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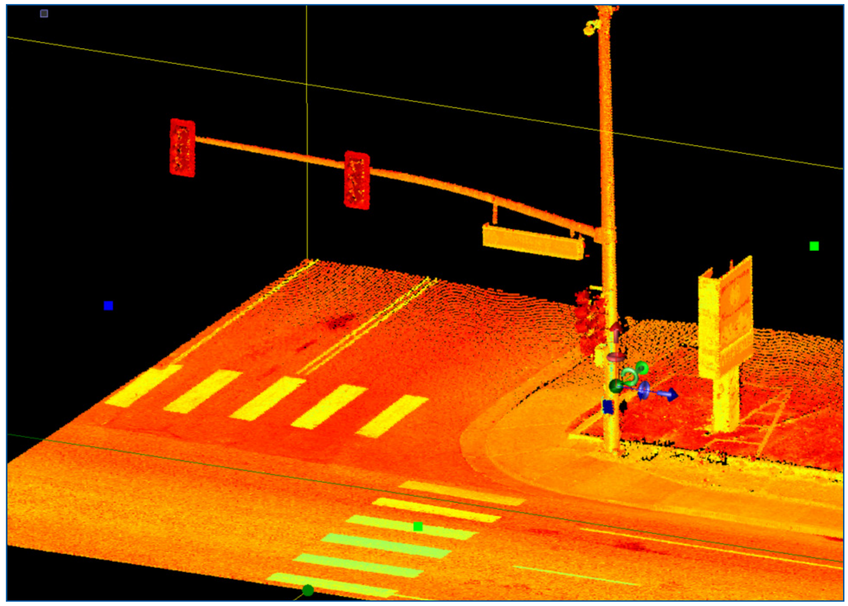
A LiDAR-Based Approach to Quantitatively Assessing Streetscapes



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This project investigates objective methods to extract streetscape features with two different classes of Light Detection and Ranging (LiDAR) processed with 3D volumetric pixels (voxels). Furthermore, this work introduces new methods for creating comprehensive streetscape descriptive statistics from LiDAR data and processed voxel data.

The first part tests the use of USGS Quality Level 1 (QL1) LiDAR data to measure street trees. In addition to street trees and buildings, which were detectable with lower-quality QL2 LiDAR data, an analyst can also legitimately extract and statistically quantify walls, fences, landscape vegetation, light posts, traffic lights, power poles, power lines, street signs, and miscellaneous street furniture.

The second part investigates high-density mobile LiDAR dataset. This facilitated our ability to compartmentalize streetscapes into smaller voxels and, in turn, to measure and quantify signage, signals, light/lampposts, street furniture, building window proportions, awnings, and enclosed courtyard restaurants.

Our results suggest that mobile LiDAR could supplement or replace conventional audit-based streetscape measuring that urban planners currently use to measure streetscapes. The output of such data collection efforts could help improve transportation studies that consider outcomes such as walkability or safety.

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ABSTRACT

Over a century of research suggests that the size and spatial location of various streetscape features impacts outcomes such as walkability, livability, and road safety. Current streetscape feature measuring/mapping techniques are limited to subjective audit-based methods, crude feature counts, or simple 2D geographic information system (GIS) processing of roadside features. This project investigates objective methods to extract streetscape features with three different classes of light detection and ranging (LiDAR) processed with 3D volumetric pixels (voxels). Furthermore, this work introduces new methods for creating comprehensive streetscape descriptive statistics from LiDAR data and processed voxel data.

As the United States Geological Survey (USGS) embarks on a national LiDAR database, with the goal of collecting nationwide LiDAR data for public use, this project first investigates what streetscape features are detectable within the common USGS QL1 standards. Previous work looked at USGS QL2 LiDAR data, and the results were limited to buildings and street trees. QL1 LiDAR data, being four times denser than QL2 data, results suggest that many more streetscape features are detectable. Several streetscape areas with QL1 coverage in Las Vegas, NV, were processed and analyzed. In addition to street trees and buildings, an analyst can also legitimately extract and statistically quantify walls, fences, landscape vegetation, light posts, traffic lights, power poles, power lines, street signs, and miscellaneous street furniture. Previous streetscape-based studies that utilized remote sensing or GIS data acknowledged the importance of these features, yet concluded they were too small to extract with conventional remote sensing data and methods. Though many more features were detectable in a QL1 dataset, some of the smallest streetscape features were still not detectable and would require denser LiDAR data.

The second streetscape LiDAR dataset this project investigates is a mobile LiDAR dataset. Mobile LiDAR collects over 2,000 points per square meter, which facilitated the measuring and quantifying of features such as small landscape furniture, traffic signage, and traffic signals that were not detectable with publicly available USGS LiDAR. The results of the mobile LiDAR analysis suggest that mobile LiDAR's density allows for much smaller voxels and to thoroughly measure smaller streetscape features in 3D. This also includes street trees, light/lamp posts, street furniture, traffic and commercial signage, building window proportions, awnings, and enclosed courtyard restaurants. Moreover, mobile LiDAR's density, which is tied to the ability to quantify features into smaller voxels, facilitated the ability to objectively measure and categorize these streetscape features in walkable, downtown-like streetscapes. This ability to compartmentalize such streetscapes into smaller cubic feet voxels to measure and quantify could supplement or replace conventional audit-based streetscape measuring that urban planners currently use to measure perceptual qualities in walkable streetscapes.

The LiDAR datasets studied can measure and quantify nearly all features found in a standard streetscape. The methods presented in this report for classifying and quantifying streetscape features into voxel height zones ultimately allows for comprehensive tabular descriptive statistics to be generated for any single or multiple features within a streetscape. With LiDAR's high precision and accuracy, this project suggests that the methods discussed provide the most objective 3D spatial location of streetscape feature data, which can ultimately be applied to transportation outcome studies and studies that measure streetscape/built environment perceptual qualities.

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1. Introduction

Light detection and ranging (LiDAR) is a sophisticated aerial surveying and remote sensing technology that is becoming widely available for public use. In the early 2000s, remote sensing technologies began to receive recognition in the greater transportation research community when the Transportation Research Board held three annual seminars as part of its inaugural National Consortium on Remote Sensing (McCord et al. 2001). Since then, remote sensing technologies are slowly becoming more mainstream in transportation research, as their accuracy and ability to identify and extract discrete features have improved. With its high precision and high-density point cloud data, aerial LiDAR has evolved to become the first remote sensing technology to achieve survey quality mapping (Csanyi and Toth 2013). As a result, LiDAR has the potential to measure quantitatively and map various features within streetscapes and the built environment in general.

For transportation researchers, it is important to distinguish between discrete collection LiDAR and navigational LiDAR. Navigational LiDAR is becoming mainstream in the transportation sector with the rise of autonomous vehicles and advances with real-time object detection (Funke et al. 2017). Discrete LiDAR, on the other hand, is focused on collecting and storing LiDAR data for analysis. The United States Geological Survey (USGS) is currently leading a multi-million-dollar annual investment into acquiring discrete LiDAR throughout the United States. Called the 3D Elevation Program (3DEP), these data are primarily collected at quality level (QL) 2 and QL1 standards. QL2 LiDAR data have a nominal point spacing of around 0.5 m, or a point density of around two points per square meter. QL1 is four times denser with a point density of around eight points per square meter, as shown in Figure 1.1. With flood risk management stated as the most important beneficiary of the 3DEP program, the USGS identified 27 other business uses to justify the program economically (Dewberry 2012). 3DEP data are currently in the early stages of being applied to fundamental transportation research.

Golombek and Marshall (Golombek and Marshall 2019) explored the limits of QL2 data by designating streetscapes in three-dimensional (3D) pixels—better known as “voxel” grids—and found that QL2 data for measuring streetscapes are primarily limited to buildings and street trees. Since understanding the impacts of street trees and other clear zone objects is an important transportation topic, that study also discussed how 3D measurement of street trees widely differs from traditional 2D-derived canopy data. Specifically, the vertical components of the street trees were defined by the vertical voxel zone or voxel interval they fell into. Though QL2 is currently the more common USGS specification, LiDAR technology is evolving rapidly, more specifically, from a point density of one point per five square meters in the mid-1990s to QL1

[1]This portion of the report has been peer-reviewed and published: Golombek, Y. and Marshall, W. “Measuring Streetscape Features with High Density Aerial LiDAR.” *Transportation Research Record* (doi.org/10.1177/0361198120944172).

standards being the norm in the near future (Abdullah 2016). With public QL1 data becoming more common and being four times denser than QL2, QL1 is expected to be able to measure discrete streetscape features objectively well beyond QL2's buildings and trees.

In relation to transportation research, finding objective methods to measure streetscapes and streetscape features is important for measuring perceptual qualities of streetscapes as well as for transportation-related outcomes such as those related to road safety. Perceptual qualities, such as "street enclosure," among many others, have long been studied and analyzed by urban planners and designers trying to understand the qualities and characteristics of streetscapes that make them more appealing and desirable. Published works on perceptual qualities began in the late 19th century with Camillo Sitte (Sitte 1889) and continued through the 20th, as Gordon Cullen (Cullen 1971), Donald Appleyard (Appleyard 1980), Anotol Rapoport (Rapoport 1990), and Henry Arnold (Arnold 1993) all produced literature addressing the importance of perceptual qualities in urban design. More recently, since around 2010, research has focused more on improving measuring techniques. The next section discusses how buildings and street trees have been measured in recent streetscape studies. Smaller and essential streetscape features —such as streetlights, signs, landscape features, and streetscape furniture— have not yet been incorporated in such studies.

In relation to road safety outcomes, conflicting research exists around the role of streetscape features. For instance with street trees, the research findings have long been contradictory over their influence on road safety outcomes (Wolf and Bratton 2006; Zeigler 1986; Dumbaugh 2005). Some studies suggest that street trees are associated with better safety outcomes (Marshall, Coppola, and Golombek 2018), while other studies find them to be hazardous (Zeigler 1986; Turner and Mansfield 1990). Aside from street trees, transportation research has also focused on how physical characteristics of other streetscape features enhance safety. Placement and characteristics of streetlights have an effect on pedestrians' perceived safety (Haans and de Kort 2012). The same is true in relation to measurements, placement, and dimensions of streetlights (Fisher 1974; Ekrias et al. 2008) as well as street sign placement for drivers (Goodenough 1976; Shoptaugh and Whitaker 1984). Along with these features, utility poles and other fixed objects in streetscapes have been shown to affect transportation outcomes (Dumbaugh 2005).

With QL1 data becoming more publicly available, the goal of this study is to determine what role LiDAR data collected at QL1 standards can play in transportation research. Specifically, this study attempts to extract and measure quantitatively the common streetscape features mentioned above, in addition to street trees and buildings common to QL2 data analysis. This study will present a comprehensive methodology for measuring 3D characteristics of streetscape features —based on voxel (3D pixel) zones—using USGS QL1 data for the purpose of compiling objective descriptive statistics of how these features are represented in 3D streetscapes. To compile descriptive statistics of where features fall from voxels, we process and compile voxel height intervals, as shown in Figure 2.1. The voxel-feature data will ultimately be converted into vector data to compile tabular descriptive statistics. If the assessment can be adequately performed with QL1 data, then it can become common practice and more widely applied in municipalities (where QL1 data already exists) and eventually in municipalities across the U.S. for assisting the assessment of 3D characteristics of features within streetscapes.

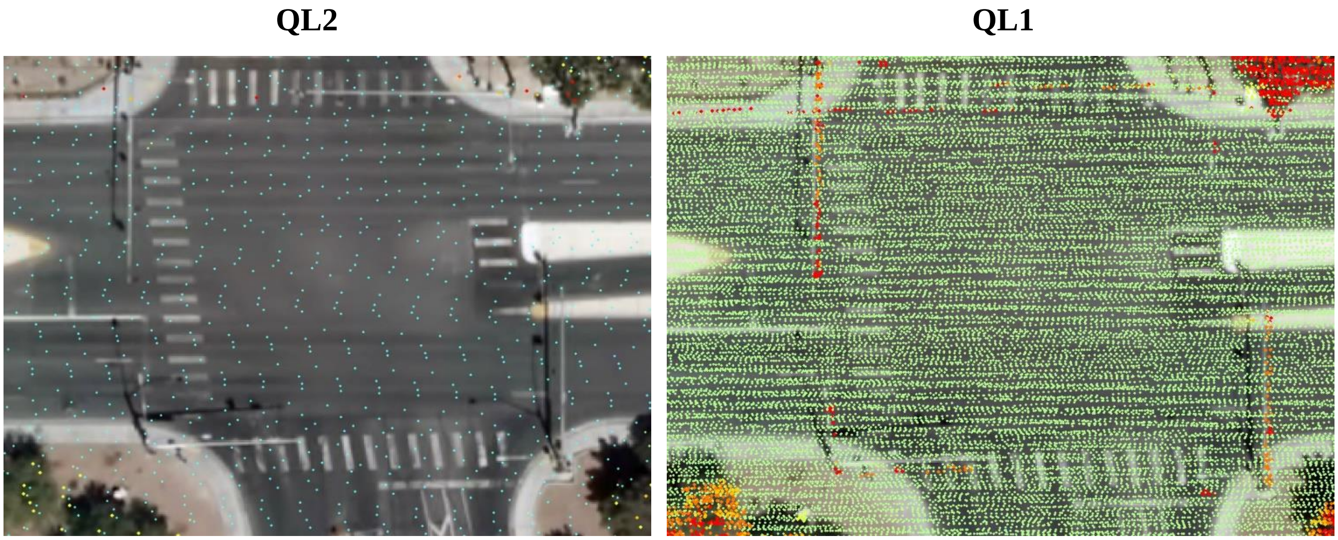

Figure 1.1 Example of LiDAR QL2 and QL1 data for the same intersection

2. Literature Review

Over the past two decades, improving remote sensing technologies and emerging geographic information systems (GIS) applications have affected transportation research in ways such as how streetscapes are measured and understood in relation to outcomes, such as livability, physical activity, and road safety. Over that time, streetscape measuring methods have evolved to become more objective.

Before implementing streetscape measuring with mapping technologies, methods were more audit-based. Ewing et al. were among the first urban design researchers to implement audit-based measurement techniques within streetscapes (Ewing et al. 2005; Ewing and Handy 2009; Ewing and Clemente 2013). These authors developed and implemented a comprehensive manual to guide field observation for quantitative measures to pair with concepts such as streetscape desirability and walkability. Brownson also compared a significant number of audit-based techniques (Brownson et al. 2009) to measure the built environment as it relates to physical activity. Brownson acknowledged that these measures are time consuming. His study listed dozens of observation-based instruments that can take up to 20 minutes per street segment to calculate for each method. According to Brownson, the auditors were often students who usually did not have a technical skillset for auditing. Yin mentioned that individuals conducting estimated measures through audits often perform subjective observations, which can be inconsistent across observers (Yin 2017).

Auditing seems to have subsided, at least to some extent, as GIS and its spatial data analytics became more mainstream. Purciel et al. attempted to implement GIS measures to offset complexities involved with manual audit-based assessments of streetscape and assessed their results against Ewing et al.'s outcomes. They used New York City to measure streetscape features and variables for five primary perceptual qualities of streetscapes: imageability, enclosure, human scale, transparency, and complexity. The data Purciel et al. used were simple 2D GIS polygon data features resulting from various public sources and tabular data. Results acknowledged correlations between GIS and observed measures that ranged from 0.28 to 0.89 (Purciel et al. 2009). This wide and varying correlation range is hard to comprehend because the GIS data and the observed measures the GIS data were weighted against contain a lot of subjectivity in the data and methods.

A study by Yin and Shiode went beyond simple GIS data and appended 3D attributes to 2D GIS features to evaluate streetscape measures related to walkability research conducted by Ewing and Handy (Ewing and Handy 2009) and Purciel et al. (Purciel et al. 2009). In Yin and Shiode's study, GIS and remotely sensed aerial photographs were utilized to extract buildings and trees, among other features. Height attributes from the assessor database gave buildings their heights, and trees were grouped into small, medium, and large categories. Yin's study built on these previous works by using remotely sensed imagery and 3D GIS to measure street-level urban design qualities objectively and test their correlation with observed data. The statistical results concluded that 3D GIS helped generate objective measures on view-related variables. Yin's data were more objective than simple 2D GIS data; yet, they were still subjective since the 3D components were simply derived from measurement extrapolations appended to 2D GIS data of features such as trees and buildings. These 3D GIS methods did, however, yield some improvements to correlations with walkability scores established by Ewing and Purciel (Yin and Shiode 2014; Yin 2017).

Harvey et al. took their objective 3D streetscape mapping techniques even further than Yin and Shiode. Harvey et al. published two research articles (Harvey et al. 2015, 2017) utilizing advanced GIS methods and high precision data (including LiDAR) to measure streetscape skeletons. In both articles, the primary focus was on the buildings surrounding the streetscapes discussed as part of the street's enclosure matrix, and the authors discussed the perceived safety of these environments. Although street trees are touched on, the authors noted that walls, fences, streetlights, and other design elements were unaccounted for because of the lack of adequate spatial data. Also, the authors noted that these features may be insignificant because they "embellish the broader streetscape already defined by buildings that dwarf them in size," alluding to their relative insignificance because of surrounding buildings (Harvey et al. 2017). It is important to note that these studies take place in high-density areas, primarily New York City, but also in Boston and Baltimore, where streetscapes are more enclosed by buildings on each side than in most other cities. The majority of U.S. urban streetscapes do not have significant buildings to fill the enclosure matrix. Therefore, the common streetscape features that are unaccounted for may be critical for mapping typical U.S. urban streetscapes since they are features of streetscape focus in the absence of buildings encroaching on roadways.

Harvey and Aultman-Hall also conducted a comprehensive study in New York City in 2015 incorporating nearly 240,000 crashes for over 75,000 road segments (Harvey and Aultman-Hall 2015). This study incorporated many variables, including LiDAR-derived 2D tree polygons, GIS building data, and cross-section width between buildings to weigh street enclosure perceptions to crash outcomes. However, this study appears to analyze 2D tree polygon coverage area only within a streetscape, neglecting LiDAR's capabilities to assess 3D tree features. For example, if two streetscapes had 15% total tree coverage, one could have significantly more tree density/biomass because the 3D characteristics are not considered. It is such characteristics that may be critical for understanding the impact of urban streetscape features on transportation-related outcomes.

The authors' recent streetscape LiDAR study (Golombek and Marshall 2019) discussed streetscape features that can be extracted from USGS QL2 data. This study determined that QL2 data are limited to extracting buildings and trees in the streetscape. Since other studies linking LiDAR building classifications with building footprints show strong correlations (J. Wang, Zeng, and Lehrbass 2012; Saraf et al. 2018), and since street trees are a significantly analyzed topic in transportation research, the study examined and found significant statistical differences between deriving 3D characteristics of trees against 2D LiDAR-derived polygons. However, QL2 data are limited in relation to usefulness for transportation-based feature extraction, as many more critical features other than buildings and trees exist in a typical streetscape environment.

Research extracting streetscape features (aside from buildings and trees) from LiDAR is limited. Recently, a cut-graph segmentation method was used with mobile LiDAR to extract urban street poles automatically, resulting in a 90% success rate (Zheng, Wang, and Xu 2017). Unfortunately, QL1 data are not nearly dense enough to apply this method, and the methods section below explains why automated processes in general are not applied to this research. Mobile LiDAR is far denser than QL2 or QL1 LiDAR, but mobile LiDAR typically requires private collection, and processing is slow and labor intensive because of its high point density. This research study attempts to analyze publicly available USGS QL1 LiDAR data to extract and measure a variety of smaller and more discrete streetscape features that could not legitimately be detected in a common QL2 dataset.

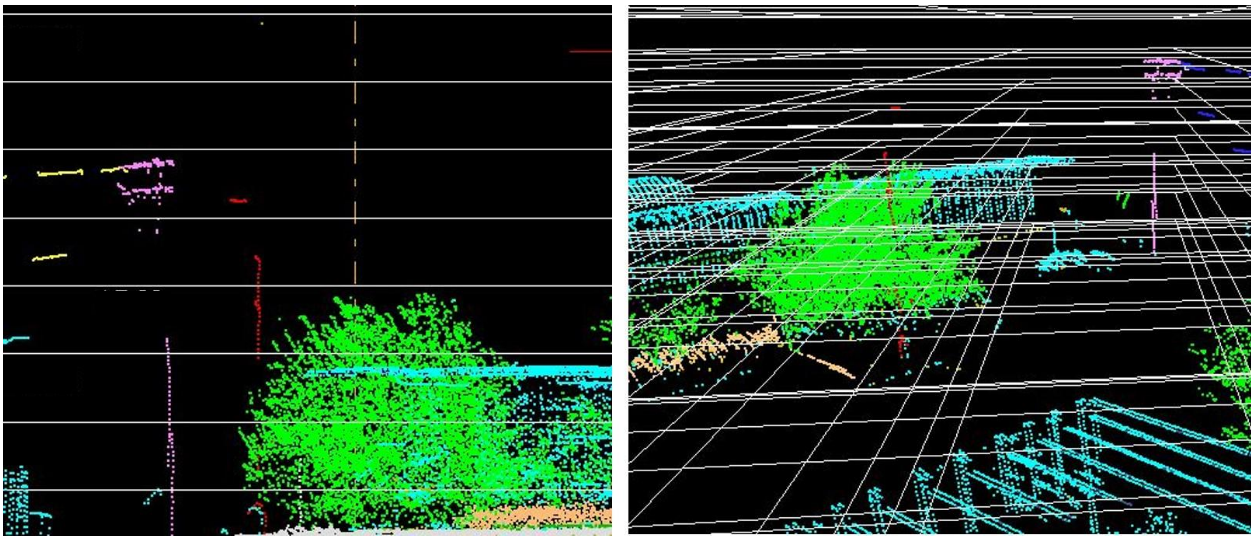

Figure 2.1 Example of voxel grid over streetscape features (left image represents a vertical view; right image represents a diagonal view)

Note: blue = buildings; green = tall vegetation; red = streetlight; pink = power pole; yellow = power lines; peach = fence

3. Data & Methods

Aside from street trees and buildings derived from QL2 LiDAR data (Golombek and Marshall 2019), other features common to typical urban streetscapes include light poles/lamp posts, power lines, landscape features, traffic signals, street signs, property walls/fences, and street furniture. Research on roadside landscape improvements has been linked to safer driving environments (Mok, Landphair, and Naderi 2006; Jody Rosenblatt Naderi 2003; Dumbaugh 2006). Quantities and positions of street lighting can also affect safety within streetscapes (Haans and de Kort 2012; Yoshiura, Fujii, and Ohta 2013). Response time to street signs affects transportation outcomes (Shoptaugh and Whitaker 1984), and measurement and location of street signs are likely correlated with response time. Roadside walls and street furniture affect various perceptual qualities when assessing streetscapes for walkability and desirability (Ewing et al. 2005; Ewing and Clemente 2013).

Harvey et al. (Harvey et al. 2015, 2017) are among the few researchers to have utilized advanced geospatial data and methods to measure streetscape features. They acknowledge, however, that publicly available remote sensing data are not advanced enough to detect these common streetscape features. Therefore, the methods presented in this study will analyze and identify approaches to mapping and measuring these distinct features that were previously cited as undetectable. In doing so, it will assess how each individual street corridor/streetscape section is statistically composed of the streetscape features the authors are trying to extract from QL1 data. Sectionalized voxel zones at specified intervals are used to understand how common streetscape features noted above can be quantified and measured in 3D. This study will show a descriptive statistics output model of these data that can be applied to transportation research studies. In geospatial terms, a voxel is a 3D pixel and will be discussed in depth later in this section. To conduct this study, an urban QL1 dataset is required.

3.1 Data

QL1 data of Las Vegas are currently publicly available via the USGS National Map website. This environment was chosen since streetscape features in urban Las Vegas, with its desert environment, appear distinct and separate from one another and will therefore provide a good baseline in relation to our ability to detect them within QL1 point cloud data. However, the large size of these datasets, which cover the area of interest (AOI), make them prone to data noise. Fortunately, USGS requires its LiDAR collection vendors to place all noise data on a separate point cloud classification layer (Hans Karl Heidemann 2018). USGS then runs internal proprietary checks to assure noise mitigation compliance. Therefore, additional noise mitigation is not necessary. The AOI is a sample section in urban Las Vegas amounting to 12 street segments, encompassing around four linear miles of streetscape, and specifically, five streetscape sample areas polygons. Six-inch aerial imagery, simultaneously collected with the LiDAR data that cover the AOI, was also used for referencing when needed.

3.2 Methods

3.2.1 Creating Streetscape Sample Areas

Since the aim is to append quantitative statistics of streetscape features within a streetscape, it is important to devise an adequate method to create individual streetscapes. Creating individual streetscape corridors means that a segment will have a cutoff, either in its center or through the intersection. A preliminary look at our sample area shows that long overhanging traffic signals and light posts may be cut off if the streetscape is divided at the intersection. Also, intersections tend to be focal areas with high activity and thus more traffic-related features. Therefore, a method to cut off the segments between the intersections rather than the middle of them is preferred for this study.

The AOI is divided into Thiessen proximal polygons (or Voronoi polygons as mathematicians call them). The ESRI ArcGIS® Thiessen polygon processing tool is used and the street intersection centroids input for the polygon center-points. Thiessen polygon datasets are mutually exclusive and non-overlapping. Thiessen polygons are used in this model because they divide the polygons (streetscapes in this case) in a clean and somewhat uniform manner and can be created with a GIS application around a designated focal point set. The intersection centers were used as centroids for this focal point set. The Thiessen/Voronoi method gives weights to high event/focal areas and is a popular model and spatial method for focusing on focal event points (Gold 1991).

Additionally, the streetscape sample areas are designed to include the full street right-of-ways that extend 10 feet to 20 feet beyond the street curb. Extending the streetscape to include these peripheral views within the streetscape is important since the majority of objects that constitute a streetscape's perceptual qualities are located off the street itself (Ewing and Clemente 2013). Furthermore, the parcel data for the AOI are joined and used to erase all non-streetscape right-of-way areas, resulting in the sample areas in Figure 3.1.

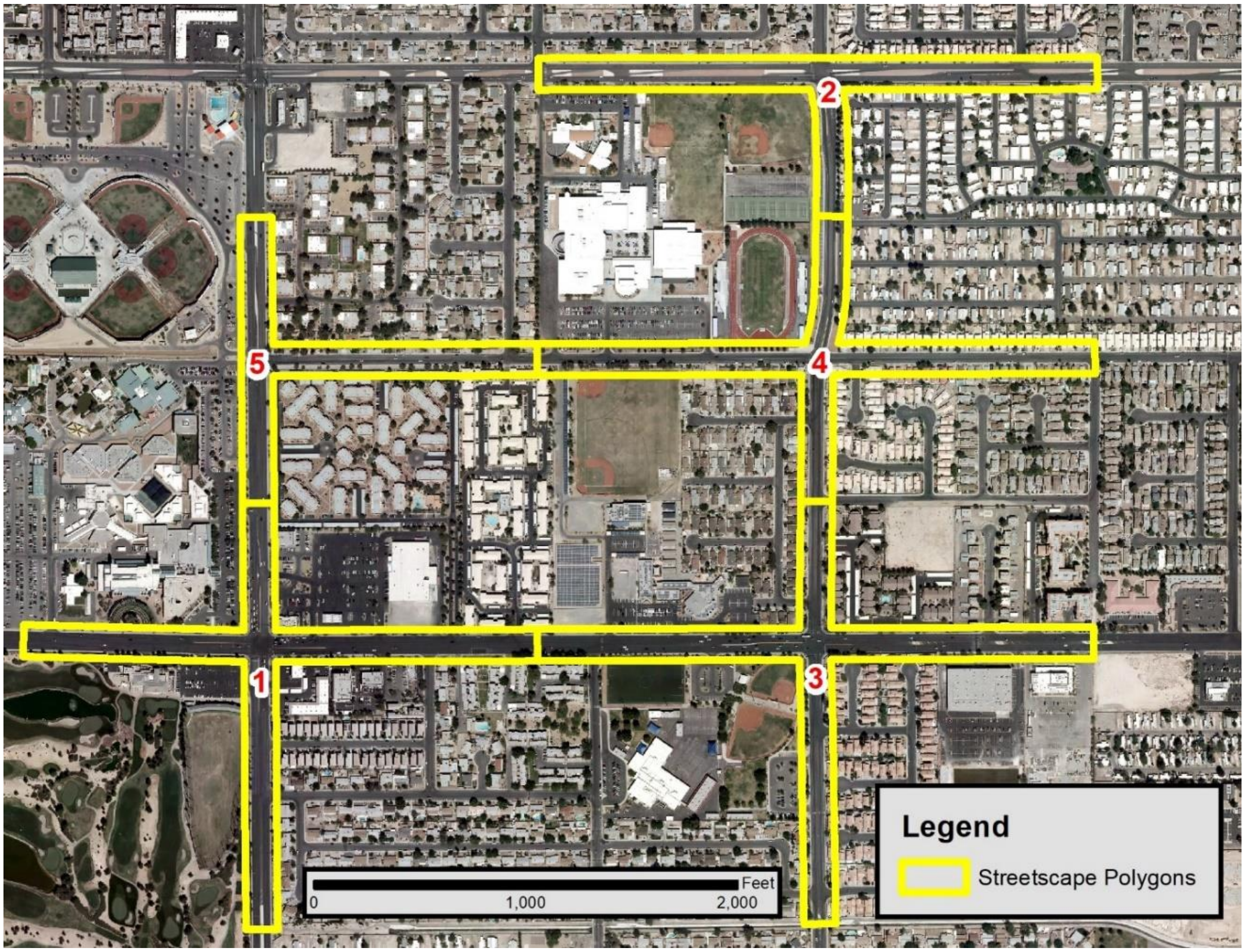

Figure 3.1 Area of interest and streetscape polygons (red numbered streetscape polygon IDs link to Tables 4.1 and 4.2)

3.2.2 Devising 3D Streetscape Extents

As mentioned, this study incorporates 3D pixels, or voxels, to quantify streetscape features. A significant component of this proposed method is voxelization of the street segments to quantify street features and understand how the features are represented in 3D space, specifically different height zones within a streetscape. As mentioned, QL1 LiDAR emits around eight survey points per square meter, so it is expected that above-ground streetscape features will absorb these points to a much higher degree than the far less dense QL2 data. This study will provide area and length statistics of discernable streetscape features within the voxel height zone in which they appear. The features will be grouped by each streetscape section/feature.

A voxel is a pixel with a height or third dimension component when analyzed with LiDAR. Figure 2.1 shows an example of LiDAR enclosed in voxels. Optimizing the vertical and horizontal height of the voxel depends on the features detected and the spacing of LiDAR data. USGS standards stress the importance of consistency of point patterns for horizontal spacing throughout a dataset and set a standard for spatial distribution of at least one point per grid cell (*39*). However, with QL1 data having nominal point spacing greater than one point per every half-square-foot, adhering to these minimum standards is not necessary because tiny grid cells would cause datasets to be large in size and difficult to process.

When setting the vertical voxel dimensions, it is important to consider occluded LiDAR data. Dense tree canopies can occlude LiDAR data. Voxels that were completely hidden from the laser instrument are considered occluded. Occluded voxels are those that are theoretically traversed by the pulses, meaning the pulses would have reached the voxel, but all energy was already intercepted because of earlier interactions of the laser pulses with canopy material (Kükenbrink et al. 2017). An in-depth study by Kukenbrink et al. is one of the few studies that address occluded voxels and attempt to minimize their presence. In a recent study investigating streetscape measuring with QL2 data (Golombek and Marshall 2019), the authors investigated Kukenbrink et al.'s results and concluded that a voxel height of 5 feet is ideal for both limiting occluded data and providing adequate vertical intervals or zones for analysis.

As QL1 data have a nominal point spacing of around 0.4 feet, and per the USGS standard for horizontal grid spacing, the horizontal cell size can be set much smaller than the 5-ft vertical spacing. However, setting the horizontal parameters too small would skew the voxel significantly. Since optimal street tree collection limits the setting of the voxel to 5 feet, this study will use the horizontal dimensions of 3 ft by 3 ft used previously in the authors' successful QL2 study. Therefore, the streetscape will be set up into 5-ft elevation zones with each classified pixel having 3 ft by 3 ft dimensions.

3.2.3 Classifying Streetscape Data

LiDAR data classification is either performed manually or by automated filtering processes. Creating bare-earth models is the most common automated process, although automated processing to filter LiDAR data specifically for trees and buildings is also common. Road and grassed areas are other features that have automated extraction capabilities from aerial LiDAR (Lodha, Fitzpatrick, and Helmbold 2007), though this study is not concerned with features on the ground. A 2012 study by Shyue et al. attempted to incorporate hybrid approaches to assist with urban feature extraction, yet that study was limited only to buildings, trees, grass, and roads (Shyue et al. 2012). Methods are emerging to extract street poles from LiDAR automatically (Zheng, Wang, and Xu 2017), though the methods specified for doing so are from street-based mobile LiDAR as opposed to open source and publicly available USGS data. Since automated methods for extracting streetscape features with QL1 data are not publicly available, the authors defer to manual classification of features common to LiDAR feature extraction in general. As mentioned above, buildings and trees are classified via automated processes.

When LiDAR hits non-solid vegetation, the energy of the light pulse continues to the ground and records each instance, or return, of vegetation hits until it reaches the ground. The exception to this is when tall and thick vegetation occlude the LiDAR. In general, LiDAR will stop at the first solid feature it hits. Therefore, three types of above-ground objects LiDAR can hit are:

1. A hanging object in space. Examples include the arms of light poles and power lines.
2. A continuous object. Specifically, an object that continues all the way to the ground. Examples include a property wall, building, power pole, and base of a light pole (Figure 3.2).
3. Vegetation. A multi-point return object such as a tree.

Type 1 above will be represented by where the point hits the voxel that contains the feature. Type 2 will also be represented by where the point hits the feature/voxel; however, the features will be captured and noted with a 3D shapefile so that the entire feature is draped to the ground through its lower voxel zones. Type 3 will utilize automated, multi-point return vegetation extraction processes common to LiDAR processing software. Vegetation multi-point returns are clusters of LiDAR points that intercept multiple targets within a short height interval. In this case, trees that are common to Las Vegas will be noted. Palm trees, for instance, tend to have small, elevated canopies with long trunks, as opposed to most deciduous trees. If necessary, the 3D draping of features will be utilized like the continuous objects (type 2), so the long standalone trunks are represented as well.

An automated LiDAR feature extraction method is preferred when extracting various feature classes covering a large area. After an extensive literature review, it appears that automated methods have not materialized to classify most streetscape features beyond street trees and buildings derived from aerially collected QL1 data. This study used common automated LiDAR processing tools available within MARS® software to classify buildings and trees. The above literature review cites research that automatically classifies streetlights (Zheng, Wang, and Xu 2017), though the dataset used was mobile LiDAR, which is dozens of times denser than publicly available QL1 data. Reviewing recent research attempting to extract urban features automatically (Zhang, Lin, and Ning 2013; Ao et al. 2017), researchers utilize manual classification of point cloud data for ground truthing their automated methods, likely because of LiDAR's highly accurate positional characteristics. These studies utilize LiDAR data densities like QL1 but do not extract any additional necessary streetscape features discussed except powerlines. The isolated nature of powerlines makes them easily detected when already classifying features manually. Since previous research focused on a manual method for automated process truthing, along with LiDAR's highly accurate output, this study utilizes similar manual classification to accurately compile the streetscape feature classes. In the case of the manually classified USGS QL1 point cloud, the data will have relative accuracy or root mean square error of within 1/3-ft vertical and within 1-ft horizontal based on USGS specs and collection metadata (Hans Karl Heidemann 2018; American Society for Photogrammetry and Remote Sensing 2014).

Merrick and Company's MARS® LiDAR processing software was utilized to classify the LiDAR data manually. MARS® has a feature to pair Google Earth with any current LiDAR view. Per Figure 3.3, this pairing allows for the LiDAR data to be present on one computer screen and Google StreetView's identical location to be present on an adjoining computer screen. With highly accurate USGS LiDAR data, the MARS®/Google dual visual setup/pairing allows for accurate and seamless classification of the various feature classes noted below.

MARS® was also used to establish and process data into the voxel zones. The features described below can be processed into the noted voxel zones. Aerial LiDAR scan angles can cause parts of small features to be missed. For example, thin overhead electric lines and arms of overhanging light posts may be captured at nadir but missed when the scan angle is too high. Therefore, ESRI ArcGIS® is used to draw polygons around feature point cloud clusters with high resolution imagery to help complete line and polygon features when necessary. A tool in MARS® will populate constructed polygons with applicable z-values. A LiDAR generated ground elevation grid is then used to subtract feature height from ground to determine the exact height above ground of classified and processed features, and to be sure they are classified into the correct voxel zone. Since the City of Las Vegas collects and maintains global positioning system (GPS) data for all its streetlights and street signs, the municipal GPS point data was also used as an additional check to confirm the streetlights and street sign base locations. The counts in this study matched the city's counts.

Figure 3.4 below shows the difference between a QL1 and QL2 dataset for the same intersection in relation to these streetscape features. Unlike QL2 data, it is assumed that many features stand out with QL1 data and can be properly classified. The authors' QL2 study (Golombek and Marshall 2019) already discussed extracting the following features:

- Tall trees (any vegetation with a trunk, not classified as landscape vegetation). Common automated processes classify street trees. The points in the first zone were manually classified when classifying landscape vegetation. The automated process was set to exclude the lowest zone because of interference of urban reflecting objects (Hollaus et al. 2010; Koma, Koenig, and Höfle 2016).
- Buildings. Buildings and houses enter the streetscape peripherally. Common LiDAR processing procedures were used to create building polygons and a height attribute helped place these features into voxel zones. Since the height is always the top voxel zone, the building is then draped through the lower voxel zones until it reaches the ground.

With high-density QL1 data, the authors attempted to explore the limits of this LiDAR data standard and to extract all additional above-ground features that make up a streetscape. These features include the following:

- Walls/fences. LiDAR points on top of walls and fences are clearly discernable. Lines are drawn across these points and are draped to ground level.
- Landscape vegetation (low brush). Although LiDAR acceptably detects vegetation through an automated process, low-lying vegetation is best classified manually as obstructions causing interference can distort data. In the present example, landscape features are easily discerned when LiDAR is overlaid with either imagery collected simultaneously with the LiDAR or pairing LiDAR street scenes with Google StreetView, as mentioned above.
- Tall trees (low zone[s] only) as noted in the QL2 description above, the lowest zones are manually classified.
- Light posts. These generally have two parts. Light post LiDAR points are clearly seen, and elevation is extracted. If the light is overhanging a street, a polygon is constructed around the clustered points and that polygon is inserted into the appropriate voxel zone. The second part is the vertical post (or non-overhanging streetlight), which is split off from an overhanging light and draped through the voxel zones to the ground.
- Traffic lights. In this sample set, traffic light points are easily discerned. A polygon is drawn around the clustered points and placed into its respective voxel zone.
- Power poles/lines. The poles are clearly distinguished. The lines are hit and miss. The poles are captured and draped. Since we know lines generally connect to poles in streetscapes, the available line points are connected, and Google StreetView is used to verify.
- Street signs. Street signs are often connected to light posts and power poles. When they are independent, they generally have a few LiDAR points. In our sample set, all signs are within the first two voxel zones, as noted in the results below.

- Additional street furniture (anything on the sidewalk or median not noted above, such as benches, bus stops, garbage cans, etc.). QL1 data successfully capture many street furniture features, such as pedestals, bus stops, large garbage cans, multiple residential mailboxes, large benches, and non-traffic signs, to name a few. Unfortunately, some are too small to distinguish, such as common fire hydrants and small benches. Most street furniture features are within the first voxel zone.

The voxel processing tool generates an individual height-zone raster grid for each streetscape feature that was classified. The raster grids are converted into vector features ultimately to calculate percentage coverage, counts, or feature length, as noted in Table 4.1. When processing is complete, descriptive statistics in tabular format of the noted features above are represented in each streetscape segment, also noted in Table 4.1.

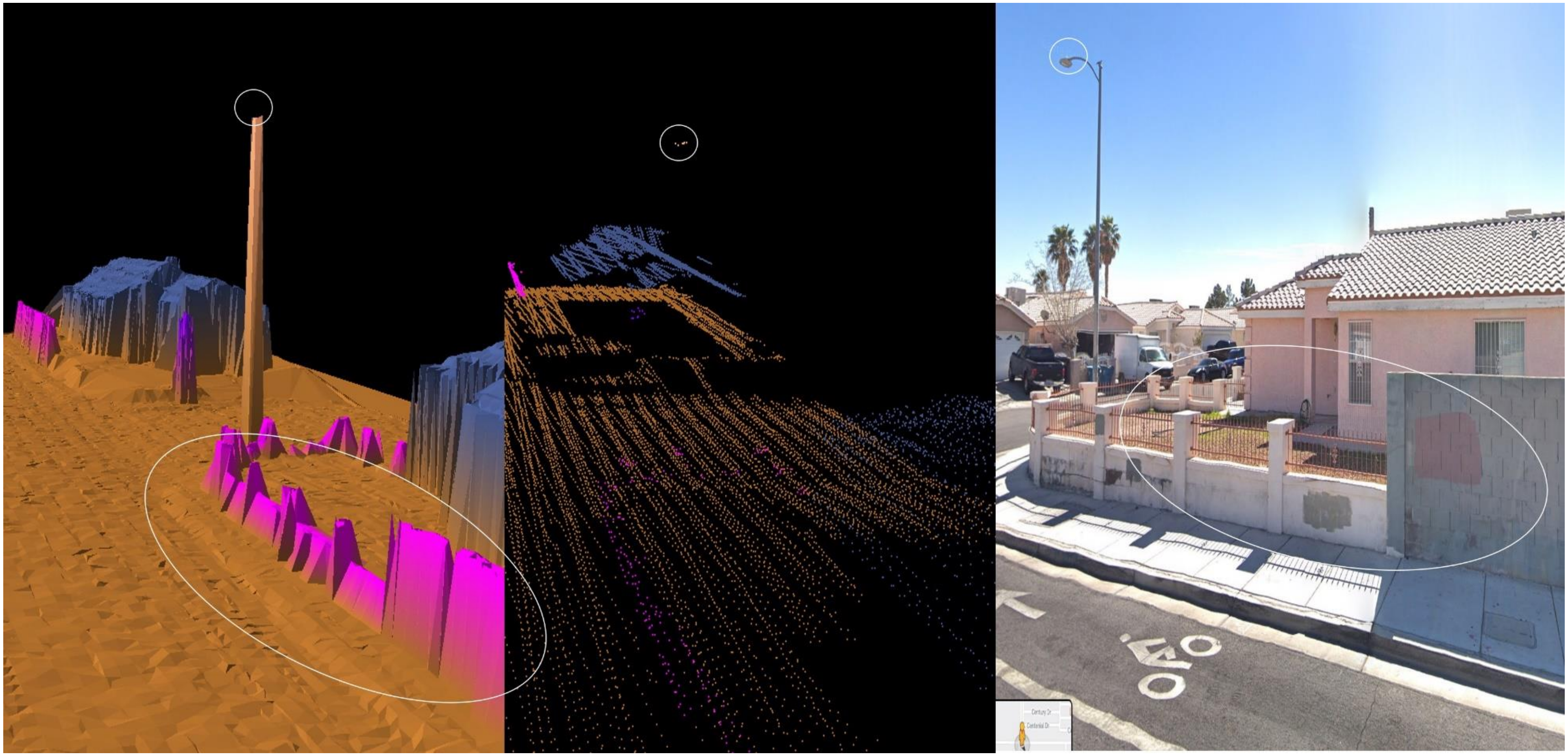

Figure 3.2 Example of draped features with light pole base, house, and fence draped to ground

Note: Fence features appear like actual fence from Google StreetView and actual fence from Google StreetView (right)

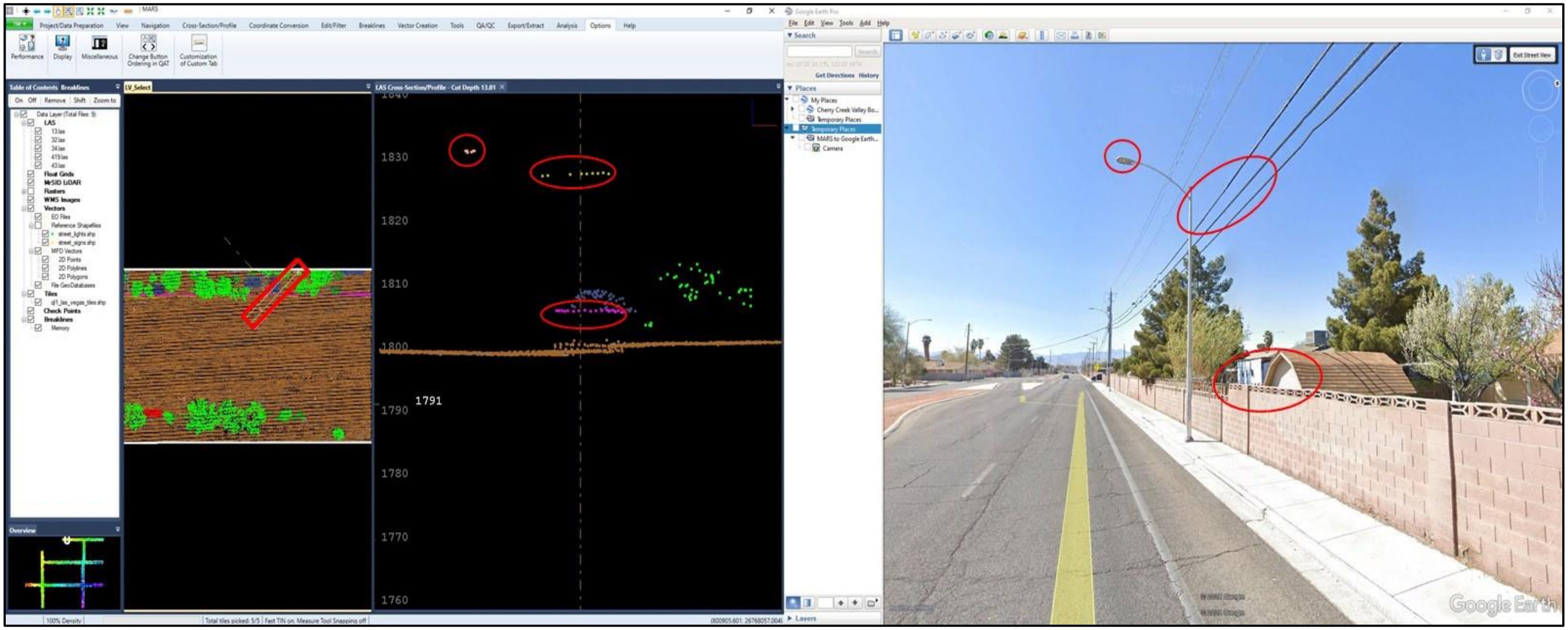

Figure 3.3 Example of Google view paired with MARS®

Notes: Rectangular box at far-left view shows profile box. Left-center view shows light detection and ranging (LiDAR) data visible in profile view. This is where manual classification occurs. Right view is paired Google view to assist with seamless manual classification.

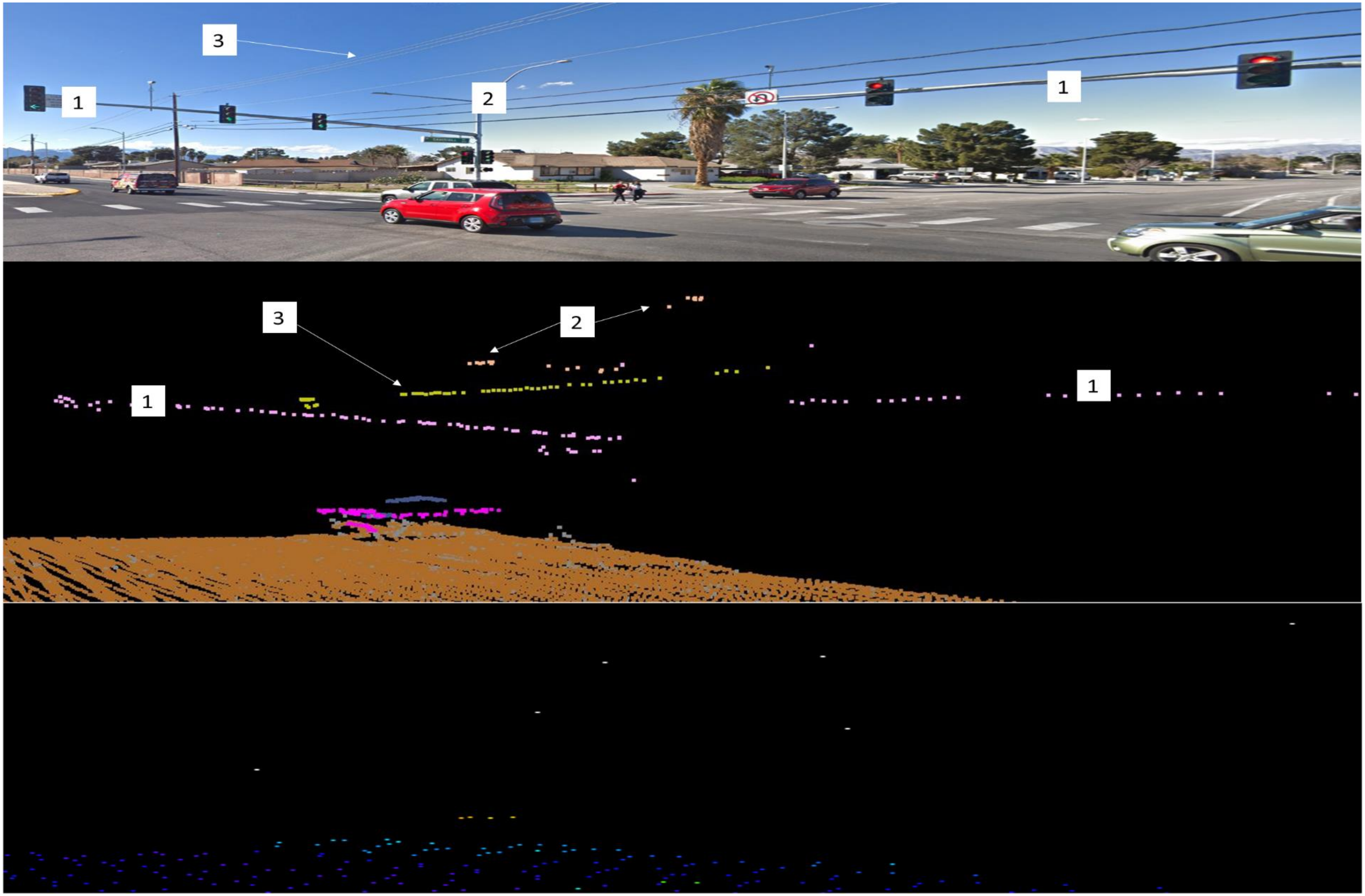

Figure 3.4 Sample views of an intersection

Notes: (top) Google StreetView; (middle) QL1 image: 1 = traffic lights, 2 = dual streetlight, and 3 = power lines, (bottom) same view with lower quality QL2 data

4. Results/Discussion

Table 4.1 Descriptive statistics of streetscape features from the QL1 sample dataset derived from voxel intervals

Streetscape Polygon	Percent Tree Coverage	Tree Density*	Landscape Area (sq. feet)	Building Area (sq. feet)	Percent Building Coverage	Over-Hanging Street Light Count**	Overhanging Street Light Area (sq. feet)**	Light Pole Only Count***	Light Pole Only Area(sq. feet)***	Sign Count	Wall Length (feet)	Traffic-Light Area (sq. feet)	Electric Pole Count	Electric Line**** Length (feet)	Street Furniture Count	Street Furniture Area (sq. feet)
Zone 1 (0-5Ft)																
1	0.05%	1.13	24453	5813	0.90%	0	0	76	955	22	2056	0	5	0	17	2759
2	0.17%	1.32	7776	10616	2.18%	0	0	48	603	21	3943	0	12	0	10	743
3	0.14%	1.11	13950	37279	5.56%	0	0	68	2321	43	3815	0	0	0	14	1056
4	0.13%	1.03	5202	78946	13.73%	0	0	31	390	27	2466	0	0	0	14	1479
5	0.16%	1.09	9693	47809	12.27%	0	0	31	389	11	1955	0	0	0	5	347
Zone 2 (5–10 Ft)																
1	2.95%	1.43	5733	5813	0.90%	0	0	76	955	22	2025	0	5	0	10	1413
2	4.13%	1.15	756	10616	2.18%	0	0	48	603	21	3557	0	12	0	5	430
3	3.44%	1.06	1233	37279	5.56%	0	0	68	2321	43	3750	0	0	0	8	784
4	3.54%	1.18	1368	78946	13.73%	0	0	31	390	27	2431	0	0	0	5	942
5	4.00%	1.31	6381	47809	12.27%	0	0	31	389	11	1955	0	0	0	4	316
Zone 3 (10–15 Ft)																
1	4.26%	1.53	0	4873	0.76%	0	0	76	955	0	0	0	5	0	4	529
2	6.08%	1.08	0	8597	1.77%	0	0	48	603	0	0	0	12	0	2	245
3	5.36%	1.19	0	36380	5.42%	0	0	68	2321	0	90	0	0	0	1	118
4	4.70%	1.25	0	78796	13.70%	0	0	31	390	0	0	0	0	0	1	115
5	6.61%	1.62	0	35687	9.16%	0	0	31	389	0	0	0	0	0	1	11
Zone 4 (15–20 Ft)																
1	3.60%	1.45	0	4218	0.66%	0	0	76	955	0	0	163	5	0	0	0
2	4.40%	1.08	0	2306	0.47%	0	0	48	603	0	0	0	12	0	2	245
3	5.08%	1.17	0	31143	4.64%	0	0	68	2321	0	90	0	0	0	1	118
4	4.15%	1.25	0	43481	7.56%	0	0	31	390	0	0	0	0	0	1	115
5	4.80%	1.61	0	22024	5.65%	0	0	31	389	0	0	0	0	0	0	0
Zone 5 (20–25 Ft)																
1	2.94%	1.38	0	3501	0.54%	0	0	76	955	0	0	468	5	0	0	0
2	2.78%	1.11	0	246	0.05%	0	0	48	603	0	0	735	12	0	0	0
3	3.80%	1.20	0	22312	3.33%	0	0	68	2321	0	90	901	0	0	1	118

4	3.06%	1.18	0	8905	1.55%	0	0	31	390	0	0	0	0	0	0	0
5	2.78%	1.74	0	9829	2.52%	0	0	31	390	0	0	657	0	0	0	0
Zone 6 (25–30 Ft)																
1	1.87%	1.52	0	1750	0.27%	1	31	76	955	0	0	0	5	1287	0	0
2	1.82%	1.04	0	123	0.03%	3	93	48	603	0	0	0	12	2641	0	0
3	3.10%	1.37	0	11156	1.66%	2	62	68	2321	0	90	0	0	0	0	0
4	2.42%	1.11	0	4453	0.77%	0	0	31	390	0	0	0	0	0	0	0
5	1.68%	1.39	0	4915	1.26%	0	0	31	390	0	0	0	0	0	0	0
Zone 7 (30–35 Ft)																
1	1.25%	1.49	0	0	0.00%	61	1891	74	930	0	0	0	4	0	0	0
2	1.02%	1.10	0	0	0.00%	43	1333	45	566	0	0	0	12	0	0	0
3	2.48%	1.30	0	0	0.00%	54	1674	64	1110	0	90	0	0	0	0	0
4	2.02%	1.01	0	0	0.00%	31	961	31	390	0	0	0	0	0	0	0
5	1.24%	1.41	0	0	0.00%	25	775	31	380	0	0	0	0	0	0	0
Zone 8 (35–40 Ft)																
1	0.72%	1.48	0	0	0.00%	6	186	4	50	0	0	0	4	640	0	0
2	0.45%	1.24	0	0	0.00%	7	221	2	25	0	0	0	12	0	0	0
3	1.87%	1.32	0	0	0.00%	5	155	8	407	0	0	0	0	0	0	0
4	1.12%	1.23	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
5	1.12%	1.25	0	0	0.00%	5	155	4	50	0	0	0	0	0	0	0
Zone 9 (40–45 Ft)																
1	0.42%	1.47	0	0	0.00%	0	0	0	0	0	0	0	1	0	0	0
2	0.23%	1.45	0	0	0.00%	0	0	0	0	0	0	0	12	0	0	0
3	1.03%	1.35	0	0	0.00%	0	0	8	407	0	0	0	0	0	0	0
4	0.34%	1.01	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
5	0.78%	1.43	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
Zone 10 (45–50 Ft)																
1	0.10%	1.15	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
2	0.15%	1.13	0	0	0.00%	0	0	0	0	0	0	0	8	2641	0	0
3	0.37%	1.75	0	0	0.00%	0	0	6	345	0	0	0	0	0	0	0
4	0.01%	1.14	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
5	0.18%	1.88	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
Zone 11 (50–55 Ft)																
1	0.00%	1.00	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0

2	0.04%	1.39	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
3	0.03%	2.00	0	0	0.00%	0	0	5	314	0	0	0	0	0	0	0
4	0.00%	0.00	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
5	0.03%	0.71	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
Zone 12 (55–60 Ft)																
1	0.00%	0.00	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
2	0.02%	1.58	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
3	0.00%	0.00	0	0	0.00%	0	0	5	314	0	0	0	0	0	0	0
4	0.00%	0.00	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0
5	0.04%	1.16	0	0	0.00%	0	0	0	0	0	0	0	0	0	0	0

All “area” units are square feet. “Length” units are feet. Measurement type is listed in each column/feature title.

*Tree Density is the total number of LiDAR tree points per voxel with tree point cloud data.

**Overhanging streetlights are those that encroach the roadway.

***Light poles are either vertical lights or the pole-only component to overhanging lights.

****Electric lines are electric transmission lines connected to power poles.

Table 4.2 Area of each sample streetscape

Streetscape Polygon	Streetscape Area (Square feet)
1	643,829
2	486,311
3	670,979
4	575,050
5	389,698

Note: Used to calculate percent coverage of some features in Table 4.1

The results of this study enable access to an array of objective descriptive data not previously available, as USGS QL1 publicly available data is relatively new. When downloading, processing, and classifying streetscape QL1 data via these methods, researchers can obtain quantifiable 3D characteristics of streetscapes to apply to various transportation research needs. Table 4.1 shows sample descriptive statistics available and how they are broken into their relevant height zones. Table 4.2 shows the areas for each corresponding polygon in Figure 3.1 above.

Note that Table 4.1 is an extensive example. For instance, the percentage of tree coverage, as a whole, for each streetscape polygon is noted in the first column of Table 4.1. The results show tree coverage initially increases and then decreases toward the higher zones. For example, the highest tree coverage recorded for any sample area in any zone is 6.61% coverage in zone 3, which is the 10- to 15-ft zone. Buildings show similar results. Table 4.1 has both linear coverage and total percent coverage for buildings. Since typical buildings or dwellings are widest at ground level, statistics show how building coverage is highest at the low height intervals and reduces in coverage as the intervals increase. For example, sample area #4 in Table 4.1 shows 13.7% coverage in the initial two zones, yet by zone 6 (between 20 feet and 25 feet above ground) coverage for this sample area is below 2%.

It is important to display an extensive example of the descriptive statistics available, since many streetscape features are detectable with QL1 data, and researchers may have an interest in quantifying different features for different reasons. These statistics can be quantified by counts, lengths, and areas. Area relates to voxel horizontal area coverage per zone. For linear features like walls/fences and power lines, feature length is detected by digitizing the classified features with a best-fit 3D polyline. For example, take 150 feet of continuous point cloud classified as wall 10 feet above ground. Given the 5-ft vertical setting for each voxel, and the continuous object draping method mentioned previously, that wall would contribute 150 linear feet in zone 1 and 150 linear feet in zone 2. For the sample areas, wall lengths were detected that varied from 1,955 square feet to 3,943 square feet. After zone 2, the voxel zones show “0” for wall length because the dataset does not have any walls or fences above 10 feet, except sample area 3 that had 90 feet of tall fence surrounding a sports field.

As mentioned in the introduction, there are conflicting research findings about the impact street trees and landscape improvements have on road safety, and one possible source of conflict has been our inability to measure these features properly. The authors' previous study exploring the limits of USGS QL2 data expresses and legitimizes voxel use for measuring trees (Golombek and Marshall 2019). Although some manual classification is involved with the QL1 process, actual objective and measurable landscape features can coincide with street tree data to assist with such research.

Evaluating buildings and how they encroach streetscapes has been done in the past. However, studies can now incorporate objective data that take into account building characteristics based on highly accurate measured outcomes as opposed to crude building outlines commonly available with open source GIS data. Furthermore, street walls/fences are objectively measured in both length and height. Although this study is limited in that not every piece of street furniture can be legitimately extracted, many can be. Ewing and Clemente (Ewing and Clemente 2013) discuss in their research the importance of these types of features for measuring perceptual streetscape qualities, such as enclosure, human scale, and transparency, which can now be objectively measured and compared with previous crude methods.

When looking at Table 4.1, it is interesting to note the diversity of height-space. Some features such as street trees are covered throughout. Others such as street furniture, street signs, and landscape features are in the lower zones. Traffic lights and overhanging streetlights do not hit a low voxel zone. Similar to previous streetscape research relying on 2D-derived polygons, these types of features have yet to be applied to transportation research incorporating their 3D measurements. The diversity of space shows how quantitative 3D groupings of data are much different than crude 2D data, and thus, can lead to different results when applied to transportation research outcomes.

The literature review noted the recent streetscape measuring studies done by Harvey et al. that have produced some extensive and comprehensive work on the topic. Harvey et al. specifically mentioned in two of their studies that smaller features such as walls, fences, streetlights, and other design elements are typically unaccounted for because of lack of adequate spatial data (Harvey et al. 2015, 2017). The above results completely change that assumption, and as QL1 data become more mainstream, so will the ability to incorporate these features into fundamental transportation research.

The role that street trees and streetscape design variables play in transportation research continues to be evaluated, and what may be the most important element to transportation research outcomes is the availability of legitimate streetscape descriptive statistics. Marshall et al. (Marshall, Coppola, and Golombek 2018) applied GIS-based descriptive streetscape statistics in a negative binomial generalized linear regression model to evaluate street trees and safety-related transportation research outcomes. Harvey and Aultman-Hall (Harvey and Aultman-Hall 2015) applied streetscape descriptive statistics, limited to 2D street trees and crude building outlines, to a binary logistic regression model. The QL1-derived descriptive statistics in Table 4.1 are far more objective and comprehensive and can have a much greater impact when utilizing spatial data to study transportation research outcomes.

Since this study involves an in-depth manual feature classification process, note the level of effort involved to classify all the features stated above. After incorporating automated buildings and trees, the process initially took between one and one-and-a-half hours per linear mile to classify each entire mile of streetscape corridor. Of course, effort depends on the complexity and quantity of features in the streetscape, though in the present sample, the effort might be reduced to near or under 1 h per linear mile if the effort repeats itself enough. Eventually, these processes could be automated, such as with machine-learning techniques.

5. Conclusions

The results suggest that QL1 data allow us to extract and quantify many features that were previously unobtainable when limited to QL2 data. Streetlights, landscape vegetation, signs, traffic lights, property walls, and many general street furniture features are apparent in urban QL1 data and can be classified, extracted, and measured at their true locations within the streetscape. We can detect streetlight and utility pole counts. For example, light pole counts for the five sample areas range from 31 to 76 (in the lowest height zone), and their corresponding area coverage ranges from 389 square feet to 2,321 square feet. Street trees and encroaching building coverage is calculated by total area coverage, and Table 4.1 shows much diversity through the various height zones—much more so than appears from simple evaluated traditional 2D polygon coverage. We are also able to obtain a viable sample of street furniture items, and (per Table 4.1) their coverage diversity is prevalent through the first five height zones. Given that most visible features are detectable within a QL1 dataset, and given that it is possible to quantify the feature classes described in the methods section of this paper, the authors are satisfied with these results as this study presents objective 3D locational and quantifiable data on most streetscape features more so than any other study they are aware of. Furthermore, previous research on this topic is limited to either crude feature counts or simple 2D representations of how these features appear in space. While 2D GIS has been widely used in planning, it is limited in relation to visualizing and analyzing physical objects, which is why it is important to consider 3D methods.

As mentioned above, this study is unique and an advancement in understanding detectable streetscape and urban built environment features with publicly available LiDAR data. This study is the first the authors are aware of that explores the limits of which features are detectable and extractable in a QL1 dataset. There are some limitations, however, and perhaps the biggest limitation is that automatic methods to extract the features noted in this study have not yet materialized. Manual classification methods are certainly feasible, especially for a trained LiDAR technician, though automated methods to classify these features will likely be more efficient in the future. Additionally, even though QL1 data require eight points per square meter, this may still not be dense enough for some smaller street furniture features, such as public garbage cans, fire hydrants, and small benches.

Since LiDAR hit the commercial market around 20 years ago, the technology has continually improved in collecting data at higher and higher densities, which will likely lead to greater and continued coverage of QL1 (or better) data throughout the U.S. The unique methodology and new concepts about measuring streetscape features presented in this study will hopefully provide transportation researchers with more definitive answers on the role that streetscape features play in transportation-related outcomes.

PART 2: HIGH-DENSITY MOBILE LIDAR FOR MEASURING STREETSCAPE FEATURES

6. INTRODUCTION

Lane widths, shoulder widths, curbs, and paint markings are all measured and designed with precise dimensions. Much less attention is given to vertical and outer streetscape features, such as trees, benches, signage, and building frontage, to name a few. At the same time, there is over a century of literature regarding how such features are important for outcomes such as livability, with writings from Sitte, Cullen, Appleyard, Rapoport, and Arnold (Sitte 1889; Cullen 1971; Appleyard 1980; Rapoport 1990; Arnold 1993). More recent research shows how these features may also impact road safety (Dumbaugh 2006; Wolf and Bratton 2006; Jody R. Naderi 2002), economics (Ewing and Dumbaugh 2009; Marshall, Coppola, and Golombek 2018), as well as public health outcomes (Brownson et al. 2009; Purciel et al. 2009). Yet, the research regarding the role streetscape features has on such outcomes remains somewhat conflicted, both in terms of the strength of the associations as well as the direction in some cases. These conflicts may be due to inconsistencies in measuring streetscape features.

Over the past decade, however, measuring-technique research for streetscape features has started to shift from audit-based methods (Ewing and Clemente 2013; Ewing et al. 2005; Brownson et al. 2009) toward GIS/remote sensing methods (Purciel et al. 2009; Yin and Shiode 2014; Yin 2017; Harvey et al. 2017). In order to further reduce subjectivity, the most recent research is now beginning to use LiDAR (Light Detection and Ranging). Research by Golombek and Marshall, for instance, explored the streetscape mapping and streetscape feature detection/extraction capabilities of publicly available aerial LiDAR data. More specifically, this research tested data derived from the national United States Geological Survey (USGS) 3D elevation program, which included Quality Level (QL) 2 LiDAR data (Golombek and Marshall 2019) as well as the four times denser QL1 LiDAR data (Golombek and Marshall 2020). These studies designated entire streetscapes into 3D pixels, better known as “voxel” grids. With the lower USGS QL2 standard, feature extraction was primarily limited to street trees and buildings, while the QL1 standard expanded feature extraction to traffic lights, traffic signage, utility poles, walls, fences, as well as some larger street furniture.

These studies showed how LiDAR could be a valuable technology for providing objective data in transportation research for perceptual quality and safety outcome studies. Still, even the QL1 LiDAR point density standard had significant limits to what it could detect. For example, an urban QL1 dataset may collect only a few points on a street sign, which is enough to know the sign exists, but it neglects the overall dimensions and appearance of the sign. Smaller landscape features, such as benches, garbage cans, and bike racks, to name a few, were not able to be detected with a QL1 dataset. Additionally, aerial LiDAR at these QL standards can detect tops of buildings but not features in a peripheral view from the ground level, such as windows, awnings, and building signage. Such features have also been shown to be important with respect to walkability.

Mobile, ground-based LiDAR, however, is dozens of times denser than publicly available QL1 aerial-LiDAR data and is collected from the vantage point of the street (Figure 6.1 shows a comparison between QL1 and mobile LiDAR data). Many tests and advances over the past 15 years have developed mobile LiDAR scanning platforms into an acceptable and accurate survey-grade feature collection mechanism (Williams et al. 2013; Haala et al. 2008). As a result, mobile LiDAR has unique potential to quantitatively and objectively map various features within streetscapes. For transportation-related research, it is important to decipher between LiDAR technology and platforms used for discrete feature collection and navigational purposes. At present, much research is being done with navigational LiDAR to support autonomous vehicle navigation advancements. This form of LiDAR differs from discrete urban collection in that it focuses on quick real-time identification of features mainly pertaining to the roadway itself, such as curbs, centerlines, other vehicles, and pedestrians (H. Wang et al. 2019; Gao et al. 2018). Discrete collection LiDAR platforms, on the other hand, focus on collecting and storing data/features for analysis for all areas within a streetscape.

The overarching goal of this study is to understand the role that mobile LiDAR can play in quantitatively mapping and measuring features in an urban environment. We will evaluate sample datasets collected with mobile LiDAR in Denver, Colorado, and propose methods to quantify streetscapes with 3D voxel grids/zones. In this study, we assess two approaches to this goal. First, we seek to present objective measuring tools as potential alternative or supplementary options to subjective audit-based approaches for measuring streetscape features related to outcomes such as walkability and livability (Ewing and Clemente 2013). More specifically, we create volumetric descriptive statistic matrices for select streetscape features that have been cited as being affiliated with transportation-related and livability outcomes. For this approach, we will evaluate several segments in a walkable town-center-type environment in Denver, Colorado. Our second approach focuses on the data gaps discussed above, where aerial QL1 LiDAR was insufficient, and created descriptive statistic matrices to incorporate these critical streetscape features, particularly street signage, traffic lights, and street furniture. Ultimately, we attempt to create objective descriptive statistic matrices that can be applied to transportation and urban research studies as well as inform municipal planning efforts.

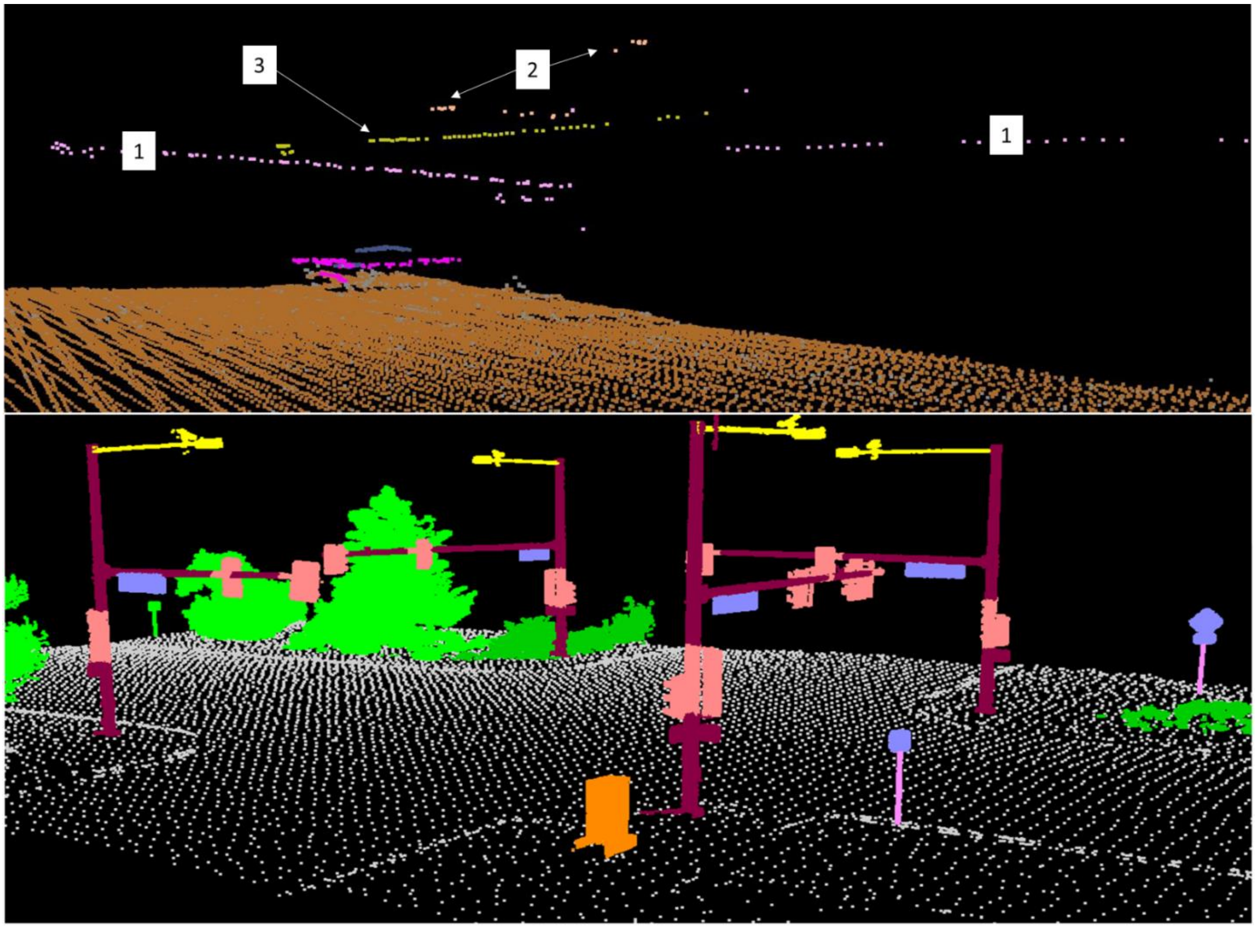

Figure 6.1 Comparison of QL1 (top) data to Mobile LiDAR (bottom) data for two similar intersections

Note: For the top image, 1 = traffic light, 2 = light posts above traffic light, 3 = power lines

7. LITERATURE REVIEW

Over the past few decades, many researchers have developed quantifiable measuring techniques for measuring walkable streetscapes. Ewing et al. were among the first, and with Clemente and Handy, they developed comprehensive audit-based techniques and published these techniques in various manuals (Ewing et al. 2005; Ewing and Clemente 2013). Ewing et al.'s measuring techniques were audit based and dependent on the auditors having the appropriate skillset with respect to the ability to visually assess and measure seemingly subjective qualities (Brownson et al. 2009). In a related study, Ewing et al. measured 20 streetscape features over nearly 600 New York City blocks related to pedestrian activity (Ewing, Hajrasouliha, Neckerman, Purciel-Hill et al. 2016). Many of the features being detected, such as street furniture, window measurements and proportions, building heights, various landscape features, and outdoors dining, tended to be measured via visual, subjective audit-based methods. Despite Ewing et al. checking for inter-rater reliability, these methods are time consuming and can still be subject to human error (Brownson et al. 2009).

Purciel et al. attempted to utilize basic GIS integration as an alternative to measuring some primary perceptual qualities. Purciel tested five of Ewing's primary perceptual qualities—imageability enclosure, human scale, transparency, and complexity—and found a wide range of correlation (0.28 to 0.89) between GIS and the field-observed measures (Purciel et al. 2009). Yin and Shiode attempted to use remotely sensed images to digitize 2D features, followed by assessor GIS data in order to create 3D streetscape features, but they were limited to a few large features such as buildings and trees (Yin 2017; Yin and Shiode 2014). These advancements are certainly important, though none can objectively measure the numerous small-scale streetscape features that Ewing et al. discuss over various studies.

Further advancing the use of spatial technologies with streetscape mapping, Harvey and Aultman-Hall addressed the streetscape measuring paradigm with respect to road safety outcomes while also incorporating aerial LiDAR (Harvey et al. 2016). They concluded that additional tree enclosure was significantly associated with a reduction in overall crashes. Harvey et al. attempted to utilize spatial technologies to further address road safety and concluded that GIS had limitations for collecting and/or addressing smaller features (Harvey et al. 2017).

Golombek and Marshall took objective streetscape measuring a step further and introduced voxel-based quantitative streetscape feature extraction of USGS QL1 and QL2 data; this step created descriptive statistics for how various features mentioned above are represented in a streetscape in 3D. These studies are among the most objective methods to date, but as also mentioned in the introduction, many smaller streetscape features were still not detectable, even with the higher-density QL1 standard (Golombek and Marshall 2019, 2020). Also, ground level vertical features, such as windows, awnings, and building signage, are important parts of perceptual quality studies but also not detectable with QL1 data.

Our research seeks to use mobile-based LiDAR to detect and collect streetscape features to assist transportation research fill the gaps where high-density public QL1 is limited. Many related studies from researchers such as Ewing et al., Harvey et al., and Marshall et al. are conducted over many square miles of populated areas, which translate to hundreds or thousands of street segments. Manual LiDAR classification of features collected with mobile LiDAR is acceptable, though it would be very time consuming; whereas, automated classification methods would streamline this process. Sending data to lower wage paying countries like India, China, or Vietnam is common business practice for making large manual classification projects economically practical, though viable automated methods are more efficient.

Currently, research is limited on automated mobile LiDAR feature extraction methods, though most research on this topic occurred over the last few years and, fortunately, continues to advance. Lehtomaki et al. utilized segmentation, segment classification, and machine-learning classification to extract various street features from mobile LiDAR, including billboards, traffic poles, light posts, cars, and pedestrians (Lehtomäki et al. 2016). An issue with these methods is that the accuracy of feature classes ranged from 66.7% to 94.3%, and the methods were only tested on 900 meters of roadway, which is not yet enough to be considered a viably tested method. Some researches, such as El-Halawany and Lichti (Sensing et al. 2011), Zheng et al. (Zheng, Wang, and Xu 2017), and Wu et al. (Wu, Wen, Guo, Wang, Yu, Wang, and Li 2017), have solely focused on automated street-pole extraction from mobile LiDAR. Their different methods of segmentation and clustering have led in some cases to a success rate of over 90% as well as a low false classification rate. Their results are encouraging with respect to the viability of automated methods.

Rivero et al. devised a method focused on the intensity value of traffic signs and utilized segmentation and clustering methods to automatically extract signs (Riveiro et al. 2016). Results successfully extracted around 80% of signs, though the authors appeared a little vague on the false positive rate. Similar methods with some imagery and point cloud processing enhancements were used by Soilan et al. (Soilán et al. 2016), which yielded slightly better results than Rivero et al. The false positive rate, however, appeared high, and like other similar examples, the test area was too small to be considered a thoroughly tested solution. Perhaps the most successful street-sign extraction methods came from Gargoum et al., who reported a near 100% success rate over three sample areas (Gargoum et al. 2018). These areas differed significantly from our sample study areas, as they were primarily in rural parts of Alberta, Canada, in areas where the signs appeared to be isolated from other nearby features. We further discuss if and how these methods can apply to our study in the methods section below.

Our current and previous studies seek to use different LiDAR standards to objectively measure features. Occluded data relate to LiDAR data not reaching all aspects of features, which we address here and in our previous studies because occluded data can prevent features from being fully captured and therefore improperly measured. Regarding the features themselves in their unobstructed environments, some urban mobile LiDAR studies addressed occluded objects. Studies by Fan Wu et al. (Wu, Wen, Guo, Wang, Yu, Wang, and Li 2017) and Han Zheng et al. (Zheng, Wang, and Xu 2017) constructed automated methods for extracting light poles from mobile data, addressed the occlusion issue, and found that complete objects were captured well over 90% of the time. Yang et al. (Yang et al. 2015) utilized methods to extract multiple features and also concluded that complete features were almost always captured despite potential occlusions. Lin et al. validated mobile LiDAR for completed tree understory collection (Y. Lin et al. 2014). From this, we conclude that feature occlusion with mobile LiDAR is limited.

Objective LiDAR-based methods have made inroads for providing data support for transportation research outcomes and perceptual quality measuring. Yet, our most recent aerial-based LiDAR-based research (Golombek and Marshall 2020) still has limitations, especially for thoroughly collecting smaller features such as signs and street furniture. Other limitations include the ability to measure ground-based vertical assets, such as building windows, which perceptual quality research considers. Mobile LiDAR has potential to fill these gaps. Automated classification methods are quickly evolving for large scale/area classification but are currently questionable regarding their exactness.

8. DATA AND METHODS

Our previous study relating to measuring streetscape features utilized QL1 data and was able to place most features into pre-determined voxel zones for the goal of creating objective descriptive statistic matrices (Golombek and Marshall 2020). Now we look to explore mobile LiDAR's dense ground-level collection capabilities to assist the transportation research community with two specific objectives.

One objective is to provide similar descriptive statistic matrices that may be used as alternatives to some of the audit-based methods for perceptual quality evaluation with more precise and accurate data. Since the research strand tends to revolve around the walkability aspects of streetscapes, we attempt to focus on the sidewalk areas of busy downtown-like sidewalks. For these streetscapes, we also evaluate mobile LiDAR's ability to collect vertical building-face data, such as window proportions, awnings, and commercial signs, which aerial LiDAR misses.

Our second objective is to determine mobile LiDAR's capability of fitting features that were too small to be identified (e.g., street signs, traffic lights, and streetscape furniture) with a QL1 dataset into a similar, but more precise, voxel matrix. As mentioned, an urban QL1 dataset may collect a few points on a vertical sign or traffic light, but does not adequately provide strong descriptive measures for signs and traffic lights. Additionally, landscape furniture features such as benches, bike racks, and fixed garbage cans are often not detected in a QL1 dataset but likely detectable with a mobile LiDAR dataset.

Mobile LiDAR should be highly effective for this level of analysis because our voxel size can be refined. Our previous QL1 and QL2 studies had voxels optimally placed at 5-ft vertical intervals. As mobile LiDAR is exponentially denser, we can create much smaller voxels that we expect will allow us to gather additional streetscape features.

8.1 Data Collection

A Trimble MX9 was used to collect data for this study. The MX9 contains a spherical imaging system and three oblique view cameras. The MX9 contains Riegl VUX-1HA dual laser scanners that measure at 1,000 KHz, with the scanner mirror rotating at 250 revolutions per second and a field of view of 360 degrees. A Real-Time-Kinematic (RTK) base station was set up for post processing purposes on a nearby National Geodic Survey (NGS) monument set at a 1-second interval collection rate. To confirm system accuracy, 13 ground control points (GCP) were established throughout the survey area no more than a half-mile apart from each other. Riegl's collection platform uses an internal "multiple-time-around" procedure, which eliminates range ambiguities and helps remove data noise.

A four-mile segment was surveyed along Montview Boulevard in Denver, Colorado, between Colorado Boulevard and Havana Street. An additional nearby mile of roadway through a mixed-use town center area along E. 29th Avenue in Denver was also collected. Each of these segments was traveled twice, once in each direction.

POSPac® was used to process telemetry of the Global Navigation Satellite System (GNSS) system, and we used RTK base station data to compute a corrected location of the vehicle path.

Trimble Business Center (TBC) software was used to register/adjust overlapping data from the multiple runs. TBC also computed point cloud colorization using the registered images that were collected in-sync with the scans.

The combined runs were exported into LAS 1.4 format and 100-ft by 100-ft tiles. A control report was run against the GCPs that returned a root mean square error (RMSE) of 0.06-feet/ 1.83-centimeter RMSE horizontal and a 0.122-feet/3.72-centimeter RMSE vertical. Point cloud density consistently averaged over 2,000 points per square meter.

We also obtained parcel data from the City and County of Denver to determine the right-of-way (ROW) for the Montview segment, as discussed below.

8.2 Methods

8.2.1 Creating Streetscape Sample Areas

Similar to our previous studies for quantitative streetscape measuring (Golombek and Marshall 2019, 2020), we seek to develop quantitative statistics of streetscape features. This first required defining streetscape corridor segments. Our previous studies used a method to divide the pre-determined segments into Thiessen proximal polygons (or Voronoi polygons as mathematicians call them).

To create a Thiessen polygon layer, only a point feature class is required, and the output Thiessen polygon dataset is configured where each individual non-overlapping polygon is closest to its associated input point. In the Montview dataset, we attempted to avoid segment cutoff at intersections since urban intersections tend to be focal areas with high activity and many traffic-related features we prefer to keep together. By establishing the input point feature class with these intersection centroids, the segment breaks occur at a subtle location somewhere between these intersections. Figure 8.1 depicts the Thiessen-based streetscape segments we created for Montview Boulevard using the ESRI ArcGIS® Thiessen polygon-processing tool.

Additionally for the Montview section, we designed the streetscape sample areas to include the full street ROW that extends beyond the street curb. Extending the streetscape to include these peripheral views is important since the majority of objects that fall within a road user's peripheral view are located off the street itself. Therefore, we utilized Denver's parcel data around the area of interest (AOI), merged the parcel data together, and used an ESRI ArcGIS® erase function that erased all non-streetscape ROW areas from our AOI. For the Montview section, we created six streetscape polygon segments utilizing this method.

For the town center area, our approach was a little different. Since the focus is more on streetscape features related to walkability, we simply digitized the areas between the curb and the building, enclosed with a crosswalk on each side. We identified six sample streetscape areas in this area, as shown on Figure 8.1, that we assess in this study.

8.2.2 Creating Streetscape Voxels for Positional Feature Analysis

A key objective of this study is to incorporate 3D pixels, or voxels, to quantity streetscape features and compile descriptive statistics. Breaking up a streetscape into voxels creates user-specified height zones. A voxel is a pixel with a height or third dimension component that can be useful for analyzing LiDAR data. We applied similar voxel methods to our previous street-feature voxel analysis studies (Golombek and Marshall 2019, 2020). In those papers, we determined that, given aerial LiDAR point densities, a 3-ft by 3-ft horizontal and a 5-ft vertical setting was optimal and appropriate.

The accuracy and density of mobile LiDAR data, however, allows more flexibility in setting voxel parameters. With over 1,000 points per meter collected, we suggest setting each voxel to a single cubic foot, or 1-ft by 1-ft by 1-ft (x,y,z) dimension. We suggest this parameter because: i) this study is attempting to compile descriptive statistics for features that were too small to extract in our previous QL2 and QL1 studies; and ii) this dimension facilitates a solid measuring basis for descriptive statistic metrics needed in the town center area. Ewing and Clemente often reference measuring features from ground to certain levels, like eye-level visibility (Ewing and Clemente 2013). If a streetscape was, for example, 500-ft long from crosswalk to crosswalk, 50-ft wide from storefront/building to curb, and 15-ft tall from ground to the above awnings, that streetscape quantitatively would total 375,000 cubic feet. If we calculate that 10 landscape trees fill 7,500 single cubic foot voxels, then we can estimate that trees comprise 2% of that streetscape.

8.2.3 LiDAR Feature Extraction Methodology/Classifying the Data

Table 8.1 provides a list of streetscape features and the minimum LiDAR standard required for extracting them. We discuss the process of extracting features with mobile LiDAR below.

For the four-mile Montview segment, the goal is to devise comprehensive descriptive statistics of streetscape features that can be applied to various transportation research studies. Other than for street sign extraction, the existing literature did not provide viable automated approaches. Even the street sign extraction methods yielded results well below 100% (with a high degree of false-positives and false negatives) and have not been thoroughly tested at a macro scale. Gargoum et al. developed automated street-sign extraction results (Gargoum et al. 2018), though testing was primarily in rural areas where signs are isolated. Even if we utilize published automated methods, we will still have to manually assess every part of the streetscape to check for false positives and false negatives. We also note, after previewing the Montview section, that many street signs are on the same horizontal poles as traffic lights, and many are small and/or obscured. For example in Figure 8.2, a “No Parking” may be on a light pole or power pole, but if it is not wider than the pole, the current automated methods would likely miss these signs. Additionally, the streetscape furniture and traffic lights require manual classification since we did not find adequate methods to automate extracting those features.

Since our four-mile sample area is not overwhelmingly large, we utilized a manual classification approach with some automated LiDAR functions. The data’s control reports, noted above, confirmed very high vertical and horizontal point-cloud accuracy. Also, automated LiDAR methods are often tested against manual classification for control, and we saw the same with automated urban mobile LiDAR feature extraction (Yang et al. 2015).We auto-filtered the data for ground points and also used an automated process to classify the remaining above-ground features together on a single LiDAR classification layer. We utilized Merrick & Company's MARS® LiDAR processing, which has a Google Earth simultaneous location feature, to follow the streetscape point-cloud in MARS®, paired with Google Earth on a separate screen, which allows a user to visually identify all street signs, traffic signals, and street furniture features (Figure 8.3).

Once completed, we utilized a voxel application tool in MARS®, which incorporates ground level and builds a user-specified voxel grid set to 1-ft by 1-ft by 1-ft (x,y,z) dimensions. This tool then applies the selected classified street furniture and street sign features into the voxel grids and exports a .dat Envi raster dataset, with each band within the .dat file representing a unique user specified voxel height zone. Each grid cell that is populated also has a count value that specifies how many LiDAR points fell into that 3D voxel grid cell. For this study, we are not very concerned with the amount of data in each grid cell, but rather the simple fact that classified LAS points are inside that grid cell. Table 9.1 presents a sample descriptive statistics output.

For the town center area, our descriptive statistic zones for the walkable streets are different because we focus more on the walkable areas between the curb and the buildings. For this, we used a different approach because we are interested in collecting and measuring features affiliated with the buildings themselves, such as the windows, awnings, and hanging signs. Our approach for collecting these objects differs because flat objects against buildings, such as windows, cannot be extracted like typical streetscape objects. Also, LiDAR often gets obstructed at windows and does not yield returns.

We extracted windows and awnings with mobile LiDAR with the help of a web-based solution by Orbit GT technologies. The Trimble MX9 platform collected panoramic images in conjunction with the LiDAR. Since the frames of the windows are well defined based on the void of LiDAR points within the frames, the Orbit LiDAR software has an interface that allows 3D feature tracing of the LiDAR data. For windows and awnings, we essentially created vertical polygons. After the windows and awnings were drawn in the 3D Orbit software interface, it exported the polygons into a Google KML file, which were then converted into 3D shapefiles. Since the features are in 3D, calculating the area of these polygons must be captured in 3D as well. For this, we created an automated model in ESRI's® Model Builder to iterate through each polygon feature and created a temporary Triangulated Irregular Network (TIN) for each window or awning polygon. We then ran surface information statistics on each polygon, utilizing the TIN as the surface, which enables the area of each polygon to be calculated. This process created area statistics for features like windows that can detected with LiDAR but not directly extracted and classified.

These streets have a handful of fenced outdoor restaurants, which are also focal features for studying streetscapes. We used the LiDAR data to locate the fenced areas and drew 2D polygons around these areas to estimate the square footage. Akin to the Montview sample, we processed the remaining streetscape features in the town center—including small landscape trees, light/lampposts, traffic signs, commercial signs (usually hanging in front of shops), and street furniture—via a single cubic-foot voxel grid. The result was then exported using .dat Envi raster data set with each zone as its own raster band.

It is also important to address the topic of occluded data and shadowing. Since mobile LiDAR emits horizontally, we need to address if features are prone to being obstructed by other features such as moving vehicles, parked vehicles, road users, or other objects. Fortunately, this collection occurred in early May 2020 when a Denver mandated stay-at-home order due to the COVID-19 pandemic was in effect, which significantly reduced traffic. Some parts of Montview Boulevard do not allow street parking, while the areas that do were mostly clear of parked cars. The mobile LiDAR vehicle operator was sure to always keep a safe distance from the few vehicles on the road. The town center's shops were either closed, or the few open restaurants were take-out only. A few street-side parked cars were present, though they did not obstruct or shadow features to a high extent. From our literature review, we concluded that features collected by mobile LiDAR are rarely occluded, and despite horizontal collection angles, features almost always tend to be completely collected.

For the Montview and town center examples, we ran automated batch exports to convert the voxel height bands within each .dat into vector polygons that were divided into square-foot 2D polygon pixels for each feature. We did this for each feature class we were analyzing. We then built an automated process through ESRI's® Model Builder interface to iterate through each individual vector polygon voxel zone for each feature class. Model Builder was then programed to perform a spatial join that adds up all populated voxels for each feature in each voxel height zone and append the data to each individual streetscape polygon. The end result places all data into shapefile attribute tables that are cleaned up and exported into Excel tables. The Excel tables are the descriptive statistics that ultimately show how each streetscape is made up of these features of interest. Table 9.1 and Table 9.2 specifically break out the features discussed above into voxel height-based descriptive statistics, where each populated cell in these tables are cubic feet counts of that feature in those height zones.

Table 8.1 Summary of LiDAR standards (QL2, QL1 or Mobile LiDAR) required to collect streetscape features

Streetscape Feature	Lowest LiDAR Density Standard Applicable to Collecting Feature
Tall Trees	QL2. QL1 for tree coverage below 5ft above ground.
Buildings	QL2.
Walls/Fences	QL1. QL1 can collect the top of walls/fences. Mobile LiDAR required for complete feature.
Landscape vegetation (low brush)	QL1. Generally matching imagery paired with QL1 will be required to collect low vegetation.
Light Posts	QL1 collects the top of general street-light boxes and the top of posts. Mobile LiDAR required for complete feature.
Traffic Lights	QL1 collects the top of traffic lights, and their connecting arms. Mobile LiDAR required for complete feature.
Power Poles/Lines	QL1 collects the top of poles, cross-arm structure and wires. Mobile LiDAR required for complete feature.
Traffic Signs / Commercial Signs	QL1 obtains some miscellaneous points on unobstructed signs. Mobile LiDAR required for complete feature.
Street Furniture	QL1 collects large items such as utility boxes and bus stop structures. All smaller items like benches and planters require Mobile LiDAR
Streetscape Building Windows	Mobile LiDAR, 3D panoramic imagery collected simultaneously is helpful but not required.
Streetscape Awnings	Mobile LiDAR, 3D panoramic imagery collected simultaneously is helpful but not required.
Open Air Courtyard Restaurants	Mobile LiDAR suggested for low fence perimeter outline. May be obtained with QL1 depending on nearby feature spacing and overhead obstructions.

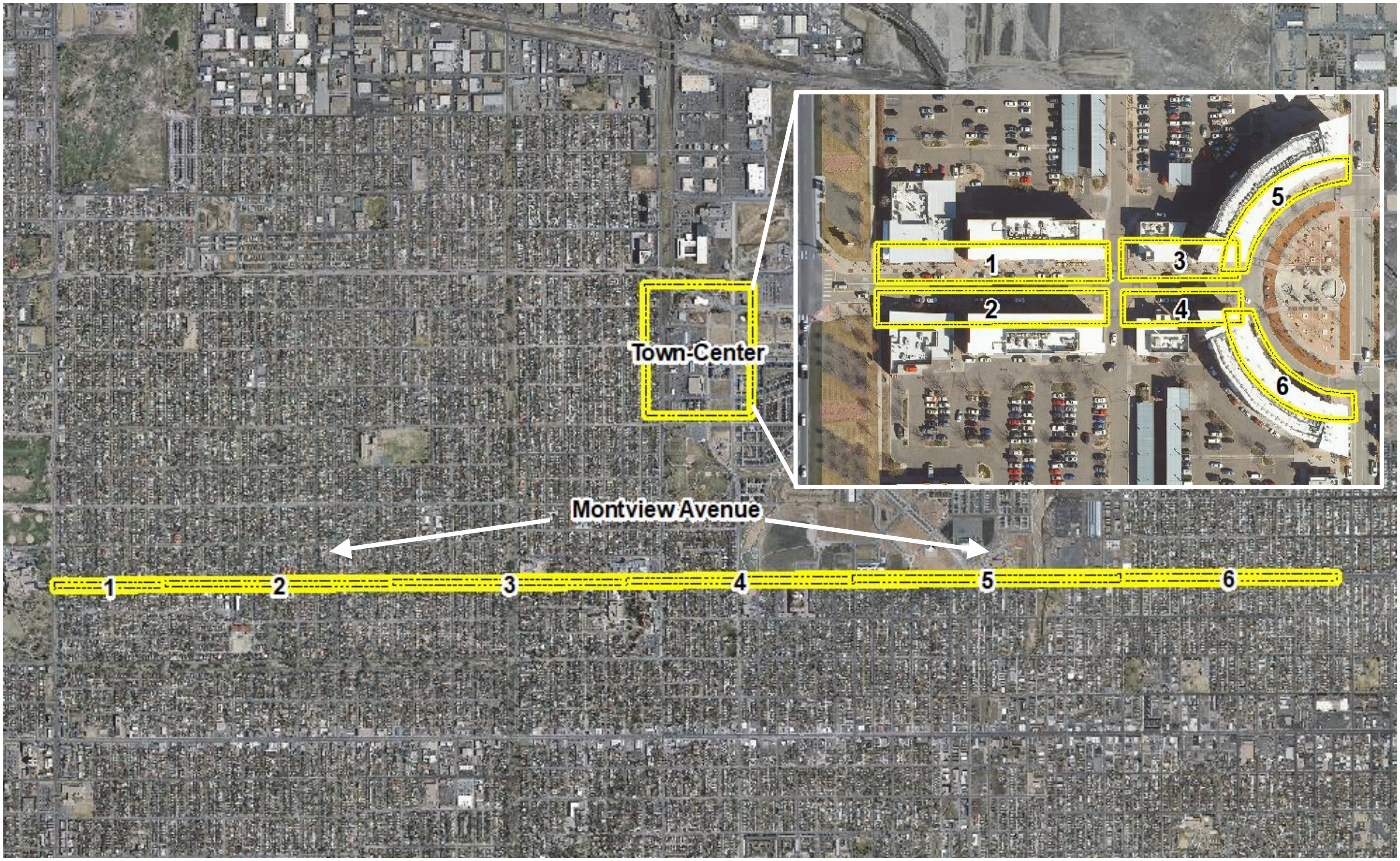

Figure 8.1 Sample streetscapes for both Montview Boulevard and the town center area to the north

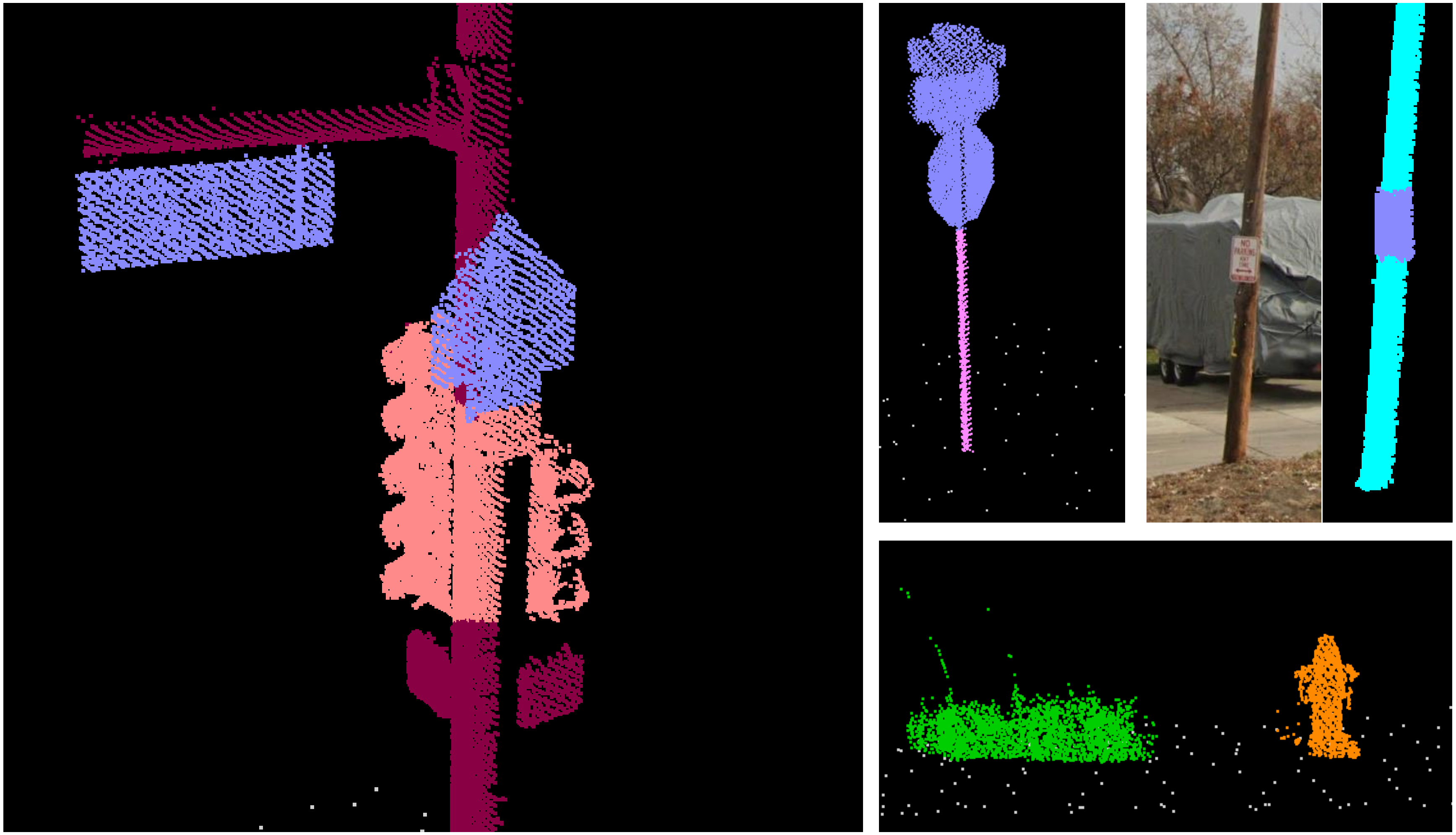

Figure 8.2 Sample features from Montview Boulevard

Notes: Left - Example of multiple features (signs, traffic signal, pole) grouped together. Top Center - Sign on pole. Top Right - No Parking sign on pole. Bottom Right - Hydrant and low landscape vegetation.

Figure 8.3 Matching spaces in Google StreetView and Mobile LiDAR dataset

9. RESULTS

Our first objective was to utilize mobile LiDAR for objective measuring and mapping of walkable streetscapes, and our second was to fill gaps for streetscape features we could not map in our previous QL1 study for more common urban streets (Golombek and Marshall 2020). Where our previous studies on this topic isolated features to five-foot vertical voxel zones, our results here allow us to isolate streetscape data into much tighter single cubic-foot voxels for more precise measuring of features. Table 9.1 shows sample results of the walkable streetscape areas. We specifically obtained volumetric streetscape data on trees, traffic signs, light/lampposts, hanging/commercial signs, street furniture, awnings, and enclosed open-air restaurants. We also obtained street-level calculations of building coverage, window coverage, and window proportions related to their buildings. Figure 9.1 shows an example of window extraction. Figure 9.2 shows an example of walkable streetscape features classified. Table 9.2 displays results of features either not obtained or obtained with poor quality from our QL1 study. We display processing results for street-signs, traffic lights, and street furniture in single-foot elevation layer voxel zones in an effort to provide descriptive statistic matrices. Figure 9.3 shows an example of single cubic-foot voxels covering a walkable streetscape.

For the town center area data presented in Table 9.1, we utilized six single-block segments shown in Figure 8.1. We obtained these values by creating a similar descriptive statistic breakdown used in our previous street-feature voxel categorizing studies (Golombek and Marshall 2019, 2020), which is similar to the Table 9.2 descriptive statistic structure. Since the results of Table 9.2 represent area/volume coverage at each voxel height zone, we added these figures together for each feature to determine total volumetric coverage, which is more in line with the sort of streetscape metrics (Ewing and Clemente 2013; Ewing, Hajrasouliha, Neckerman, Purciel-Hill, et al. 2016; Ewing and Handy 2009) that we are trying to objectively enhance. Whereas traditional methods may show crude tree counts and estimate their sizes or count windows and estimate their proportion, Table 9.1 shows that trees comprise between 2,347 cubic feet and 7,502 cubic feet of the six sample streetscapes. Table 9.1 also shows that window coverage range from 26% to 61% for the sample streetscapes. This is important to note since public aerial LiDAR is unable to obtain vertical building information.

As another example, areas 5 and 6 are very similar in size and shape and have the same number of trees. Yet, area 6 has nearly three times the amount of actual tree coverage per Table 9.1. Some descriptive statistics that public aerial LiDAR would not show is that area 2 appears to have twice the street furniture coverage as area 1, yet a similar amount of street furniture features. Also, the complete commercial and traffic signage coverage in Table 9.1 was not collectable with QL1 data.

Table 9.2 includes the results of our Montview Boulevard analysis. In Table 9.3, the numbers next to each abbreviation designate the lower part of the height zone; so height, for example SS_1 (SS = Street Signs), would be from 1 foot above ground to 2 feet above ground. TS (TS = Traffic Signal) starts at TS_10, where the first height zones where traffic signals are present are around 10 feet above ground, since TS_10 is the voxel height zone from 10 feet to 11 feet. Street Furniture (SF) starts at ground, though we eliminate the zero to 1-foot zone because many features at this level may be confused with misclassified ground points. Street furniture included benches, garbage cans, bus stops, permanent non-traffic signs, permanent décor, and any miscellaneous features that would not fit into any other common streetscape feature class.

For the Table 9.2 Montview sample, we can clearly see where signs, signals, and street furniture are most prominent. For street signs, it appears that most activity is between 8 feet and 12 feet, since before 8 feet and after 12 feet, these zones show much less activity. We see more than a doubling of street sign face coverage between 7 feet and 8 feet, and this statistic more than halves after 12 feet. Traffic signals do not populate voxels until 10 feet above ground. As the socioeconomics change, so do the traffic signals. Montview Boulevard begins in an affluent, highly tree-covered area. The traffic signals appear lower because many of them are flashing signals on the street sides. Farther east, as Montview transitions from Denver to Aurora, we see more traffic signals, which appear to be higher above ground. Table 9.2 highlights additional examples of objective street feature measurements that, if applied to discussed transportation outcome research, could reshape results.

Table 9.1 Descriptive statistics of streetscape features from high-density mobile LiDAR derived from voxel intervals for the town center district for compiling perceptual quality statistics

Area ID	Trees Volume	Trees Points	Street Sign Area	Street Sign Points	Light/Lamp Area	Light/Lamp Point	Hanging Sign Area	Hanging Sign Count	Street Furniture Area	Street Furniture Count
1	6124	10	126	5	252	9	138	7	412	19
2	7280	10	95	4	386	10	141	5	882	21
3	3022	3	121	5	91	5	89	3	339	12
4	2347	4	79	3	109	5	52	2	106	6
5	2847	6	60	3	276	6	94	3	135	4
6	7502	6	113	4	268	6	63	3	138	6

Area ID	Streetscape Area	Building Length	Building Face Area*	Window Count*	Window Area*	Window Percentage*	Awning Area*	Enclosed Open Restaurant Area
1	3652	281	3091	44	1373	44.4%	579	1007
2	3990	282	3102	47	1527	49.2%	473	636
3	2861	119	1309	20	343	26.2%	31	56
4	2926	118	1298	28	455	35.1%	56	165
5	6175	207	2278	58	1239	54.4%	1382	0
6	6488	207	2277	61	1385	60.8%	1361	120

All area and volume units represent are in square feet and cubic feet.

*Statistics are based on the ground level views, up to the top of the first story or awning.

Table 9.2 Descriptive statistics of streetscape features from high-density mobile LiDAR derived from voxel intervals for Montview Boulevard

Area ID	SS_1	SS_2	SS_3	SS_4	SS_5	SS_6	SS_7	SS_8	TS_10	TS_11	TS_12	TS_13	TS_14	SF_1	SF_2	SF_3
1	0	3	5	5	8	10	42	95	26	25	25	24	17	63	54	46
2	2	12	11	11	11	21	102	242	31	25	27	22	37	215	191	109
3	0	3	0	0	0	23	127	253	64	81	87	101	57	332	334	256
4	0	3	9	21	33	44	121	238	101	94	96	93	58	254	266	269
5	3	13	12	22	26	23	117	248	113	111	109	112	77	803	661	468
6	0	2	6	22	22	18	114	244	61	60	58	53	20	305	445	301

Area ID	SS_9	SS_10	SS_11	SS_12	SS_13	SS_14	SS_15	SS_16	TS_15	TS_16	TS_17	TS_18	TS_19	SF_4	SF_5	SF_6
1	116	102	102	95	52	16	18	16	0	0	0	16	34	31	25	23
2	289	292	292	267	105	20	15	13	38	16	15	7	2	67	24	19
3	308	298	283	231	110	68	51	56	37	50	44	28	16	191	129	134
4	260	222	227	193	92	31	30	44	36	5	30	83	113	193	138	96
5	287	265	206	137	38	12	6	22	41	24	23	89	170	394	354	267
6	306	279	188	107	11	2	0	21	15	29	101	106	161	210	94	105

Area ID	SS_17	SS_18	SS_19	SS_20	SS_21	SS_22	SS_23	SS_24	TS_20	TS_21	TS_22	TS_23	TS_24	SF_7	SF_8	SF_9
1	10	8	31	33	43	21	17	12	63	74	47	25	7	12	11	0
2	14	13	2	0	0	0	0	0	0	0	0	0	0	9	4	4
3	63	51	38	12	5	13	13	9	4	0	0	0	0	113	99	40
4	20	18	91	89	69	5	5	0	165	128	69	18	4	103	13	4
5	96	83	113	98	112	48	21	13	209	182	125	40	2	262	295	289
6	56	86	77	48	21	18	0	0	102	64	3	0	0	79	94	67

Area ID	Square Footage per Tile	Total Ind. Signs	Total Traffic Light Units	Total Street Furniture Items
1	250,888	34	9	11
2	510,972	75	10	32
3	521,185	91	17	37
4	508,772	95	26	42
5	601,701	107	35	89
6	485,807	101	24	38

SS = Street Signs, TS = Traffic Signals, SF = Street Furniture

All units are in cubic feet of coverage.

Numeric figures after each abbreviation indicates voxel height zone above ground.

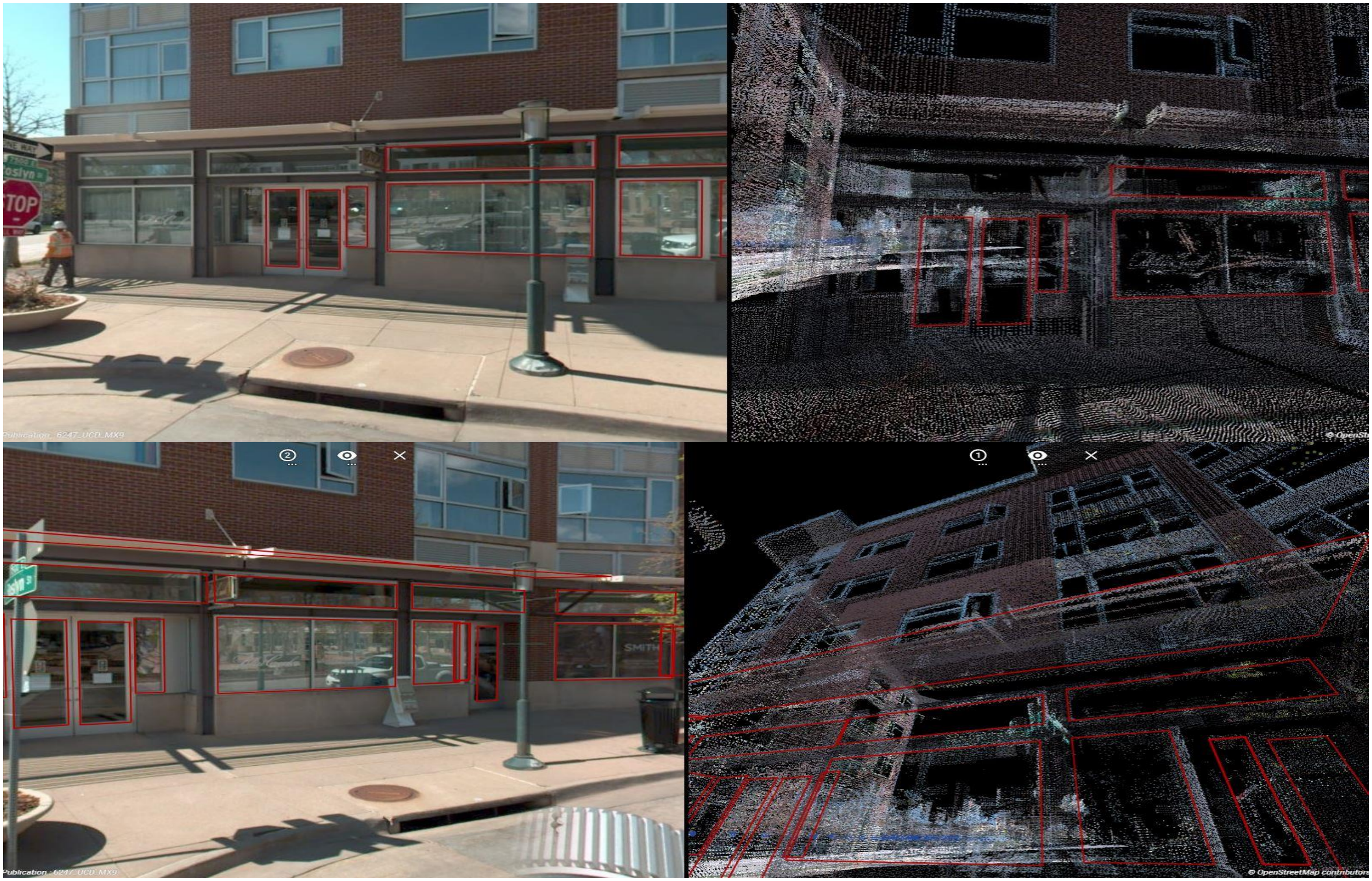

Figure 9.1 Example of collecting windows off imagery and LiDAR point cloud

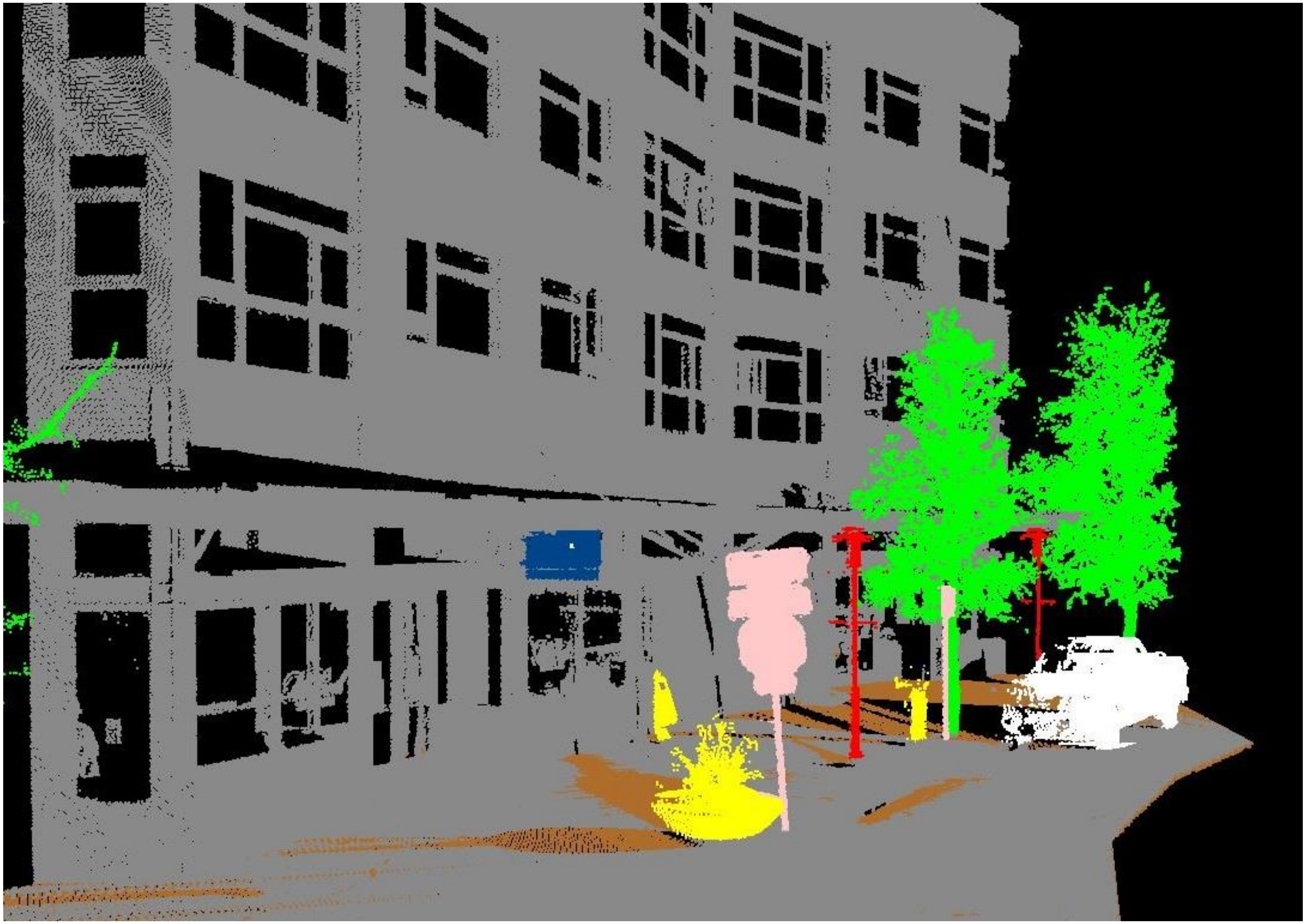

Figure 9.2 Sample of feature classification in the town center streetscape

Notes: Trees are green, traffic signage pink, lamposts red, street furniture yellow, commercial sign blue, parked car white.

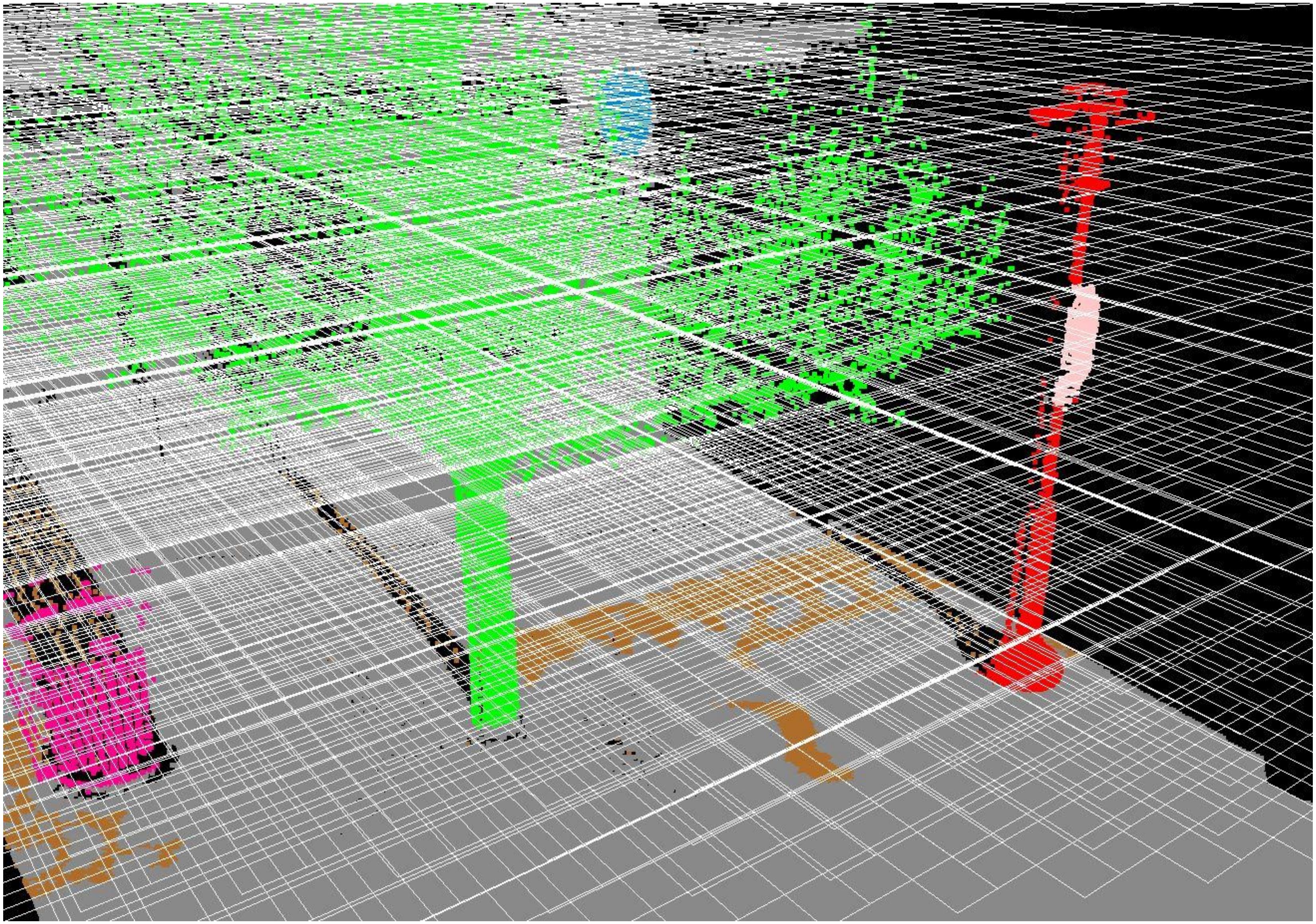

Figure 9.3 Example of single cubic feet voxels covering walkable streetscape area

10. CONCLUSION

Mobile LiDAR data have proven to be useful for the objective measuring of walkable streetscapes and infrastructure components that enclose a streetscape. Our results provide complete volumetric calculations of various features, such as street signage, ranging from 60 cubic feet to 126 cubic feet, and hanging commercial signs, ranging from 52 cubic feet to 141 cubic feet of total coverage throughout individual streetscape segments. Our results also provide examples of actual window areas, and we see significant discrepancies between window area as a proportion or percentage of the building's street level face, ranging from 26% to over 60%. Enclosed open-air restaurants range from zero to over 1,000 square feet. This level of descriptive statistics provides a unique niche for mobile LiDAR that cannot be obtained with publicly available aerial LiDAR.

For urban streets, our results also show that mobile LiDAR enables access to more refined descriptive statistics of critical features that cannot be obtained from a standard aerial QL1 or QL2 level collection effort. Although our previous aerial QL1 and QL2 studies contribute significantly to dividing a standard streetscape into 3D voxel zones for providing detailed streetscape descriptive statistics, mobile LiDAR facilitates smaller features like street furniture, traffic signs, and traffic lights. Whereas common aerial efforts are more limited to wider voxel zones, mobile LiDAR collected features easily fit into single cubic foot voxel zones. For example, we see that street signs appear most prevalent between 8 feet and 12 feet; we also see street furniture most prevalent at lower height zones and topping off around 10 feet.

We believe mobile LiDAR analytics has the potential to quantitatively supplement and/or replace time consuming, and possibly subjective, audit-based streetscape measures. For instance, the town-center area represents walkable streets that are similar to areas analyzed by Ewing et al. Ewing et al. considered factors such as enclosure, human scale, and imageability (Ewing and Clemente 2013) by visually assessing items—such as street trees, street lamps/lights, window area, hanging signs, planters, bike racks, and fenced restaurant seating—that we can now quantify with mobile LiDAR. Moreover, this research can also contribute to traffic outcome studies, as various researchers remain conflicted regarding the roles that street trees and other streetscape features have on road safety outcomes. Marshall et al., for instance, recently completed a study suggesting that street trees are associated with better road safety outcomes, which runs counter to conventional wisdom (Marshall, Coppola, and Golombek 2018). Our results have the potential to improve the objective measuring of streetscapes, which can supplement the audit-based efforts and help resolve long-standing inconsistencies over what features actually lead to better outcomes.

It is important to point out some potential limitations for a larger scale study of this nature. First and foremost, this study utilized manual classification methods. If this study was performed on a larger scale, similar to the hundreds of blocks that cited research utilizing audit-based or GIS-based methods, it would be important to improve automated LiDAR classification methods. Per our discussion above, the automated methods appear to be improving, with significant advancements over the past few years. Still, some features have no affiliated automated methods and may still require manual classification. Regardless, any automated improvement will significantly reduce the amount of time it takes to properly classify data. Additionally, shadowing due to parked vehicles is a limitation. As mentioned, the COVID-19 pandemic heavily reduced parked vehicles; however, city coordination, or perhaps coordination with street-sweeping days, may be necessary to limit parked vehicles when collecting data.

This research shows mobile LiDAR to be a valuable tool for quantitatively mapping streetscape features in 3D. Paired with our previous USGS aerial LiDAR studies, we believe our work addresses nearly all above-ground streetscape features for the purpose of quantitatively mapping them in 3D utilizing a voxel-based method. Utilizing our unique methods will hopefully provide transportation and urban design researchers valuable tools to help assess the roles that various streetscape features play in transportation outcomes.

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