APPENDIX J — LIDAR AUTOMATED DATA EXTRACTION REPORT

Computational Consulting Services (CCS) was contracted by Dewberry because CCS is generally recognized as the firm that is best able to automatically extract information from LIDAR raw "point cloud" data, without that data first being processed into bare-earth datasets. CCS was tasked to satisfy the following objectives:

- To automatically identify, classify and geocode building centroids within selected areas of four LIDAR datasets.
- To calculate the LAG and HAG elevations for all buildings automatically extracted from the LIDAR data.
- To investigate direct and indirect methods for calculating the top of bottom floor elevations and to actually calculate top of bottom floor elevations for geocoded buildings.
- To determine the extent of building characterization (roof slope, presence of decks and porches, 2-D footprints, etc.) that can be achieved when using LIDAR, and to determine the system parameters required to achieve those results to assist with calculating top of bottom floor elevations, and
- To provide Dewberry with the necessary data to perform an independent statistical analysis of the results when compared to actual survey data.

For Mecklenburg County, NC, Prince George's County, MD, Harris County, TX, and Beaufort County, SC, Dewberry provided CCS with some ECs from various sources that CCS refers to as *control data* or *control homes*. CCS did not use these certificates to *control* anything, but merely for in-house comparisons. With few exceptions in Mecklenburg, Prince George's and Beaufort Counties, these certificates helped CCS to evaluate its own data; in several cases, CCS data helped to identify blunders in ECs intended to assist CCS in evaluating its data. When the processed CCS data was provided to Dewberry, other ECs were compared with the LIDAR data, and the CCS data was close to expectations in these three counties.

For Harris County, there were problems with the LIDAR data (first-return rather than last-return data normally required for bare-earth datasets) and with the ECs that could not be reconciled. For these reasons, Dewberry decided to abandon the evaluation of the Harris County dataset.

Because of errors in automated building extraction and LAG/HAG/top of bottom floor estimations, Dewberry concludes that there is marginal value in using totally automated techniques when it is relatively simple to generate accurate building footprints from digital orthophotos so that more-reliable and accurate automated processes can be used to estimate LAG and HAG elevations that adjoin building footprints. None of the techniques automatically estimate top of bottom floor elevations acceptable for FEMA's criteria of 4 ft or less at the 95% confidence level, except in situations where houses are essentially slab on grade and do not involve basements, split levels or split foyers.

It is for this reason that Dewberry emphasized the need for communities to provide building footprint files so as to avoid the complexities caused by having an 80% success rate, for example, in extracting buildings automatically. With building footprints, the majority of the problems listed in this report become non-issues.

FINAL REPORT

Evaluation of LIDAR Data in Obtaining Structural Elevation Data

January 31, 2004

Prepared for:

Dewberry, LLC
8401 Arlington Blvd.
Fairfax, VA 22031-4666

Contract Number: S/C-0267-002, Task Order #002

Prepared by:

Computational Consulting Services, LLC
4270 Donna Marie Court,
Haymarket, Virginia, 20169
Dr. Nick Gorkavyi, Principal Investigator
Dr. Tanya Taidakova,
Dr. Hao Shen,
Ilya Gorkavyi,
Email: comconinc@aol.com
Phone: (703) 754-7263

Table of Contents:

Executive Summary

The primary goal of this project was to investigate the use of LIDAR data for obtaining structural elevation data: Lowest Adjacent Grade (LAG), Highest Adjacent Grade (HAG) and Top of Bottom Floor (TBF). A secondary goal was to determine how well the building locations, elevations, roof geometry and other features could be extracted from LIDAR data. This report describes the methods and techniques, employed through intelligent software, for automatically determining this information, and focuses on the capabilities and limitations of LIDAR to support the generation of Elevation Certificates (ECs).

Determining building elevation data is done in two steps: 1) extraction of building footprints, and 2) analyzing the LIDAR data for each footprint to determine the LAG, HAG and TBF. The quality of the LIDAR data was the major driver affecting our ability to automatically extract building footprints. LIDAR data quality includes the penetration of the laser energy through foliage, the density and distribution of data points (statistics), and the sensitivity of the LIDAR system. When we used LIDAR data that had good penetration through foliage such as that for Mecklenburg County, NC and Prince Georges County, MD the percent of extracted footprints was approximately 80% to 90%. For high quality LIDAR data like that for Beaufort County, SC, Computational Consulting Services LLC (CCS) was able to automatically extract 90% to 95% of the building footprints with high accuracy.

The LAG and HAG can be directly derived from LIDAR data with a simple algorithm. Results of the project show that the automated determination of LAG can be accomplished with high accuracy and reliability. The average error in CCS' LAG calculations was about 0.5 to 1 ft or 15 to 30 cm for 95% of the buildings that were successfully extracted. The accuracy and reliability of automated determination of the HAG was also fairly good – approximately 1 to 2 ft. CCS also determined that the accuracy of the LAG and HAG calculations is highly dependent on the LIDAR data quality and corresponding statistics.

In most cases, determining the TBF elevation cannot be done directly, but can be estimated using indirect methods. These indirect methods apply a set of rules based on information that includes: LAG and HAG elevations, building area, and average and maximal elevation of buildings. After extracting several thousand buildings from the provided LIDAR data, CCS' average error for automatically determined TBF was about 1 to 3 ft. In all cases of properly extracted footprints, CCS found the central point coordinates for homes with an accuracy of 2 to 4 meters. Average roof heights, maximal roof heights, area and length of building perimeter were also determined with a high level of accuracy.

The most technically challenging aspect of this project was the inconsistencies and errors in the control data. In many cases, the accuracy of the control data from sample ECs was less than that of the LIDAR data. CCS estimates that the errors in control data

were approximately 3 to 4 ft, while the LIDAR data for Beaufort County had an RMSE for elevation of approximately 8 cm. This lack of accurate control data did not allow CCS to fully exploit the capabilities of the LIDAR data and optimize the software parameters.

Results of this project show that high quality LIDAR data provides enough information for reliable determination of LAG, HAG and TBF estimate using:

- Profiles of elevation of homes in different directions,
- Distribution of pixels of homes and adjacent ground by elevation; and
- 3-D building geometries constructed from the LIDAR data.

The broad spectrum of buildings and foliage conditions do not allow 100% automation when it comes to processing LIDAR data. Human intervention is necessary for verification and validation, quality assurance of the final results, and improvement of the LAG, HAG and TBF calculations. Based on the data processed for this project, CCS estimates that human intervention can reduce error in the LAG calculations to approximately 0.5 ft and error in the HAG calculations to approximately 1 ft for 95% of the buildings. CCS also estimates that, with some human intervention, the accuracy for the TBF estimations can be consistently 1 to 2 ft.

Results of this project show that processing remote sensing data, specifically LIDAR data with its 3-D information, is efficient and accurate. Moreover, LIDAR provides a cost effective means for generating building ECs for large areas when employed properly and used in conjunction with intelligent data processing software.

1 Introduction

The Federal Emergency Management Agency (FEMA) contracted to Dewberry & Davis LLC (Dewberry) to evaluate more efficient and effective methods for generating the elevation registry of structural elevation data for the National Flood Insurance Program (NFIP). Under subcontract to Dewberry, Computational Consulting Services (CCS) was tasked to investigate the capabilities and limitations of using remote sensing data, specifically light detection and ranging (LIDAR) technology, for generating EC data described below.

LIDAR is an optical sensor, mounted on ground vehicles and aircraft, that pulses laser-light in near-infrared wavelengths and takes specific measurements from the light reflected by various objects. LIDAR provides many advantages over other remote sensing systems such as photogrammetry and radar, because of its capability for rapidly collecting high accuracy, high resolution, 3-dimensional (3-D) data over large areas as a surveying tool. The operating principal of LIDAR is based on measuring the time difference between a transmitted pulse of light and the reflection received from an object. LIDAR systems can operate at frequencies of more than 50 kHz with centimeter accuracy. Each laser pulse is tagged with location coordinates using global positioning system (GPS) and an inertial measurement unit (IMU). These measurements are represented in 3-D space as “point clouds” (see Figure 1) that can be converted into detailed polyline and polygon objects (i.e., terrain models and buildings) using feature extraction software developed by CCS. Most LIDAR systems also provide the capability to measure multiple reflections from a single laser pulse, which can occur as the light passes through foliage and reflects from leaves and branches as well as the ground.

The individual reflections are referred to as returns (see Figure 2) and commonly designated as a first return, second return, etc. through the last return. Multiple-return data is unique to LIDAR systems and provides the ability to filter obscuring objects such as trees. LIDAR receivers have the capability to measure the intensity of the reflected light, which can be used to determine the material type of the reflected object. Critical parameters for achieving the desired results for this project are density and spacing of the LIDAR measurements – referred to as “postings”. Table 1 provides a top-level summary of the LIDAR operating parameters and their effect on data measurements and project results.

Figure 1 — LIDAR 3-D Point Cloud

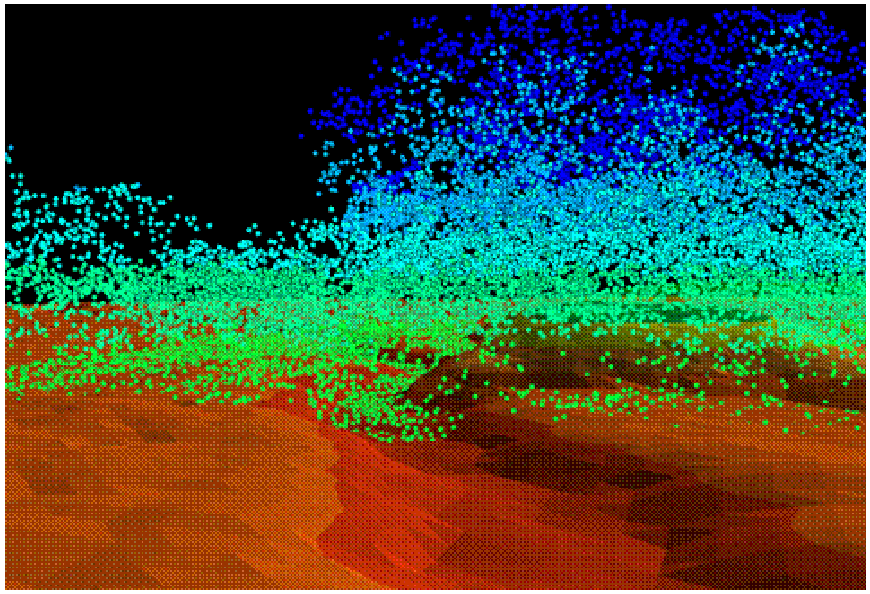

Figure 2 — Multiple-Return LIDAR Data

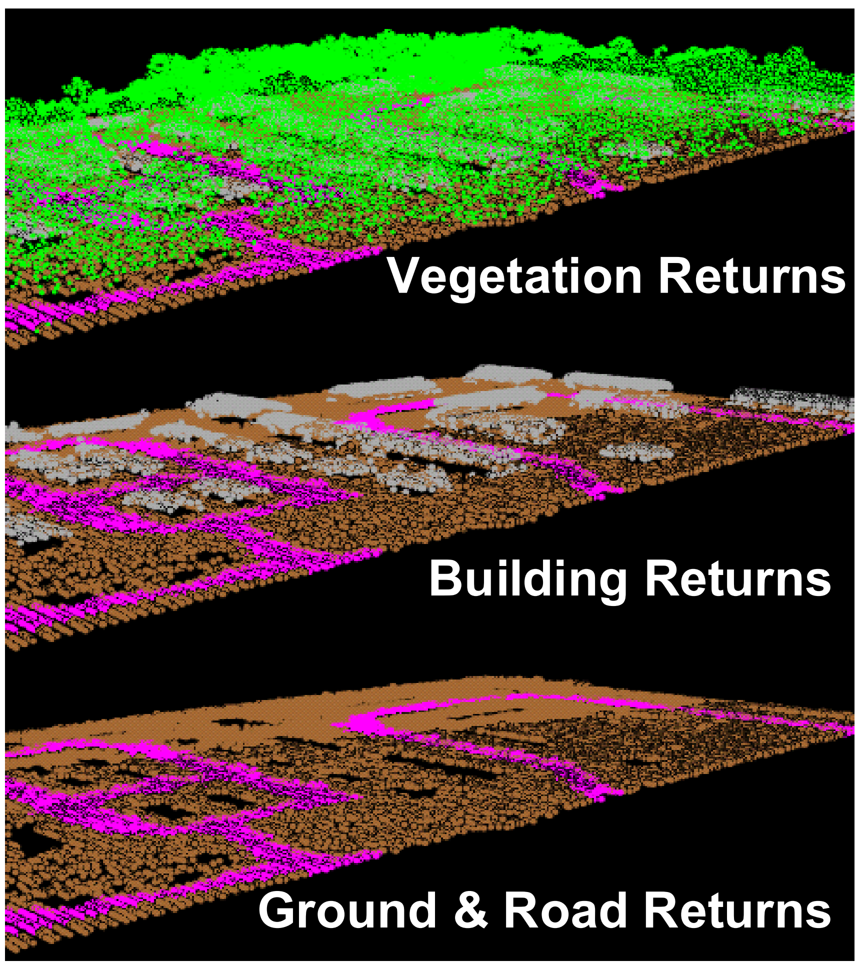

Table 1 — LIDAR Data Parameters

LIDAR Data Parameters	Affect on Derived Information
Distance measurements from LIDAR (dynamic range and receiver response)	Determines accuracy of terrain and building elevation calculations
Number of measurements per unit area and distance between those measurements (laser repetition rate, scan angle and other system design settings)	Influences ability to extract object details and resolve closely spaced objects
Measurement of multiple reflections (returns) from single light pulse (receiver and electronics design)	Provide ability to filter objects such as foliage that obscure buildings and terrain
Intensity measurements (receiver and electronics design)	Allows determination of general material types for reflecting objects
Laser-light footprint or spot size on reflecting object/surface (system optics)	Influences ability to extract object details and resolve closely spaced objects

2 Project Goals and Objectives

The overall objectives of this project is to determine the capabilities and limitations of using LIDAR to prepare ECs, assess the influencing factors (point spacing, foliage density, etc.) on data accuracy and results, and investigate the software techniques and methods for extracting information from the available LIDAR data. Specific objectives include the following:

- Characterize the ability to identify, classify and geocode building centroids within selected areas of the provided LIDAR data,
- Calculate the lowest adjacent grade (LAG) and highest adjacent grade (HAG) for the buildings extracted from the LIDAR data,
- Investigate direct and indirect methods for calculating the top of bottom floor (TBF) and calculate the TBF for each of the geocoded buildings,
- Determine the extent of building characterization (roof slope, presence of decks and porches, 2-D footprint, etc.) that can be achieved when using LIDAR, and the system parameters required to achieve those results to assist with calculating TBF, and
- Provide Dewberry with the necessary data to perform an independent statistical analysis of the results when compared to actual survey data.

3 Overall Data Processing Approach

CCS followed a procedure to meet these objectives that included type-classifying the LIDAR data points as ground and non-ground. The ground points are used to generate a digital terrain model of the earth and the non-ground points are further analyzed to distinguish buildings and structures from other objects on the earth's surface. Data points associated with buildings are then transformed into polylines and polygons that represent geometry and elevation profiles. The individual buildings are compared to the local terrain elevation data for determination of the LAG and HAG. Further analysis is performed to directly and indirectly determine the elevation of the top of the bottom floor. Figure 3 provides a process flow diagram that illustrates this procedure, which is further described in Section 4.

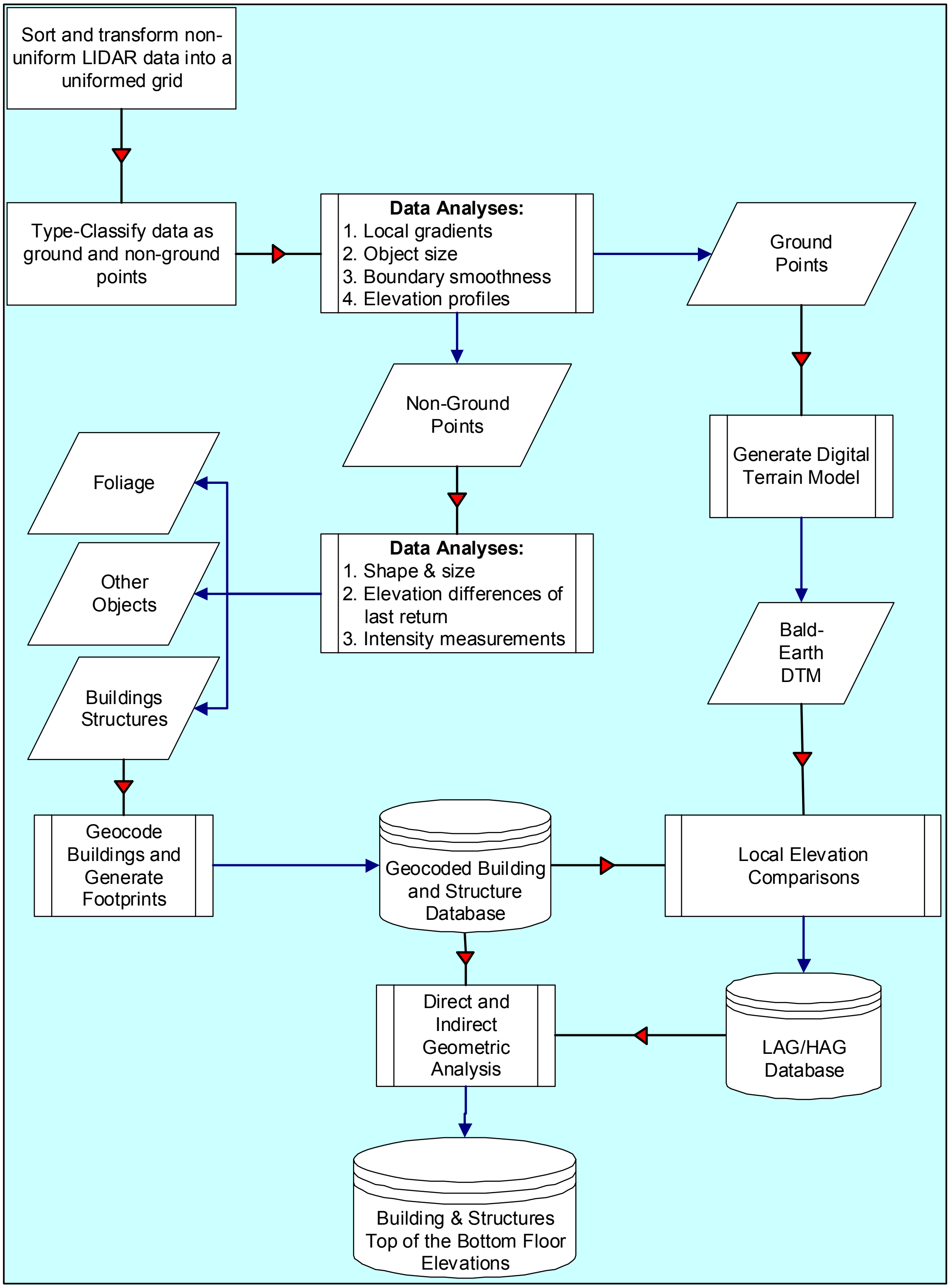

Figure 3 — Data Processing Procedure

4 Identifying, Classifying and Geocoding Buildings

CCS has developed software tools and algorithms to automatically identify buildings and determine their perimeters (footprints) from LIDAR data. These automated tools are designed to process large quantities of data collected over relatively large areas in a two-step process with minimal human intervention. The first step separates data points into two broad categories as "ground" and "non-ground" points using algorithms that analyze data based on local elevation gradients, boundaries and size of data clusters with high elevation, and the smoothness of those clusters. Ground points include the earth's surface, roads, and hydrology. The second step in the process is to further classify the non-ground points as buildings/structures, foliage, and other man-made objects such as bridges and storage tanks based on an object's shape, size, 3-D geometry, and reflective properties. Figure 4 illustrates the top-level process, which is further described below.

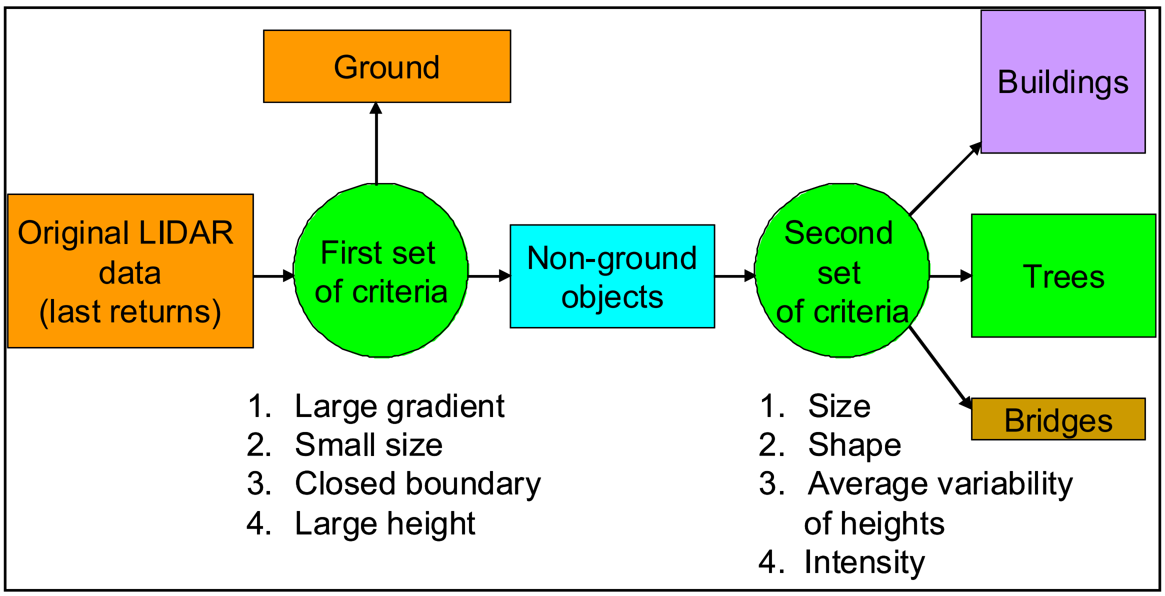

Figure 4 — Top-Level Process for Type-Classifying LIDAR Data Points

Type-Classification of Ground and Non-Ground LIDAR Points

Dewberry provided CCS with multiple LIDAR data sets collected using different systems with varying operating parameters for different geographic areas. All LIDAR data were delivered to CCS as a set of x, y, z points with non-uniform distribution about the x, y plane. CCS pre-processed the data to sort and re-distribute the points into a uniform grid with a specific pixel size. Pixel size selection is critical to correctly type-classify the data points and directly affect the ability to identify objects and features using the LIDAR data. The pixel size must be sufficiently small to maximize resolution, while large enough that the statistical distribution of the LIDAR data results in at least one measurement for approximately 90% of the pixels. In most cases two or three measurements are contained in a pixel. Within each pixel, CCS identifies a minimal height (Z_minimal) and a maximal height (Z_maximal), then type-classifies the pixel as ground (natural terrain, roads, and hydrology) or non-ground (buildings/structures, bridges, and foliage).

To type-classify the data points as ground and non-ground points, CCS first determines which of the data are attributed to buildings and structures by analyzing local elevation gradients within clusters of pixels. In Figure 5, elevation values were converted to brightness (lighter shades are a higher elevation) to show that, in many cases, the human eye can quickly differentiate objects of the same height based on their geometry - delineated by a local elevation gradient. CCS has replicated this ability in software. Algorithms analyze the pixel data and identify buildings and their perimeters based on large elevation changes over short distances within a geometrically bounded area. This first step allows for rapid differentiation of data attributed to a building (classified as non-ground points) from many ground objects of the same height (i.e., rock outcroppings, hills, elevated highway, etc.). All data points that are clearly attributed to buildings are type-classified as “non-ground-buildings” points.

The analysis of elevation gradients and perimeter smoothness does not provide 100% accuracy in classifying ground and non-ground points. There are several objects such as narrow, short-span bridges that meet many of the criteria for being classified as a building, because of their shape, size and elevation.

To further improve the identification and definition of buildings and structures, reduce false alarms and minimize misclassified points, additional algorithms analyze other geometric parameters of the LIDAR data. Using space averaging, CCS generates a smooth surface as pseudo-ground and compares this pseudo-ground with Z_minimal from the last LIDAR return. Any large elevation deviations from the pseudo-ground are classified as non-ground data, which eliminates ground objects from being misclassified as non-ground. This technique was performed on data shown in Figure 5, which shows all of the data points – including buildings (non-ground points) and two bridges (non-ground points). After analyzing the data against the pseudo-ground, the non-ground data are removed leaving only those points type-classified as ground (see Figure 6). As can be seen from Figures 5 and 6, the data associated with the buildings have been properly type-classified as non-ground points and those data removed. The data associated with the large bridge was also properly type-classified as ground points and that data was retained. The data associated with the small bridge was classified as non-ground points, because of similar properties as a large building or structure. These data points were tagged for further analysis in step 2.

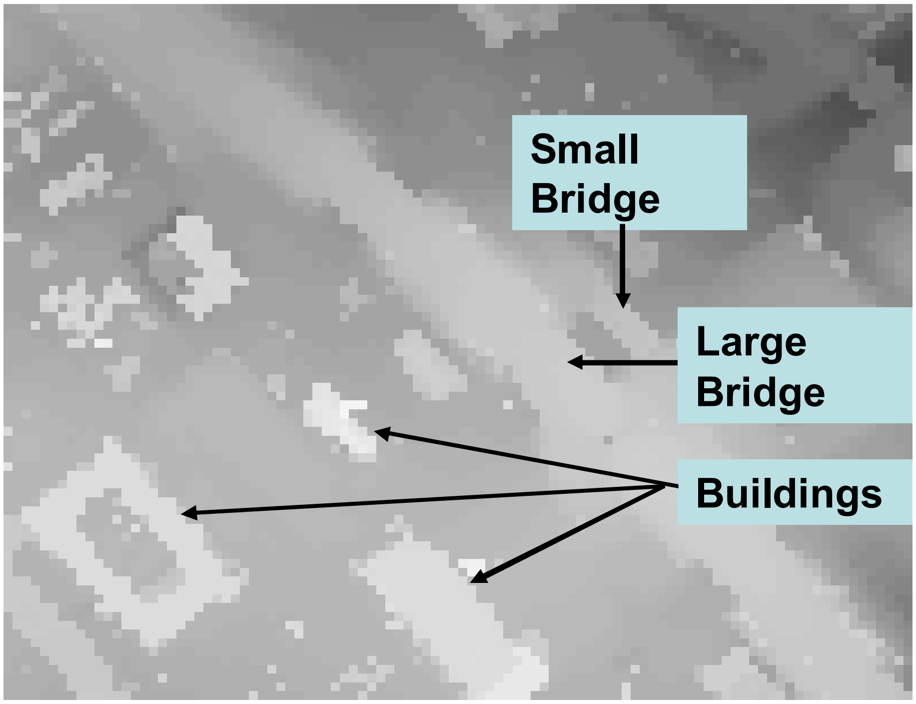

Figure 5 — LIDAR Elevation Data Displayed as Grayscale Image

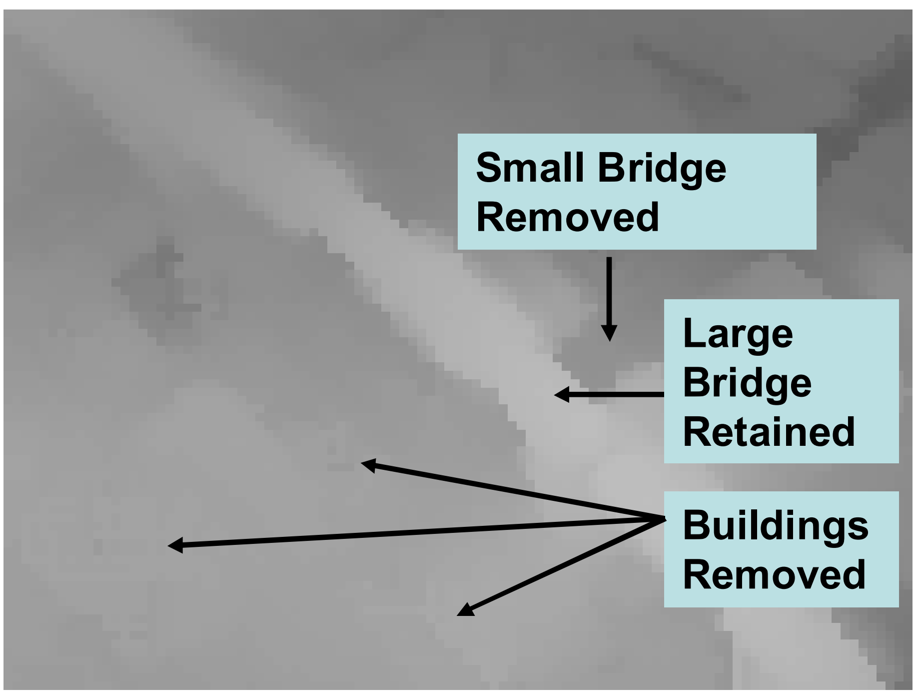

Figure 6 — LIDAR Elevations Minus Buildings

Identification of Buildings, Foliage & Other Objects within the Non-Ground Dataset

Once the LIDAR has been type-classified as ground and non-ground data points, a set of algorithms are used to differentiate data associated with buildings from those associated with foliage and other objects such as bridges, storage tanks, and towers. The methods and techniques applied during step 2 consider size, shape, local elevation variability, and the reflective properties of the object.

Reliably identifying non-ground data points as those associated with foliage is quite challenging. Dense groupings of trees often form geometric shapes of similar height profiles as buildings and can satisfy both elevation and elevation gradient criteria for classification as a building. To determine if a cluster of similar-height pixels is attributed to foliage, CCS applies an algorithm that measures the level of fluctuation or variability of the elevation profile. With high quality data (dense data points with multiple returns), foliage is determined using the last return measurements. Comparing the difference between Z_minimal and Z_maximal of the last LIDAR return provides an effective means for identifying foliage and discriminating between a building and cluster of trees with the same elevation profile. The average differences between Z_minimal and Z_maximal of the last return data is much greater for trees than buildings due to laser light penetrating through the branches and leaves to the ground. Using this method, stands of trees with geometries and elevation profiles similar to a building are correctly classified as trees. Figure 7 illustrates this phenomenon for an area in Beaufort, SC using a 4-foot pixel size. Figure 7a shows the foliage density using the raw LIDAR data. Figure 7b is a plot of Z-maximal of the last return and Figure 7c is a plot of Z_minimal of the last return. Figure 7d shows the data after all objects with significant elevation variability within a cluster of pixels are filtered – showing only a single building. To improve the identification of LIDAR data associated with foliage, CCS can consider the intensity of returns. Trees and their leaves reflect laser light with greater intensity than returns from buildings and their asphalt or other light absorbing materials.

Once the foliage data is properly identified, the final step is to discern buildings and structures from other objects; this is done by assessing overall shape and geometry of an object. To characterize the shape and geometry of an object, CCS uses the ratio of area and square of perimeter. Long objects such as bridges have a ratio that is smaller than typical buildings and structures.

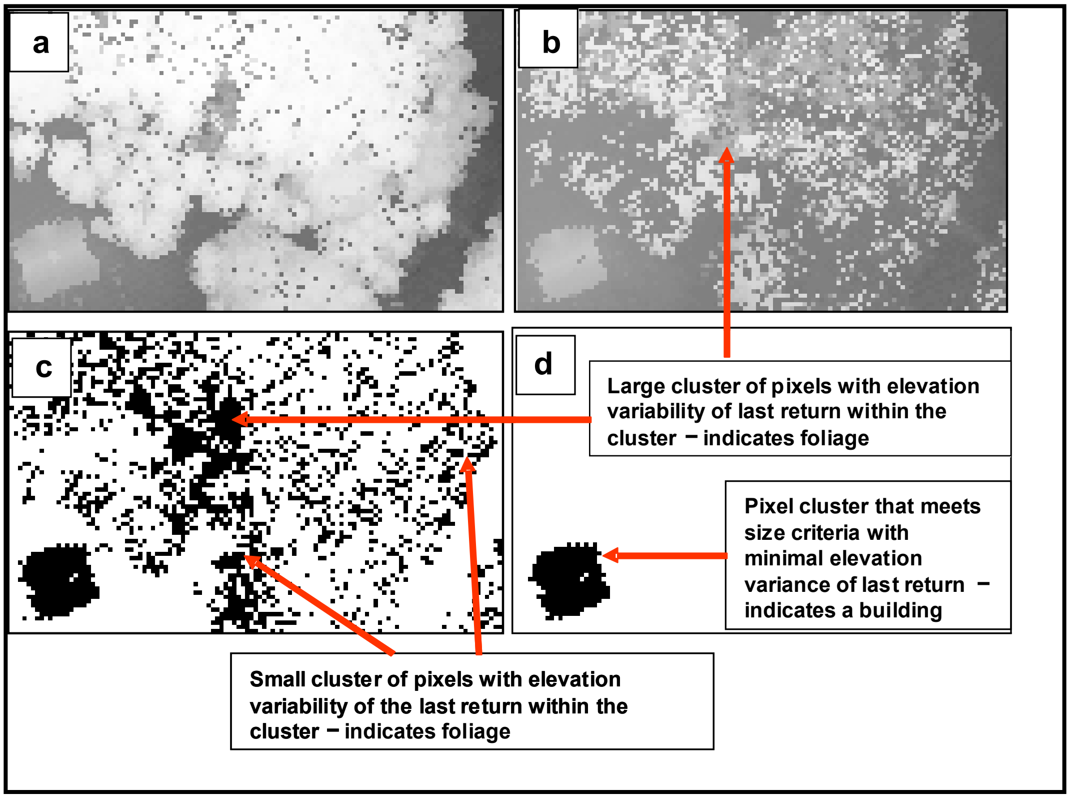

Figure 7 — Dense Foliage Area (Tile 2040_168 (Beaufort County, SC, 4 feet pixel).

a. **Raw LIDAR data.**
b. **Z_maximal from last returns**
c. **Z_minimal from last returns**
d. **All pixels clusters that satisfy building criteria for height, elevation gradient, and elevation fluctuation**

Determining Building Boundaries and Footprints

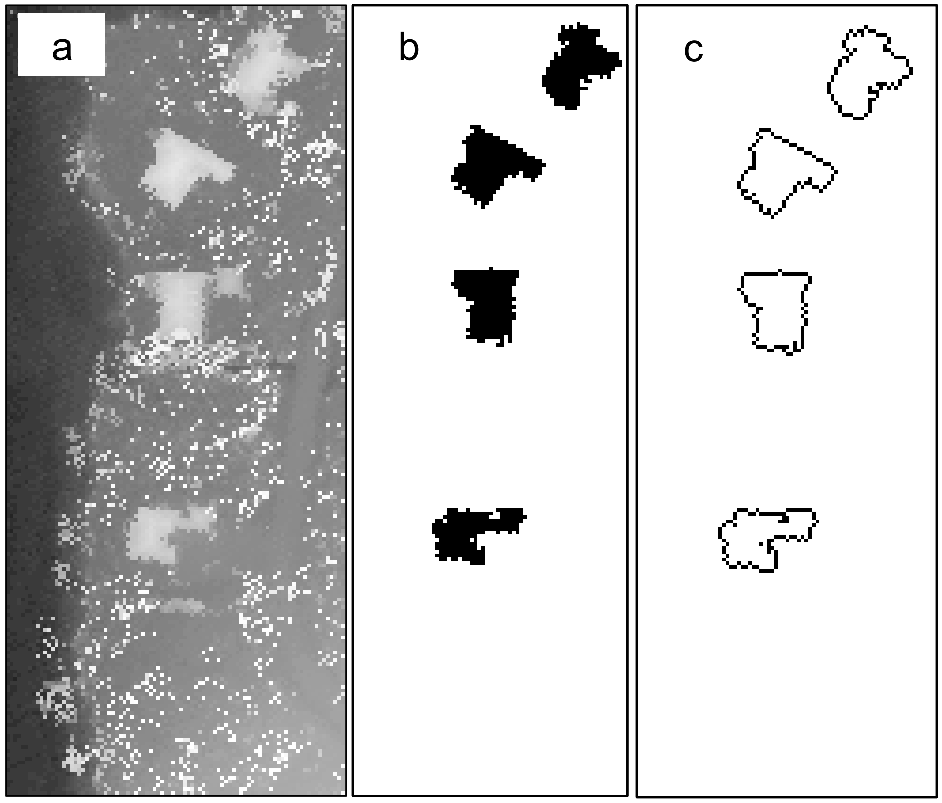

Figure 8 — Building Extraction from LIDAR Data with Footprints and Boundaries

Using the data points determined to be returns from buildings, CCS applies an algorithm that determines the footprint and the boundary of a building based on its elevation gradient. The footprint of a building is a set (cluster) of pixels within a closed boundary – typically defined as the building roof and ground interface in a 2-dimensional plane. Figure 8 shows the extraction of four buildings from LIDAR data (tile 2040_180, Beaufort County, SC, 4-foot pixel) with their footprints (Figure 8b) and boundaries (Figure 8c) determined.

The criteria for determining building boundary based on an elevation gradient varies somewhat based on the local environment, but in most cases CCS looks for 1-meter elevation changes per pixel. For accurately determining the LAG and HAG, it is important that boundary pixels consist of LIDAR returns from the edges of the building roofs and walls and definitely separated from the surrounding ground pixels. With the building boundary delineated, the footprint is established. The footprint provides the geometry necessary to calculate the building centroid with high accuracy – typically one to two pixels or 2 - 3 meters. The centroid of a building is its geometric center. For buildings with complex geometries, the centroid may not be located within the building footprint, (although a simple set of algorithms can be used to shift the centroid inside the closest part of footprint). Software determines the centroid in pixel coordinates (integer values), which is then converted to geospatial coordinates (UTM or State Plane). Figure 9 shows the results of this process where the building footprints are calculated using the LIDAR data and overlaid on an ortho-rectified aerial photograph. The quality and accuracy of the building footprints from LIDAR are usually better than aerial photographs, because photographic imagery is not perfectly ortho-rectified (see building "lean" in the right part of Figure 9).

Figure 9 — LIDAR Building Footprints

5 Lowest Adjacent Grade (LAG), Highest Adjacent Grade (HAG), & Top of Bottom Floor (TBF)

CCS has developed logic for determining the LAG, HAG and TBF using LIDAR data. This logic and accompanying methods and techniques are illustrated in Figure 10 and described in the following sections.

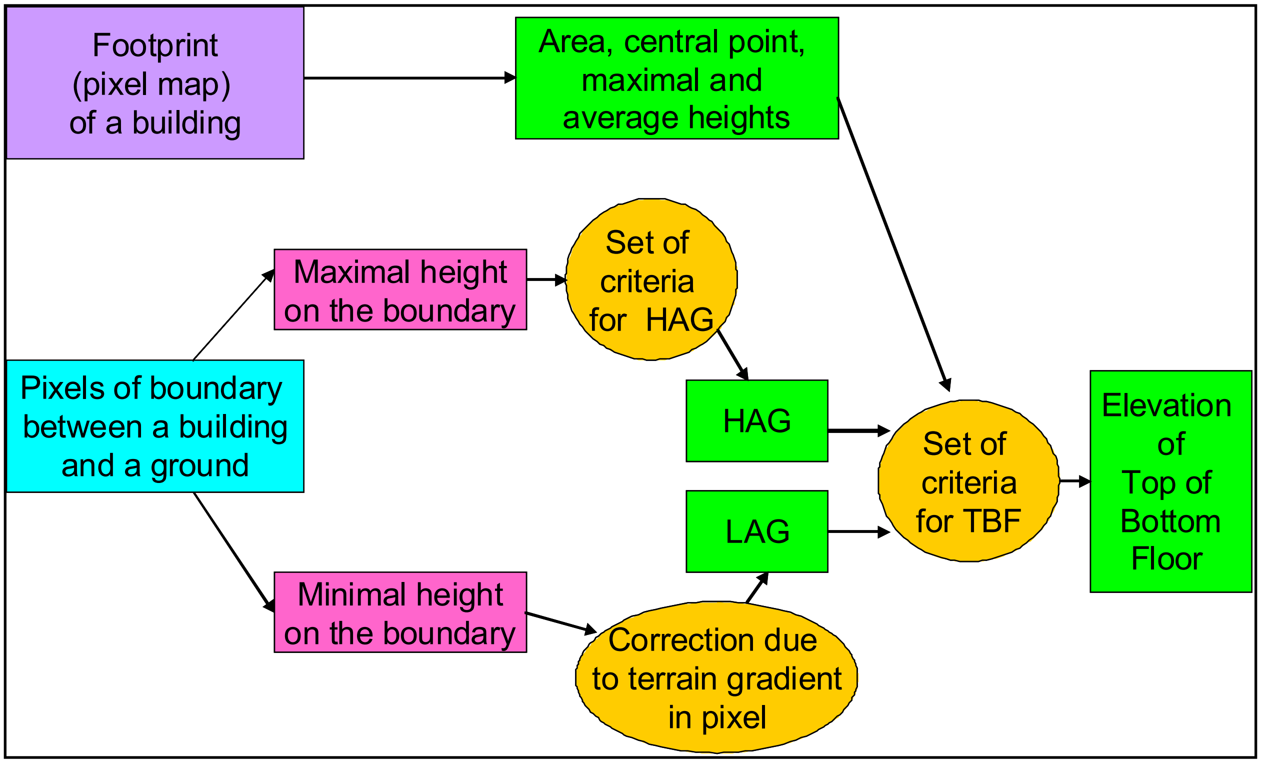

Figure 10 — Process Flow for Determining HAG, LAG and TBF

5.1 Determining the LAG and HAG

To determine the LAG and HAG, CCS generates a Digital Terrain Model (DTM) and investigates the elevation profile of each building boundary using the local terrain. The DTM is established using the LIDAR data type-classified as ground points with surface objects filtered from the data. This is illustrated in Figure 11 where the left image shows a surface plot of all data, and the right image is the ground only (after the surface clutter is removed).

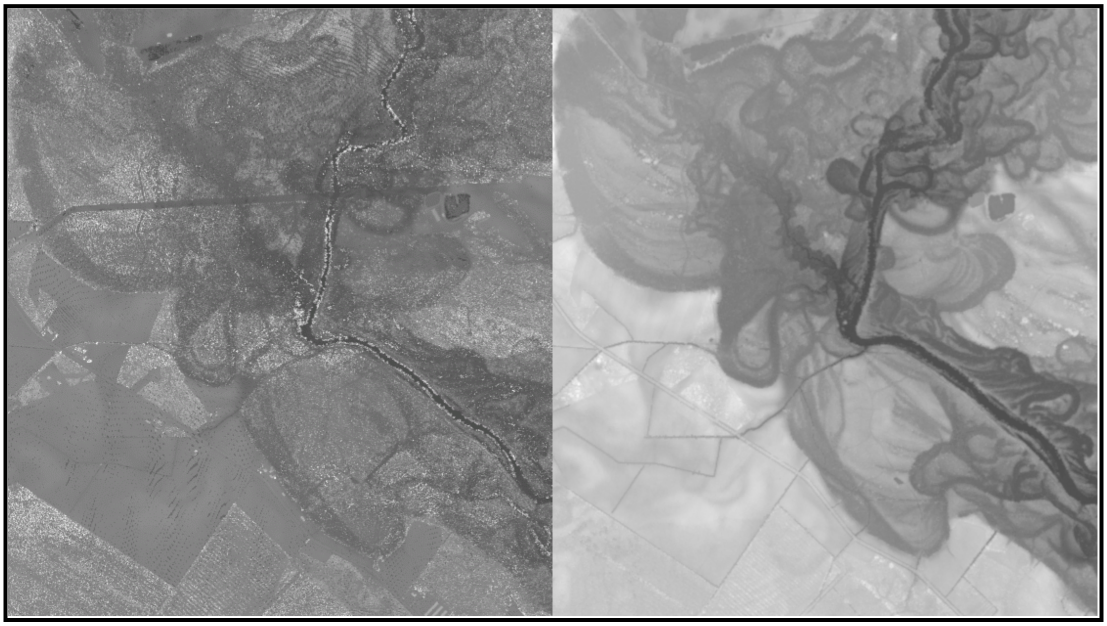

Figure 11 — Digital Terrain Model from LIDAR

To determine the LAG and HAG, CCS can determine heights from the last LIDAR returns in the set of building boundary pixels that are adjacent to the building. A first approximation of the LAG = LAG_1: minimal elevation value from pixels surrounding the building. The first approximation of the HAG = HAG_1: maximal elevation value from pixels defining the building boundary (see Figure12). Comparing LAG_1 and HAG_1 with control data, LAG_C and HAG_C shows that, in most cases, LAG_C is slightly higher than the first approximation, LAG_1, and that first approximation can be considered the lower limit of the actual LAG. In most cases, the actual HAG is slightly lower than the first approximation, HAG_1 that can be considered as the upper limit of the actual HAG.

The difference between the actual LAG and LAG_1 is a function of slope of the ground surface around the home and the accuracy of LIDAR measurements. The equation LAG_2 below was used for calculating a second approximation:

LAG_2 = LAG_1 + K*(Size_of_pixel)/2
K is a Slope Coefficient = tangent (Alpha);
Alpha is an angle that is close to the surface inclination around the home.

Figure 12 illustrates the approach for determining LAG_2 by using the local slope of the ground surface around a building. For the entire project (four counties), a K value of 0.144 (8.2 degrees) was used and is an indication of the LIDAR measurement accuracy and biases. As the equation indicates, pixel size (selected based on LIDAR point density) is a significant factor in determining the LAG and HAG. For the data processed in this study, LAG_2 = LAG_1 + 1.15ft for 16-foot pixels and LAG_2 = LAG_1 + 0.288 ft for 4-foot pixels. It should be noted that the Coefficient K can be better determined using a larger set of control homes.

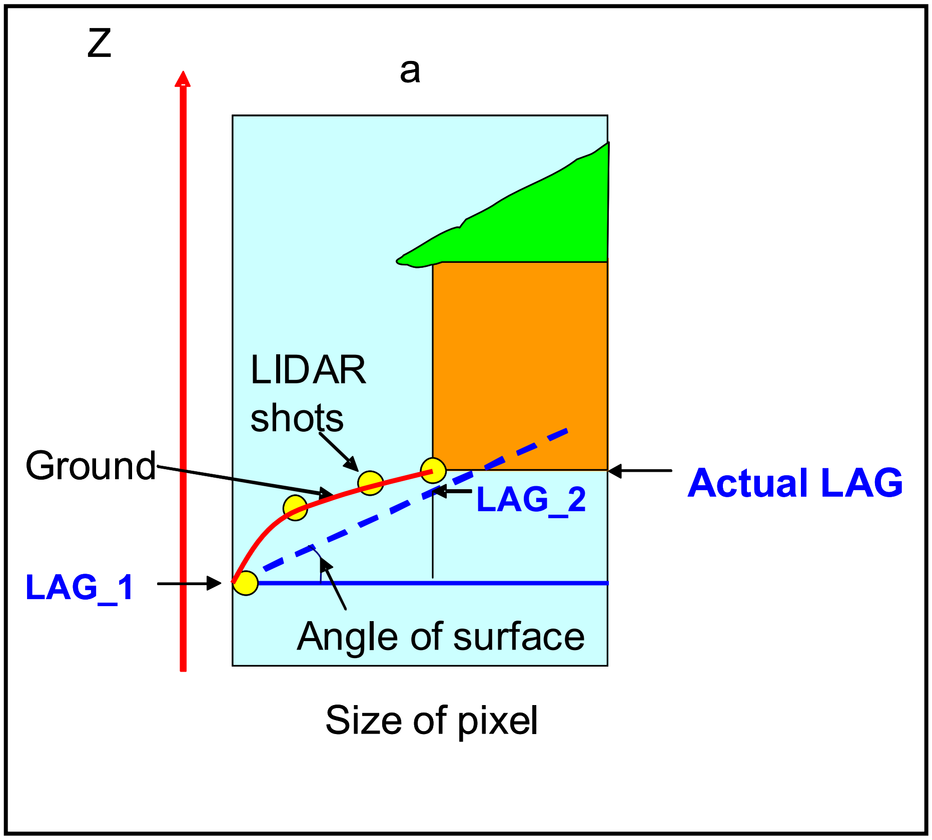

Figure 12 — Determination of LAG_2 from Local Ground Slope Estimate

The most important factor affecting the accuracy of the HAG is definitive delineation of the building boundary. Houses and other structures often have protruding and projecting features with different levels such as decks, balconies, porches, stairs and garages. In some cases, LIDAR data does not provide enough information to identify these features, which are subsequently included in the building footprint – creating differences between maximal value of the ground surface elevation near a building, HAG_1, and the actual HAG. To characterize and adjust for these potential error sources, CCS uses a second approximation of HAG, HAG_2, where we analyze the distribution of heights within the boundary and filter a few of the largest elevation values (10% - 20% of pixels). **Error! Reference source not found.**Figure 13 illustrates this principal. As with improving the accuracy of the LAG determination, applying a larger set of control data will improve the results for HAG calculations.

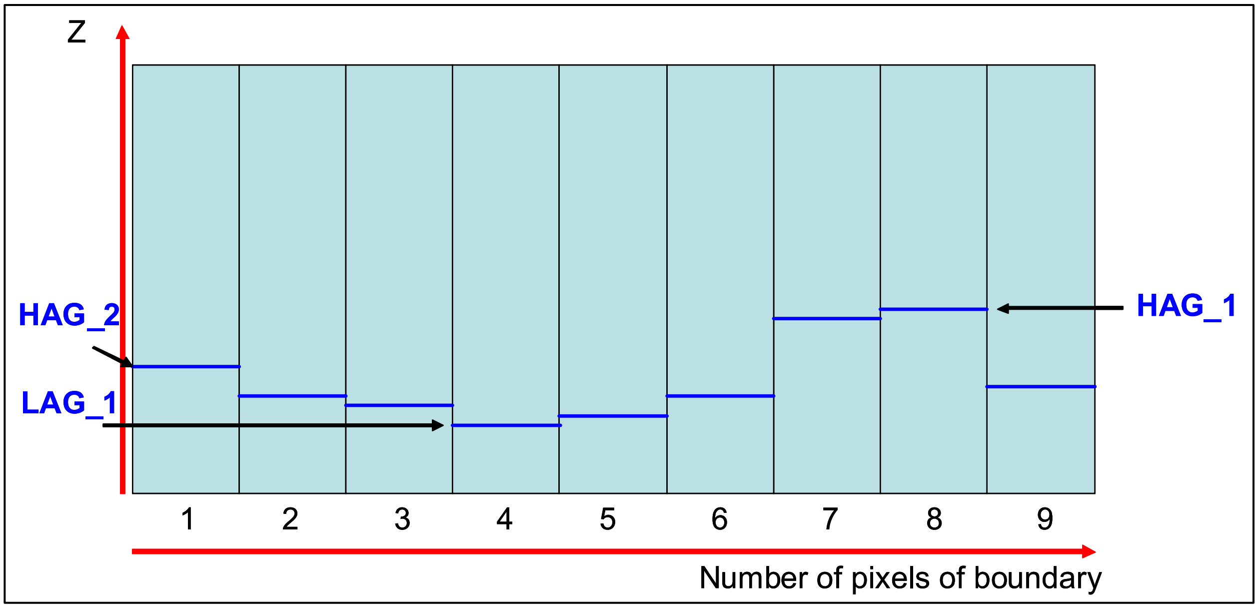

Figure 13 — HAG Corrections using Building Boundary

5.2 Calculating the TBF

LIDAR is an optical technology and does not penetrate the solid surfaces of a building; therefore, CCS cannot directly measure the TBF elevation. CCS also cannot directly determine whether a basement is finished and used as living floor. However, LIDAR data does provide sufficient information, in many cases, for estimating the TBF elevation using information derived directly and indirectly. Direct derivation of the TBF elevation relies on elevation measurements from building features indicating an entrance such as decks and porches. Indirect derivation of the TBF is based on inferences made from LAG, HAG and other building features like roofs.

For indirect derivation of the TBF, CCS uses the LAG and HAG as the primary data sources for determining the elevation of the TBF in conjunction with building roof height above ground (maximum and average) and the building size. The building roof height and size are easily calculated, if CCS has determined, with high confidence, all pixels defining the building footprint and the distribution of elevation measurements within the footprint. In some instances, elevation measurements are affected by returns from overhanging trees, and these values must be filtered before determining the maximum and average building heights. Figure 14 shows a 3-D rendering of a building, the LAG and HAG depicted as the lower line, and the TBF depicted as the upper line. To indirectly derive the TBF for the building shown, CCS used a simple rule that estimates the TBF = LAG + 4 feet (for a high building: maximal relative roof height greater than 20 feet above ground) where TBF must be higher than HAG. For small homes with maximal relative height of roof less than 20 feet above ground, CCS estimates TBF = HAG.

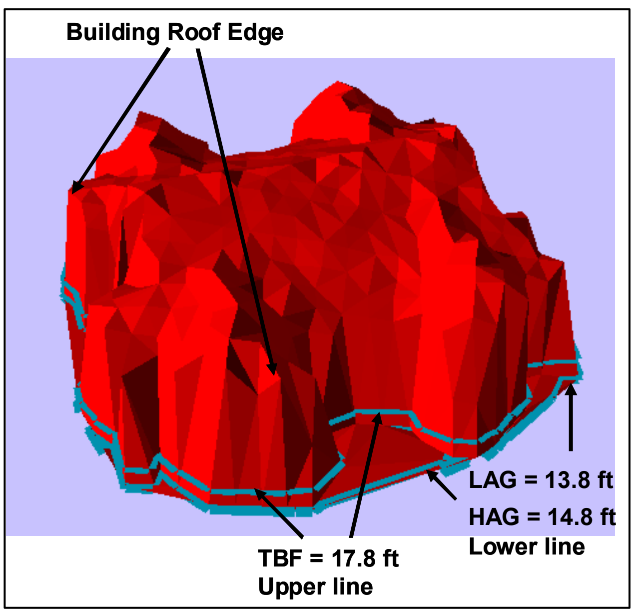

Figure 14 — 3D shape of building N 56 from tile 2056_144 (Beaufort County, SC, 4-foot pixel)

CCS can improve the TBF elevation estimate by further investigating detailed information related to the building's roof profile and features. For example, Figure 15 shows a distribution of elevation measurements in an area measuring 27 x 27 pixels around building # 56 from tile 2056_144 (Beaufort County, SC). The values for LAG (13.84 ft) and HAG (14.8 ft) have good agreement with the Peak of Ground

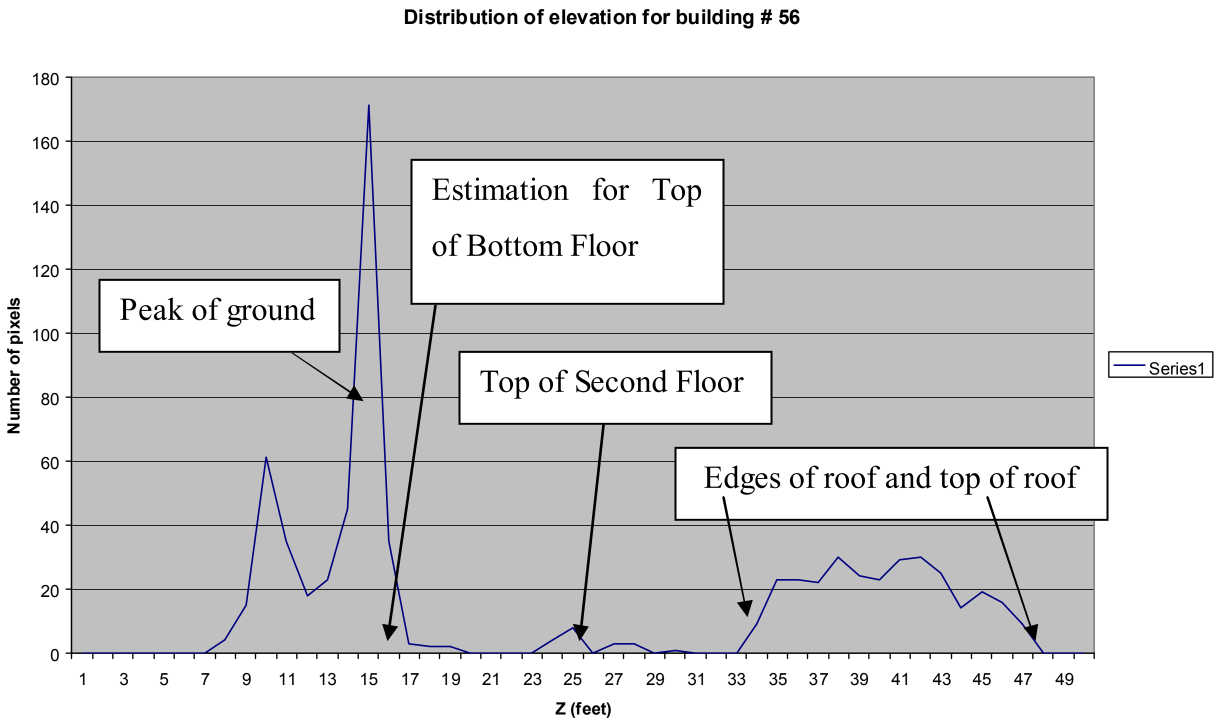

Figure 15 — Distribution of Elevation Data in and Around Building #56

measurements, and the elevation of the roof edge is approximately 34 ft. If CCS can consider the roof edge as the ceiling of the second floor/story and the height of each building floor/story is 8 to 9 ft, CCS can estimate the top of the second floor as 25 to 26 ft (34 ft – 8 to 9 ft). In addition, Figure 15 also shows that there are more than 10 LIDAR returns from a building feature at 25 ft. Since these 10 LIDAR returns are likely from a 2nd-story balcony, it adds additional confidence to CCS' estimate. By subtracting another 8 - 9 ft for the height of the first floor ceiling, CCS arrives at an estimate for the TBF elevation between 16 and 17 ft. This value is slightly greater than the HAG calculation (14.8 ft) and slightly less than the TBF value derived indirectly from the LAG (17.84 ft). These results show that the TBF elevation estimate indirectly derived from the LAG and HAG provides reasonably good accuracy of approximately 1 foot.

To employ this technique, a set of rules for indirect derivation of TBF elevations must be specified for different types of buildings and varying levels/densities of foliage obscurants. Figure 16 shows the general distribution of building roof heights for 1,971 buildings in Maryland. These 1,971 buildings were grouped by structure height: 1) 18 - 20 ft (single-level homes); 2) 24 - 25 ft (two-level homes); and 3) 31 - 34 ft (three-level homes). The roof height for garages and other small structures in this dataset range from 10 to 13 ft, and multiple-story buildings ranged from 37 ft to nearly 100 ft.

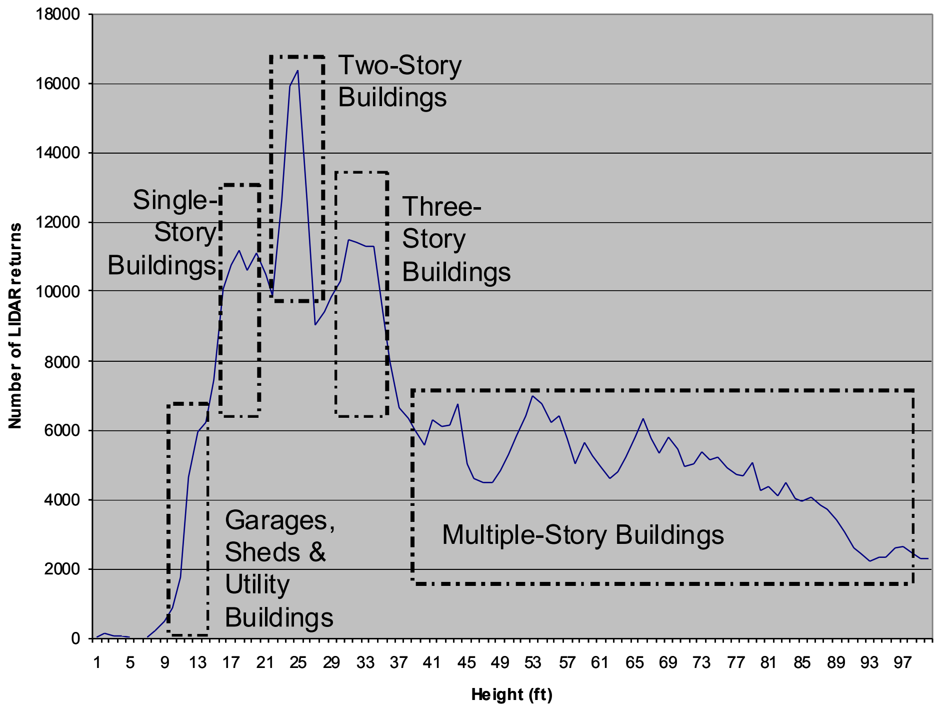

Figure16 — Roof Elevations for 1971 Buildings in Prince Georges County, Maryland

To improve the calculation of the TBF elevations CCS considers direct methods using information about building features such as the presence of decks and balconies. Figure 17 shows details of a building that includes a second floor deck or balcony. If CCS can accurately and reliably determine the presence of these features, it provides a robust and complimentary means for improving the TBF elevation calculations because decks and balconies are typically at the same elevation as the building's first or second floor.

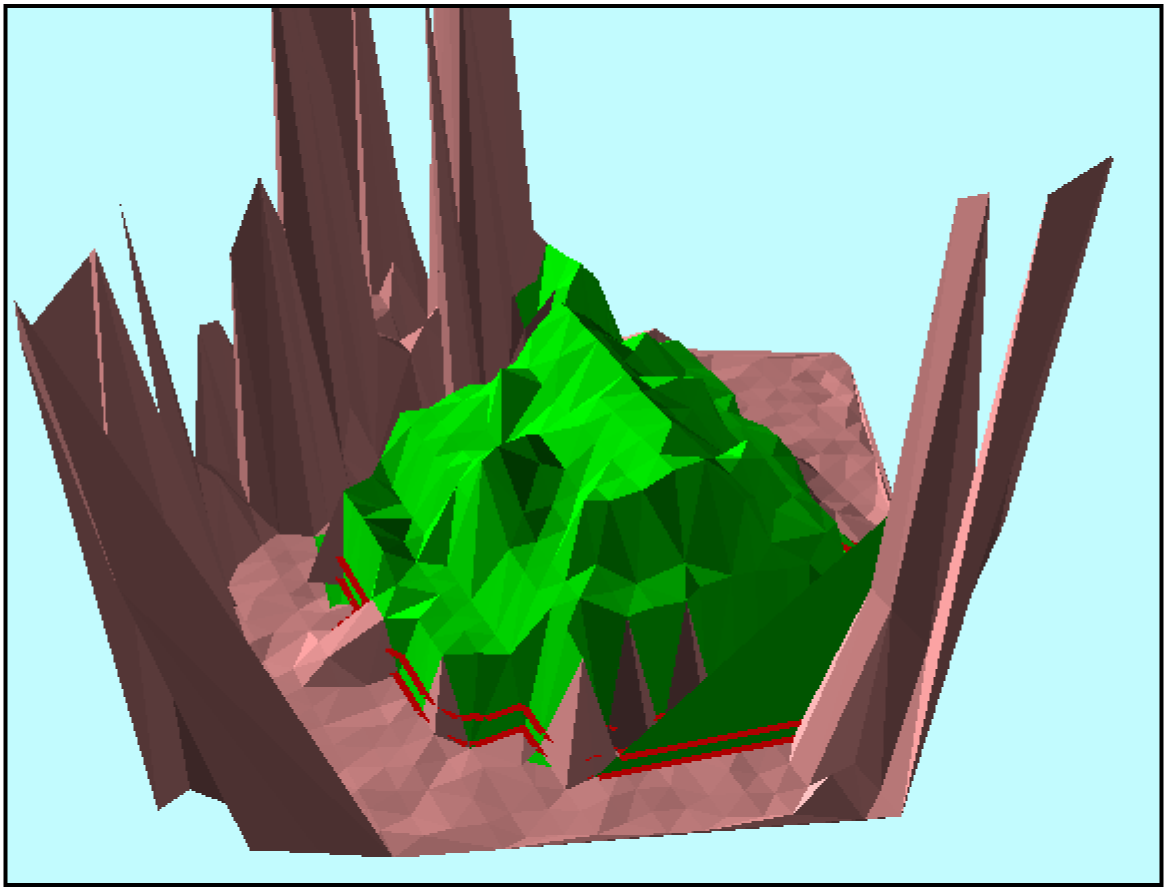

Figure 17 — Building # 101 (tile 2068_140, Beaufort County, SC) with Second-floor Balcony/Deck

Accurately determining the presence of a bottom-floor deck requires detailed analysis of elevation measurements in and around the buildings. Figure 18 shows three residential buildings with decks of varying size and shape. Analyzing the elevation measurements, CCS determines the presence of decks based on the small variation in elevation across a surface or area.

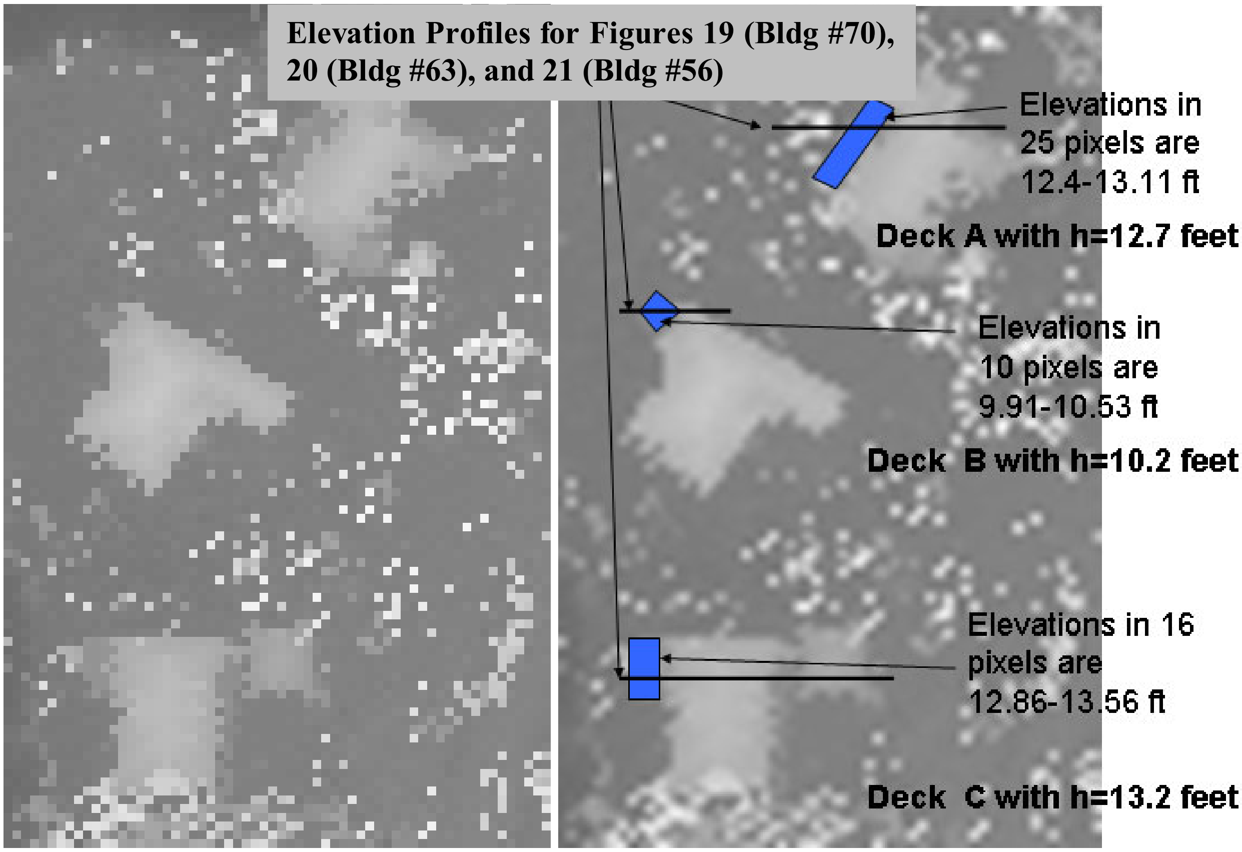

Figure 18 — Presence of Decks and Balconies Adjacent to Buildings and Homes

In Figure 18, CCS has identified three residential homes with first-story (bottom floor) decks (Beaufort County, SC (tile 2040_180)). In the left panel, Z_minimal data from last LIDAR returns is shown. In the right panel, decks are identified with lines identifying elevation profiles that are depicted in Figures 19 through 21 (footprints and boundaries for these buildings are shown in Figure 8). In Figure 8, the building footprints do not include decks for the upper two buildings (A and B). The footprint for the bottom building, C, includes a relatively high deck, but does not include a relatively small garage, separated from the building. To determine the elevations of decks, CCS assesses specific elevation profiles such as those depicted in Figures 19, 20 and 21. Unfortunately, the number of buildings with first-story decks is limited, therefore, limiting the application of this technique as a sole method for indirect derivation of the TBF elevations.

When CCS combines the direct derivation techniques with the indirect derivation, we achieve good results with broad application to a wide variety of building elevation profiles.

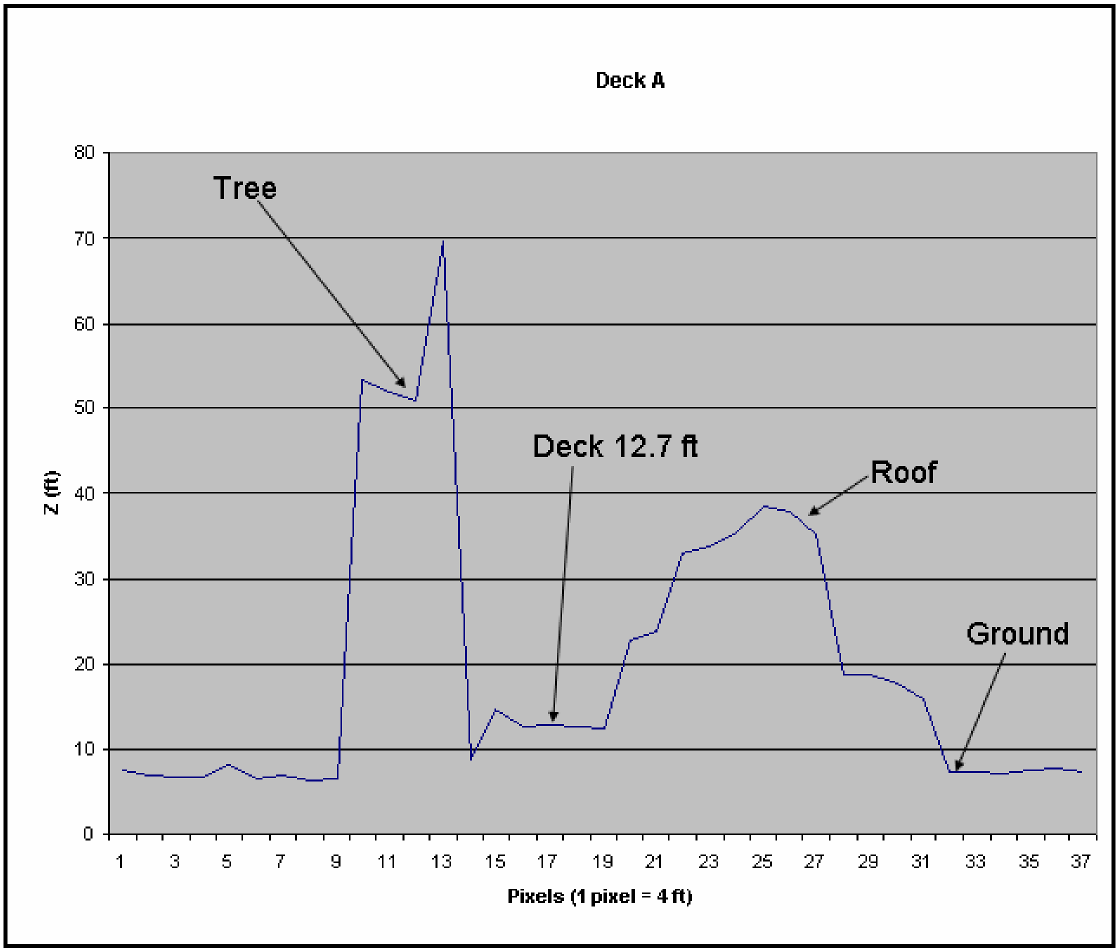

Figure 19 — Profile of Elevation for Building # 70 (tile 2040_180).

In Figure 19, CCS determines the deck elevation of 12.7 ft. Comparing this value with results from the indirect derivation using the LAG = 6.85 ft, HAG = 12.6 ft; TBF = 12.6 ft, CCS shows very good results. CCS further confirms the TBF calculation in Figure 19 by assessing the roof features. As can be seen, there is a 10 ft difference between the roof and deck. This offset indicates the top of the second floor. The second elevation offset (20 ft above deck) shows the roof edge and likely the ceiling of the second floor.

The example shown in Figure 20 also yields very good results. The deck elevation is 10.2 ft, and is very close to the indirect derivation for the TBF elevation of 10.62 ft using a LAG = 6.62 ft and a HAG = 8.33 ft.

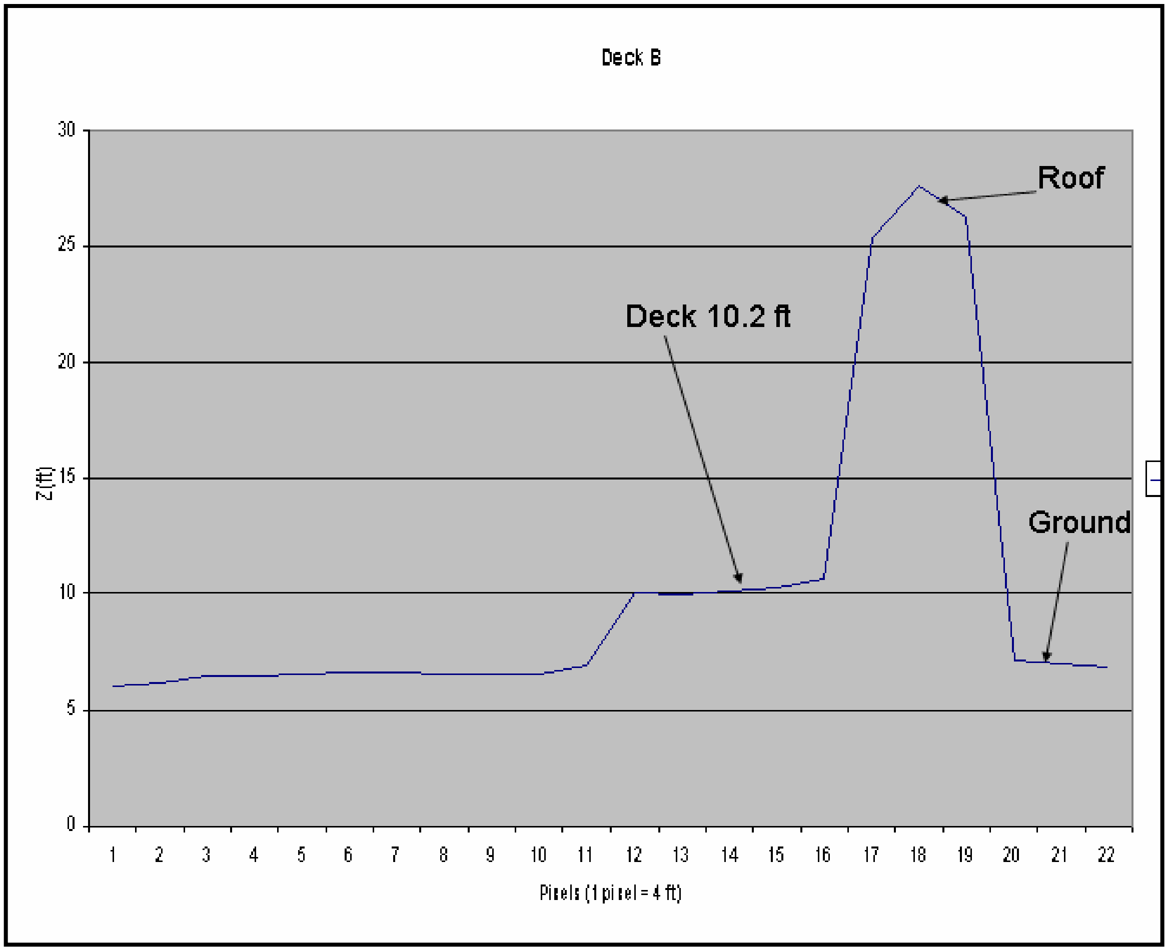

Figure 20 — Profile of elevation for home # 63 (tile 2040_180)

The elevation profile of building # 56 (tile 2040_180) in Figure 21 shows the deck height of 13.2 ft. In this particular case, deck is high, which resulted in the 2.5 ft difference with an indirectly determined TBF of 10.69 ft using a LAG = 6.69 ft and HAG = 7.90 ft.

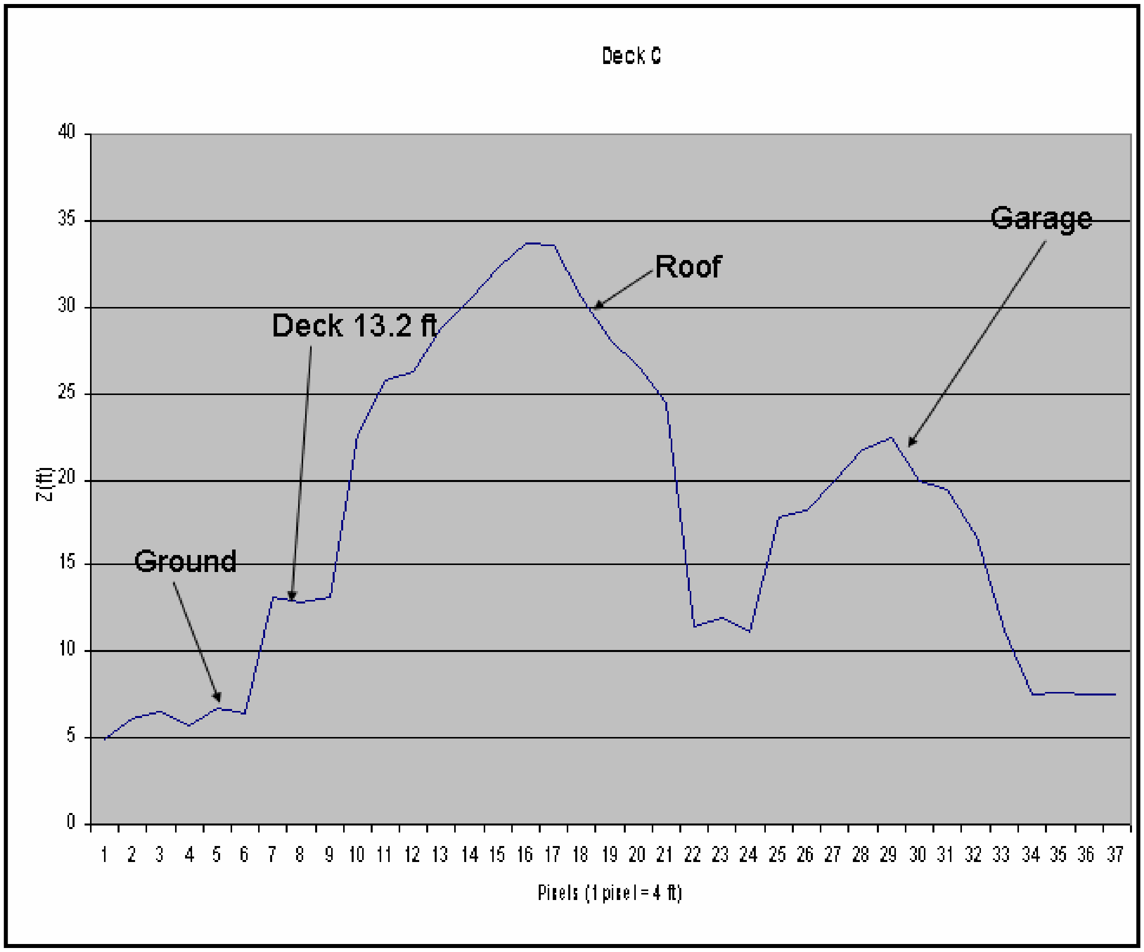

Figure 21 — Elevation Profile of Building # 56 (tile 2040_180)

6 Technical Challenges and Capabilities Associated with using LIDAR

The greatest advantage of using LIDAR over traditional methods is the ability to automatically and efficiently extract buildings using intelligent software. Since nearly all of the analysis is performed using a computer, building and terrain extraction from LIDAR data is quite fast: processing time for one tile (1 square km) that includes 100 to 1000 buildings is just a few minutes after the software parameters and extraction criteria are defined. Also, the use of intelligent software allows CCS to quickly prepare the data for manual checking, human intervention when the software encounters a unique scenario, and data quality assurance.

LIDAR systems can be an effective means for determining surface and terrain features with a high level of accuracy. As with most tools and instruments, the utility of LIDAR is highly dependent on system parameters, operating procedures and the algorithms and software used to process the collected data. The following paragraphs describe technical challenges associated with using LIDAR to determine LAG, HAG and TBF. These challenges are grouped into two major categories: 1) data collection, and 2) data processing and interpretation.

Data Collection

All LIDAR systems do not function or perform the same, nor do they provide the same information content and quality of data. A discussion of operating parameters (i.e., laser pulse rate, scanning angle, etc.) for a LIDAR system is outside the scope of this project; however, there are a set of data parameters that can be specified for all LIDAR data collections. The first of these parameters is *holidays* – areas where no data was collected or has been corrupted. The presence of holidays in the data forces interpolation during processing and feature extraction, which degrades accuracy calculations and can cause a building or feature to be omitted from the dataset.

Point data density is another significant driver in producing quality results. The denser the data, the greater accuracy can be achieved for DTM, LAG, HAG, and TBF determinations and the finer resolution for extracting object features. The content of the data also plays an important role in the ability to extract critical information. Data content is a function of the LIDAR system design, which determined the capability of the LIDAR system to take intensity measurements, capture multiple returns, filter and compensate for instrument noise, and correct biases in the data for sensor position and attitude. The data content, quality and operating environment affect CCS' ability to process the data, the algorithms applied and the consistency of results. The following section describes the challenges directly related to processing collected LIDAR data.

Data Processing and Interpretation

The selection of pixel size (influenced by data density) plays a critical role in feature extraction, DTM generation, and resolving and discriminating objects on the ground. Figure 22 illustrates the affect of pixel size on the ability to extract buildings. Panel “a” shows a plot of Z_maximal and Panel "b" shows a plot of Z_minimal. Panel "c" is a pixel map of the extracted buildings. Note that buildings extracted using Z_minimal from the last returns are smaller than the actual buildings by up to one pixel on each side of the buildings. As result, the processing of LIDAR data with a large pixel (18 ft) can result in small buildings (< 36 ft in width) being omitted. In addition, some building features are filtered as noise.

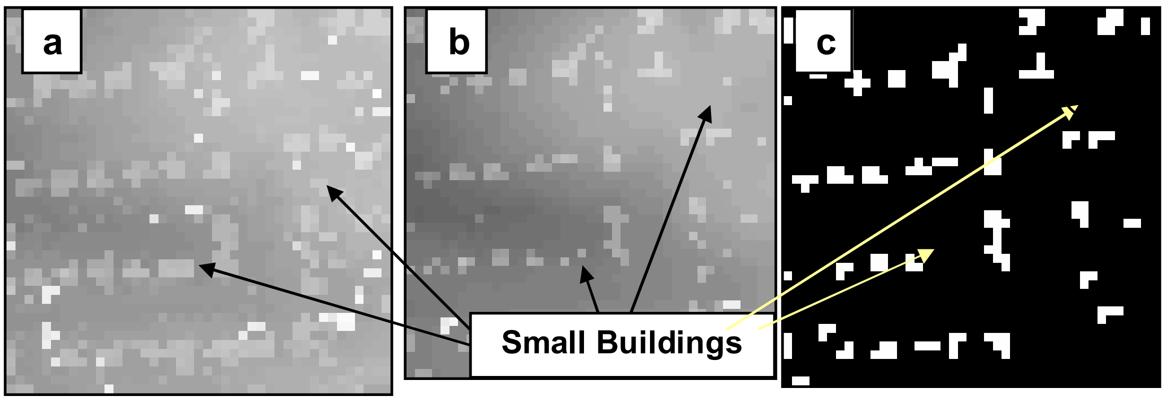

Figure 22 — Small Buildings Lost in Extraction Process using Large Pixels (16 ft)

As stated in Section 5, developing a universal set of building extraction criteria and rules is not feasible, which creates several limitations when considering a fully automated process. The following bullets are examples of unique situations, where human intervention is necessary to achieve the desired results:

- Typically, buildings are smaller than the tile size. Large structures such as the main terminal of Logan Airport (Boston, MA) are nearly 1 km long and do not satisfy this criteria. If the threshold criteria for building size were increased to account for these large buildings, other large objects such as a city block or island would be extracted as a building – creating several false extractions.

- Another difficult situation involves multilevel large parking garages that have exterior ramps leading from the upper levels to the ground. These types of structures can not be automatically extracted using the current software because the ramp has a gradual include that does not meet elevation gradient criteria, and there is not clear differentiation between the ground surfaces. Figure 23 illustrates this situation that often occurs in other similar cases such as rail stations and airports that have gradually inclining access ramps.

- Sometimes buildings have a very long, narrow shape (i.e., block of town homes) and the software considers such objects as a non-building due to its similarities with bridges or dense lines of trees.

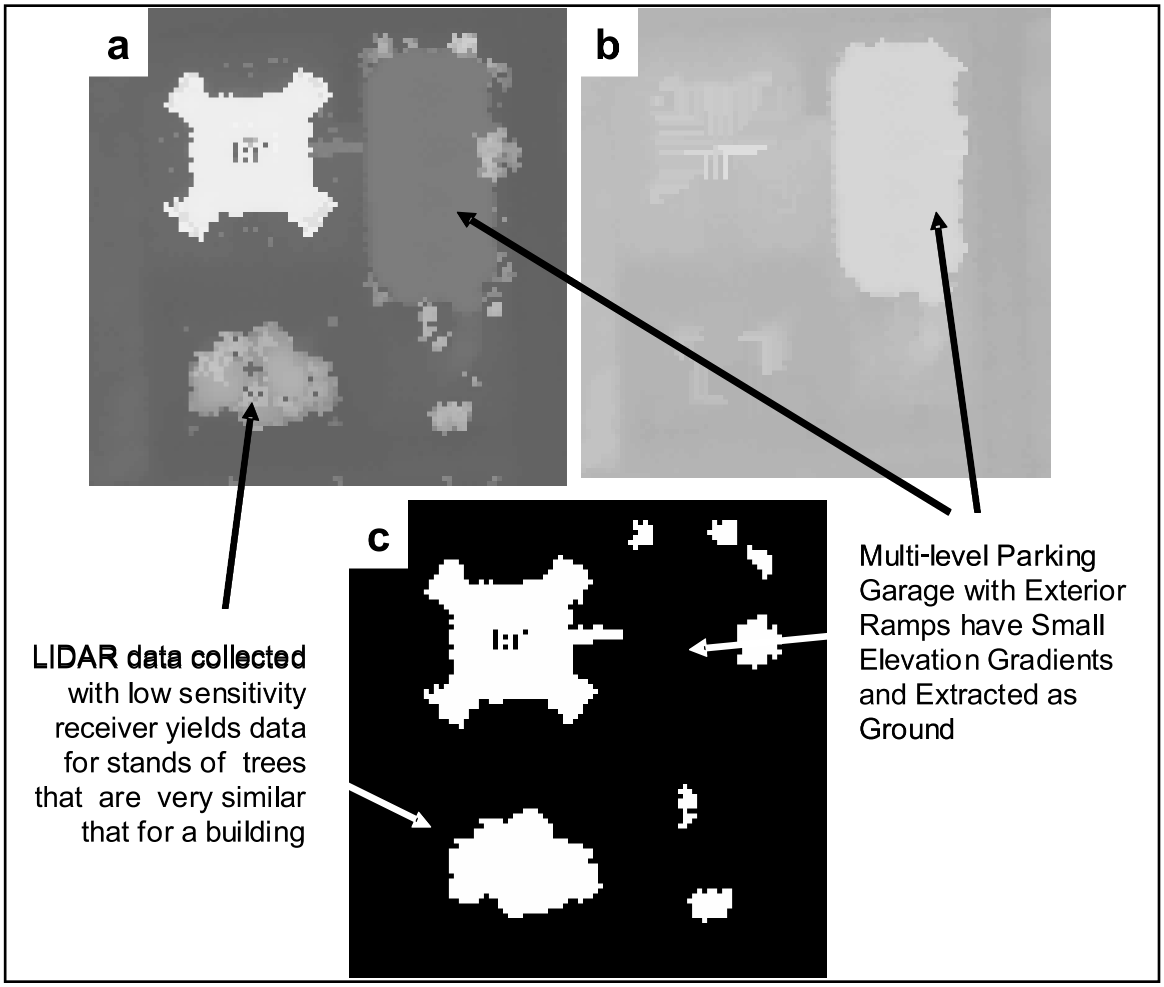

Figure 23 — Scenarios Affecting Automated Building Extraction

LIDAR Data Collected for Harris County (5 ft pixels)

- Small buildings and dense clusters of trees sometimes have very similar parameters, see Figure 24. One key challenge for automated building extraction is the merging of buildings that are very close together and are co-located with dense trees. Several LIDAR systems do not provide good penetration of the foliage, which greatly affect CCS' ability to achieve quality results. Figure 24 shows a typical sample of such LIDAR data with good statistics but bad penetration of the foliage. This type of data requires special attention and custom filtering algorithms; however, even the most intelligent software is limited to the quality of the information provided. The best way to avoid the problem is to use LIDAR equipment that can achieve good foliage penetration and collect the LIDAR data after the trees have dropped their leaves.

- Another challenge of processing LIDAR data is associated with a limited field of view; CCS software currently analyzes objects within a single tile (data set for an area). A highway in the corner of a tile sometimes has very similar features to a part of a building. This is not just a limitation of software, a person could also not be able to discriminate or identify the same object. The solution would be to compare this tile with other adjacent tiles (expanded field of view) to see/analyze the surrounding area and the entire set of object features. Figure 25 shows an example of the limitations of analyzing a single tile and the results of an expanded field of view.

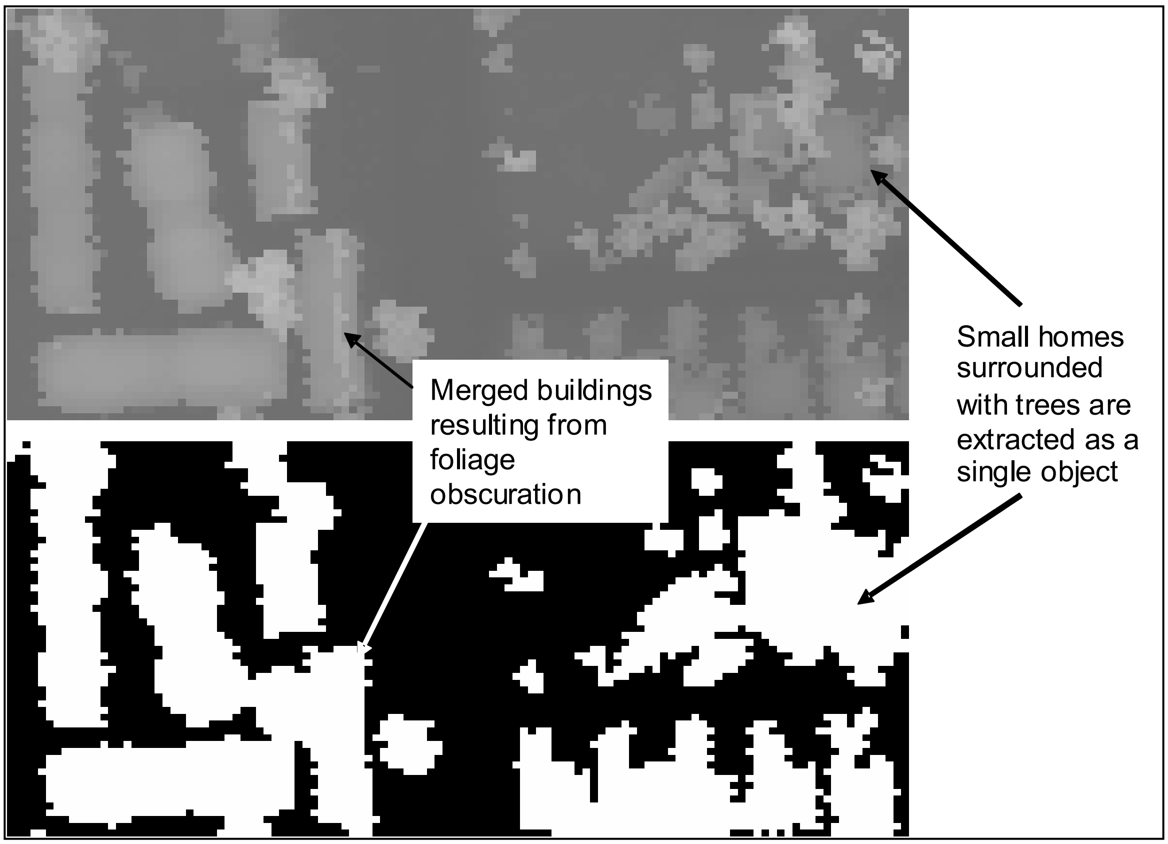

Figure 24 — Effects of Dense Foliage on Building Extraction

As stated earlier, the quality of building extraction is a strong function of the quality of the LIDAR measurements. Building extraction quality can range from 50% to 99.5% as a result. Central issues for building extraction include: 1) penetration of laser beam in foliage or trees, 2) statistics (density and spacing) of LIDAR shots, which determine the size of the minimal possible pixel, and 3) interaction of the laser beam with specific buildings and their materials. Items #1 and #2 have been discussed throughout this report. Item #3, reflective and absorption properties of building materials, also affect the ability to process LIDAR data. Buildings with very dark or transparent roofs, typically tar and asphalt or glass, do not reflect the laser energy and buildings can be missed during processing. Some examples are shown below in Figure 25.

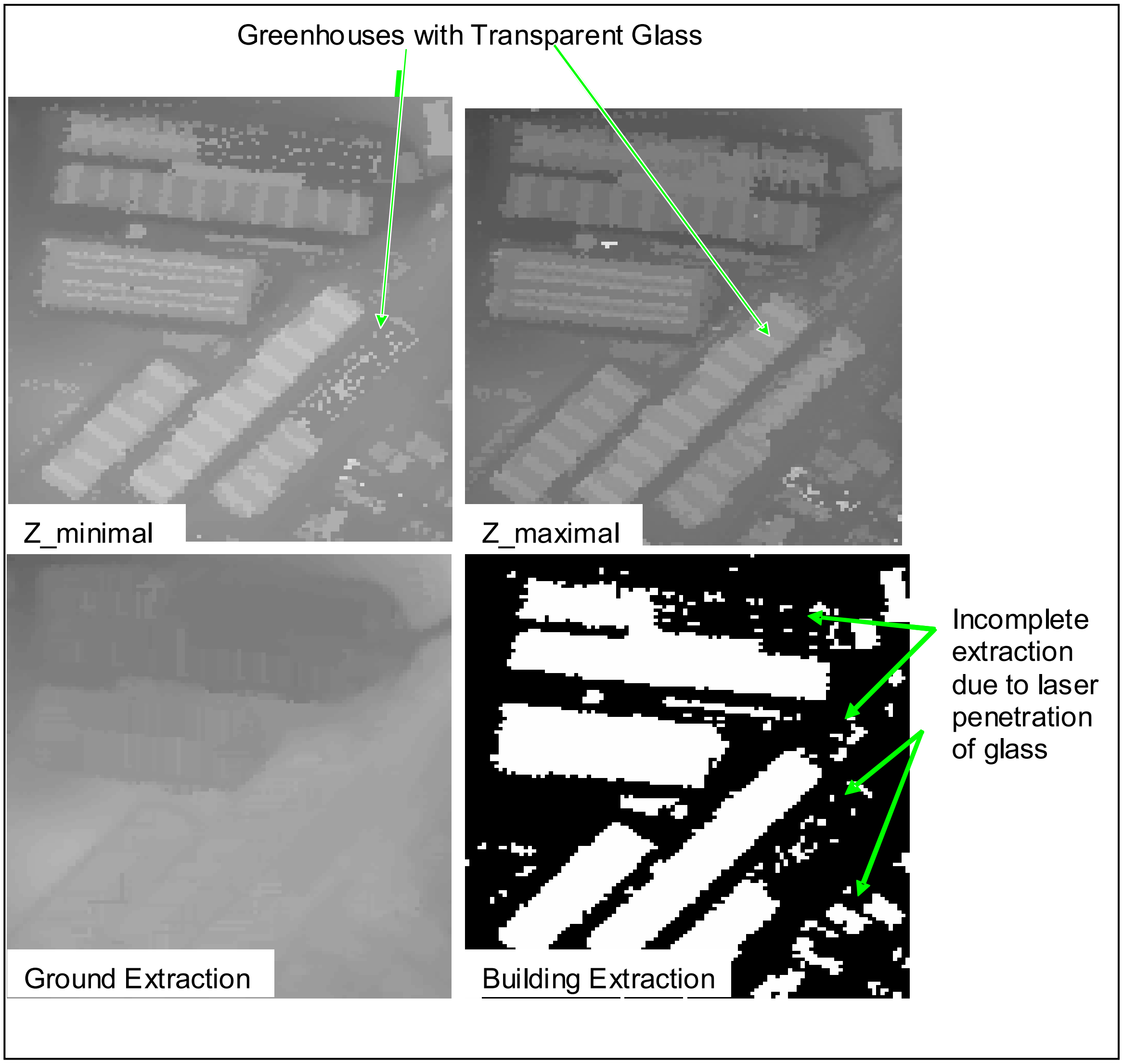

Figure 25 — Building Material Affect on Building Extraction