Bollandsås, et al 2013, 4699). They also find that increased resolution of the DTM does not increase classification accuracy of less geometrically shaped features. However, this method still relies on predominantly human identification of features off of a lidar-derived raster.

Humme, Lindenbergh, & Sueur use lidar data to identify field systems in forested areas of the Netherlands (Humme, Lindenbergh, & Sueur 2006). Here, the authors use a bare earth model and filter the large-scale topography away with Kriging methods (Humme, Lindenbergh, & Sueur 2006, 1–2). However, after this analysis, the study identifies the field systems off the filtered images using a visualization technique to illuminate the topography at a very low level and then manually labelled them. They hope that in the future, the field embankments around the individual field systems could
be automatically extracted using a Hough transform, instead of manually extracted 
(Humme, Lindenbergh, & Sueur 2006, 5). However, that hope has yet to be realized.

More specifically, the study of field systems and terraces in Mesoamerica has 
interested archaeologists for decades. While some of the earliest discussions of terraces 
relied on mapping by hand and excavation (Healy, Lambert, et al 1983), archaeology 
rapidly adopted remote sensing technologies, first including satellite imagery (Chase & 
Chase 1998, 61). In the same region around Caracol, Belize, A.S.Z. Chase & 
Weishampel use lidar to investigate the flow of water and estimate soil erosion on 
agricultural terraces (Chase & Weishampel 2016). Here, the lidar data are converted to a 
DEM and then flow direction, flow accumulation, and slope rasters were calculated 
(Chase & Weishampel 2016, 360). Then, using the "Map Algebra and the Hydrology, 
Surface, and Topography toolboxes" in ArcGIS, they estimate the movement of water and 
how the water affected the terraces (Chase & Weishampel 2016, 361). Recent work at La 
Corona, Guatemala, as described at the most recent Annual Meeting of the Society of 
American Archaeology, is using lidar data to identify settlements across a heavily 
forested 2,100 km² area (Bower, B.). This expansion of data to detail larger landscapes 
has allowed better visualization and understanding of the historical landscapes (Chase, 
Chase, & Chase 2017).

All of these archaeological research projects use lidar in a variety of ways. 
However, the studies identifying features rely on human, manual extraction, which 
should be much slower than computerized, automated extraction. This research project 
aims to take this next step and develop methods of computerized extraction, as is done for
non-archaeological features.
3.1 Methodology

The lidar data in this project were collected by the Plaza of the Columns Complex Project, a research project with which Dr. Nawa Sugiyama, a member of the thesis committee, is affiliated (Sugiyama, et al 2018). This multiple return lidar data, collected by aircraft, were portioned into a large number of .las files, each geo-referenced to a portion of the total area of approximately 170 km$^2$. The research project also includes a wealth of field research, much of it mapped, including information on the type of fields, buildings, and other structures on parts of the ground. The methods are separated into three sections, one for each of the main research questions.

Terraces

This research attempted to develop algorithms to identify terraced field systems on mountainous terrain and whether those field systems are made with modern technology or with older processes. First, well-studied and mapped areas with field systems on mountainous terrain were used to develop the initial algorithms. To identify the field systems, the research created a bare earth model. There are a variety of methods to do this, the simplest being to use ArcGIS's LAS Dataset to Raster tool (ArcGIS c). Only the ground return points were used in calculating the model. Since the .las files for this project were correctly classified into only two categories — (1) Unassigned and (2) Ground — this was relatively simple. Where multiple 'ground' returns existed within the
defined pixel size — 0.5x0.5 meter (m) — the minimum value was used. After studying these results, the deficiencies of this bare earth model were left in place, as attempting to remove modern materials and structures without removing archaeological structures and features was too nuanced and difficult, especially given the chances for modern re-use of any given location. While this means that the raster used for this research has non-ground points, and could be argued to not truly be a bare earth model, it is the best representation of the bare ground without removing or masking any archaeologically relevant features.

Once the bare earth model was successfully completed, various algorithms that have defined field systems in previous modern research were tested to determine which methods work best with this data. The most successful was the Geomorphons Application, developed by Jasiewicz and Stepinski at the Space Informatics Lab, University of Cincinnati (Jasiewicz & Stepinski 2013). This application classifies each pixel into one of the ten most common landform elements — flat, peak, ridge, shoulder, spur, slope, hollow, footslope, valley, and pit — depending on user-defined length scales for elements, degrees of 'flatness,' and an optional buffer around each pixel (Jasiewicz & Stepinski 2013, 5, 6–8). Then, attempts were made to classify the rater data into objects and define terrace edges. If the previous step was successful, each terrace would be graded with a best approximation of the same 0-3 classification that the manually-identified field systems were graded (further information about this system is available on page 20).

After any success in that subsection of the project, this process was tested on a
second, similarly well-studied area, to see whether the initial programming worked or whether it applied only to the first, very specific landscape. Then, if successful, the algorithms would be modified until they worked to identify field system varieties in both of the first two areas, and tested on a third (and fourth, fifth, etc.) area that had also been manually classified. The minimum goal was for eighty percent classified identification accuracy as compared to the manually classified data. Had the algorithms been able to predict what was already known, they could have been tested on areas where field testing has not yet occurred. If the algorithms functioned to at least the minimum goal, the research would progress to attempting to adapt the algorithms for that specific mountain field systems to other field systems in other parts of the valley.

Springs

An attempt was made to identify the springs mentioned by many, including by Sanders, Parsons, & Santley (Sanders et al 1979). The source(s) of water in the Basin of Mexico and Teotihuacan Valley are not well understood, but their constraints would have greatly limited and controlled agricultural production. As Sanders, Parsons, & Santley understand, the San Juan springs were dying by the mid-20th century, limiting the amount of information modern remote sensing techniques can gather (Sanders et al 1979). A map of a small number of the San Juan springs are shown in Evans' research (Evans 2016, 53); these springs were located and digitized by georeferencing her map to the lidar data and an ArcGIS provided Base Map (World Topography). Another series of springs near Texcoco are shown in Sanders, Parsons, & Santley (Sanders et al 1979, 274). An attempt was made to digitize the Texcoco springs, and to find and digitize other spring system
maps. However, as discussed in Chapter Four (see page 38), these attempts failed. Had the springs been identifiable in either the lidar data or in satellite data, attempts would have been made to find other springs across the larger landscape.

**Structures**

Finally, the research explored the development of algorithms to differentiate between archaeological and modern structures outside the main civil-ceremonial center. However, a full identification would likely require spatially fine-resolution multispectral imagery to help differentiate between construction materials, which was not yet available to the project. The attempt to differentiate between modern and archaeological structures was, and will be, a very difficult one, as some of the modern structures are built along the roads and field systems aligned along the Teotihuacan urban grid system. Within the area studied by Millon, Drewitt, & Cowgill, their information on structure type could be used for accuracy calculations (Millon et al 1975). Outside the boundaries of the Millon map, there is no current database of Teotihuacano structures. There, it would be impossible to calculate accuracy, but might provide useful information for future archaeological research.

From the Geomorphon Application classifications, the possible structure identification followed a similar pattern to that of the field systems. Classified rasters were grouped into objects. Next, linear and then rectilinear objects were identified. If the previous step could be completed, these objects would be compared to a 15.5°N alignment. Finally, the objects that aligned would be compared to the Teotihuacan unit of measurement of 83cm.
3.2 Accuracy and Complications

There are multiple levels of analysis of the archaeological record in the Teotihuacan Valley that can be compared to and support this research. For the most precise analysis, there are archaeological excavations within the Valley, although few of them outside of the civil-ceremonial center. While excavations give the best understanding of Teotihuacan's history, the archaeological record has its limits. For example, inorganic materials are preserved better than organic materials; items within storage areas or under stone buildings tend to last better than those dropped in fields and plowed over many times over many years; and objects can be used over many years and in multiple ways and can enter the archaeological record at many times in the objects life. The complexities of how humans are using any given material at any given time are, understandably, complex. Therefore, the depth of understanding of any specific excavation depends upon the artifacts and features excavated and the cumulative knowledge about the cultures and environments of that excavation. Two last limitations: excavation is expensive in time and money, so the extent excavated is limited, and excavation destroys what is below the surface, so it cannot be re-excavated when technologies and techniques improve.

In the terraced field surveys, a slightly less precise analysis, "ground truthing," is also being performed on accessible field systems in the Valley (Sugiyama, Chase, et al 2018, 515). This level of analysis does not involve any digging into the ground, but is performed by archaeologists knowledgable about the cultures that were (and are) present in the area. Ground truthing may involve looking for obvious land surface features and
earthworks, artifacts on the ground after plowing or other surface disturbances, and identification of structures and buildings in the area which may belong to particular time periods. Any of these elements are compared to excavated examples to classify them to a culture or period. Current research involves any terraced area expected to be of archaeological significance being classified on a subjective four point scale, where an area graded as a zero (0) is considered certainly modern only and an area graded as a three (3) is considered as certainly of archaeological origin as possible, with classification of one (1) and two (2) in between. However, areas are only ground truthed if two conditions are met. The first is that the area must be accessible to archaeologists, so the land-owners and tenants must agree and permit their movement (therefore, the land cannot be a military base). Second, as the ground truthing process is slow and time is limited, the area must have been classified as a 1, 2, or 3 by the archaeologists manually classifying the lidar data. This has a three major limitations that affect the accuracy and completion of this form of analysis: the surface features may not be entirely indicative of all occurrences at that location in the past, the area may not be accessible to the archaeologists, and the archaeologists manually classifying the data may have been wrong. However, as this is the most accurate analysis available for the Valley, it will have to be considered correct in comparison to the less precise analysis methods.

The next level of analysis involves manual classification of the lidar data. Here, a team of undergraduate volunteers, including some of whom had spent a field season in the Valley, were trained in identifying field system terraces on the same classifications as those used by the archaeologists in the Valley. Then, they created a ArcGIS shapefile
where they drew lines on every terrace edge that they classified as a 1, 2, or 3. The classification here is mostly subjective, rather than based on specifics, such as the height of the terraces being more or less than a given value. The classifications are based on how straight and parallel the terrace lines are, as well as the distance between terraces and the amount of slumping between a terrace and the fields. However, as modern machinery can be used on and to modify fields previously used archaeologically, this can be a very difficult classification. Compared to current ground truthed results, the manual classification of the lidar with a 3 (most certainly archaeological) has a 75% accuracy (Sugiyama et al 2018). The accuracy for manual classifications of level 2 is 61% and for level 1 only 7.7%, although sample sizes of ground truthed terraces are small (only ten percent of the terraced areas have been ground truthed). One of the confounding factors likely complicating the manual extraction is the vegetation growing on and around the terraces. Here, underreporting is likely, as in the lidar data only the vegetation is clearly visible, and so no ground level structures are identified or classified.

Finally, the automated classification provides another level of analysis, likely the least accurate. The aim was to match classified terraces from the most successful algorithm to ground truthed data where it exists, and where it does not, to the manually classified data. An accuracy goal of 80% of the automated terraces classified as 3 to match the manually classified level 3 terraces was set. Features which existed in the same location both in any successful lidar-derived data and in the field work would have been considered accurate. Features which exist in one or the other but not both would be considered inaccurate. As the goal was to match the classifications of not entirely
accurate data, the final results will also not be entirely accurate, either. The accuracy problems are unsurprising, however, because fields which were used in the 6th century CE may have also been in use in the 10th, 16th, and/or 21st centuries, with different techniques and tools used at different times. Thus, the classifications are limited to archaeological — meaning hoe marks — or modern — mechanized plowing — and not to a specific time period. The precise date of a field system's use (or uses) will be uncertain, as all pre-Columbian dates will have used hoes instead of horse-drawn plows or mechanized plows. Ideally, though, the large scale identification of features on the landscape, even to a very general date, would have allowed archaeologists to better focus their efforts to preserve and understand Teotihuacan.
CHAPTER FOUR: RESULTS

4.1 Introduction

Archaeologists have often wanted to understand how people use their entire landscape. However, until recently with cheaper remote sensing data, landscape scale projects were difficult, expensive, and very time consuming. Of course, the manual identification and classification of features across that landscape is also time consuming and prone to human errors. This research aimed to find methods to automate portions of that process and speed up the processing of large quantities of data.

In each of the three research questions, an attempt was made to find ways to filter and modify the lidar data so the filtered results identify and then classify specific archaeological features: terraces, springs, and structures. Each research question resulted in limited success, but certain directions and methods clearly were superior to others.

In this thesis, only two specific 500x500m areas have been used to illustrate the terrace and structure examples to limit the possibility of individuals using the information to locate archaeologically interesting locations and loot them. With only two areas described, features only in those areas might be raided. However, the results are applicable across further areas.

4.2 Terraces

The first research question involved the identification of terraces in field systems.
As Figure 1 (on page 26) shows, human vision can easily identify terrace edges, and, relatively easily and with a bit of training, classify them into four classifications levels (0–3: from certainly non-archaeological to certainly archaeological). However, given all of the other features and structures across the same areas, the complexity of the landscape is obvious, as is the amount of time necessary to manually draw and class each interesting feature.

The goal was to go through three steps: find a method of identifying terrace edges that identifies the most terraces; sort as many as possible non-terrace features out; and then find methods to classify those terrace lines in the same classifications as the manual classification, but by using more specific identifiers (for example, terraces tend to be x far apart or have slopes below them of y, etc.). Frustratingly, the first step was not successful, so the later two steps could not be completed.

Despite the eventual failure, a number of methods were attempted to identify terraces. Initial attempts tried to use image filtering methods. These unsuccessful attempts included trying to filter out objects smaller than terraces features with low-pass filters, and then trying to find ways to highlight the terrace edges with high pass filters, including both low- and high-pass Gaussian and Butterworth filters (Gonzalez & Woods 2008 273–277, 284–286). Low-pass filters accept, or pass, low frequency components while rejecting higher frequencies, resulting in a blur or smoothing effect; high-pass filters do the opposite, and are equal to one minus the low-pass filter value in any pixel (Gonzalez & Woods 2008, 145, 281). However, given the preponderance of small trees around the lower elevation terraces and large structures near large trees, this was too
complex for the tested methodologies.

A second, more successful method used the geomorphology of the local environments around each pixel. Here, the Geomorphons Application was used, as
discussed in the Methodology on page 17. As explained in more detail there, the Geomorphons Application has three variables: search radius, flatness, and skip. After some experimenting, it was determined that the best identification of terrace lines was using the default search cell variable (25), a flatness of three degrees, and a skip cell of five, which broadened the local geometry to measure across a slightly larger region.
As is visible in Figure 2 (page 27), the application returns a raster where each pixel is classified into one of ten generalized landform elements. Looking at this image and comparing it to the more commonly viewed hillshade DEM (see Figure 1 on page 26), specific groups of types of landforms are characteristic of specific features. If the
types of landform elements visible are limited to four types — ridge, shoulder, slope, and footslope — it becomes clear that the terraces edges are usually shown by footslopes (in yellow) on the top and downhill side of each edge, with slopes (in blue) on the other side and occasional ridges and shoulders (red and dark red) between them, as shown in Figure 3 (page 28). However, not all terrace edges are identified by this pattern, perhaps because some terrace edges are more worn down or eroded than others. This is particularly true of the terraces missing ridge or shoulder areas at their tops, which shows they are much flatter than other terrace edges.

Next, the goal was to simplify and clean up the landform elements into clear lines at the edge of each terrace (and only each terrace, so not highlighting any of the many other features), that, in theory, could later be classified by archaeological relevance. The best attempt to simplify and neaten the lines involved a number of, thankfully simple, steps within ArcGIS. First, the pixels of footslope and slope in the raster were each extracted into their own rasters.

Then, a number of tools in the Spatial Analyst, Generalization toolbox were used. Majority Filter, which replaces cells in a raster based on the majority of their contiguous neighboring cells, was used, with eight neighbors and the threshold of number of neighbors needed to replace the cell set to half (ArcGIS f). This created two rasters, one for footslope and the other for slope (see Figure 4 on page 30).
Next, Boundary Clean, which smoothes the boundary between zones by expanding and shrinking, was used (ArcGIS a). Here, the technique to sort which zones to change was 'descend' — where zones with larger total areas have a priority to expand into zones with a smaller total area: here, non-footslope or non-slope zones are more
predominant, and therefore expand into footslope or slope zones, cleaning and shrinking them (see Figure 5 on page 30).

This is the first point where it is very obvious that some of the terraces no longer have, or never had, clear and continuous footslopes. Thus, they will not be identified and turned into lines to be classified. With hindsight, it is clear that the landscape, the lidar data obtained, and/or the calculations, including the Geomorphons Application, yield too many discontinuities. Some of these calculational losses of terrace edges may be due to substantially eroded terraces, such as in the top left of Figures 5 as compared to the same location in Figure 2 (page 27). Here, human vision clearly identifies a terrace, but one with an irregular and incomplete slope, and so no distinctive footslope, ridge, or shoulder morphologies could be automatically detected.

After that, the rasters were thinned (still in Spatial Analyst, Generalization, Thin), with corners rounded and the maximum thickness of line features defined as 2m (ArcGIS j). Subsequently, the rasters were turned into polylines (a vector form), with a 2m dangle length using the Raster to Polyline tool (ArcGIS h). Now as a vector, the editing tool 'Extend Lines' was used three times, each extending the ends of lines to any other end of line within 5 meters (ArcGIS d). The Data Management tool, Features, Unsplit Line, which dissolves lines based on grid code, was used to combine the polylines that were touching into single features (ArcGIS k).

At this point, as is clear in Figure 6 (page 32), the footslopes (yellow) and slopes (blue) are thin vector polylines that highlight the middle of local areas matching those geomorphologies, but they still are very busy and include many features around structure
and road edges, especially.

Finally, an attempt was made to select the footslopes which were terraces and remove those that were not. Selecting by location was used to select footslopes within 4m of slope lines, which can be seen in Figure 7 (above). The 4m value was chosen by experiment, as larger than 4m selections kept too many non-terrace features, while smaller than 4m selections lost too many terrace features.

Last, many of the remaining shortest footslope lines, often not on terrace edges, were removed by selecting by attribute for footslopes greater than or equal to 15m in length.
This is where progress halted. As is clear in Figure 8 (page 33), the footslope lines include many objects that are not terrace edges, especially around trees and roads. Another attempted step worked to find footslope lines more than 10m from other footslope lines, giving priority to the longest footslope lines (those most often terrace edges). However, a method to successfully do so was not found.
Interestingly, areas with predominantly modern terraces have similar problems. A second example area, as seen in Figure 9 (below), has the modern features of extremely straight terrace edges, regular spacing and sizing between terraces, relatively large spaces between crop rows (mechanized plows are larger than hoes), and distinct raised terrace edges.

Figure 9: Hillshaded Lidar of Modern Terraces
However, when this section is run through the Geomorphons Application, it is clear that there are still irregularities. In Figure 10 (page 36), the same four colors as earlier describe the same four local morphologies, with yellow footslopes, blue slopes, red ridges, and dark red shoulders. In this more technically modern example, there are many more distinct ridges (red) along the top of terrace edges, but not everywhere. Footslopes (yellow) still generally run downhill from each terrace to the lower terrace, but terraces in more complex areas (see the bottom right of the image) lack that morphology. Finally, the slopes (blue) that nicely paralleled the footslopes in the first example still run along at least one side of the terrace edge. Yet in some areas they run on either side of the terrace ridge edge, leaving a footslope missing.

After the various tools are run in ArcGIS (through the selection for footslopes within 4m of slopes and for footslopes equal or longer than 15m), the modern terrace lines, while definitely clearer than the first example's terrace lines, are still lacking in places where the human eye immediately identifies a terrace — especially along the flatter terraces through the vertical center of the image. On the left and top right of the Figure 11 (page 37) are also a number of places where either vegetation or uneven terrace edges resulted in an assortment of clusters of footslope lines. Clearly, while the clarity of the terrace edge identification is significantly better in the modern area, the terraces are neither completely nor singularly identified.

From this end point, classifying the terraces were to include measuring how parallel the lines are to one another. However, given that many of the terrace lines are missing and lines exist where they should not, this would not be a productive analysis,
and so was not done. Similarly, methods were not attempted to identify how smooth and steep the terrace edges, as previous steps could not be finished. These inadequacies show the complexity of the methodological challenge and may suggest that current lidar analysis methods have constraints limiting their effectiveness. Perhaps the edge detection
and surface morphology analysis can provide only so much information, and automated methods must only be only one step in the analysis process.

At this point, it seems like the manual method that the undergraduates completed was far more successful, even if they had small errors as compared to the ground truthed areas (see page 22 for a discussion of their accuracy).

Figure 11: Most Complete Terrace Identification, Modern Terraces
4.3 Springs

The second research question involved identifying the locations of springs known in the valley, and, if they existed in the lidar data, finding common patterns to identify other possible spring locations.

For the spring mapping, two maps could be found. From the first map, made with mapping software in 2016, there are a handful of springs shown south-west of the civil-ceremonial center of Teotihuacan (Evans 2016, 25). This map was georeferenced into ArcGIS and each spring received a point. However, as the scale of the original map meant that each spring point on it was approximately 250m across, there is substantial uncertainty as to the exact locations of these springs.

As can be seen in the lidar data in Figure 12 (page 39), the springs do not seem to align with any obvious features. Given the speed of decline noticed by Sanders, Parsons, & Santley in the 1970s, it is likely these springs have fully dried up and been plowed or built over (Sanders et al 1979, 256–258). While there may be archaeological features near and around the old springs (so knowing their location is worthwhile), their locations cannot at this time be used to find or identify spring locations in other areas of the Valley.

The second map, made in 1979 shows a series of springs to the north of Texcoco, outside of the boundary of the lidar data (Sanders et al 1979, 274). However, as the map was originally hand drawn and clearly not to scale or direction, attempts to georeference it, predominantly using the points where rivers merged, failed. The georeferencing attempt can be seen in Figure 13 (page 40). Because of the heavy use of water and the canalization of many rivers in the Valley, it is suspected that the last 40 years of use has
changed the structure and direction of many of the rivers, leaving the spring locations lost.

Figure 12: Georeferenced Springs
Approximate spring locations marked by red points
Therefore, while the springs located near the civil-ceremonial core were mapped and digitized (perhaps a second time, given the use of mapping software to create the map) and that data can be used to inform future archaeological excavations, most of the goals of this research question were not successfully completed, as the data were too...
sparse and old to identify spring locations. As discussed in chapter six on page 63, fieldwork might be able to identify some of these locations, and perhaps, with historical satellite data, find a combination of traits to identify spring other locations.

4.4 Structures

The third, and last, research question regarded the identification of structures of potential Teotihuacano origin. While the identification of a structure as dating to that period would unquestionably need more information than the lidar data can singularly provide, identifying rectilinear structures that align with the primary orientation of the city would speed up the investigatory process.

The first challenges of this process was to identify the edges of structures. This succeeded slightly better than finding the terrace edges, as the 90° angles of standing structures against the ground show up dramatically in lidar data. However, it is likely that there were some limitations in the data itself. The creation of the bare earth model used the minimum value of lidar return in each pixel (0.5 x 0.5 meters) area to determine the pixel value. The assumption was that the lowest elevation return was the best estimate of the actual ground surface. The substantial detection of edges where there are trees, though, suggests the lidar returns may not have reached the ground.

As the investigation was primarily interested in structures around hillside terraces, the general increase of the elevation of the ground and the roads and other structures embedded into the ground complicate the matter. In addition, the limitation of only having lidar data, and no high-resolution satellite data, limited the number of lines of evidence, and thus limited the possible results.
To begin, attempts were made to use ArcGIS' Spatial Analyst tools for segmentation and classification of rasters. However, because all the data were purely elevation, the primary classes that the ArcGIS tools could find were the changes in elevation, as can be seen in Figure 14 (above). In this image, structures can be seen as different within bands of similar elevation ground surface, but any surface at a specific
height, say 57m, will be classified the same, whether building or ground surface. Therefore, the generalization methods, including Raster Classification after either the Segment Mean Shift and the Train ISO Cluster Classifiers created Esri Classifier Definitions, failed (ArcGIS g).

After those attempts, the data was moved into Matlab to try using high-pass filters and edge detection to find the sudden changes in the values (i.e. the edges of buildings). The Laplacian filters, an isotropic filter at 90° or 45° increments, uses a filter mask to take an approximation of the second derivative of the image to highlight sudden intensity changes in the image (Gonzalez & Woods 2008, 160–162). However, it just resulted in a mess of tree and building groups that does not contain all of or only the structures (see Figure 15 below).

![Figure 15: Laplacian](image1.png)  ![Figure 16: Sobel](image2.png)
For more precise edge detection, the use of methods which rely on horizontal or vertical lines are difficult, as the orientation of the data is north, but many of the structures are oriented off north. For example, the Sobel operator convolves two matrices to determine approximations of the horizontal and vertical first derivatives of the image and then combines them for the result (Gonzalez & Woods 2008, 167).

The Sobel, as can be seen in Figure 16 (page 43), does strongly recognize the edges of rectilinear structures. However, it also strongly sees larger trees. Given that many of the buildings are not aligned with the image's north and the possibility of lidar returns not reaching the ground, it is not surprising that structures are not better identified than trees. With the addition of an infrared band image, the trees might be able to be removed, but without that, it proved very difficult to remove them. This filter result might, however, work well assisting the manual identification of structures (a semi-automated process), as the structures do strongly stand out to the human eye among the trees. Similar problems complicated all of the attempted anisotropic filters, including the Prewitt and Roberts filters, also first derivative filters which calculate the gradient at each pixel (Gonzalez & Woods 2008, 165–168). These three filters — the Roberts, Prewitt, and Sobel — can also be used to identify diagonal edges (45°) with 2D masks to calculate the gradient in those directions, but this was not attempted, as the image is not more oriented in that direction, either (Gonzalez & Woods 2008, 707–712).

The Laplacian of the Gaussian edge detection method eventually worked best at filtering out trees and other non-rectilinear structures and strengthening the rectilinear structural edges, but, as can be seen below in Figure 18 on page 47, it is a long way from
Figure 17: Laplacian of the Gaussian
Threshold of zero, sigma of five

perfect. Using the Matlab command "Output_image=edge(input_image, 'log', threshold, sigma);" the filter combines a Gaussian low-pass filter, which blurs noise (and other small portions of data, such as the smaller trees), and a Laplacian high-pass filter, which finds dramatic changes in the values of the pixels by convolution (Gonzalez & Woods
2008, 714–719). Here, as one would expect, the different threshold and sigma (the standard deviation of the Gaussian) values dramatically changed the final image. If the threshold is given to be zero, then all of the outputs will have closed contours, because it would include all zero crossings. However, sadly but unsurprisingly, this creates a very busy image, as every single zero crossing creates a lot of lines (see Figure 17 on page 45). Had the zero threshold and a larger sigma value created a less busy image, it would have substantially simplified a possible translation in to an ArcGIS polygon vector format.

The best Laplacian of the Gaussian filter ended up using the default threshold and a sigma of five. As you can see in Figure 18 (page 47), while many of the structures are visible, the structures are not tightly rectilinear and are also not closed polygons. In addition, to determine which edge outlines are actually structures would require manually studying the original lidar data or other satellite data, which defeats the purpose of automated identification. As the filters could not succeed at filtering out many of the other features of the image, it would likely be faster for humans to individually draw rectilinear polygons above each of the structures in the lidar while in ArcGIS and then analyzing their orientation (using the Calculate Polygon Main Angle tool) and, subsequently, their size (comparing to use of Teotihuacan units) (ArcGIS b).
4.5 Overview of Results

In general, the research did not succeed at creating automated identification or classification methods. The analysis of springs identified the locations of the springs mapped in Evans, but not those in Sanders, Parsons, & Santley (Evans 2016; Sanders et
al 1979). However, the springs are not identifiable in the lidar data, as they have presumably dried up and been plowed and/or built over. While further fieldwork might help identify locations, the identification of other possible spring locations would require historical high-resolution multi-band images to find possibly wet areas in addition to the fieldwork identified locations.

The analyses of both the terraces and the structures were not completed, as the data could not be simplified and consolidated to include only or all of the sought features. Having further sources of data, including satellite images, would likely improve the ability to identify structures from trees, but may not substantially assist in the identification of terrace edges compared to the fields and road edges if they are covered in similar vegetation. As the automated attempts were not successful, that leaves either manual methods or newer computational methods to identify or classify archaeological lidar data.
CHAPTER FIVE: DISCUSSION

5.1. Introduction

In archaeology, the use of mapping and remote sensing is rapidly growing due to increasing access and understanding. However, all previous studies using lidar data have involved manual human identification of features after analysis, the use of lidar data to calculate water movement across a 3D surface, or visibility calculations. As of this point, no one has succeeded at discovering automated methods to identify archaeological features. This research attempted to identify three features within the Teotihuacan Valley: terraces on field systems, springs, and structures in the landscape.

5.2 Terraces

The terraced field systems around the hills of the Valley have been used over many centuries of farming. Because they have been used, on and off, for so long, the terraces have maintained their shapes. These shapes — with a peak at the terrace edge, a slight slope into the field, and a more dramatic slope down to the next field — mean that their visibility in fine-resolution lidar data is remarkably clear. Had the terraces been left idle to erode away, the lidar data would be much less clear, and identification, manually or automatically, would be nigh impossible without fieldwork. However, because of the regular cultivation, dating specific terraces to particular periods is more difficult. Identification of a specific period requires not just excavation, but excavation that discovers di-
agnostic artifacts or other datable evidence.

Thankfully, identification of more general periods — pre-Columbian without horses or plows versus Columbian and/or modern with horses, plows, and, later, machinery — is simpler. As discussed in chapter three (see page 22), if the terraces and field systems have not regularly been farmed with mechanized equipment, the terraces tend to be less exact, with wobblier lines and perhaps less steep slopes on the edges. The plow lines in those fields are also less straight, whether operated by humans or horses. If the field has not been cultivated by plows and horses, then the hoe marks can also be distinctive, although, given the likely time since the technological changes, the signs may be somewhat eroded or hidden. Of course, these terraces might be those least clear in the lidar data, resulting in the loss of the most interesting archaeological features first.

The attempt for automation stumbled at the stage of the identification of terraces. While human eyes clearly identify smooth lines of terraces in the hillshaded DEM created by the lidar (see Figure 1 on page 26), the distinction between terrace edges and the edges of roads, especially, could not be differentiated. While structures may have been able to be removed by using a layer of slope changes (very high slopes suggest the wall of a structure) to define areas as certainly not fields, even trees, with their uneven growth and edges, were not able to be computationally discerned from terraces. Thus, this point may be where manual efforts should be added to finish the identification and classification.

The manual identification and classification of the terraces and field systems covered by the extent of the lidar data was performed by a team of undergraduate volun-
teers, some of whom had spent previous summers in Mexico doing fieldwork, in the Sociology and Anthropology Department under Dr. Nawa Sugiyama (Sugiyama et al 2018). Their classifications, into the four categories described on page 20, were predominantly qualitative, without quantitative measurements.

An example of the differences between the manual and automated classifications can be seen in Figure 19 (below). In both example areas, automated identifications label non-terraces as terraces and miss positively identifying other terraces, while manual classifications seem partial and may not closely follow all of the terrace edge. Here, both methods show the limits of feature identification — even if one limit is human, manual patience and the other methodological.

Figure 19: Manual versus Automatic Identification & Classification
Yellow lines are automatically identified. Manually identified and classified lines are red for not archaeological (class 0), orange for class 1 (no examples here), green for class 2, and blue for class 3 (definitely archaeological). Left image shows the first example; right image shows the second, more modern, example area.
Had this project been able to successfully identify terrace edges, the classification into those four categories would have struggled, as numerical descriptions for the classes would need to be developed for the computer. Without specific training examples, computers cannot (yet) take human qualitative descriptions about how parallel, or straight, or slumped geometries are and turn the descriptions into quantitative groupings. To create specifics for classification, the task would have involved, for example to differentiate types of terraces, the calculation of many average distances, the fitting of mathematical functions to describe the smoothness of the lines, or measurements of the different slopes.

Perhaps it is not surprising that other research within archaeology has not succeeded at this attempt either. The most similar research, identifying field systems on a Hawaiian island, merely mapped geomorphological changes across the landscape (McCoy, Asner, & Graves 2011). It did not try to identify separate features from the landscape as a whole. This is equivalent of how the Geomorphons Application was used in this project (see Figures 2 and 3 on pages 27 and 28). As this was the last fully successful step of the terrace identification, it indicates this may be as far as this technology and methodology can reach.

Other options could be used in the future. One might be to combine the automated results and manual efforts, which might reach a balance between fast mathematical computations and human knowledge. Neural networks are receiving a great deal of attention (Koehrs 2017). While no one is entirely sure how they identify specific features in images, and they often make amusing mistakes (the preponderance of giraffes identified where they are not in Microsoft Azure’s Computer Vision API is one potent example),
they do seem to be hopefully promising in their ability to learn from many inputs (Shane). The bulk of research classifying and identifying objects in lidar data with neural networks is in the flourishing field of autonomous vehicles, although the lidar data are most often combined with visual, multi-band images (see Matti et al 2017; Prokhorov 2009). Here the lidar data are fine-scale, but also of a relatively small spatial area, and with only a few 'types' of objects to classify: most often vehicle or not vehicle. Other studies have used neural networks to identify biomass in forests (Ayrey & Hayes 2018), where it is relatively easy to imagine training a computer to calculate the volume between first and last returns of the lidar.

To use a neural network with this research's data, the training database would need to be large, and, as most studies have done, might require additional multi-band visual images. The training database could be a modification of one portion of the manually identified (or, after enough time, ground truth identified) terraces, with other portions of the Valley — or new areas outside the Valley with similar agricultural systems and histories — automatically identified or tested. If the neural network were successful at correctly identifying terraces (or other features), it would be potentially fascinating to investigate at which other sites the computer could identify terraces. Using neural networks, it might be possible to identify other field systems without terraces, even within the Valley, where identical cultures produced very similar fields with identical technologies where terraces were unnecessary. Non-mountainous, non-terraced field systems would be more difficult to identify, because there are not substantial differences in slope between fields and because there are many more structures and other confounding land-
scape features on the more level Valley floor. The extent of the ability of neural networks to learn slight distinctions in these sorts of cases is so far unknown.

5.3 Springs

For a city the size of Teotihuacan, large amounts of food and water would need to be delivered daily. The growing of food and the construction of irrigation systems and canals was necessary for the continuation of the society. As the amount of rain was not regularly enough to grow staple food crops, it was necessary for the Teotihuacanos to control the movement and use of water (Cowgill 2015, 30). As such, a number of researchers have suggested that springs were eminently important. Two maps of different springs systems could be found, but their data were insufficient to identify any signal of springs in modern imagery. As Sanders, Parsons, & Santley discuss, the outflow of the springs near San Juan Teotihuacan church was rapidly dropping over the 20th century (Sanders et al 1979, 256–258). Thus, it is likely that many of the springs in the area have dried out as modern, industrial pumps have lowered the water table and substantial irrigation systems have re-routed many of the local rivers.

The biggest problem facing future research determining spring location is the combination of modern and historical data. Historical records showing spring location are sparse, at best, while concurrently stressing their importance. Modern images, while very common, cannot find what no longer exists, and lidar data are unlikely to be able to uniquely identify them. As lidar data read the elevation of the ground level, for springs to be visible they would need to (still) have a low point or other geomorphologically distinct form, either natural or manmade. If historical satellite imagery or aerial photographs can

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be found with fine enough spatial resolution, then perhaps the historical descriptions and few maps could locate possible spring locations where water appears surrounded by areas of unusually damp and/or fertile land.

As springs in relatively arid locations tend to be places people spend time, they also tend to have archaeologically significant artifacts around them. If even some of the springs can be precisely located, there is a chance for the protection of the sites from further destruction. With more time and money, excavation of the springs and their surroundings could occur, possibly educating about both the practical functionalities of the water system and the cultural meanings of water.

5.4 Structures

Starting around 100CE the city of Teotihuacan, for whatever reason, adopted a city plan with a very precise, planned orientation of 15.5°N (Cowgill 2015, 125). From that date on as the city expanded, the orientation was sustained within the civil-ceremonial center, in the urban city surrounding it, and on roads leading out of the city. Questions remain as to how strong the control of the suburban and rural areas was. Orientation data, where it exists, could provide clear evidence of possible political and social controls.

Structures outside the city's core cover a large area: imagining how much area would have been necessary for food production quickly leads to that expectation. Sanders, Parsons, & Santley surveyed a large area in the 1970s, but their attention was on locating archaeological settlements across the full Basin of Mexico (Sanders et al 1979). The lidar used in this research attempted to identify structures that have been used,
reused, or built directly on top of, since the Teotihuacan era. However, at the first step, the identification of specific polygons for each structure, the attempts for automation fell short, suggesting methodological constraints in image analysis.

Three main traits could identify above-ground structures of that period, but none of the traits is unique to Teotihuacano period buildings. The first trait is the famous orientation of the city. Once polygon shapes are determined, their principle orientation is easily calculated in programs including ArcGIS. Of course, the orientation is not limited to structures of this age, although earlier structures are unlikely to be at that orientation. As the city defined roadways and building grids throughout the Valley, later structures and roads often followed along, just as modern British motorways and A roads often follow old Roman roads.

Secondly, Teotihuacan also had common building materials, including adobe and Teotihuacano cement for walls and floors, with flat rooftops. While this information is useful for in person, field identification, it is not visible in the lidar data. With additional remotely sensed imagery, especially multi-spectral, it would be possible to identify different types of materials on the tops of structures (presumably their roofs). However, there are two complications: there is modern use of similar construction materials, and modern materials can replace older roofs. Also, collapsed structures without roofs and low walls might confound this method.

The last trait that could help identify structures of Teotihuacano origin is the unit of measurement. At 83cm, the value is specific enough to need both fine enough spatial resolution of the bare earth model and, then, the acceptance of some estimation in the
measurements (Sugiyama 2010). To identify structures with sides measuring multiples of 83cm would require finer spatial resolution, though. The bare earth model created for this research had 0.5m pixel sizes, to allow faster calculations. Possibly, after the identification of likely buildings from the first two traits, a finer resolution bare earth model in smaller areas could be used to measure the wall lengths of a limited numbers of buildings.

Additionally, measuring the structures would include complications due to pixel mixing. If a structure does not end specifically at the exact edge of a pixel (or between the lidar returns on each edge of a pixel), then the pixels just off the side of the structure edge may include measurements of both structure height and whatever is next to the structure (often the ground). There are various methods to approach this. In this research, the minimum value of each pixel area was used to give each pixel a value, meaning that as long as there was one pixel of ground, then the ground value would be the pixel value. However, using this example, if a pixel crossed both part of a structure and the ground and had returns on both, the whole pixel would read as the ground value, shrinking the actual size of the structures wall length. If the average of the return values is taken for the pixel and if the ground around a structure is perfectly flat, then the amount of the pixel value from various portions could be estimated. However, as stated, that requires perfectly flat ground, instead of a constantly varying real ground. Therefore, that method is less useful in practice.

Similarly to the terrace identifications, it is possible that using newer technologies, such as neural networks, could identify rectilinear structures. Contrarily, augment-
ing the automated results with manual products could accomplish the identification and classification. To aid in identification, additional satellite imagery would help differentiate between, at a minimum, living trees and solid structures. Given the height of the trees in the lidar data, as mentioned before (see page 41), it may also help to have more returns in the lidar data, so more are likely to get through the larger trees.

From the identification of rectilinear structures, it would be relatively simple to calculate the orientation of the structures. However, the materials and size of the structures would be much more complicated. Currently, field work to identify evidence of older portions of walls and to measure structure walls would be easier and more accurate than attempting to identify structure age from roof materials and dimensions from mixed pixels. If structures could be identified as likely to have originated during the Teotihuacan period, focused archaeological investigations of any of those sites could dramatically increase our understanding of the food production for the city and the lives of the rural and suburban population, including those perhaps under lesser 'state' control than the urban populace.

5.5 Further Research

The end results of each research question leave some features unidentified and no features classified. From here, a number of methods could be used to further the identification and classification of features. Simplest, the addition of satellite data, ideally multi-band with fine spatial resolution, would support easier automated classification. The additional bands of data would allow other ways of separating objects other than their elevation and, in situations where automated methods cannot reach
necessary accuracies, would support manual efforts. Another option would be to aim for semi-automated methodologies, instead of fully automated. This could work by assisting the manual drawing of features (e.g. providing the human classifier information on the highest local points or peaks), which can also help mitigate the many random biases introduced when multiple people are manually identifying and classifying points. The semi-automated process might introduce its own biases, but they would be likely to be small and systematic.

A distinct argument for manual input involves the wealth of knowledge by archaeologists (or others studying the area). For this project, information on vegetation's relationship with different features (e.g. along terraces or ruined structures), upper limits on the curvature of terraces, or ranges of feature size could all be combined with the lidar (and, possibly satellite) data to add constraints and limits to feature identification.

Computationally, there are also a few other options for continuing research. The Hough transform seeks to find imperfect versions of particular features (Gonzalez & Woods 2008, 733–738). This method has been mentioned as a goal for automated identification of archaeological features, especially curvilinear, but has not yet been successful (Humme, Lindenbergh, & Sueur 2006, 6). Water flow methods or segmentation using morphological watersheds could also help with the identification of specific groups, and those methods could even provide a water flow model to search for a hierarchical terrace structure (Gonzalez & Woods 2008, 769–774). Given the constraints of feature identification from lidar, it is likely that some to all of these future research options could be used to fully identify and classify lidar data.
5.6 Discussion Overview

As the currently available automated imagery processing methods were not fully successful at identifying or classifying the features in this study, it is necessary to look both at reasons for the failures as well as other possible methods to answer the questions. While archaeological data are by their nature complex and fragmentary, the ground level or above ground level identification of objects is a common goal across image processing in many fields. The repeated failures of filtering and classification methods to identify only and all of a type of feature explains the continuing research and development of other image processing methods.

Neural networks provide a cutting edge methodology, where computers 'learn' from human described images. The simpler and more accurate, if slower, method is the manual description of images, which can be combined with automated techniques to create semi-automated methods. The human eye remains very good at identifying and grouping objects, as it has evolved to do. While the amount of imagery available for analysis and the amount of time necessary for a human to classify objects is substantial, it is still the best method available, especially for complex and messy human landscapes like this one.
CHAPTER SIX: CONCLUSION

6.1 Terrace Research Question Conclusions

The first part of the first research question — can archaeological terraced field systems on a mountain be identified using lidar data? — culminated in a simple 'no.' The terraces were too diverse and the landscape complicated enough that both filtering operations and uses of local geometry to classify the landscape could not identify all or only terrace edges. However, as other research has also been halted at this point, where edge detection and surface morphology analysis cannot proceed, it may be a constraint of image processing of lidar data rather than an archaeological data question.

As the first part of the question was unsuccessful, the ancillary questions regarding the classification of different terraces and the expansion to other mountain field systems in the Valley or non-mountain systems in the Valley floor could not be accomplished either. Following those results, accuracy calculations are accordingly non-existent.

As mentioned previously (see page 53), identification of terraces might be possible with additional high spatial resolution imagery, manual production of information, and/or substantial training data and the development of a neural network. However, given most archaeological investigations are relatively small scale and the types of agricultural features to be identified often vary at least slightly by culture, in the near future it is likely that the fastest and most accurate method of identification and
classification requires manual analysis of lidar or other data supported by ground truthing and other fieldwork.

As in McCoy, Asner, & Graves’ work in Hawaii (McCoy, Asner, & Graves 2011), the results at the end of the Geomorphons Application's classification could be used to indicate the local geomorphology in the landscape for human visual interpretation. However, this could be simply done by showing the hillshaded lidar data as a visual instead. In either case, despite the lack of automation, the addition of the visual display aids human understanding and identification of features, including terraces.

6.2 Spring Research Question Conclusions

Similarly to the terrace portion of the research, the spring identification generally failed, albeit for different reasons. For Evans' map, which could be georeferenced to current maps, the springs were identified, but were not visible in the lidar data (Evans 2016). As it appears that at least those springs have dried up and been plowed or built over given their locations on the research data and in google maps imagery (Google), it is dubious that other local springs exist either.

As Sanders, Parsons, & Santley's map was unable to be georeferenced (it was presumably produced from a sketch) and was outside the area surveyed by the lidar, springs could not be located in the landscape (Sanders et al 1979, 274). Given their description of the rapidly decreasing water rates in the springs, in all likelihood they are also dry and erased from the surface landscape (Sanders et al 1979, 256–258).

Despite the importance of springs and the related water system in the literature, it was more difficult than expected to find information on specific spring locations.
Because the two established maps did not furnish enough data to find the springs in the lidar data, other springs could not be found by a similar structure in the Valley and accuracy measurements could not be determined.

If historical fine spatial resolution multi-band imagery could be acquired, and if some springs could be precisely located (with similar precision to the lidar and visual imagery) with fieldwork, then it might be possible to combine the current lidar data with those new data to identify similar features across the bands and then use ArcGIS' Spatial Analyst tools, or other methods, to find matching features (also presumably springs). Without the additional information, however, springs are unlikely to be identified. Even so, unmentioned springs lost by time may not be detectable. If springs can in fact not be detected, this would limit the further research on modern and ancient water networks and agricultural irrigation systems and so could shed no light on our understanding of Teotihuacanos' cultural and symbolic perceptions of water.

6.3 Structure Research Question Conclusions

The attempt to automatically identify and classify structures was, likewise, in vain. The structures, often similar heights and sizes to nearby large trees, were too diverse to identify purely with these techniques for analyzing the lidar data. As such, it was impossible to test the accuracy of the identifications. Currently, without more advanced methodologies such as neural networks for image identification, manually outlining structures with polygons in ArcGIS is likely to be the easiest and most accurate method of structure identification.

If rectilinear structures can be identified in any way, by neural network training as
mentioned previously in chapter five (see page 57) or by manual labor, then primary orientation can be determined. This could limit the number of structures which might be of Teotihuacano origin, as structures not aligning to the 15.5°N orientation of the city are unlikely to be associated with that culture. However, it would be likely that many structures that do match that orientation might be later additions, because later buildings and road network placement are influenced by the past.

While satellite imagery might also assist identification of older structures, the likelihood of structure reuse, the continued use of building materials such as adobe, and the replacement of roofs on old structures with modern materials, such as sheet metal, impede the imagery's use. Archaeological structures would be very likely to be dismissed as modern and not further evaluated.

The use of the Teotihuacan unit of measurement might further limit structures to those of Teotihacano origin. However, the requirement of precise enough data (i.e. small enough spatial resolution pixel sizes) needs substantial computing power or very small areas to be analyzed. This step would logically occur after the number of structures to be analyzed was limited by orientation and possibly material.

In all of these subsequent portions of the third research question, field work would be essential for two reasons, even with more advanced methodologies. It would check the computerized classifications, and it would determine whether structures with the correct orientation and sizing were actually built and used during the Teotihuacan culture or whether they are later structures built in similar ways due to the continuation of Teotihuacan's local legacy.
6.4 Overall Conclusions

This research project attempted to use currently available automated geospatial technologies in a field where they had not yet been used. Lidar data have been used in archaeology as a pretty background to images; to aid manual classification of landscape features; as a 3D surface to study movement (of humans and of water, most commonly); and to study the 3D visual landscape (see Thompson 2017; McCoy, Asner, & Graves 2011; Chase & Weishampel 2016; & Chase, Chase, et al 2010). Archaeology had not published any attempts to develop automated methods to identify typical archaeological features across the landscape. Since the research was generally unsuccessful, it suggests that the complexity of archaeological landscapes and/or the difficulty of automated feature identification may be beyond the attempted methods.

With the security and intelligence communities, the development of autonomous vehicles, and research by Google, Microsoft, and Intel, among others, to automate computer understanding of imagery, technologies relating to the identification of 3D objects are rapidly changing and developing. Very soon, it is likely that programs and dedicated hardware will exist that will allow users to upload training data and images and rapidly receive very correctly identified objects.

Remote imagery has been much more commonly used over the last decade than before, but is still expanding, as into multi-spectral and higher spatial resolution imagery. Even now, there is more imagery than can be manually analyzed. As soon as automated, or even semi-automated, image classifications are more developed and accurate,
archaeology will happily accept and adopt the new technologies, as it always has in the past. This automated, faster, and relatively accurate synthesis of disparate data should provide archaeology with new insights about human-landscape interactions.
REFERENCES


BOWER, B. This ancient Maya city may have helped the Snake King dynasty spread: Lidar maps and hieroglyphics suggest La Corrona wasn't so isolated after all. Retrieved April 22, 2018. [https://www.sciencenews.org/article/ancient-maya-city-snake-king-dynasty-la-corona-archaeology]


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