

Spring 4-15-2019

Drivable Space Datasets Created by Airborne LiDAR and Aerial Imagery

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**DRIVABLE SPACE
DATASETS CREATED BY
AIRBORNE LIDAR AND AERIAL IMAGES**

by

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**BACHELOR OF SCIENCE
THE UNIVERSITY OF NEW MEXICO
JULY, 2018**

THESIS

Submitted in Partial Fulfillment of the
Requirements for the Degree of

**Master of Science
Civil Engineering**

The University of New Mexico
Albuquerque, New Mexico

May 2019

Dedication

I would like to dedicate this thesis to my parents, grandparents, in-laws, and my wife. They have encouraged me to never give up and always give my very best. I could have never done this without them. This thesis is also dedicated to my advisors and colleagues of the Civil, Construction and Environmental Engineering Department.

Acknowledgements

I am honored to express my appreciation to Dr. Susan Bogus-Halter, my committee chair person and advisor. I would have never been in this position if she did not offer me the opportunity to pursue my Master's Degree. Dr. Bogus has guided and encouraged me through the entirety of this Master's program. I would like to give thanks to Dr. Su Zhang who has been a mentor and friend through this educational experience. I could not have done this without his wise direction. I would also like to thank Dr. Fernando Moreu for serving on my committee. I appreciate the insight and guidance that Dr. Moreu has brought to this thesis.

Much gratitude must go out to my colleagues in the Civil, Construction and Environmental Engineering Department for sharing their experiences and insight with me in order to succeed in a graduate level program. This thesis would not have been what it has become without my dear colleagues.

Drivable Space Datasets Created by Airborne LiDAR and Aerial Images

By

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Bachelor of Science Civil Engineering, University of New Mexico, 2018

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Abstract

The civil engineering and construction industries are currently using geo browsers such as Google Earth to access satellite and aerial imagery to create and update design drawings for roadway construction, which leads to inaccuracies in the construction phase and in effect, delays the time, and increases the cost of a project. Technological advancements in the civil engineering and construction industries have enabled the design processes to be more efficient and accurate. This research focuses on using the cutting-edge technology of airborne LiDAR and aerial imagery to extract roadway network information from an urban area, which can be used to enhance the durability and serviceability of transportation infrastructure in a complex environment. Research results revealed that the time, cost, and completeness of extracting roadway network information from LiDAR data and aerial imagery are more advantageous than that of digitizing from Google Earth, which involves designing roadway network information based on the designer's best judgment. Research results also showed that there are still limitations with this approach as it relates to the

accuracy of detecting the edges of the drivable spaces in an urban environment, mainly due to the failure of the extraction process to distinguish between drivable spaces and adjacent sidewalks or other paved surfaces. Future improvements for this extraction process will need to consider better edge detection methods to improve accuracy in urban environments. The process used for the procedure will be made readily available to the civil engineering and construction industries to enable the users to apply it to their work. Utilizing LiDAR data and aerial imagery to extract drivable space information has advantages over the current industry-adopted method, including being better in time efficiency and cost effectiveness.

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Chapter 1: Introduction

The civil engineering industry is responsible for designing plans for drivable spaces, such as roadways, multiuse paths, and parking lots. Roadway and multiuse path centerline datasets exist to assist engineers with design of these drivable spaces. Existing centerline datasets, however, do not contain drivable space attributes, such as widths, lane markings, signage, and area (Landa & Prochazka, 2014), which are useful for design. Therefore, engineers often use satellite images to provide this additional information.

Satellite images (such as from Google Earth or Google Maps) are commonly used to design drivable spaces. Satellite images are referenced into the AutoCAD drawings and underlay the new engineering designs. This is an easy way to design when you do not have accurate CAD files of the existing roadway or path. The drivable space is clearly represented by the satellite image and the engineer can create plans based off what they see, which is also known as digitization. The current way to design, digitizing, is convenient and cost effective for engineers; however, it can result in issues during the design and construction phases when the digitized data do not agree with the ground truth information.

Digitization is common when dealing with on-call contracts. On-call contracts are when a project has an undefined scope, non-specific start time, and has a two-year limit for completion of work. Digitization and on-call projects go hand-in-hand and create unfortunate complications for a project.

Because the civil engineering industry uses satellite images as the base of their designs, complications often arise. During the construction phase, the use of design drawings based on satellite images and digitization leads to inaccuracies in the design, and in effect, results in time extensions and cost increases during the construction phase of the project. This has led to the assumption that a set of design drawings that utilize a satellite image will fall short of desired results. The motivation for this research is to identify an improved method for designing drivable spaces that addresses some of the shortcomings of using satellite images.

Initial review of literature indicates that two potential alternatives to the use of satellite images for identifying drivable spaces are aerial images and Light Detection and Ranging (LiDAR) (Hu, Tao, & Hu, n.d.). Aerial imagery and LiDAR are known to be highly accurate; because of this, combining both datasets should be highly effective in terms of extracting accurate data on drivable spaces (Rahimi, Arefi, & Bahmanyar, 2015). Therefore, this research proposes to answer the following questions: 1) How accurate is LiDAR and aerial imagery extraction of a drivable space in reference to the existing field conditions? and 2) What are the advantages and disadvantages of using LiDAR and aerial imagery compared to the use of satellite images?

To answer these questions, the following steps will be undertaken: 1) extracting drivable space information using aerial imagery and LiDAR data and converting this data from a raster file to a CAD file so it can be used for design, 2) develop a toolset for data extraction and conversion and 3) validating the

accuracy of the newly developed drivable space dataset and analyzing the cost, time, and completeness of the extraction process versus the digitization process. The focus of this research will be a complex urban environment as it consists of many attributes, such as: sidewalks, roads, buildings, and vegetation that will need to be separated out during analysis.

Chapter 2: Literature Review

This study expands on current work of Zhang, et al. (2019). The research explores different areas of interest relative to the current work as presented in the following paragraphs.

2.1. LiDAR Technology

The research team obtained airborne LiDAR data for a project funded through the Transportation Consortium of South-Central States (Tran-SET). The aircraft used for gathering the LiDAR was a helicopter. A simple summary of LiDAR is given: “LiDAR consists of a transmitter and a receiver. Short light pulses with lengths of a few to several hundred nanoseconds and specific spectral properties are generated by the laser. At the receiver end, a telescope collects the photons backscattered from the atmosphere” (Wandinger, 2005).

The UNM Earth Data Analysis Center (EDAC) acts as the hub for the LiDAR data, which are organized and kept as “tiles”. These tiles can range in many sizes and are meant to form a grander image of what the LiDAR collected. Along with LiDAR data, EDAC also carries aerial imagery, which is similar to an image from Google Earth. All of the LiDAR data and aerial images are currently attainable for this project.

Because LiDAR is a popular source of data, recent studies create algorithms that can analyze and categorize the LiDAR data. In Li et al. (2015), the point clouds, another term for LiDAR data, represent a topological surface and use a series of algorithms to categorize what is road and what is not. This is described

as a candidacy process. The algorithm is literally voting on what is and is not road data.

Different techniques of attaining desired attributes from LiDAR data are innumerable and there is an attraction for these processes to be automated. For a process to be automated, segmentation-based filtering must be considered (Narwade & Musande, 2014). Similarly, morphological filtering, meaning: algorithms examine layers of data for any delineations of objects, must also be considered. This is able to be accomplished through elevation measurements of the points in the point cloud (Zhao & You, 2012).

LiDAR has many more capabilities than just creating morphological topologies, including interactive modeling. In the study by (Chen, 2011), it explored ground video with a combination of airborne LiDAR to develop a three-dimensional model to represent highways. The concepts developed in this study follow a similar trend of SBF and morphological filtering. The results of the study provide an avenue for detecting lanes and ground from LiDAR data. Airborne LiDAR is able to capture a robust amount of information of large areas. A large area is considered to be one thousand kilometers or greater. An example of this would be a forested area.

A forested area is not only a large area, but also a complex area for detecting road networks. Any type of detection underneath tree canopies is only made possible through LiDAR. It is noted that this is only a detection process, not an extraction process, yet similar principles apply. A digital terrain model (DTM) is the only piece of data considered, which is gained from LiDAR processing.

Object Based Image Analysis (OBIA) is used to achieve appropriate three-dimensional geometric features. OBIA is a great process for picking out drivable spaces from LiDAR data (Ferraz, Mallet, & Chehata, 2016).

2.2. Aerial Imagery and LiDAR

Researchers use a combination of aerial imagery and LiDAR to extract road networks and its features (Kumar, McElhinney, Lewis, & McCarthy, 2013). This combination of aerial imagery and LiDAR has major benefits, such as: attaining road edges, lane markings, curb and gutters, and signage. As previously mentioned, LiDAR provides high accuracy of elevation data of a topology, and aerial images provide the sharpened details. Studies that combine aerial imagery and LiDAR fluctuate between mobile and airborne LiDAR (Wu, Xu, & Zheng, 2017). This does not affect the desired results of extracting drivable space.

Because aerial imagery and LiDAR are highly accurate, meshing the two forms of data should provide a precise extraction process of drivable spaces (Rahimi et al., 2015). Similar methods of extracting drivable spaces from only LiDAR also apply when extracting drivable spaces from both aerial imagery and LiDAR. A Hough Transform is a popular way of detecting drivable space edging. With a combination of a process known as a ribbon snake, the algorithm is able to make road candidates and validate edging. Color from the aerial image is another way to detecting drivable spaces. Drivable spaces are typically constructed out of asphaltic materials; therefore, the color intensity is different as compared to a building, vegetation, or concrete sidewalks (Hu et al., n.d.).

Being able to delineate between different features of an aerial image and LiDAR is of high importance. A great use for this is road inventory. Because aerial imagery and LiDAR provides an excessive amount of details, it is possible to obtain detailed features for road inventory. Time and money are constantly a main concern with any industry; therefore, an extraction process for drivable spaces that can save both time and money, is attractive to many people (Landa & Prochazka, 2014).

All studies that attempt to extract drivable spaces share common values: time, money, and resources. They all follow a similar step: segmentation and classification, which proves to be the most extraneous part of developing an effective algorithm.

2.3. Segmentation and Classification

The greatest challenge for the previously mentioned studies is to segment and classify aerial imagery and LiDAR data. An algorithm must be developed in order to “rule” whether the data are a part of the drivable space, or not. It is not as easy as just telling the algorithm to pick out only the road characteristics. The algorithm must know where the roads end and begin, its width and length. Not all roads are perfectly constructed, and all roads change over time due to the vigorous use of vehicles.

Segmentation is the process of combining similar attributes from either an aerial image and/or LiDAR data into one value. Similar attributes include: ground, low vegetation, high vegetation, buildings, and sky (Chen, 2011). Segmentation is a demanding process because there are many parameters that can be used in

order to segment an aerial image and LiDAR data, such as: height, intensity, and shape.

The segmentation process is not to be confused with classification, which is the process of naming the segmented values. Classifying the segmented values is when the names like ground, low vegetation, buildings, etc. are given to the segmented data. Classifying the segmented data can be determined from a training session, where the algorithm learns what to classify as road and not road through multiple test trials (Jeong & Lee, 2016).

Hu, et al. (n.d.) provides an in-depth study of a segmentation and classification process that in the future can be used to develop reliable three-dimensional city models. The process incorporates Hough transform, which is generally used for extracting straight lines in geometry, but in this case, it is used to detect road edges from LiDAR data and an aerial image. A Hough transform algorithm has a vital role when detecting and validating the accuracy of the extracted drivable space.

Segmentation and classification are the most important part of extracting drivable space information. It is important for the present and future as Jeong & Lee (2016) mentions in their study. The study focuses on autonomous vehicles, which is a present and future technology that must have accurate and precise data on road networks for safety, design, and construction purposes. By following a similar OBIA process, which is used to determine drivable space through light intensity, detecting drivable spaces is possible through an interface that can perform those type of algorithms.

Chapter 3: Methodology

The purpose of this study is to produce a drivable space dataset for civil engineering design and construction. To achieve the desired results, a multi-step process must be followed, which can be seen by Figure 1. This flow chart describes the three-step methodology, which will be described in further detail in the following sections. This methodology will ensure that the drivable space dataset is created properly and is reproducible.

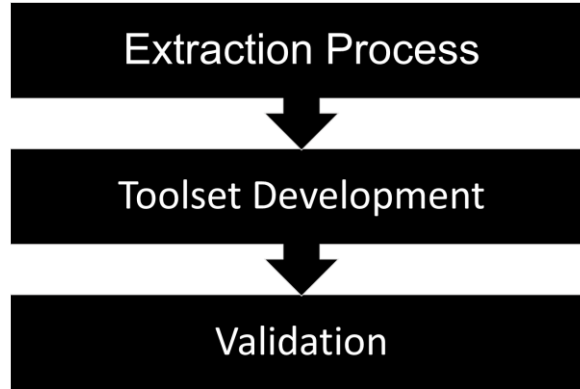


Figure 1. Methodology

3.1. Study Area and Dataset

The designated LiDAR data and aerial imagery encompass the southwest portion of the University of New Mexico (UNM) and its surrounding neighborhoods. The study area can be seen in Figure 2. The figure represents Central Albuquerque and the black bordered region represents the study area. The location was chosen due to the fact that it is familiar to the researcher and easy to access. It is important to have an accessible area in case any physical

examination is required. Not only is the physical study area easily accessible, but also its data is easily attainable.

The Earth Data Analysis Center (EDAC) has the study area on record. EDAC provides open source network where anyone can find and use geographic information system (GIS) data. The aerial image data were obtained from the EDAC website known as RGIS by simply searching for the area of desire in their search engine while the LiDAR was obtained from the USGS website, which was collected by the Mid-Region Council of Governments (MRCOG) and found by searching for the area of interest in their search engine. The aerial image data were collected in 2016 and the LiDAR data were collected in 2010. The data size for both the aerial image and LiDAR data were approximately one and a half gigabytes, which is appropriate for what it represents. This is important because intuitively, the greater the file size the longer the extraction process will take. The study area is half of a square mile. The aerial image and LiDAR are both captured at half foot resolution; therefore, the data is greatly sharpened in appearance when zooming in and out. This is of high value in order to examine the complex area.

The complexity of the area is represented as a dense urban city and is displayed by the aerial image in Figure 3. The figure shows that the area is a grid structure design, which is convenient for analysis purposes. Because of the high density, an extraction process will be a challenge to develop. The multiple parameters considered from the sets of data are buildings, cars, trees, shadows,

and concrete drivable spaces. A simple and efficient software program is required to work around the listed parameters.



Figure 2. Study Area Map

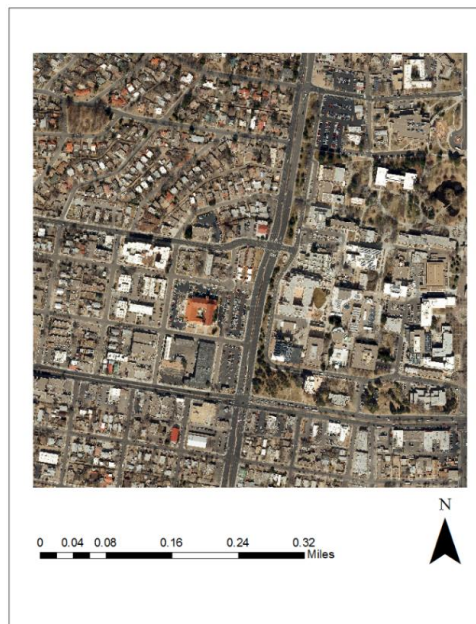


Figure 3. Aerial Image

The software used for this study is ArcMap, which comes from a line of ArcGIS programs. ArcMap is the typical civil engineering and construction industry software for developing a GIS. Therefore, it is important to develop an extraction process for the standard design technique used amongst civil engineering design and construction, which is known as digitization. All tools from the stocked toolbox are used to create the extraction drivable space dataset.

3.2. Extraction Process

Extracting a drivable space from aerial imagery and LiDAR is achievable by following an object-based image analysis (OBIA). The description of this process is in the name; objects are identified and extracted based on an object's similarity, which incorporates area, height, and color. Aerial Imagery and LiDAR provide the required characteristics for OBIA to be performed. Figure 4 will be used to represent the extraction process used in this study. In addition, Appendix A contains screen captures of the entire extraction process.

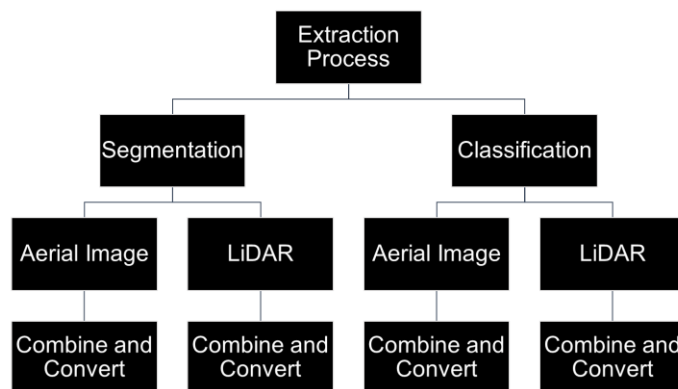


Figure 4. Extraction Process

3.2.1. Aerial Image Segmentation

The aerial image encompasses three major color bands: red, green, and blue, and because the segmentation process is crucial to creating initial separation between objects, the 'Segment Mean Shift' tool is required to segment the aerial image. Segmenting is important because it is a major step in identifying the drivable space from everything else. Segmentation is a broad process, similar to the top of a funnel, and the process will only focus more and more on the drivable space as it goes on.

There are three parameters for the segment mean shift tool: spectral detail, spatial detail, and minimum segment size in pixels. The spectral detail focuses on the difference between species. For example, if there are multiple trees, spectral detail distinguishes between the different types of trees. The spatial detail separates objects based on height. The higher the spatial value, the greater chance it will segment trees from ground. The minimum segment size in pixel determines how many cells to encompass in a single pixel. The spectral detail, spatial detail, and minimum segment size in pixels used are: 14.5, 15, and 20. These chosen parameters gave the best segmentation of the drivable space. It is also noted that the aerial image came with an associated coordinate system, which is NAD_1983_HARN_StatePlane_New_Mexico_Central_FIPS_3002_Feet. This is important to know for the segmentation process for the LiDAR. The segmented aerial image can be seen in Figure 5. When examining the figure, it can be seen that the details of the original aerial image, which is on the left-hand side, are lost compared to the segmented aerial image, which is on

the right. Furthermore, the drivable spaces of the segmented image are represented by a similar grayish color. This correlates to a similar pixel value, which will be used in the classification process.

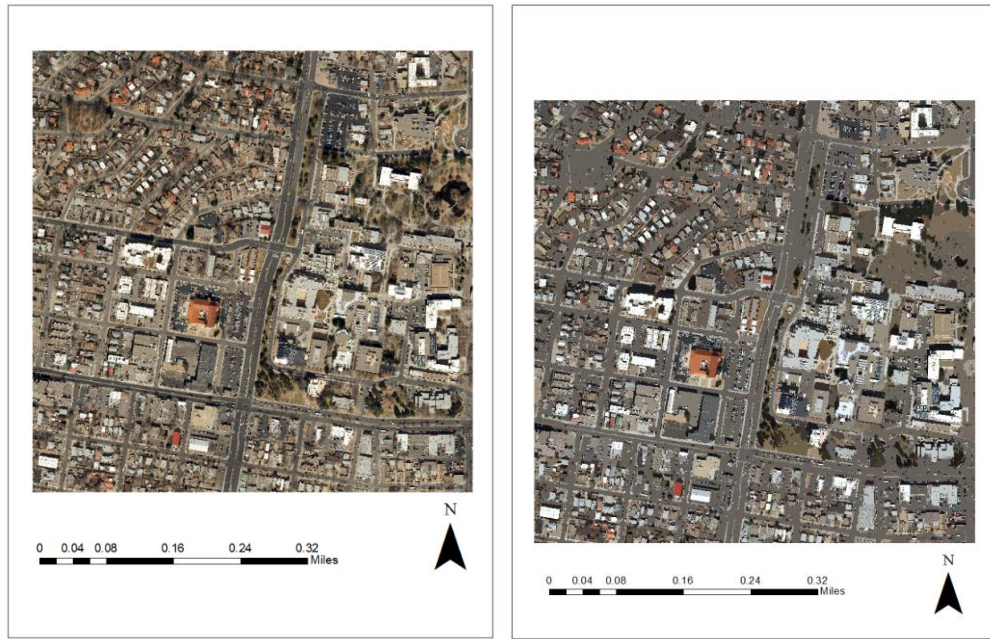


Figure 5. Left: Aerial Image, Right: Segmented Aerial Image

3.2.2. LiDAR Segmentation

The LiDAR data involves four tiles that make-up a large area. The raw LiDAR must be converted to a LAS format, where LAS stands for LiDAR Data Exchange File and is the standard format for storing and sharing LiDAR data. To do this, the 'Create LAS Dataset' tool is used. When creating the LAS dataset, the coordinate system associated with the aerial image must be imported to the LAS dataset for appropriate geographic referencing. The attained LiDAR data does not have any associated classifications, which would classify every type of object captured by LiDAR. The classification system used is 'LAS 1.4', which is the common system for modern GIS work. It is crucial to know what classification

system being used because the same number can either represent the same or different type of objects based on the system. In this case, the 'Classify LAS Ground' tool is used to discern ground points. Then, the 'Classify LAS by Height' tool is used to create three separate classes: Low Vegetation, Medium Vegetation, and High Vegetation, based on the data points elevation.

Though classification tools are being used for the LiDAR data, this does not mean the segmentation process is being bypassed. In fact, the process thus far is preparing the LiDAR data to be segmented. Thus, the LAS dataset must be converted to a raster by using the 'LAS to Raster' tool. Two raster images are required from the LAS dataset: a digital terrain model (DTM) and digital surface model (DSM). Before simply using the 'LAS to Raster' tool, the properties of the LAS dataset must be altered. The appropriate 'Returns' and 'Classifications' must be turned on or off to achieve the DTM and DSM. For example, when obtaining the DTM, the 'Ground' class should be checked, along with 'All Returns'. When obtaining the DSM, 'All Classes' should be checked along with 'Return 1'

The DTM and DSM are then input into the 'Clipping' tool, along with a boundary feature of the aerial image; the boundary is achieved by using the 'Reclassify' tool to set only one class of the aerial image and then convert the single classified aerial image to a polygon by using the 'Raster to Polygon' tool. The DTM and DSM are now the same size, in terms of square mileage, as the aerial image. Then, a DHM must be created by utilizing the 'Raster Calculator' tool. Firstly, a conditional statement is made by changing any points from the DSM that are less than the DTM to be represented as the DTM. Secondly, the

DHM is attained by subtracting the DTM from the DSM. Lastly and most important part, another conditional statement must be formed that picks out all recognizable building points, which is anything greater than 2.2-meters. The final raster image will be considered as the 'DHM_Buildings'. After the 'DHM_Buildings', the DTM is then analyzed further.

The DTM is used over the DSM because the edges of the drivable spaces are more evident by examining it with the naked eye. Due to the advantage of the DTM, the 'Slope tool' is used to sharpen the DTM, so the drivable spaces are more detectable. Finally, the 'Iso Cluster Unsupervised Classification' script is used to segment the entire DTM into two segments. The parameter includes: 'Number of classes', 'Minimum class size', and 'Sample interval. The chosen values for the parameters are: 2, 100, and 10. After the previously mentioned procedures, the classification process is then pursued. The produced raster image is known as 'DTM' and is shown in Figure 6. The image shows to colors where it seems that the black portions of the image are corresponding to the drivable spaces. Further processing will be performed in the classification portion.

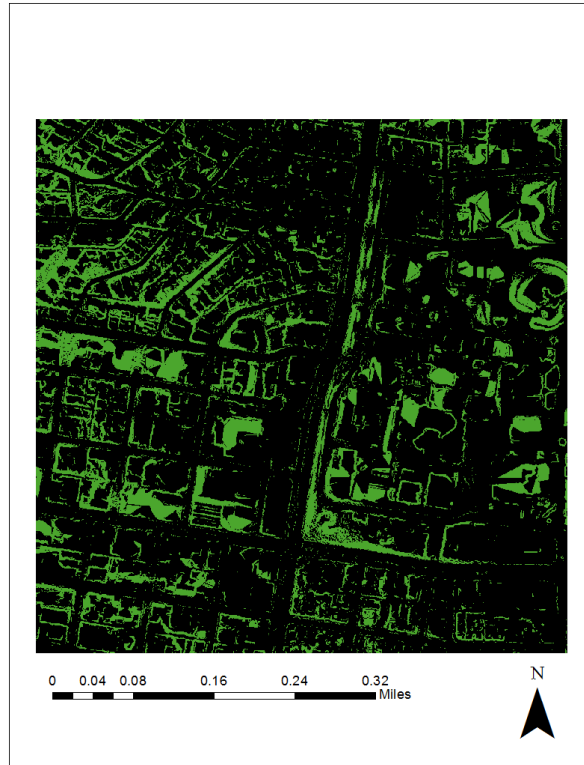


Figure 6. Segmented LiDAR

3.3. Classification

There are two classification desires for the aerial image and LiDAR: drivable space class and non-drivable space class. A series of tools must be used to make the two classifications. During the classification process, the tools naturally clean-up the image in order to achieve an aesthetically pleasing look, which is important for visual representation of the data.

3.3.1. Aerial Image Classification

The 'Raster Calculator' tool is used for the process. For the aerial image, a conditional statement is developed that classifies the pixels with a value of one-hundred and six as the drivable space class and everything else as non-drivable space class. The pixel value of one-hundred and six is chosen based off of the

identify selector tool. The computer cursor is placed over the segmentation that appears to encompass the drivable spaces. Once the conditional statement is developed, the raster image appears to be a larger than the drivable spaces in the aerial image; therefore, the 'Shrink' tool is used, which shrinks the raster image for an optimum fit. This raster image can be called, 'Raster1'. Another raster image must be created to further the classification process.

The raster image needed for the second part of the classification process for the aerial image is known as the Normalized Definition Vegetation Index (NDVI) raster. The NDVI raster is represented in Figure 7 where the vegetation of the image is represented by the bright colors (a lighter grey tone). This process requires the use of the 'Image Analysis' window in ArcMap. In the 'Image Analysis' window, the 'Function Template Editor' icon must be selected; then, a 'Geometric Function' is created by right clicking over the aerial image name in the 'Function Template Editor'. The 'Geometric Function' method of choice should be 'NDVI' and the required band indexes are '4' and '1', which correspond to the red band and alpha band. This creates a temporary raster layer that must be exported in order to save the raster image and perform remaining procedures. The described raster image can be recognized as 'Raster2'.

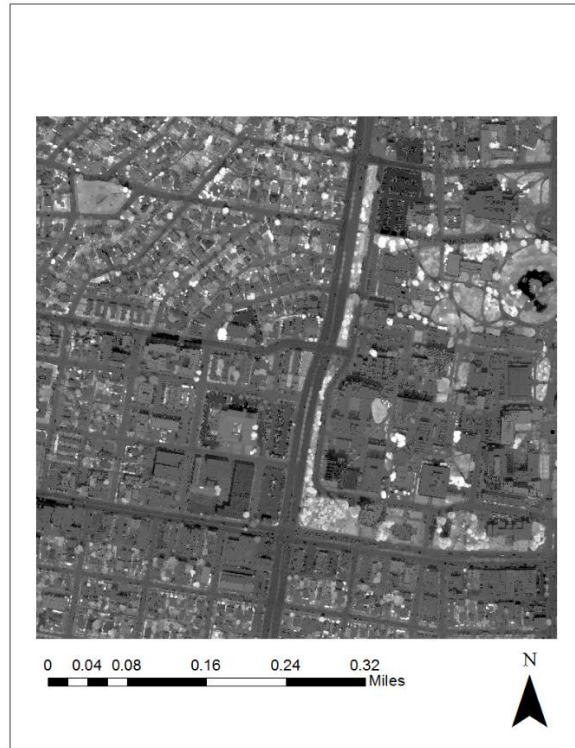


Figure 7. NDVI Image

The 'Raster Calculator' is used to perform another conditional statement that classifies the vegetation. The conditional statement reads as follows: If the 'Raster2 pixels' do not equal '0', then classify them as '0', and if the 'Raster2 pixels' do equal '0', then classify them as '1'. After the vegetation is classified from the 'Raster2', the 'Raster Calculator' tool is used to further classify the drivable spaces from 'Raster1' because by examination, it is noted that vegetation exists among the drivable space class. Therefore, a multiplication statement is created to multiply 'Raster1' and 'Raster2' together, which will create a new raster image, 'Raster3', with a more accurate drivable space class and non-drivable space class.

To improve 'Raster3' accuracy, or best fit for the two identified classes, 'Generalization' tools are used. The generalization tools clean-up 'Raster3' by eliminating "salt and pepper", which are random pixels that do not connect to the drivable space class. The order of 'Generalization' tools are as follows: 'Majority Filter', 'Expand', 'Focal Sieve', and 'Expand'. The combination of these tools eliminated majority of the "salt and pepper" and created an optimum fit of the drivable space class with the aerial image as a reference. The drivable space class and non-drivable space class have been identified in 'Raster3', but the desire is to extract the drivable space class.

The 'Pick' tool is used to extract only the drivable space from 'Raster3'. It is a simple procedure in where the function reads to pick from 'Raster3' any pixel with the value of '1', which is the drivable space class. An extracted drivable space class is important because the drivable space extracted from the aerial image must be combined with the extracted drivable space from LiDAR.

3.3.2. LiDAR Classification

The LiDAR data thus far has been put through a segmentation process that leaves two segments, which is recognized as 'DTM'. To execute the classification process, the 'DTM' is reclassified by using the 'Reclassify' tool. This allows for only one class to remain, which is the drivable space class. Only pixels with the value of '1' remain and all other values are considered to be 'NoData'. It is important to further clean up the 'DTM'; therefore, the 'Plus' tool is used to add the 'DHM_Buildings' from the segmentation process and the 'DTM'. This now creates a raster with two classes: the drivable space class that is represented as

a pixel value of '1' and a building class that is represented as a pixel value of '2'. The result is called 'DTM2'. A seamless raster must be created from the 'DTM2'. The 'Reclassify' tool is used again, in order to sharpen the resulting image.

In order for the resulting image to better fit the existing drivable spaces, the 'Region Group' tool is used, which combines neighboring pixels to sharpen the image. After that, the new pixel value of drivable space is known by using the identify tool; therefore, 'DTM2' can be reclassified to only contain the drivable space. The 'Reclassify' tool is used once again and must state that any pixel values from '1-28' equal 'NoData', pixel values of '29-2222' equal '1', and pixel values from '2223-5140 (maximum pixel value)' equal 'NoData'. 'DTM2' is then left with the drivable space class with a value of '1'. The extracted drivable spaces from the aerial image and LiDAR are ready to be converted into polygons in preparation of combining the two datasets. The extracted LiDAR is shown in Figure 8 where the black colored regions represent the drivable spaces.



Figure 8. Classified LiDAR

3.4. Combine and Convert

Both drivable space datasets are separately converted from their raster form to polygons by using the 'Raster to Polygon' tool. After the polygon data is obtained, the boundaries of the two datasets are cleaned-up by using the 'Regularize Building Footprint' tool. The polygon datasets are more aesthetically pleasing as a result. Finally, the two datasets can be combined.

The 'Union' tool is used to combine the two extracted drivable space datasets. This results in numerous polygons overlapping each other; therefore, the 'Dissolve' tool, which is a part of the 'Data Management' toolset, is used to form the numerous amounts of polygons into one singular polygon dataset. Figure 9 represents the extracted drivable space as a polygon dataset. The extracted drivable space dataset is then exported into a CAD file that industry may be able to use for engineering design and construction.



Figure 9. Extracted Drivable Space

3.5. Toolset Development

Of course, it is not expected that the civil engineering and construction community would follow this entire procedure every time a drivable space dataset is required. This procedure is made into a semi-automatic process (a toolset) for users in industry. Developing the toolset is completely done in ArcMap by using 'Model Builder'. This forms one toolset that will be readily available to the civil and construction industry. The process for creating the toolset is displayed in Figure 10.

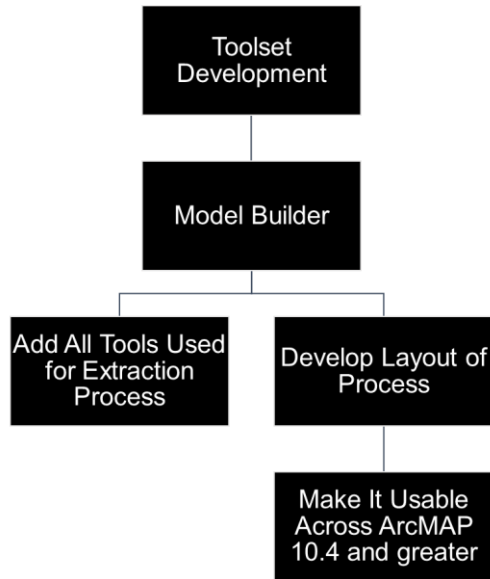


Figure 10. Toolset Development Flow Chart

Model builder is a convenient and simple way of creating a custom toolset. All the tools used for the extraction process are dragged and dropped from the arc toolbox into the model builder space. Simultaneously, as each tool is dragged and dropped into the model builder space and connection is made by using the connection tool within the model builder tool bar. Following that logic produces a toolset that is ready to use.

However, to make the toolset available to all ArcMap users, parameters must set, such as providing a scratch space option, where the tool stores all intermediate data. Intermediate data is all the data produced before the final output. The other parameters involve input files: aerial image, NDVI image, and LiDAR data. The final parameter are the finer details, such as: the coordinate system and reclassification fields. Figure 11 shows the display when the toolset is open where all the previously described parameters are represented.

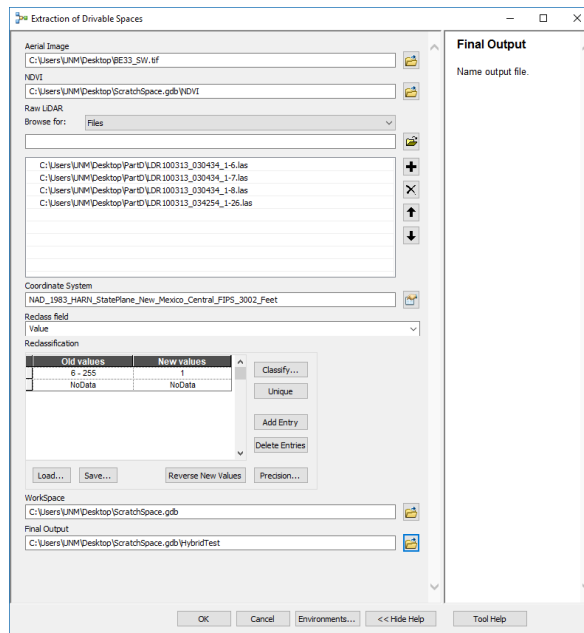


Figure 11. Toolset Display Window

3.6. Validation

The extracted drivable space and the developed tool must be validated in the areas of accuracy, efficiency, and completeness. The validation process is represented by Figure 12.

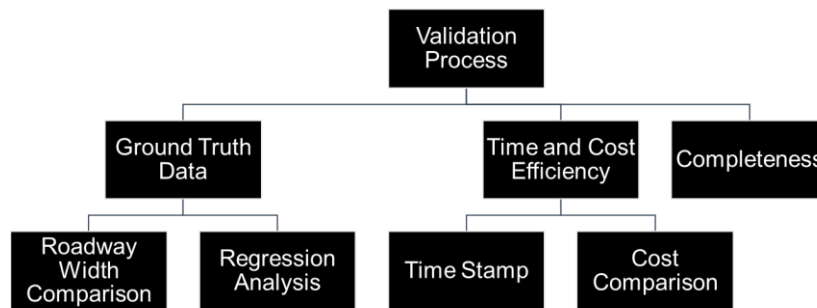


Figure 12. Validation Flow Chart

The ground truth data portion of Figure 12 represents the validation of accuracy where the extracted roadway widths will be compared to manually obtained roadway widths of the study area. There will be a total amount of fifty comparison points in order to provide sufficient results. An add-on tool for excel will be used, known as Analyse-IT, to perform a regression analysis on the fifty points. The regression analysis will provide a best fit line and therefore, provide an empirical formula to represent the data. This means, if there are delineations in the data, the equation can provide correction. This process will be further expanded on the analysis section of the research.

Time and Cost efficiency is important for validation because the civil engineering and construction industry require efficient tools and resources that promote timeliness and low costs. The developed toolset will be compared to the current way of engineering design, digitization, by recording the time stamps of the two methods.

In order to compare cost efficiency, the price of the ArcGIS software will be compared to civil engineering and construction on-call contracts. On-call

contracts are an abstract way of doing business because no scope, start date, or location is provided for the project. This results in having to conduct a digitization method; therefore, it is suitable to compare the cost fluctuations between on-call contracts and the ArcGIS software.

The final portion of the validation process will be based on a percentage of completion of the extracted drivable space compared to what can be digitized. Because roadways are of high importance in the civil engineering and construction industry and require design drawings, nineteen roads, which encompass both major and minor roads of the neighborhoods and businesses surrounding the southwest portion of UNM. Figure 13 shows the same aerial image from the extraction process; however, the black bordered region represents the southwest portion of UNM and therefore, the roads enclosed in that area will not be included in the completeness validation. This is because a lot of the drivable spaces on campus are constructed out of concrete, which may create potential discrepancies for the developed toolset to distinguish between drivable spaces constructed out of asphalt. It is intended that the completeness of the drivable space is sufficient for valuable representation of drivable space and design use.

The next chapter will provide the final results of the developed drivable space extraction method which are represented by an extraction process, toolset development, and validation.

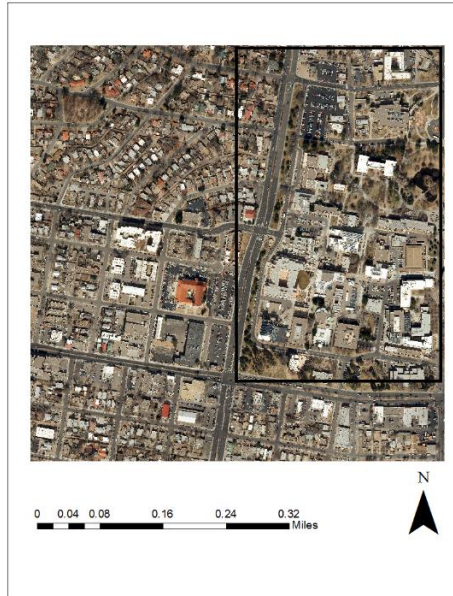


Figure 13. Southwest Portion of UNM

3.6.1. Ground Truth Data

To ensure the toolset provides accurate results for implementation in the civil engineering and construction field, the widths of drivable spaces were measured. Fifty random points were generated using the “Create Random Points” tool in ArcMap. The reason for choosing fifty points is because that provides enough data to determine the significance of the process. The points were distributed across the drivable space dataset and compared to the aerial image to reference what type of drivable space it refers to and where the drivable space resides.

The ground truth data for the widths of the drivable spaces were obtained by using a measuring wheel. The wheel was chosen due to the large widths of the drivable spaces. The width was measured from edge of curb to edge of curb because that is a standard way of measuring drivable space widths in the civil

engineering and construction industry. All fifty measured widths were recorded to compare to the widths from the extracted dataset. To measure the widths of the extracted dataset, the measurement tool was used. It is important to reference the aerial image during this portion in order to verify that the same fifty points are being analyzed. Another means of verification will come from the use of a Geographic Positioning System (GPS) tracker.

The Garmin Etrex 20 GPS tracker was used to verify the coordinates of the fifty points referenced in the extracted dataset. The Etrex 20 is GPS tracker that was readily available for the use of this process. According the Etrex 20 manual, its margin of error is plus or minus twelve feet.

Before obtaining the ground truth data and verifying their points, the coordinates of all fifty points must be obtained. Because the points are geo-referenced as they are generated, it will only require a few additional steps to calculate the Latitudes and Longitudes.

The attribute table of the validation points is used to carry out the process. In the attribute table four fields are added: Latitude, Longitude, Lat, and Long. At separate instances, the Latitude and Longitude are used to calculate the associated coordinates in decimal feet. Then, the Lat and Long fields can be calculated to obtain the coordinates in a format of degrees, minutes, and seconds. Figures 14 display the dialogue boxes representing the Latitude coordinate system in decimal degrees and the Lat coordinate system in degrees, minutes, and seconds. The parameters are set appropriately for both fields. The

same parameters can be used when setting up the Longitude and Long fields except for of course changing it to the appropriate name.

Once the fields are created, the calculation of the coordinates can be performed. To perform a calculation such as this, the name of the field must be right clicked on and then choose calculate geometry. The geometry parameters of the Latitude and Longitude fields are represented by Figure 15, while Figure 16 describe the geometric parameters of Lat and Long. Once “OK” is clicked, the fields will be populated with its appropriate coordinates.

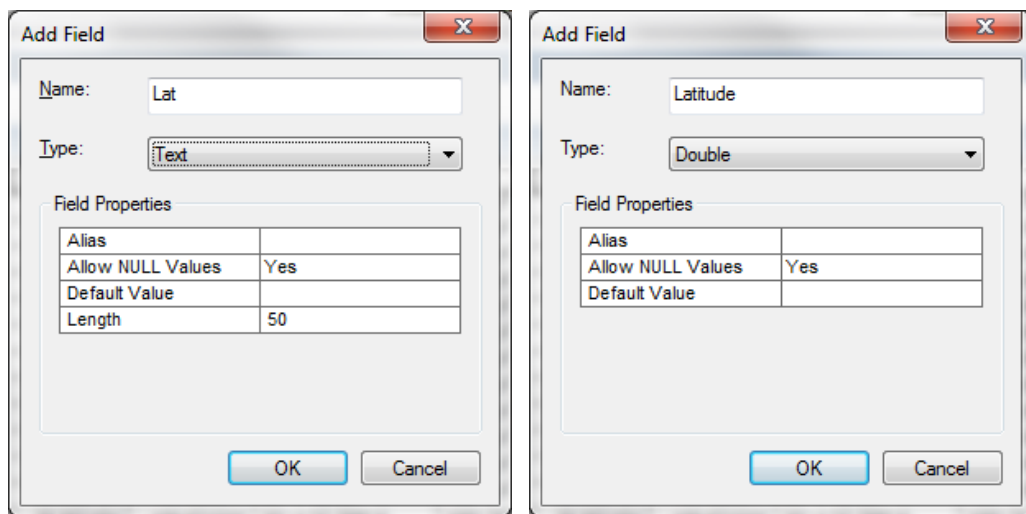


Figure 14. Left: Decimal Degrees, Right: Degrees, Minutes, and Seconds

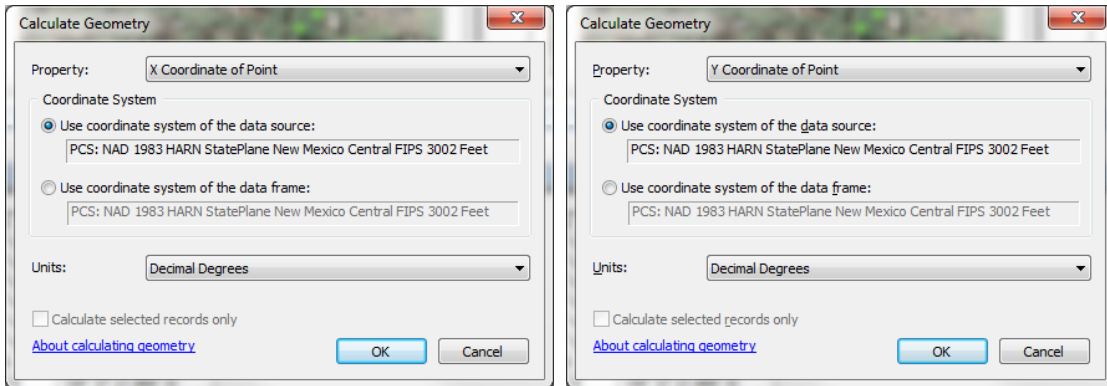


Figure 15. Decimal Degrees Parameters; Left: Latitude, Right: Longitude

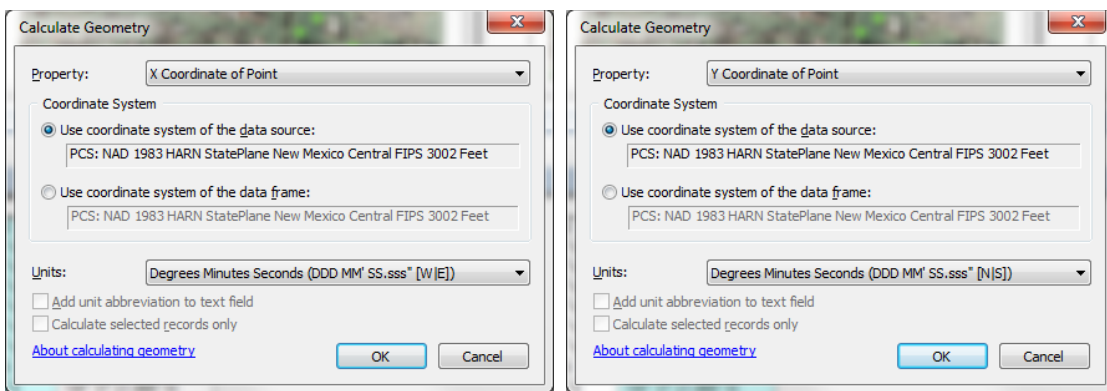


Figure 16. Degrees, Minutes, Seconds; Left: Lat, Right: Long

The software package, Analyse-it, was used to see if the data could be fit to a model as a way to validate the results.

3.6.2. Time and Cost Efficiency

As previously mentioned, time is money. Industry requires efficient tools and equipment in order to complete the job. Costs of industry lead to overhead, labor, designer, and equipment costs. The more time spent on a project directly correlates to an increase cost. Industry efforts are to be efficient and produce quality results. The mentioned costs are typically tracked by the hour, and this

leads into the differences in time cost between digitization and the extraction process.

The time it takes to digitize an aerial image depends on the scale of the project. The process can take anywhere from five minutes to one week. It requires intense focus and keeping a steady hand. For this case, the study area contains many roads and parking lots to be within a one and half square mile area using ArcMap as the interface.

To measure the time efficiency of the developed process and the current method, digitization, the roads and parking lots will be digitized in ArcMap by creating a feature class that allows for the manual drawings of polygons. There are approximately thirty total roadways and parking lots. The time will be recorded in how long it will take to perform the digitization process and compared to the developed extraction process.

3.6.3. Completeness

The completion of the dataset is evaluated by utilizing the digitized drivable spaces that was previously mentioned and the dataset obtained from the developed extraction process. The aerial image does include combination of nineteen major, minor roadways, and parking lots, which will provide a significance comparison of what is represented by the extraction process. The extracted dataset will be visually compared with the digitized dataset to account for any discrepancies.

Chapter 4: Results

By applying the analysis method presented in Chapter 3 and following the detailed procedure listed in Appendix A, the data followed an analysis procedure for accuracy, time and cost, and completeness. The analysis procedure is also represented in Figure 17. The entire procedure was carried out using the results produced by the developed toolset as described earlier in Chapter 3 and it is represented by Figure 18. The colored transparent regions of the Figure 18 represent the drivable space. By overlaying the extracted dataset over the aerial image, the results are easier to witness.

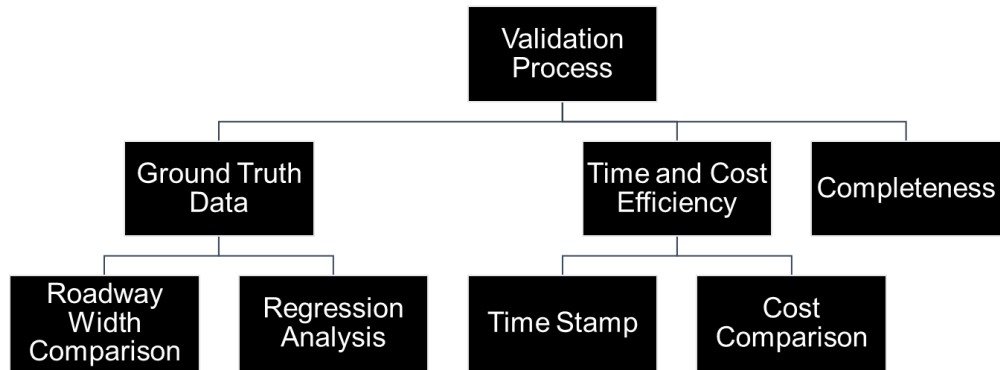


Figure 17. Analysis Flow Chart



Figure 18. Extracted Drivable Space

4.1. Ground Truth Data

This section relates to the accuracy of the extraction process. To ensure the accuracy of the extraction process fifty reference points were used for validation. Figure 19 represents the fifty points overlaying the aerial image of the study area. The dots across the image represent the fifty validation points. The data obtained from the fifty validation points are represented by Table 1, which represents the fifty points' coordinates. The OID* simply represents the point

number and the second column is the Latitudinal coordinate while the third column is the Longitudinal coordinate associated with its point. The measurements associated with the fifty points are represented in Table 2. The first column represents the point number while the second column represents the ground truth measurements obtained by the measuring wheel and the third column represents the measurements obtained from the extracted dataset. The data represented in Table 2 was used to create a best fit regression model as discussed in Chapter 3 and is also displayed in Figure 20 where the x-axis represents the extracted data and the y-axis represents the ground truth data.



Figure 19. Validation Points

Table 1. Coordinates

OID*	Lat	Long
1	35° 5' 0.275" N	106° 37' 38.873" W
2	35° 4' 59.918" N	106° 37' 34.720" W
3	35° 4' 56.312" N	106° 37' 51.725" W
4	35° 4' 50.660" N	106° 37' 50.008" W
5	35° 4' 49.338" N	106° 37' 33.138" W
6	35° 4' 55.960" N	106° 37' 36.778" W
7	35° 4' 53.725" N	106° 37' 22.706" W
8	35° 5' 8.228" N	106° 37' 26.231" W
9	35° 4' 51.252" N	106° 37' 21.966" W
10	35° 4' 51.213" N	106° 37' 23.676" W
11	35° 4' 53.733" N	106° 37' 27.091" W
12	35° 4' 58.021" N	106° 37' 44.100" W
13	35° 4' 52.298" N	106° 37' 27.255" W
14	35° 5' 13.492" N	106° 37' 28.149" W
15	35° 4' 51.570" N	106° 37' 36.733" W
16	35° 5' 1.017" N	106° 37' 46.905" W
17	35° 4' 47.739" N	106° 37' 51.153" W
18	35° 4' 50.619" N	106° 37' 36.493" W
19	35° 5' 11.874" N	106° 37' 32.288" W
20	35° 5' 2.650" N	106° 37' 39.687" W
21	35° 4' 57.913" N	106° 37' 36.185" W
22	35° 4' 57.768" N	106° 37' 33.603" W
23	35° 5' 12.991" N	106° 37' 21.255" W
24	35° 4' 51.774" N	106° 37' 28.536" W
25	35° 4' 49.026" N	106° 37' 35.218" W
26	35° 5' 13.333" N	106° 37' 30.535" W
27	35° 5' 10.150" N	106° 37' 29.104" W
28	35° 5' 5.964" N	106° 37' 32.594" W
29	35° 5' 11.765" N	106° 37' 23.189" W
30	35° 4' 54.274" N	106° 37' 36.503" W
31	35° 4' 58.640" N	106° 37' 26.127" W
32	35° 5' 6.562" N	106° 37' 32.599" W
33	35° 4' 59.047" N	106° 37' 25.103" W
34	35° 4' 51.442" N	106° 37' 31.060" W
35	35° 4' 50.743" N	106° 37' 49.957" W
36	35° 4' 48.049" N	106° 37' 28.926" W
37	35° 5' 9.245" N	106° 37' 30.532" W
38	35° 5' 0.661" N	106° 37' 23.976" W
39	35° 4' 57.197" N	106° 37' 40.170" W
40	35° 5' 0.157" N	106° 37' 51.201" W
41	35° 4' 56.074" N	106° 37' 41.962" W
42	35° 4' 55.674" N	106° 37' 41.791" W
43	35° 5' 1.475" N	106° 37' 41.559" W
44	35° 4' 52.725" N	106° 37' 45.980" W
45	35° 4' 48.203" N	106° 37' 37.054" W
46	35° 4' 48.973" N	106° 37' 24.755" W
47	35° 5' 1.502" N	106° 37' 51.684" W
48	35° 5' 1.160" N	106° 37' 31.405" W
49	35° 5' 3.146" N	106° 37' 40.348" W
50	35° 4' 57.469" N	106° 37' 40.010" W

Table 2. Measurements of Ground Truth and Extracted Dataset

	Ground Truth Data	Hybrid
Point No.	Measuement (ft)	Validation (ft)
1	32.8	59
2	32.8	52
3	32.8	28
4	32.8	100
5	85.28	97
6	32.8	200
7	32.8	88
8	42.64	67
9	85.28	88
10	85.28	93
11	29.52	20
12	39.36	15
13	104.96	106
14	19.68	25
15	85.28	104
16	32.8	45
17	42.64	85
18	85.28	106
19	85.28	112
20	104.96	120
21	85.28	96
22	42.64	31
23	85.28	90
24	32.8	77
25	85.28	120
26	26.24	35
27	32.8	34
28	88.56	144
29	88.56	91
30	88.56	107
31	88.56	94
32	88.56	112
33	88.56	97
34	32	71
35	32	71
36	32	39
37	36	44
38	36	56
39	32	42
40	32	48
41	32	47
42	32	38
43	32.8	143
44	29.52	48
45	29.52	29
46	49.2	46
47	32	31
48	32	49
49	32	46
50	32	61

The results of the regression model introduced in Chapter 3 are displayed in Table 3 and Figure 20. This model was developed to see if there was a correlation between the modeled data and the ground truth data. A good relationship would confirm the accuracy and effectiveness of the extracted dataset.

A polynomial six regression model was the best fit for the ground truth and comparison data (see Figure 20) based on the R^2 value. The linear regression model and the preceding polynomial models, two through four, had R^2 values that were very small.

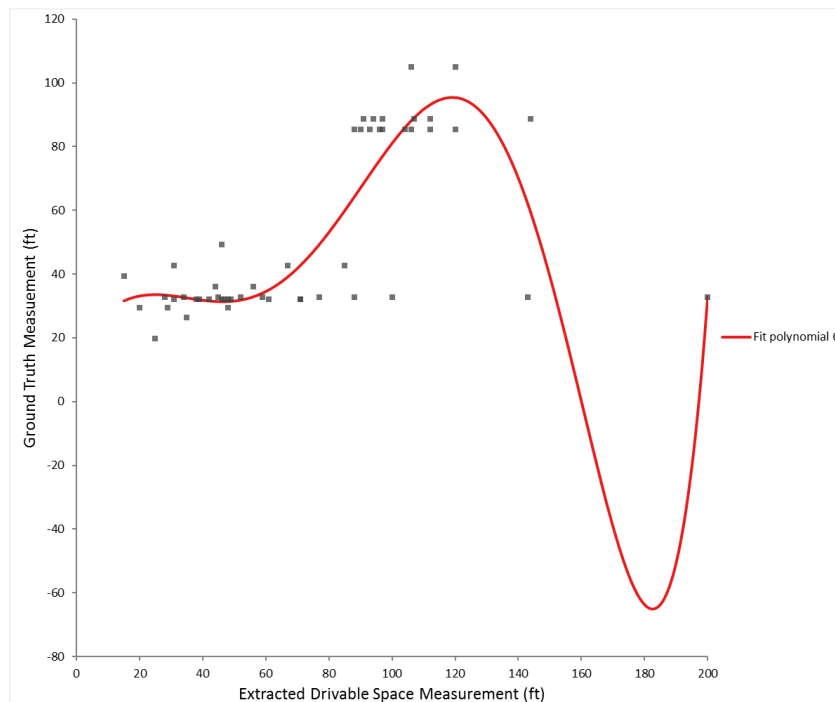


Figure 20. Best Fit Regression Model

The R^2 value identifies whether the model best represents the data, which in effect determines if the extracted dataset is valuable. The closer the R^2 value is to '1', the better the data is represented by the model. Table 3 shows that the R^2 value represented by the polynomial six regression model is 0.746. This is

simply saying that approximately 75% of the variation of the ground truth data, y-values, is explained by the extracted dataset, x-values. Because the R² value is greater than 0.5, that means that the statistical results of the extracted dataset are valid.

Table 3 also shows the root mean square error, RMSE. The RMSE value describes the average error of the extracted dataset. The RMSE value is approximately 15-feet. This means that extracted dataset widths, x-values, are likely 15-feet inaccurate, which is based off of the ground truth data, y-values. It can also be said that the extracted dataset is inaccurate by comparing to the ground truth data. Although the extracted dataset is inaccurate, that does not mean that the extracted dataset is insignificant.

The p-value, which is a probability estimation, represents the significance of the extracted dataset. The p-value comes from a statistical probability represented by a bell curve where results should have a p-value less than 0.05 to be considered significant. The p-value shown in Table 3 is <0.0001. Therefore, based upon the description of a p-value, the results of the extracted dataset are significant and that the extracted values are not a random distribution of inaccuracies.

Equation 1. Model Formula

$$y = 17.53 + 1.485x - 0.03794x^2 - 3.97e-05x^3 + 1.053e-05x^4 - 9.601e-08x^5 + 2.41e-10x^6$$

y = Ground Truth measurement (ft)

x = Extracted Drivable Space measurement (ft)

Table 3. Accuracy and Effectiveness Results

R ²	0.746
p – value of model	< 0.0001
Root Mean Square Error (RMSE)	15 ft

In reviewing the results of the polynomial six regression model, it is realized that the model does not represent the data very well despite it providing the best fit. By examining Figure 20 it is noted that there are two clusters of data and multiple outliers.

It was mentioned that the equation that represents the model provides a way to predict the ground truth data values; however, this may only be true for extracted values, represented on the x-axis, within a range. Looking closely at Figure 20, the best fit curve drops below zero in regard to the ground truth data, represented on the y-axis. There cannot be a negative measurement in this sense. Based on that interpretation, it seems that any extracted measurement that exceeds approximately 150-ft would result in an inaccurate measurement of the ground truth measurement.

It can also be seen in the model that the two clusters vary along the x and y-axis and this is due to the different sizes of roadways. The difference between minor and major roadways are two to three lanes in some cases. By having the two clusters of data, the accuracy of the model is suited for extracted values that lie within a range of 20-60 feet and 80-100 feet.

At this point in time, a model is unable to adequately represent the data; however, future efforts could focus on improving the model, potentially by breaking out the data by road width.

4.2. Time and Cost Efficiency

The time required to digitize each roadway varies due to the difference in shape of the roadways. Each roadway requires three to five minutes of digitization; therefore, that provides a time frame of two to five hours for a typical project. Figure 21 shows the digitized drivable spaces. The green regions of the figure represent the roadways, and the beige regions represent parking lots. There is a total of fifty-seven drivable spaces represented by the digitized map. This is a long process, which has the potential to take up a quarter of an eight-hour working day. That is extra time an engineer has to spend digitizing when that is not the purpose of an engineer. An engineer typically has multiple projects at a time; therefore, spending nearly four-hours digitizing is inefficient to the work schedule.

The process developed in this study was ran using the aerial image, NDVI image, and the LiDAR data. The process took a total of 6-minutes and 33-seconds. This is forty times faster than the digitization process. An engineer can simply run the tool in the background of a computer and perform any other tasks without misdirecting time to inefficient procedures. The only information required for this process is the aerial image, NDVI image, and LiDAR data. It is quick and simple. For an on-call contracted project, this semi-automatic tool is a perfect

replacement for the digitization process. The time efficiency of the extraction process is a big benefit for industry use.

Not only is the time efficiency improved, but also the cost efficiency of the process is improved using the proposed extraction process. It is common for on-call contracted projects to fluctuate in costs ranging from thousands to millions of dollars. Recalling the definition of an on-call contract, the scope of work is undefined, which leads to cost changes. With fluctuation in cost of this particular type of project, digitization can develop costs due to an increased number of hours an engineer must spend on the ever-changing project.

A major problem when digitizing is when no site exploration is performed, which leads to misrepresentations of aerial images and digitization. The costs will continue to stack up as a result of digitization, but this will not occur by using the semi-automatic extraction process.

In order to compare the cost of digitizing and the developed extraction process, a typical civil engineering wage will be estimated. The average civil engineer makes approximately \$33 per hour. If the engineer has to work on digitizing for three to five hours, which comes from the time range it would take to digitize the study area, and the engineer must perform this type of work twice a month, then, the estimated cost for utilizing the digitization technique will be between \$2,500 and \$4,000. This range of costs will be used to compare the extraction process.

The only cost required for to perform the extraction process is for an ArcGIS license, which range in values. The lowest priced license with ArcGIS

costs \$800 while the highest priced license costs \$6,000. This is an annual price paid to utilize the ArcGIS software. This initial investment in the ArcGIS software has the potential to mitigate tens of thousands of dollars that would occur for inefficient digitized drawings.

The ArcGIS software is the only cost required to perform the extraction process because the aerial image and LiDAR data are readily available to the public. The aerial imagery data are available on the RGIS website, which is owned by EDAC, while the LiDAR can be found at the USGS website, which was collected by MRCOG. The extraction process comes with an inexpensive price and secures thousands of dollars a year by fitting in the process of on-call projects.

Therefore, the price comparison of an annual investment for extraction process versus the accrued costs due to the inaccuracies and changes that come with digitizing on-call projects, the extraction process dominates. The cost of digitizing can range from \$2,500 to \$4,000 of just labor costs while the cost for an ArcGIS license ranges from \$800 to \$6,000. The extraction process has a higher cost efficiency due to LiDAR and aerial images being able to capture fine details of a project area and being readily available.

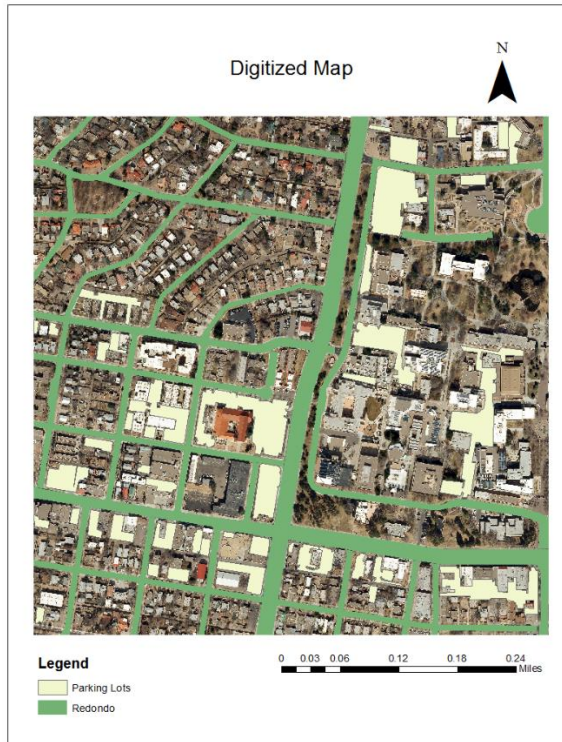


Figure 21. Digitized Roads

4.3. Completeness

The extracted drivable space dataset was also checked on completeness. The completeness of the extracted dataset is just as important as the accuracy of the dataset. The developed process is meant for industry use; therefore, the extracted dataset must be sufficient to be applied to real world projects and an incomplete dataset will not suffice to being efficient. Time is money, and if the process is inefficient, then the process can negatively affect the industry rather than positively affect it.

To capture the completeness of the extracted dataset, the current technique of industry design of projects was carried way, digitization. Digitization is manually drawing/outlining the drivable spaces with the cursor on the

computer. To clarify, digitization is the current technique of designing on-call contracted projects.

On-call contracts can be defined as such: the setting of a definitive location or timetable is undetermined, the project typically does not last for more than two years, and a scope is not clearly defined. Design drawings for on-call contracts are hard to come by due to the insufficiency of details for such a project; therefore, digitization is the chosen technique to design for these types of projects.

By analyzing Figure 22, it is noticed that there is only one road not completely captured; that is represented by the red circle to the right of the figure, which is located on the Drivable Space Map. Though part of the roadway is captured by the extraction process, that roadway is considered incomplete; therefore, the roadway is insufficient. It is insufficient to maintain consistency that the industry demands an efficient process, where partial completion of a road does not meet the standards. This means that fifty-six of the fifty-seven drivable spaces were captured by the extraction process, which leads to a completeness of 98.2%. The completeness of the extraction process is statistically sufficient based upon the number of drivable spaces captured by the developed process compared to the number of drivable spaces digitized.

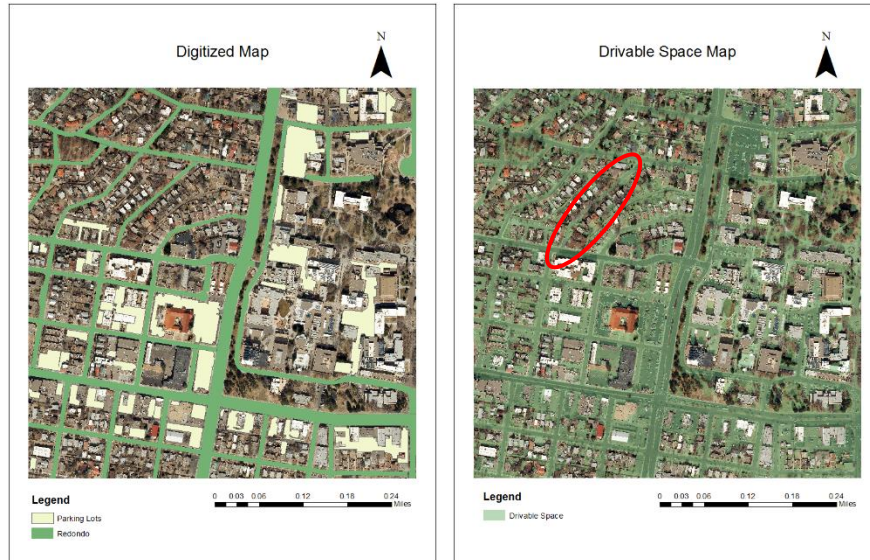


Figure 22. Completeness; Left: Digitized Map, Right: Drivable Space Map

4.4. Findings

The extraction process has proven to be beneficial to a degree, based on time and cost effectiveness, and completeness. Though this is true, the extraction process is not ready to be employed into civil engineering design industry because of its lack of accuracy detecting the edges of the drivable spaces.

However, this extraction process can be used in planning and development of a city, geographical representation of drivable spaces, and cost estimating. A city planning department can utilize the extraction process when designing the future development of its city, whether it is drainage, housing, or businesses.

Geographers partake in the digitization method for capturing drivable spaces frequently. The extraction process would simplify their work by providing generic dimensions of drivable spaces and they can alter the dimensions of the polylines to fit the portion that is to be digitized. In regard to cost estimation, an engineer

can utilize this extraction process to make an estimate of the construction cost of a portion of drivable space needing to be reconstructed.

4.5. Limitations

The limitations associated with this research are its complex study area, being a dense urban area, and the limited ability to graphically model this process, which is also due to the complexity of the urban environment as drivable space dimensions, particularly widths, are varying. Provided a rural study area, this extraction process should perform better due to the scarce number of objects within that type of environment.

4.6. Future Work

To improve upon the developed extraction process, a pursuit towards edge detection of drivable spaces should be taken. An edge detection tool would be able to detect the drivable space edges by utilizing the elevation data provided by LiDAR. The edge detection tool would be able to identify between elevation differences and create a straight edge to contain the drivable space. This is one step that can improve this extraction process.

Another tactic to improve the extraction process would be to obtain LiDAR data with a higher resolution such as two to three inches. That would also assist in the differentiation of drivable spaces and objects that are close in elevation, such as: curb and gutters, which are typically six inches tall.

Chapter 5: Conclusion

The purpose of this study was to address the current issue with civil engineering design and construction in regard to drivable spaces. There is an issue with the design and construction of drivable spaces because there are limited details to be provided for a project without defining the scope of work and can begin at a moment's notice. The civil engineering and construction industry currently handle this issue by using a method known as digitization.

Digitization is manually drawing boundaries, centerlines, etc. by outlining its appearance as displayed in a satellite image. This method exists due to the lack of information provided with an on-call project, which is described in Chapter 1 and Chapter 3; therefore, site exploration rarely occurs. Digitization is inefficient, time consuming, and costly in labor of approximately \$2,500 to \$4,000 and that is not including corrections that correlate to a lack of site exploration. These limitations related to digitization motivated the research included in this thesis.

To solve this issue, a semi-automatic process is created to extract drivable spaces from a complex urban environment in order to bypass a digitization process by using ArcMap as the interface. The process requires highly accurate data, which corrects the lack of site exploration, and the datasets used for the study are aerial imagery and LiDAR. The study answered the following questions: how accurate is the extraction toolset and what are its advantages and disadvantages?

The extraction process goes through two major components: segmentation and classification. The aerial image and LiDAR go through the two components separately and are combined at the end of the process. The combination of the two datasets allows for an optimum chance of capturing all drivable spaces in the data frame. The process is created into a singular toolset by using Model Builder that can be opened across many versions of ArcMap. The final output file for the tool exports the file into a CAD file in order to perform roadway design.

The results of the study show that the extraction process has a difficult time in detecting the edges of drivable spaces, especially when they are adjacent to other paved spaces, such as sidewalks. The total time for the extraction process is 6-minutes and 33-seconds while the cost to perform this process can range from \$800 to \$6,000 depending on the type of ArcGIS license purchased. The results explain that the extraction process has limited use in civil engineering design, but can be useful in other disciplines like city planning and development, geographic processing, and cost estimating. The completeness of capturing drivable spaces is 98%. The extraction process is a great way to visually represent drivable spaces.

The developed tool for performing the drivable space extraction process can be downloaded by using the following link: <https://github.com/edac/Drivable-Space-Extraction/archive/master.zip>.

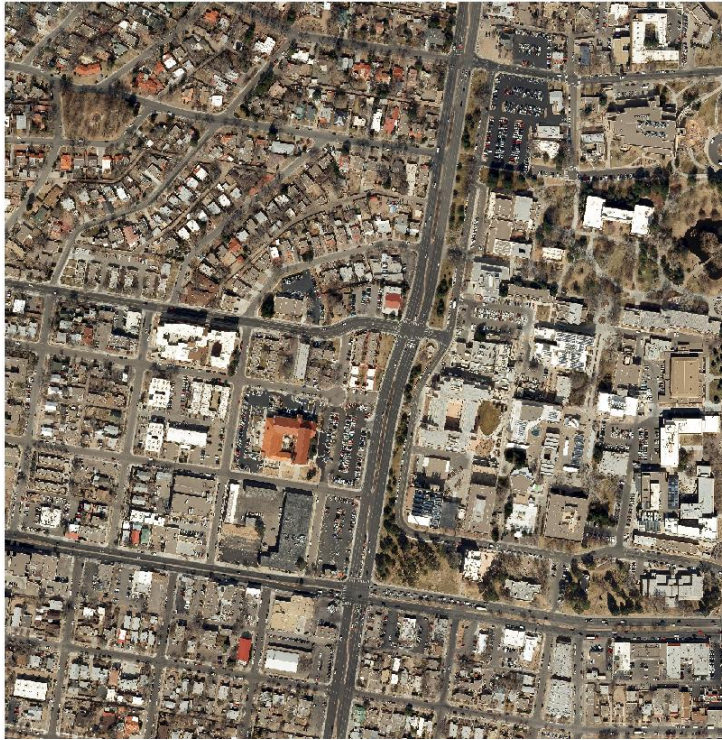
To improve the results of this process in the future, an edge detection tool must be created that works in ArcMap and that uses a higher resolution LiDAR

dataset. Edge detection would correct the inaccuracy of the extraction process by recognizing edges within a digital elevation model. LiDAR data with a resolution of two to three inches would assist in the determination of curb and gutter and drivable space within a digital elevation model. Combining an edge detection tool and high-resolution LiDAR would bring the extraction one step closer to becoming readily available for civil engineering and construction use.

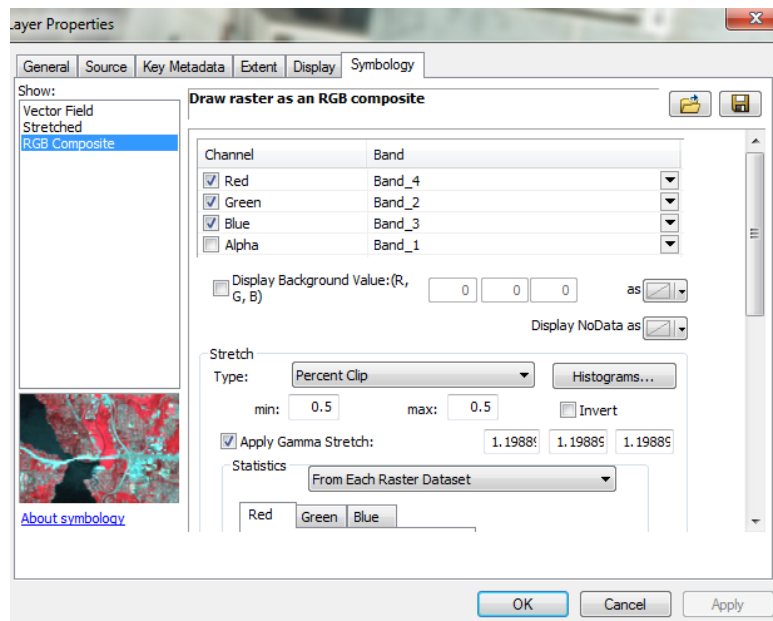
Appendix A. Extraction Procedure

Aerial Image Extraction Process

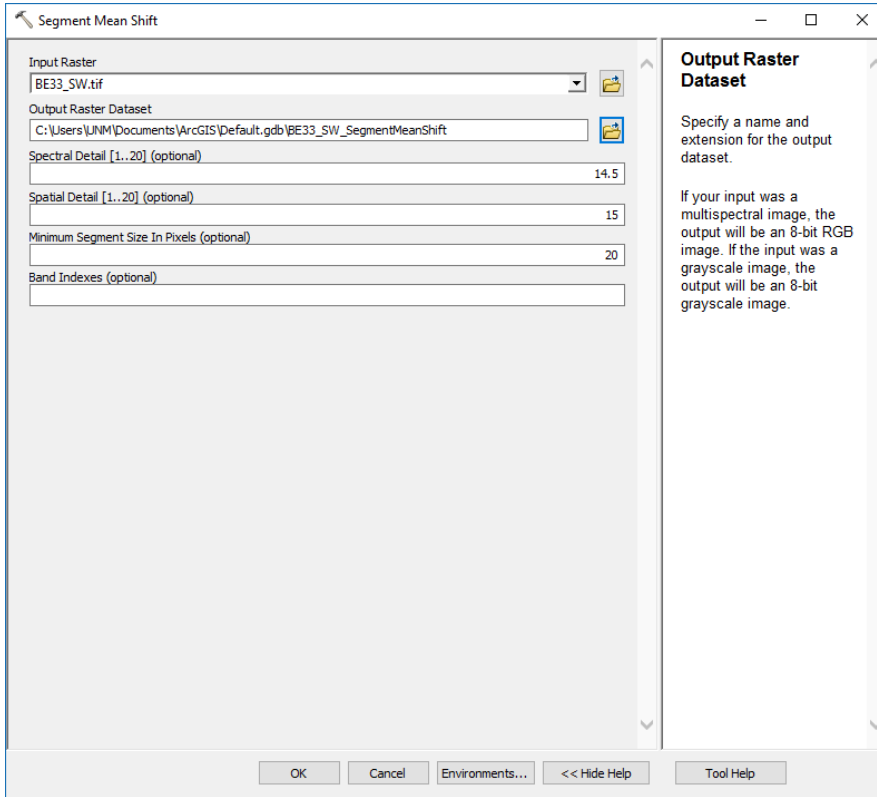
Step 1: Add BE33_SW.tif raster to ArcMap



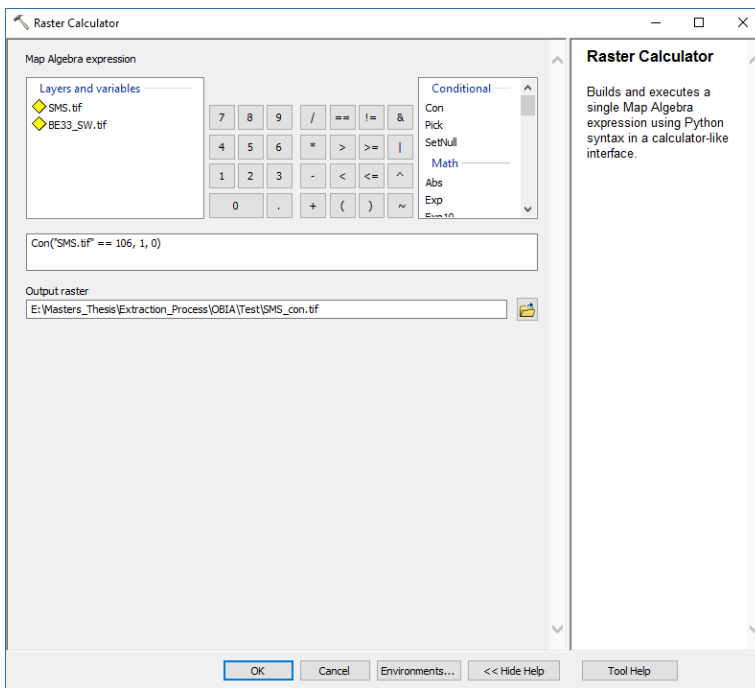
Step 2: Color-infrared look



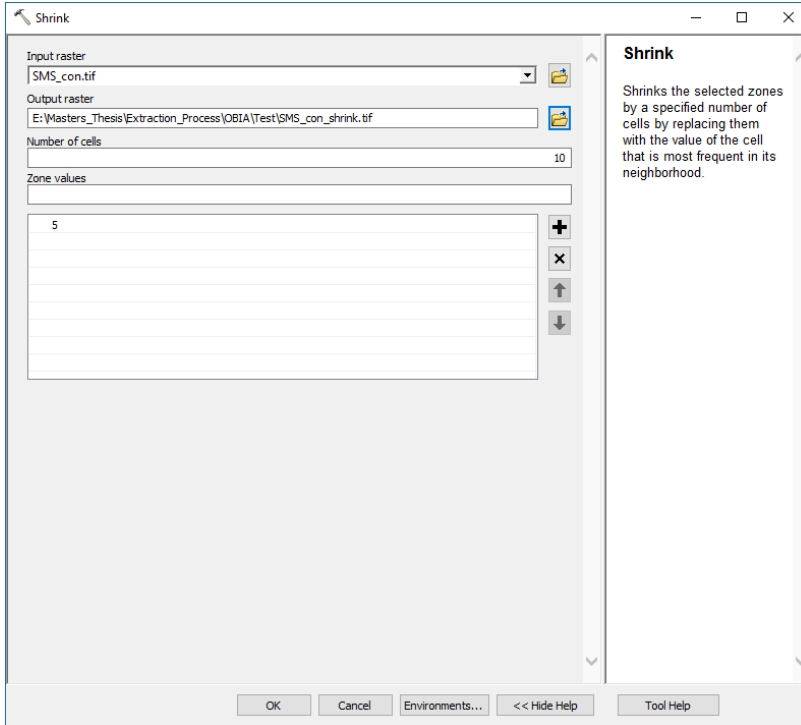
Step 3: Segment Mean Shift tool



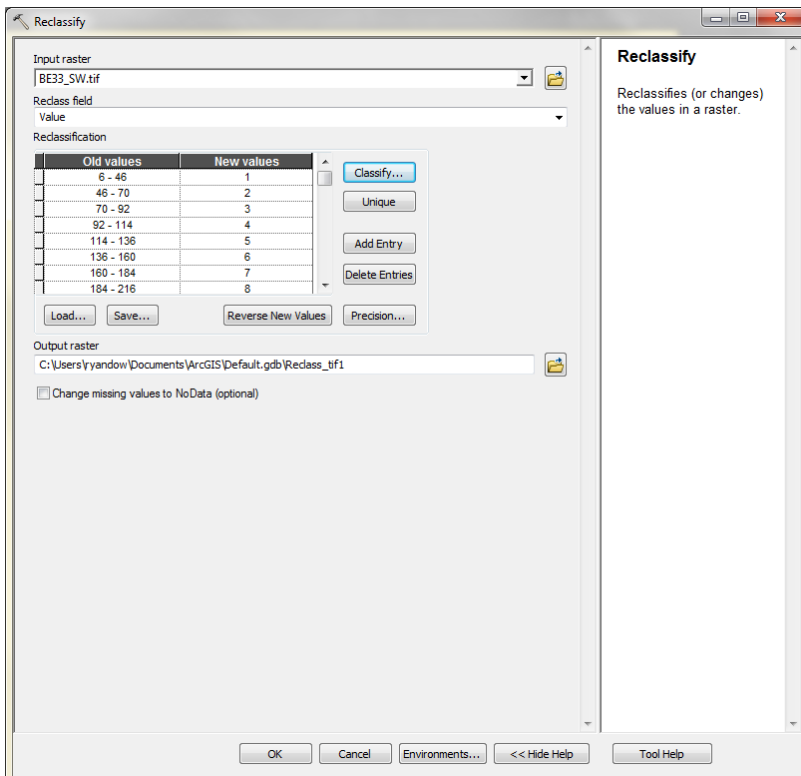
Step 4: Raster Calculator

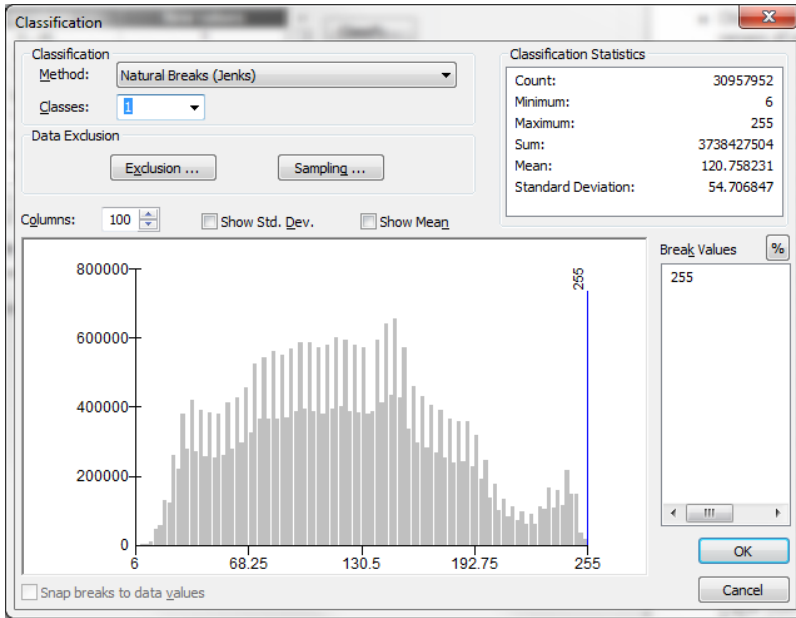


Step 5: Shrink tool



Step 6: Create Boundary for LiDAR Segmentation





Reclassify

Input raster: BE33_SW.tif

Reclass field: Value

Reclassification:

Old values	New values
6 - 255	1
NoData	NoData

Buttons: Classify... Unique Add Entry Delete Entries Load... Save... Reverse New Values Precision...

Output raster: C:\Users\JNM\Documents\ArcGIS\Default.gdb\Reclass.tif1

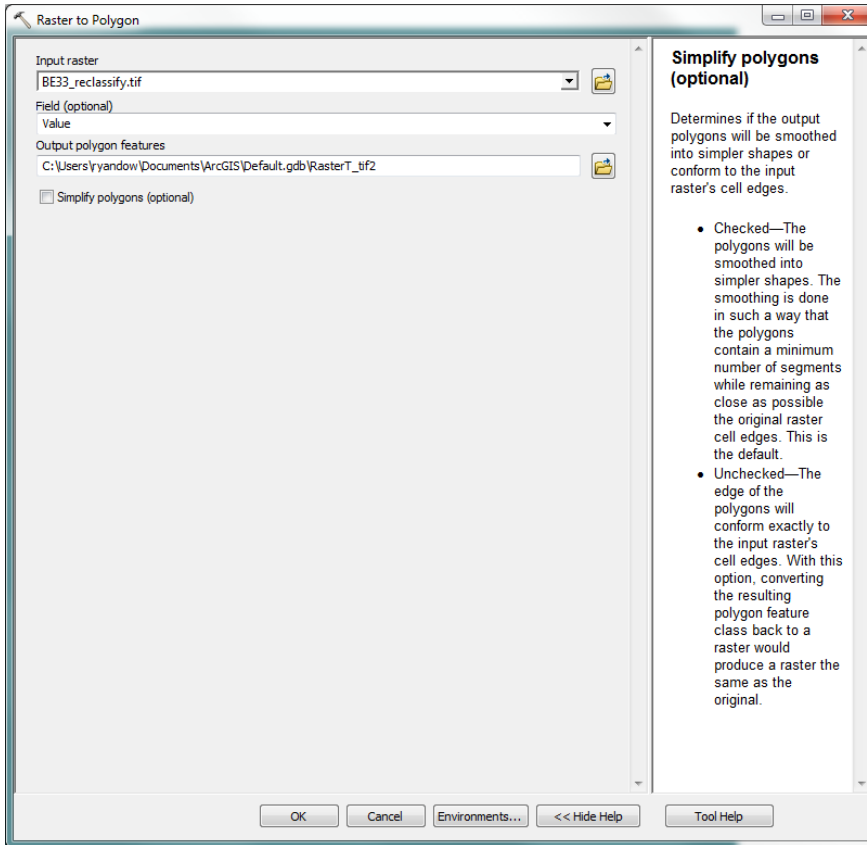
Change missing values to NoData (optional)

Reclassification

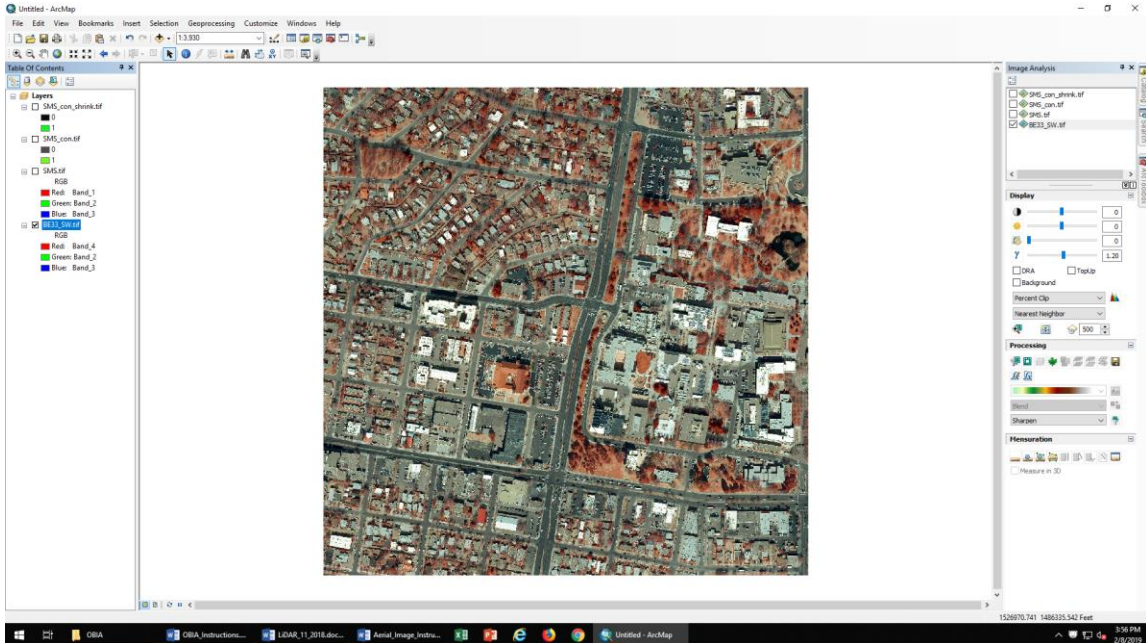
A remap table that defines how the values will be reclassified.

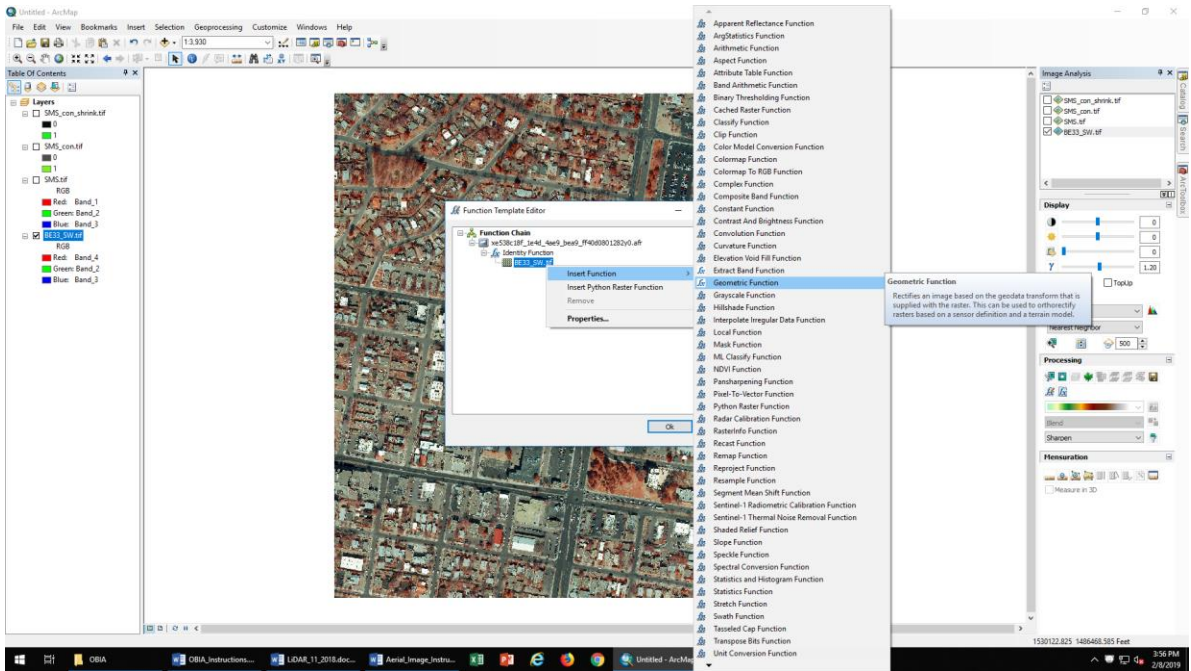
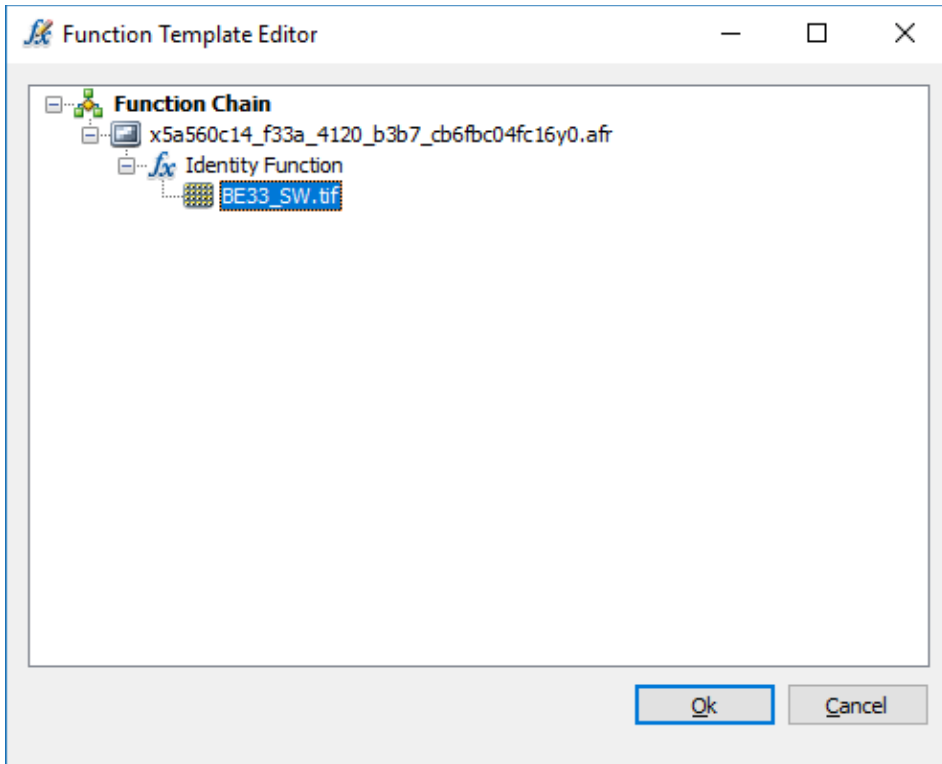
- Old values—The ranges of values of cells in the input raster. Acceptable settings are a single value, a range of values, a string, or NoData. A list of single values can be specified by separating each with a semicolon (;). A range of values can be specified by using a hyphen (-) as the range separator.
- New values—The new value to assign the values or ranges of values. Only integer values are supported.
- Classify—Opens the dialog box allowing

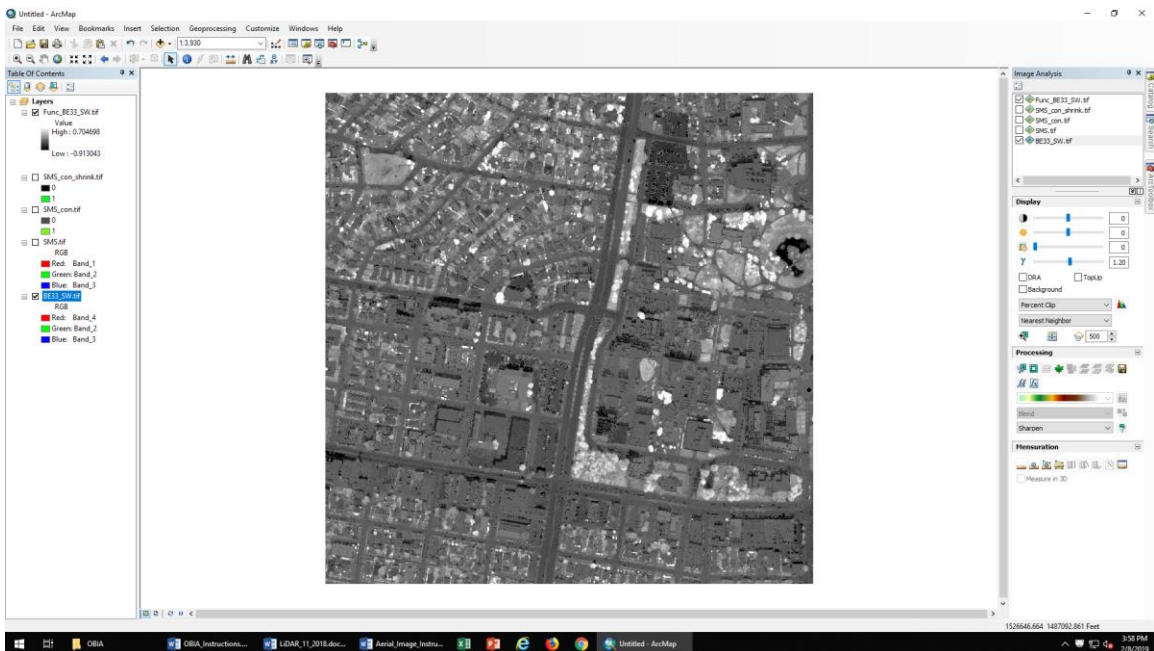
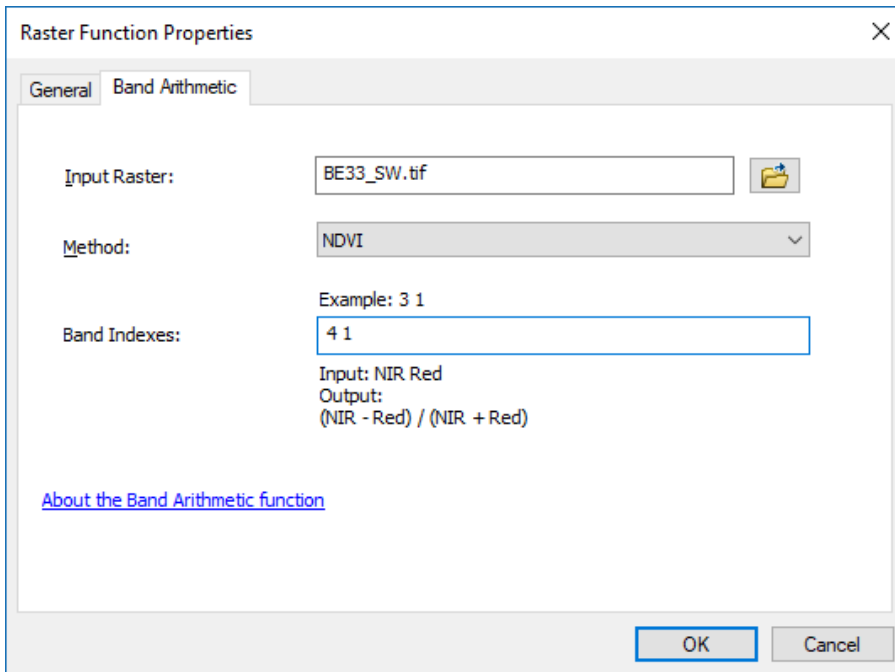
OK Cancel Environments... << Hide Help Tool Help

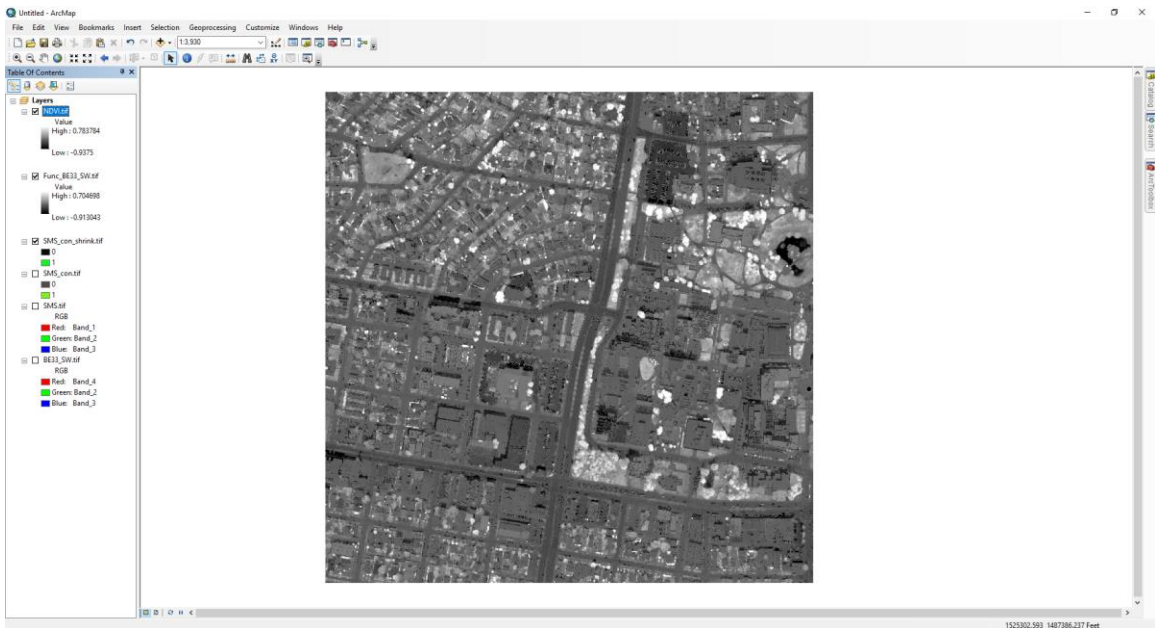
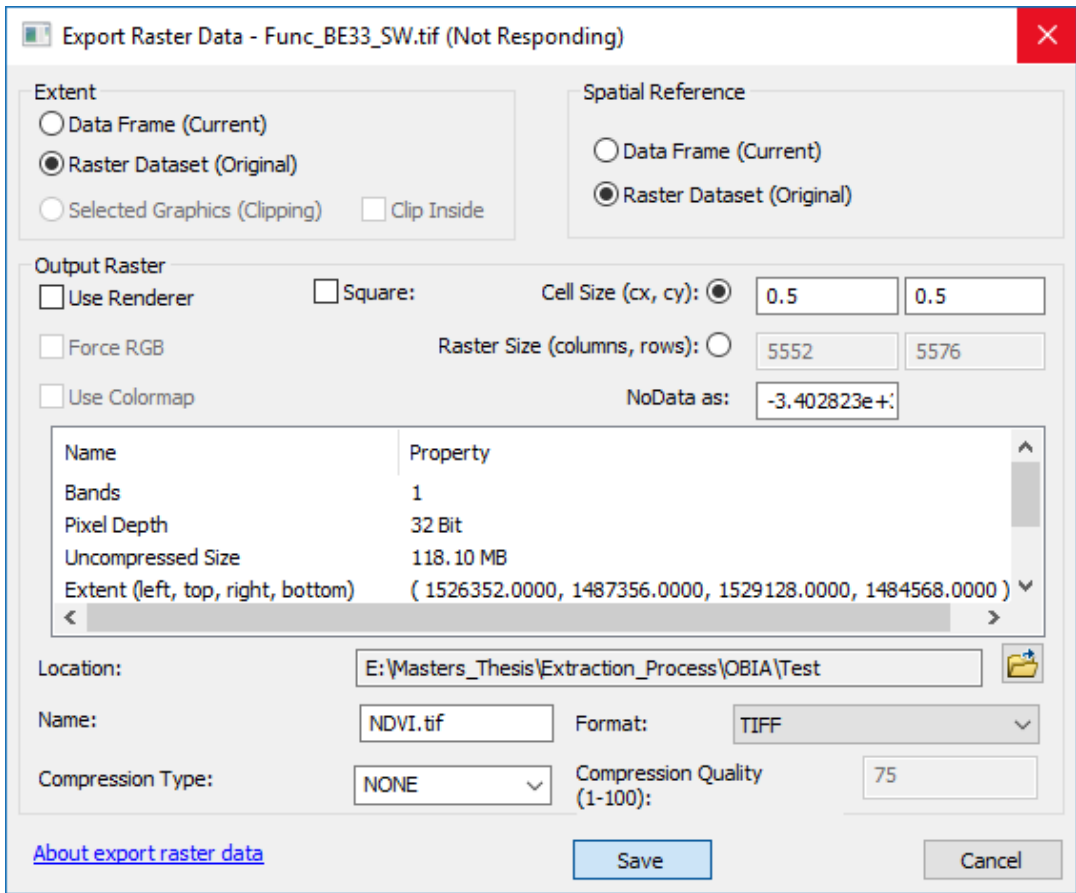


Step 7: NDVI

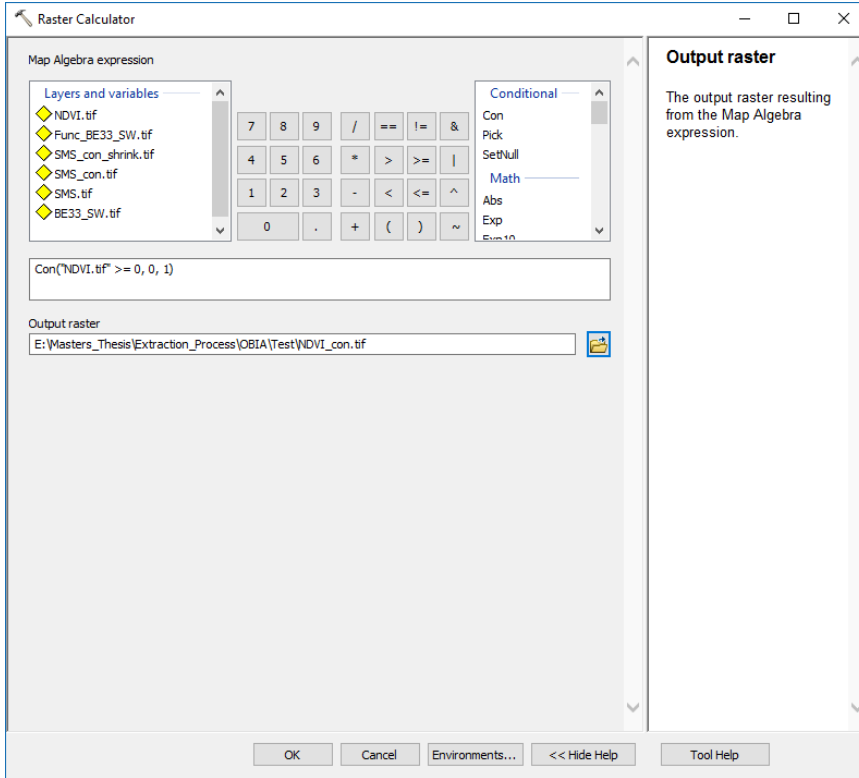




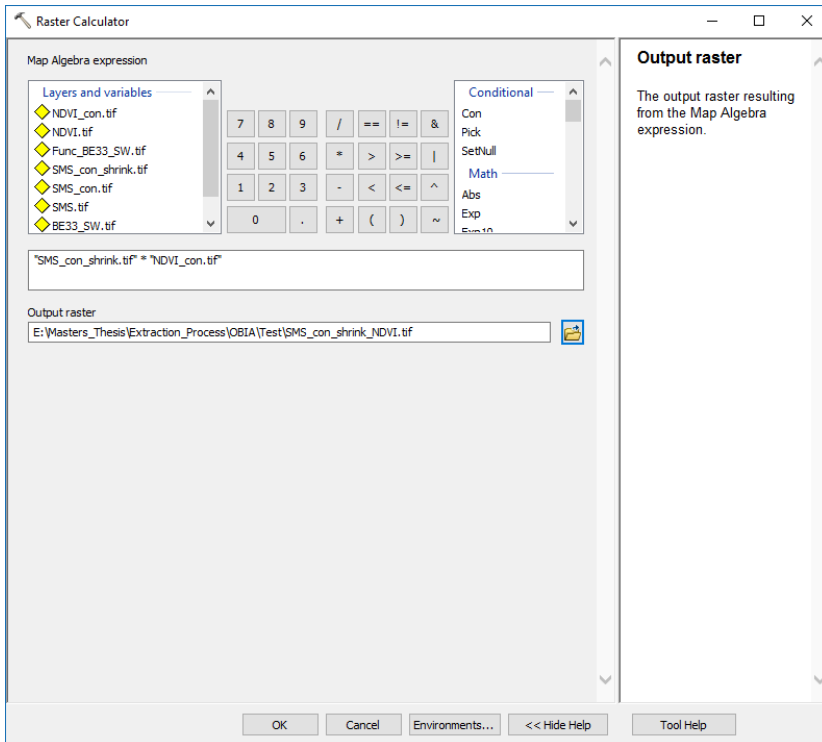




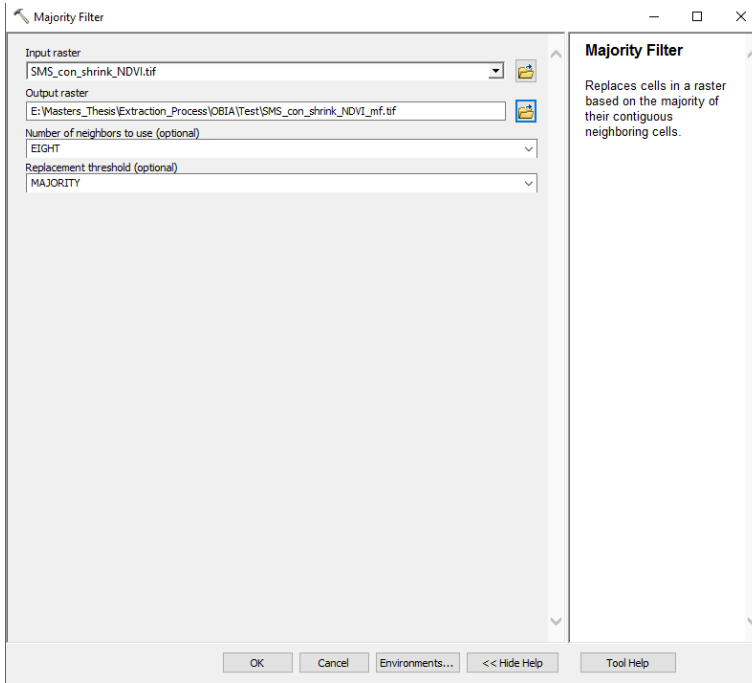
Step 8: Raster Calculator



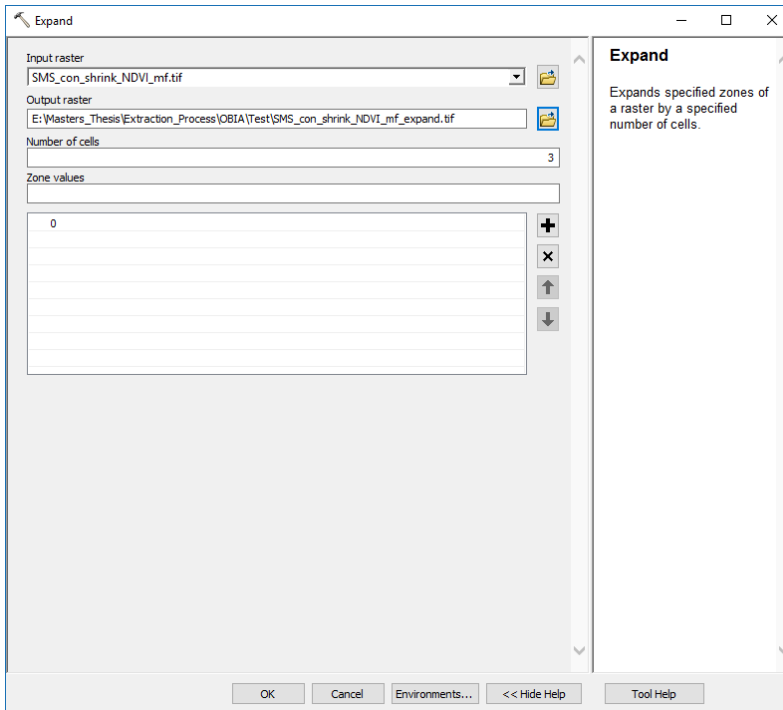
Step 9: Raster Calculator



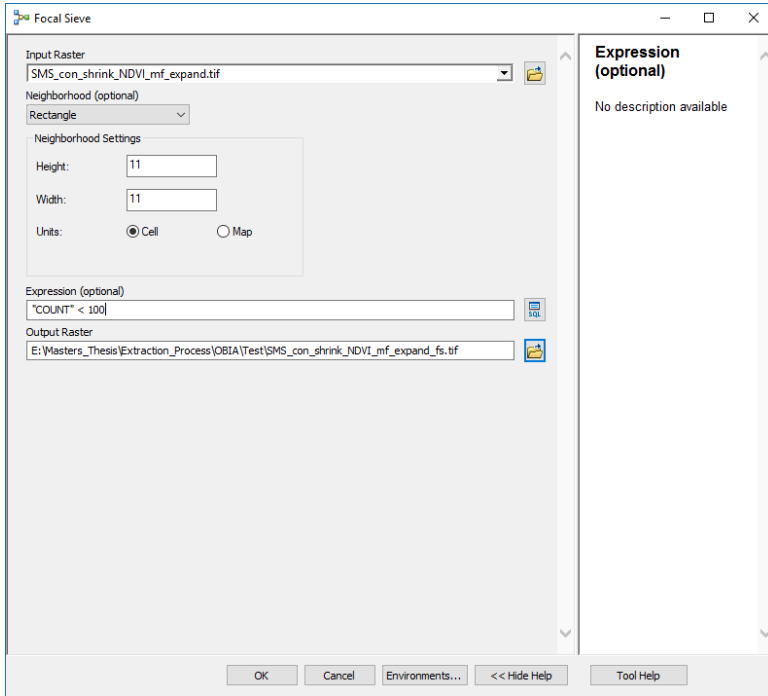
Step 10: Majority Filter



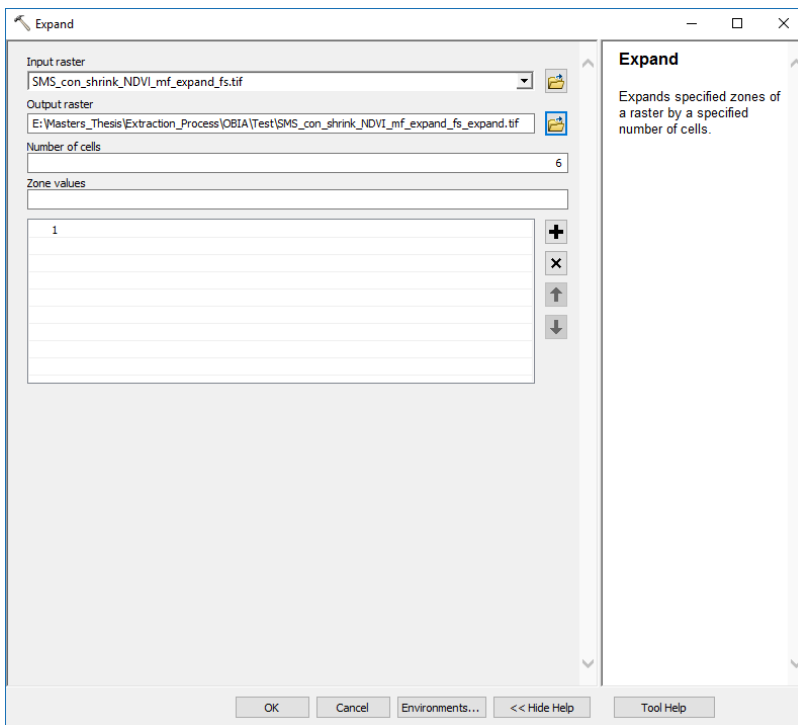
Step 11: Expand



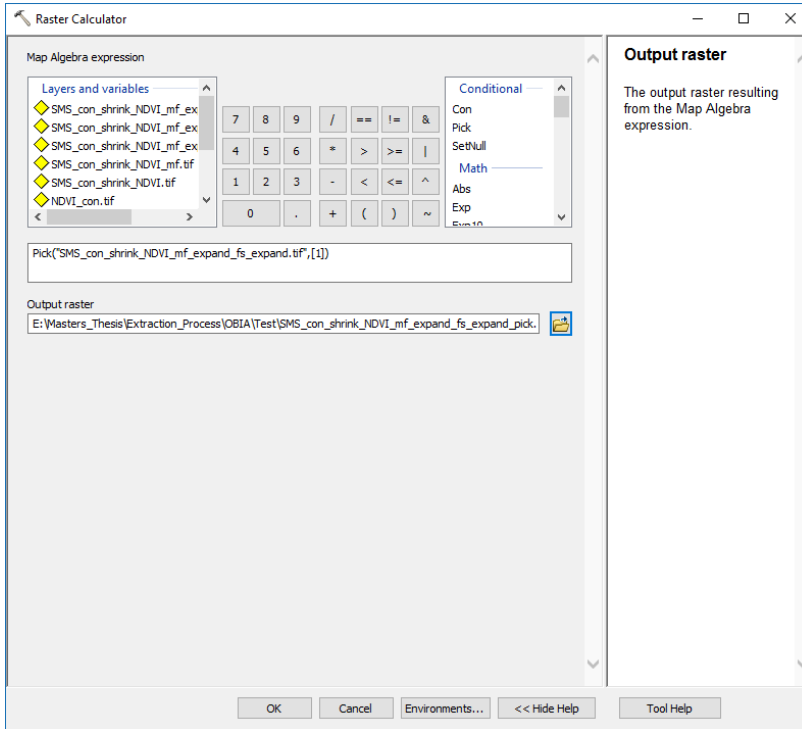
Step 12: Focal Sieve



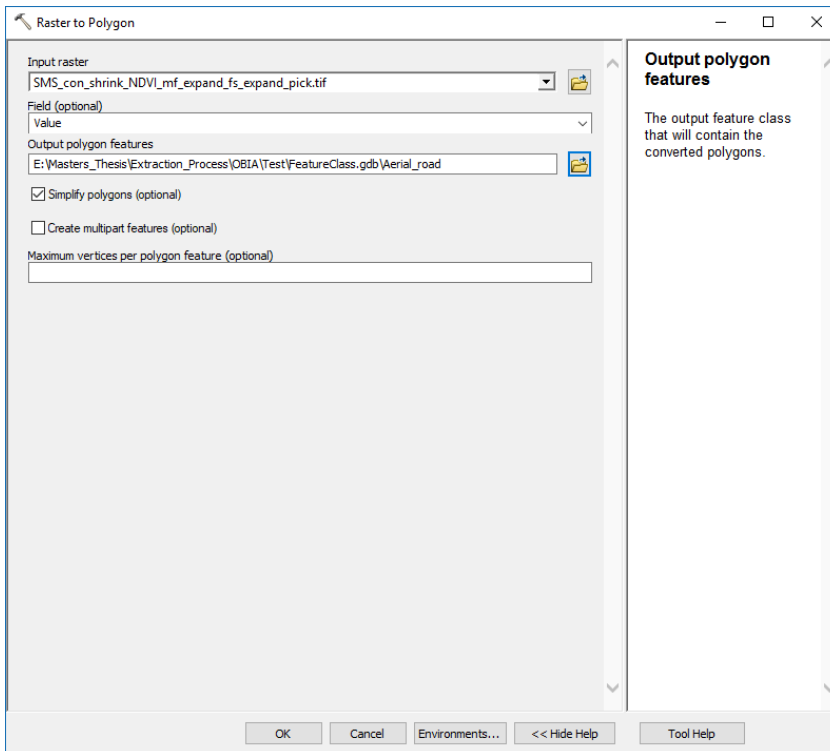
Step 13: Expand



Step 14: Raster Calculator

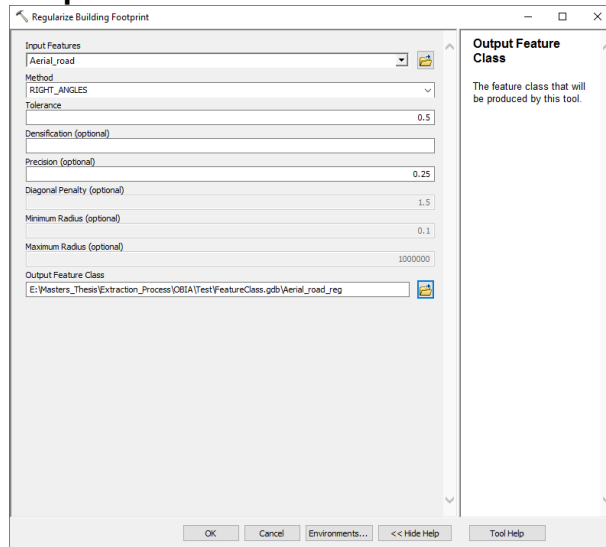


Step 15: Raster to Polygon



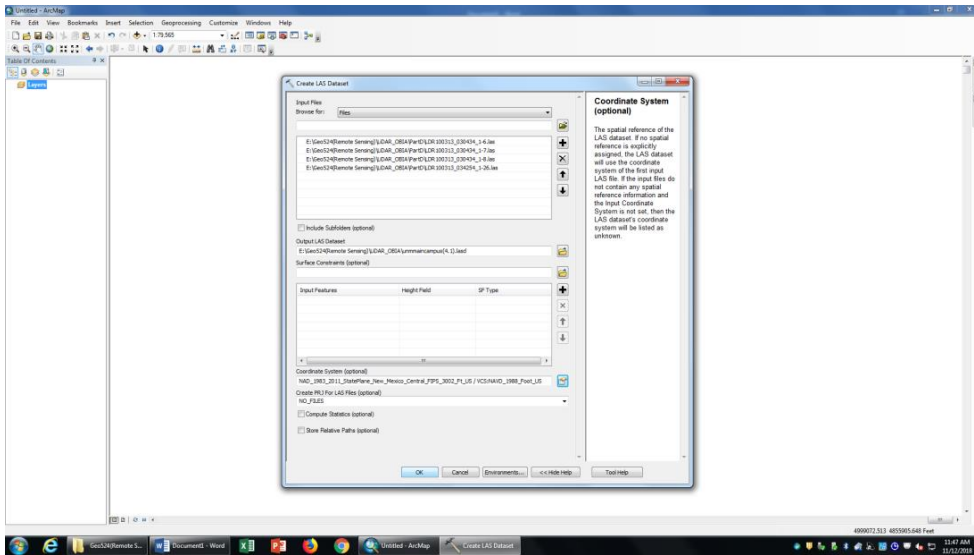
Step 16: Regularize Building Footprint

Densification should = 0.25

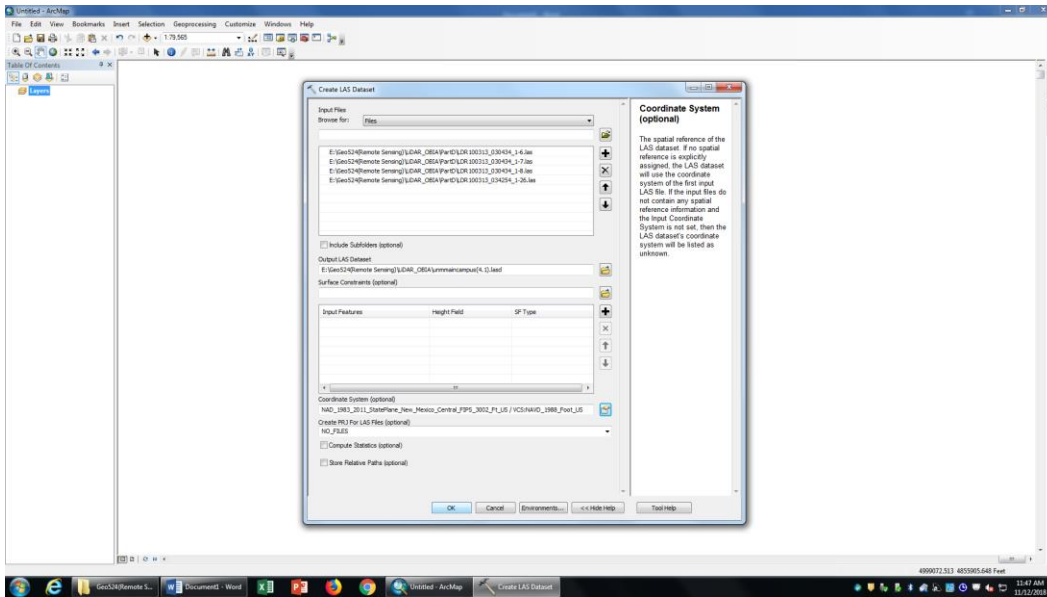


LiDAR Drivable Space Extraction Process

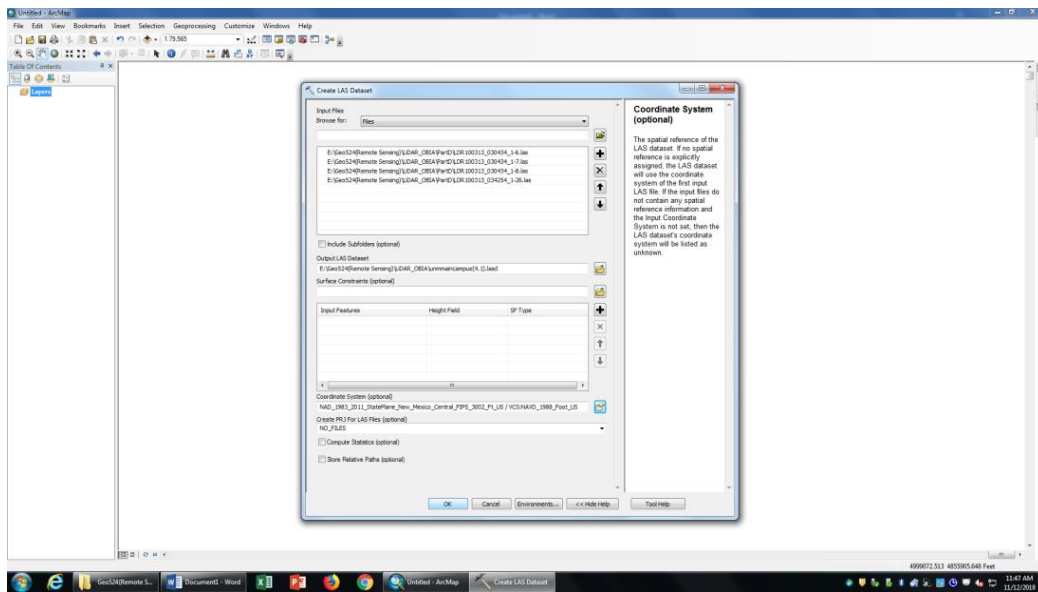
Step 1: Create LAS dataset



Step 2: Classify LAS ground



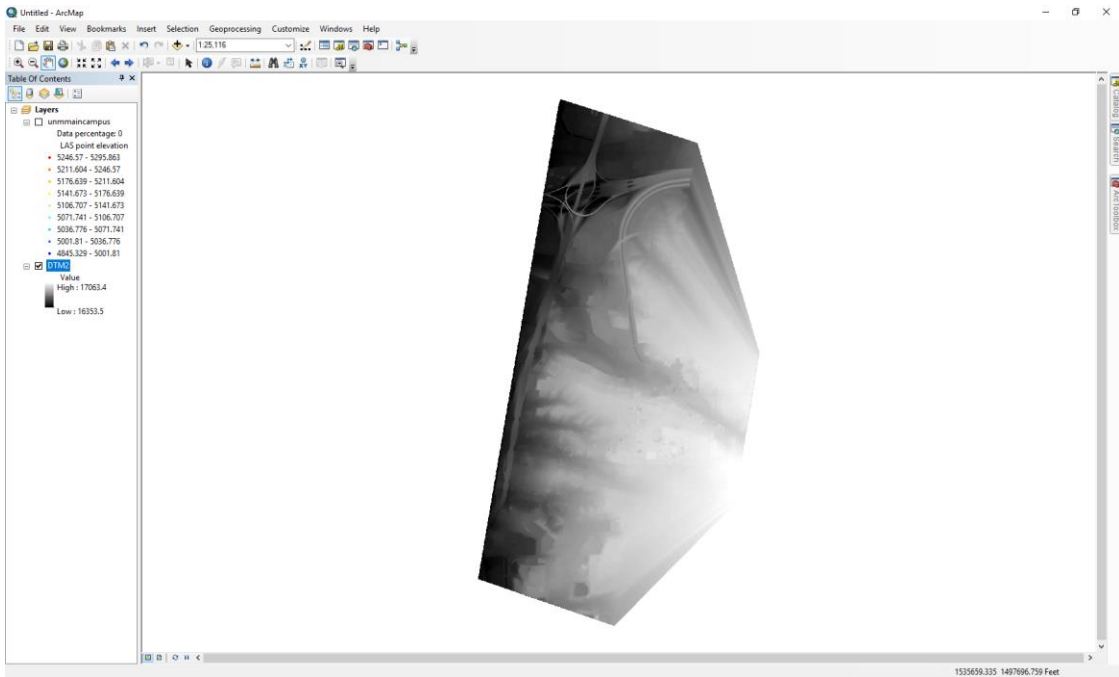
Step 3: Classify LAS by height



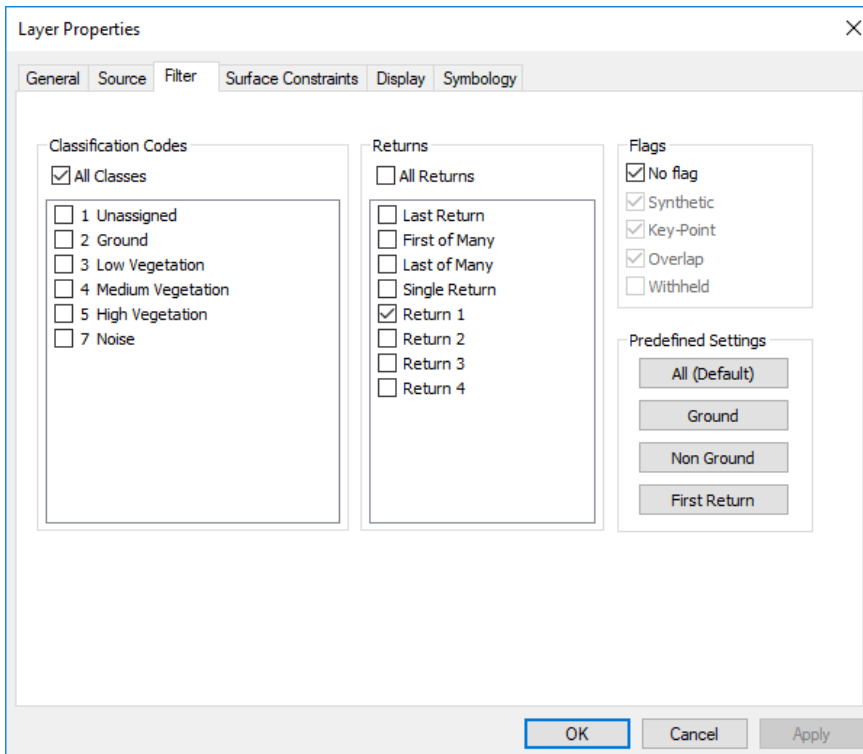
Step 4: Create DTM

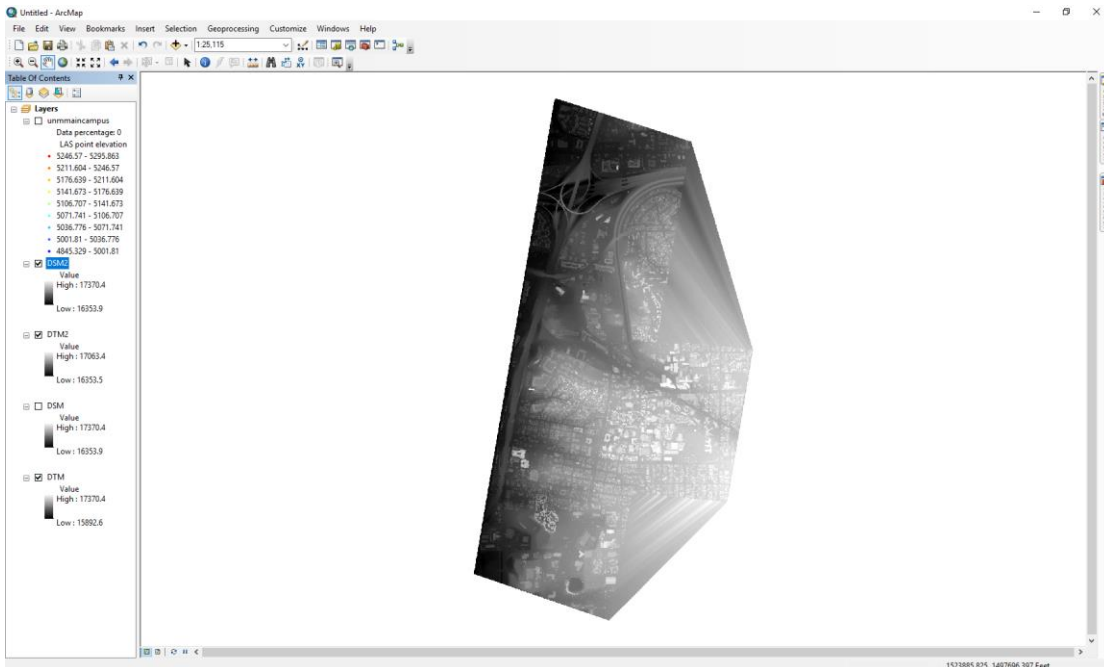
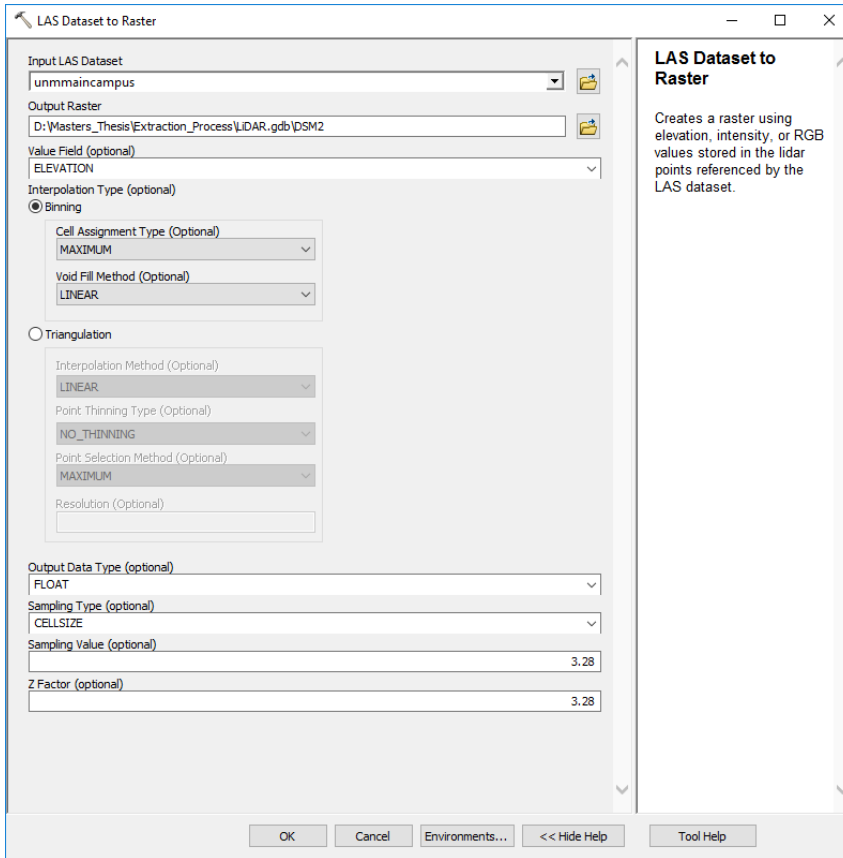
The screenshot shows the 'Layer Properties' dialog box with the 'Surface Constraints' tab selected. The dialog is divided into three main sections: 'Classification Codes', 'Returns', and 'Flags'. In the 'Classification Codes' section, 'All Classes' is unchecked, and '2 Ground' is checked. In the 'Returns' section, 'All Returns' is checked, and 'Last Return' through 'Return 4' are unchecked. In the 'Flags' section, 'No flag', 'Synthetic', 'Key-Point', and 'Overlap' are checked, while 'Withheld' is unchecked. Below these sections are 'Predefined Settings' buttons for 'All (Default)', 'Ground', 'Non Ground', and 'First Return'. At the bottom of the dialog are 'OK', 'Cancel', and 'Apply' buttons.

The screenshot shows the 'LAS Dataset to Raster' dialog box. The 'Input LAS Dataset' is 'unmmmaincampus'. The 'Output Raster' is 'D:\Masters_Thesis\Extraction_Process\LDAR.gdb\DTM2'. The 'Value Field (optional)' is 'ELEVATION'. The 'Interpolation Type (optional)' is 'Binning'. Under 'Binning', 'Cell Assignment Type (Optional)' is 'MINIMUM', and 'Void Fill Method (Optional)' is 'LINEAR'. Under 'Triangulation', 'Interpolation Method (Optional)' is 'LINEAR', 'Point Thinning Type (Optional)' is 'NO_THINNING', and 'Point Selection Method (Optional)' is 'MAXIMUM'. The 'Resolution (Optional)' is empty. The 'Output Data Type (optional)' is 'FLOAT'. The 'Sampling Type (optional)' is 'CELL SIZE'. The 'Sampling Value (optional)' is '3.28'. The 'Z Factor (optional)' is '3.28'. A 'Z Factor (optional)' section on the right explains that the factor is used to convert Z linear units to match XY linear units, with a default of 1. At the bottom are 'OK', 'Cancel', 'Environments...', '<< Hide Help', and 'Tool Help' buttons.

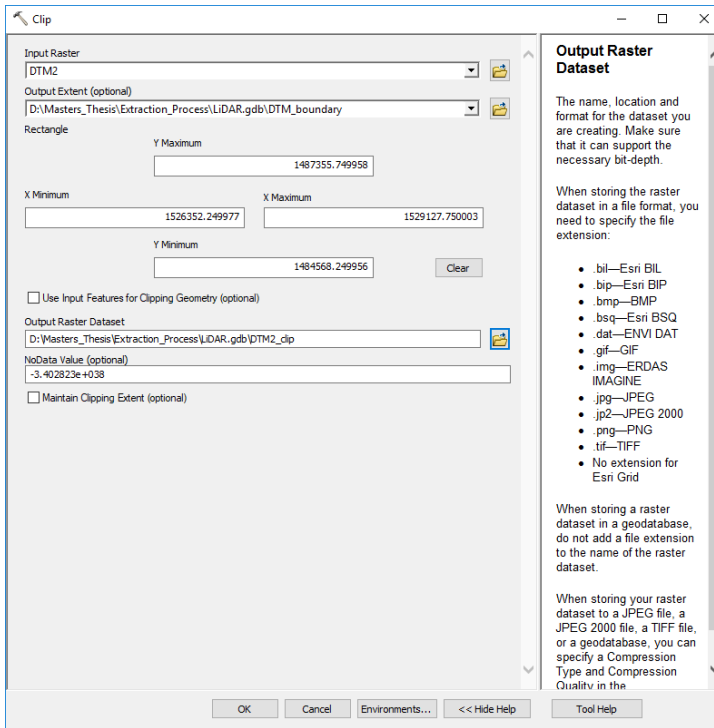


Step 5: Create DSM

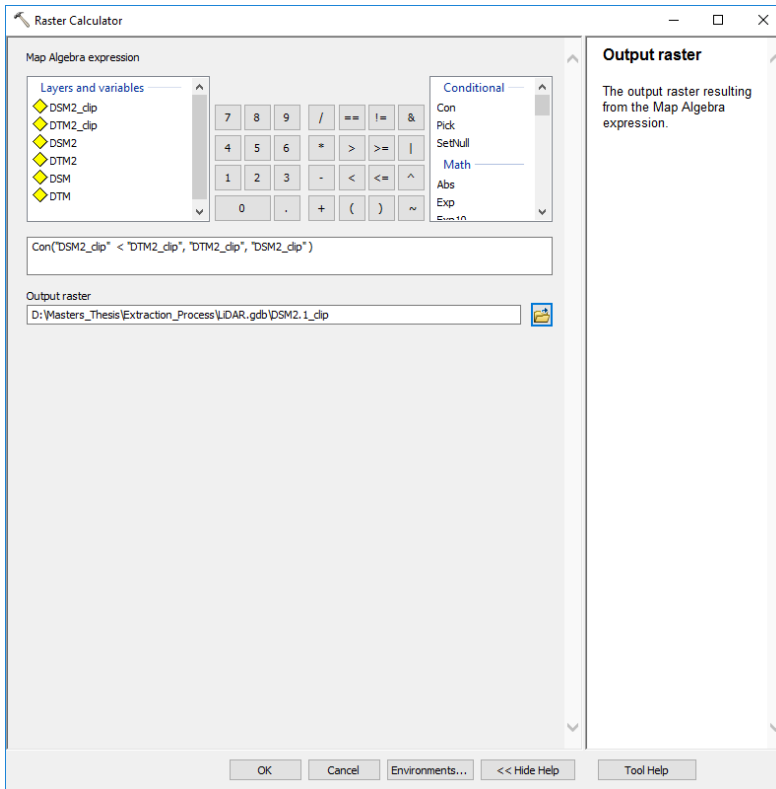




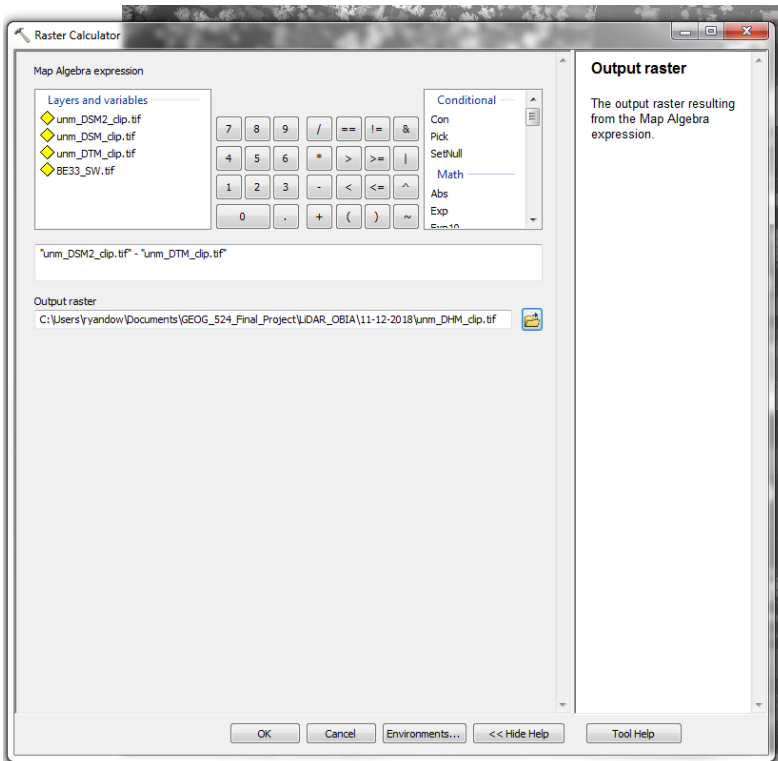
Step 6: Clip



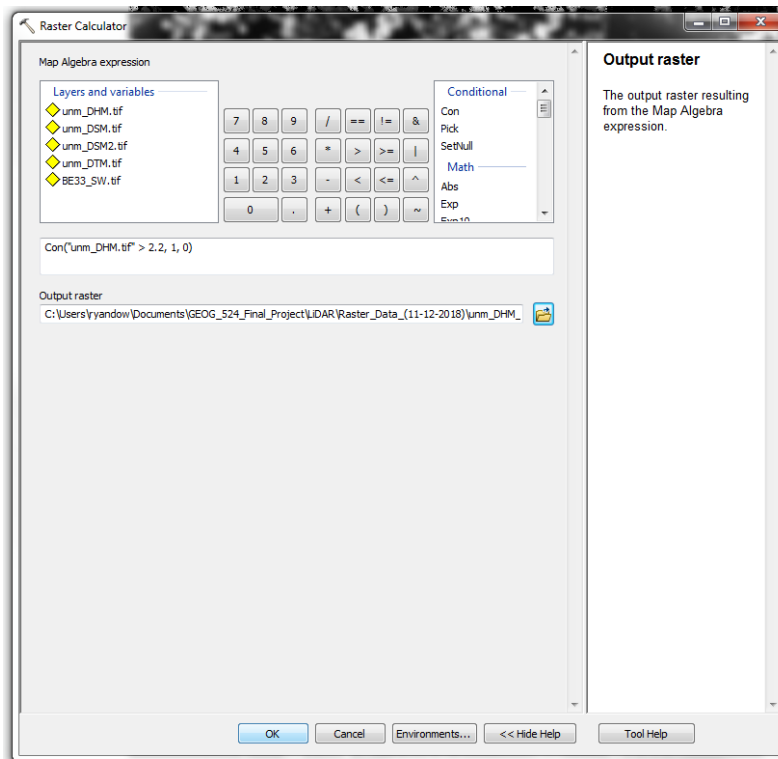
Step 7: DSM Updated



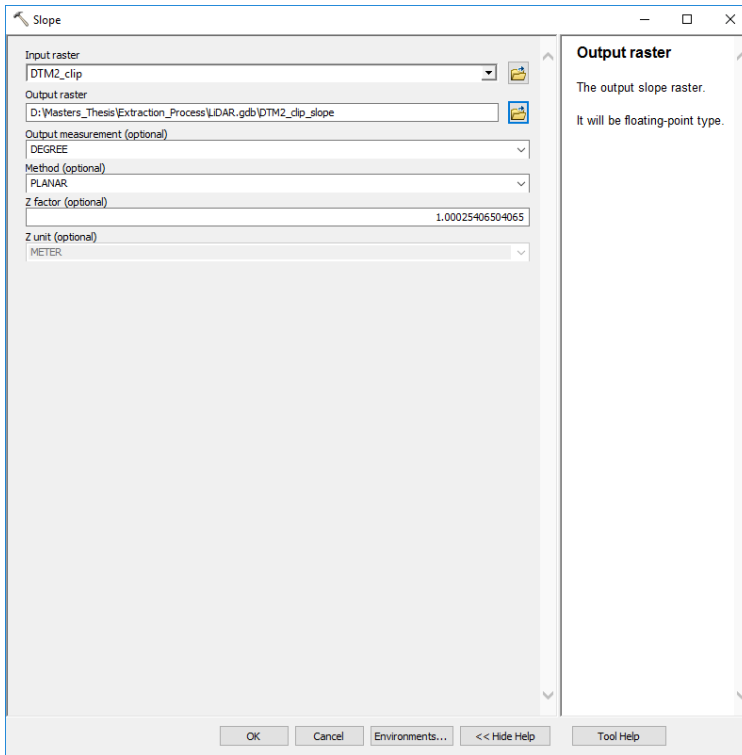
Step 8: Create DHM



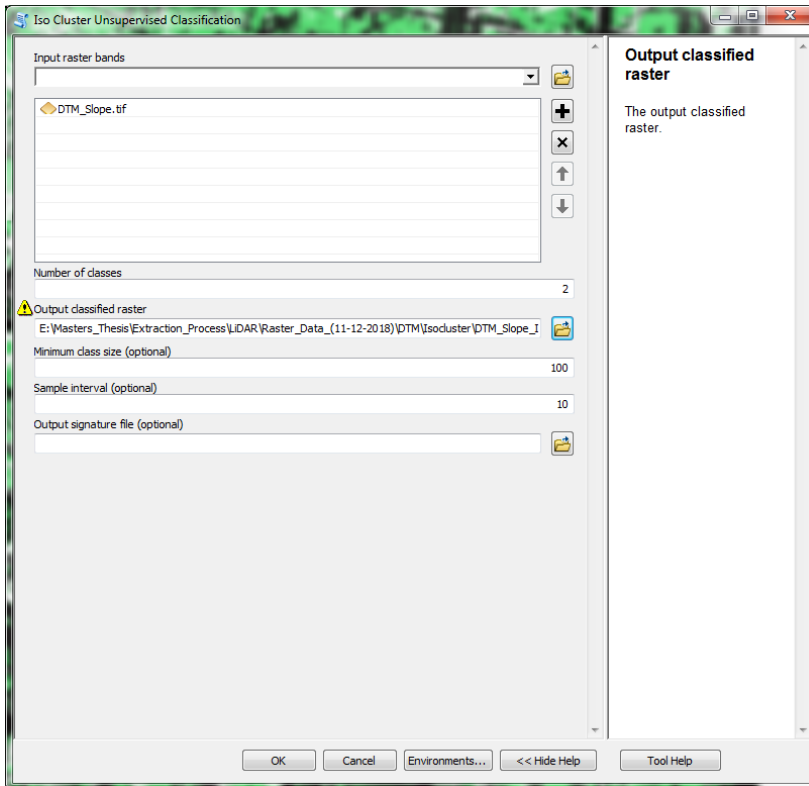
Step 9: DHM with only Buildings



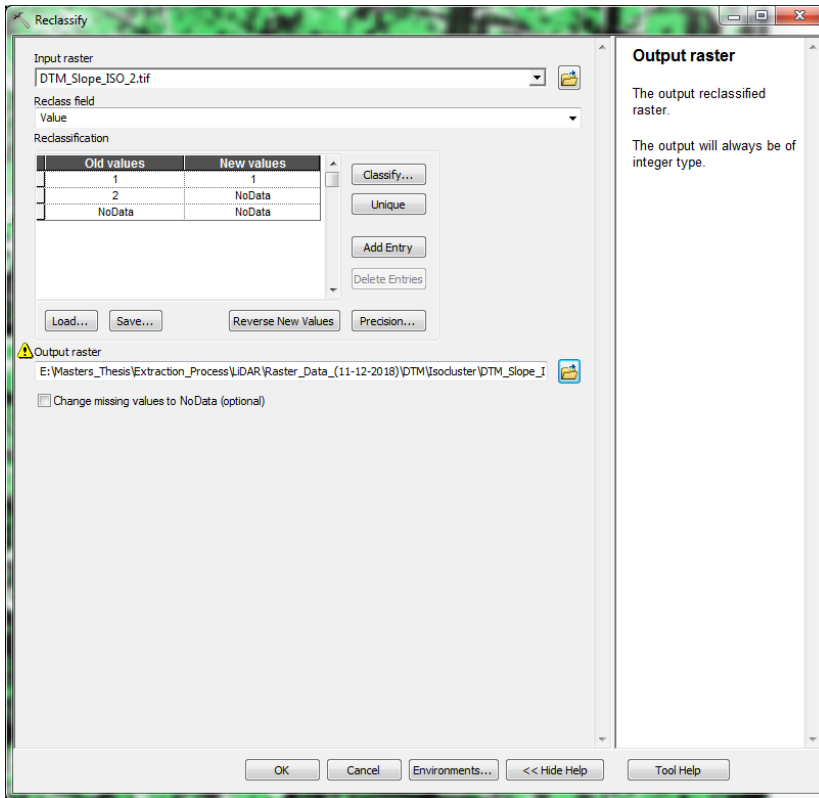
Step 10: DTM Slope



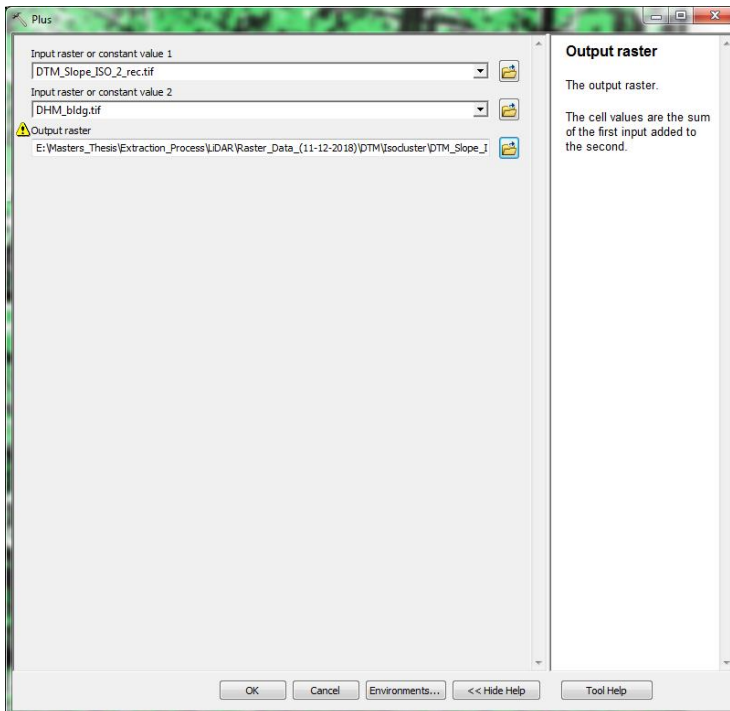
Step 11: DTM Slope using ISO Cluster Unsupervised Classification



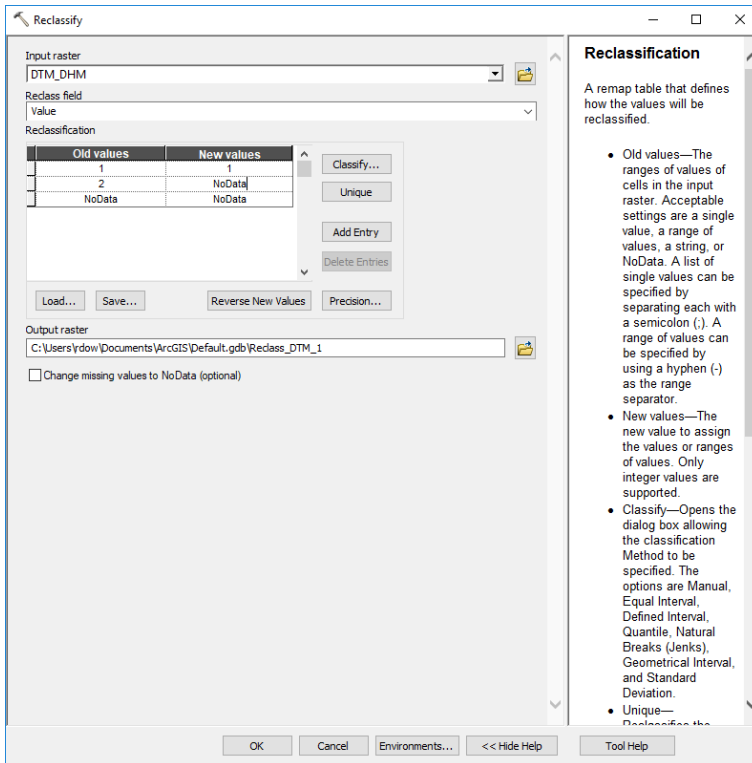
Step 12: DTM Slope ISO must be reclassified



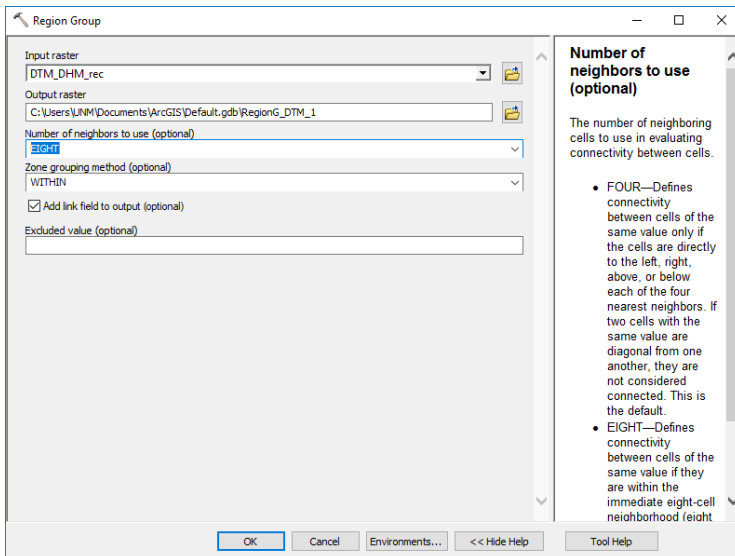
Step 13: Add DTM Slope ISO Reclassified and DHM Building



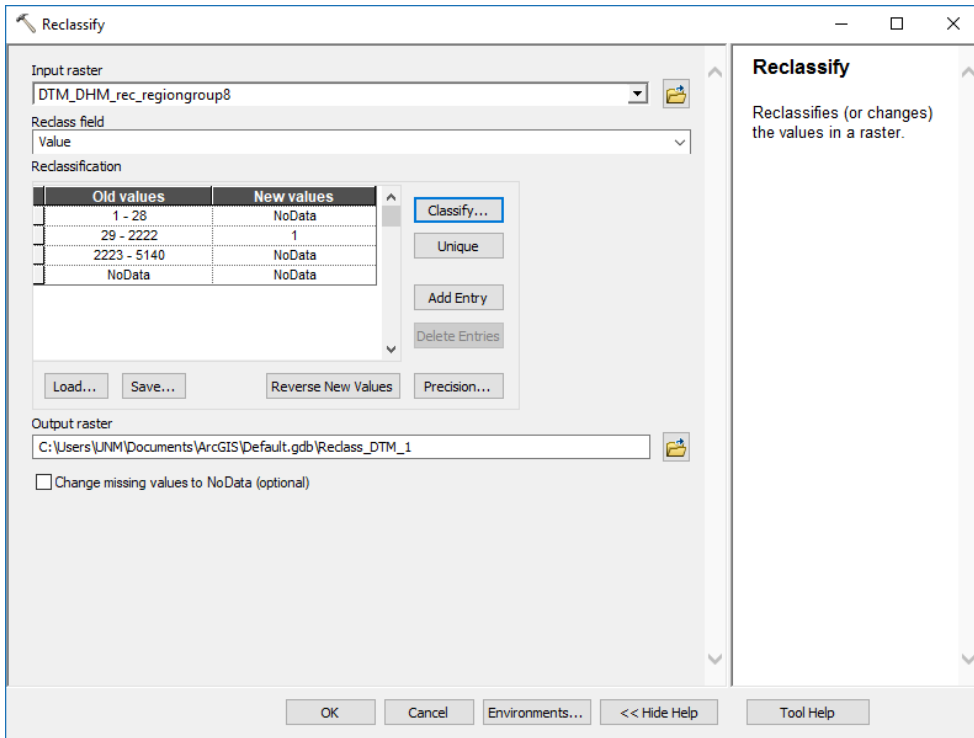
Step 14: Reclassify the DTM + DHM



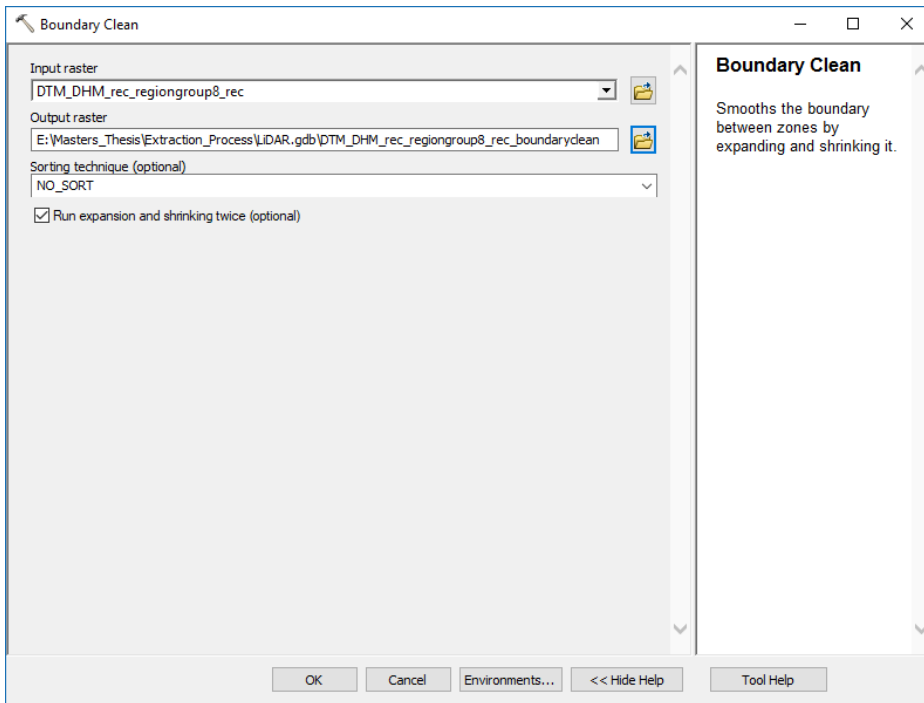
Step 15: Generalize the DTM + DHM Reclassified raster



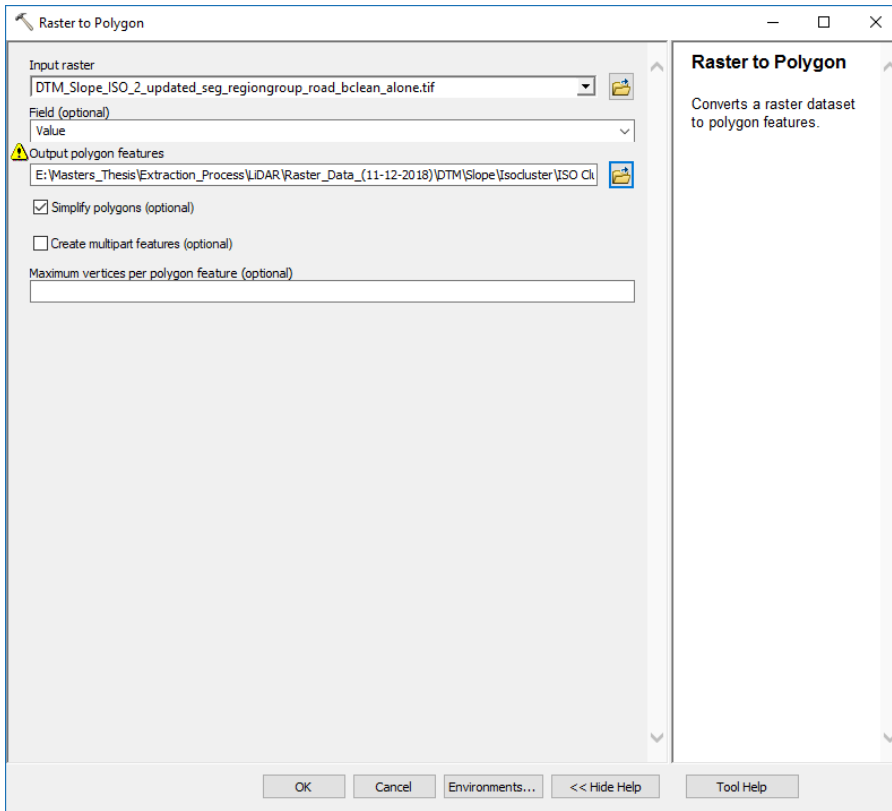
Step 16: DTM + DHM Rec. Region Group must be Reclassified



Step 17: Boundary Clean tool

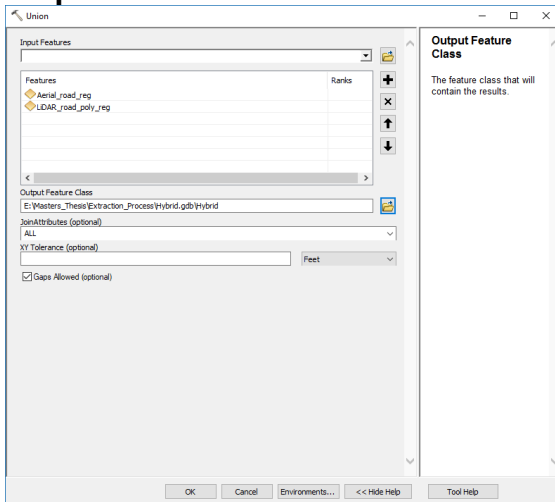


Step 18: Raster to Polygon

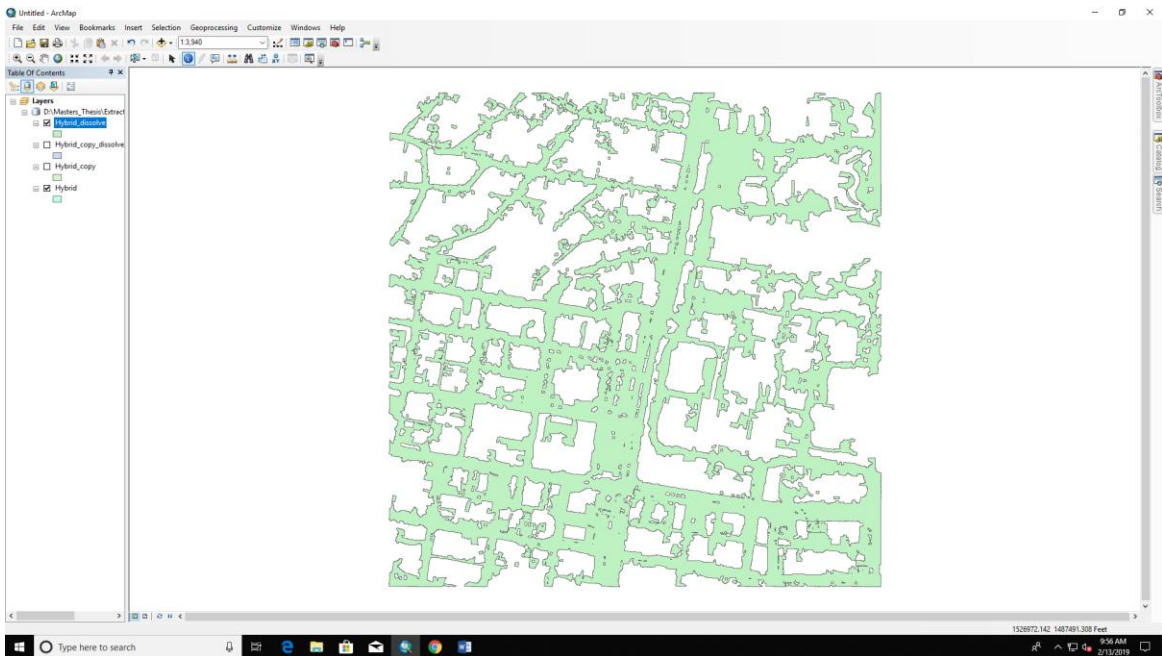
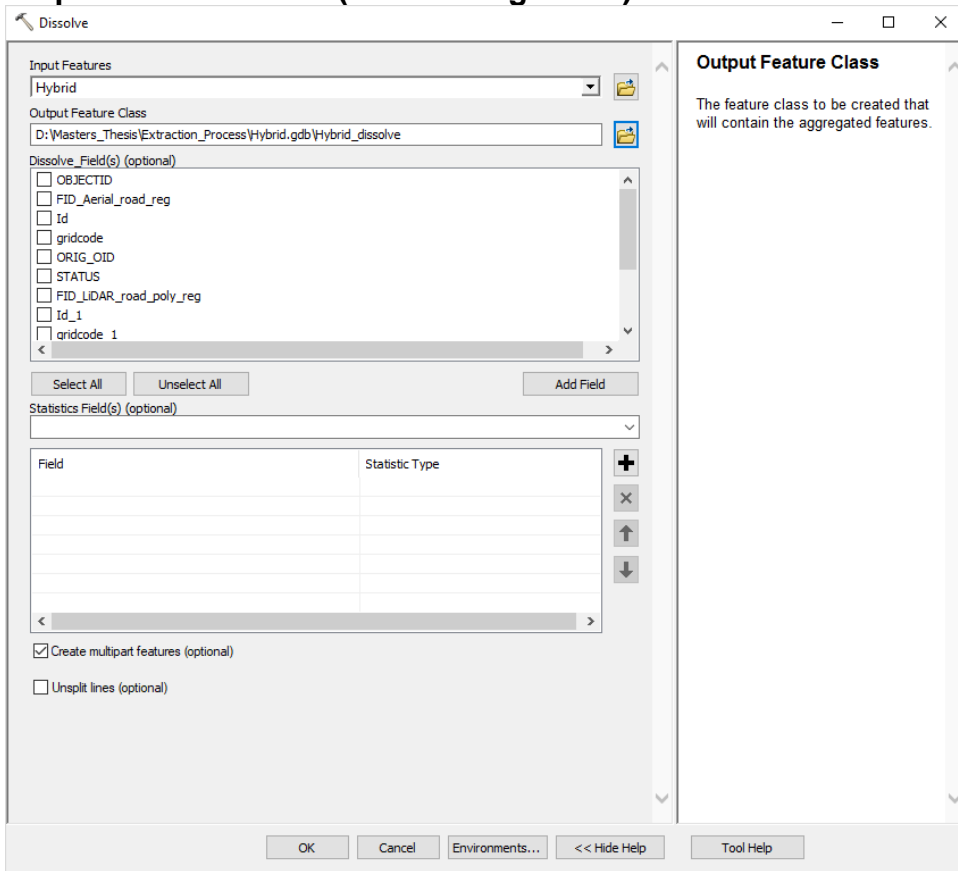


Combination of the two sets of data

Step 1: Union Tool



Step 2: Dissolve Tool (Data Management)



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