An airborne LiDAR-based methodology for vineyard parcel detection and delineation

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An airborne lidar-based technique to delineate vineyard parcels from surrounding land uses is proposed and assessed in the Texas Hill Country American Viticultural Area near Austin, Texas, USA. Although most vineyard site analyses are based on multispectral aerial and satellite images, this study takes advantage of the height-based uniqueness of vineyard land uses inherent in the vine-trellising structure to differentiate vineyard areas from non-vineyard areas. A normalized digital surface model was created from lidar data and smoothed with a focal statistics method to identify vine rows and delineate vineyard land-use parcels. A simple unsupervised classification of the three study sites was performed to identify low vegetation areas. The vineyard areas were extracted from the low vegetation class and compared with manually digitized versions. The results suggest that lidar-based data sets can efficiently differentiate vineyard from non-vineyard land use. Our study yielded a mean classification accuracy of 97.55% and successfully extracted vineyard parcel area (mean accuracy 88.79%).

1. Introduction

The ability to accurately assess and quantify land area dedicated to viticulture (Vitis vinifera) is of great interest to vineyard managers, vineyard owners, wine associations and government organizations (Gong et al. 2003, Delenne et al. 2010). However, funding in-field surveying remains difficult because of the costs associated with hiring technicians, purchasing equipment and processing and analysing the collected data. Alternatively, remote-sensing analyses can provide a quick and cost-effective means by which vineyards can be inventoried over large areas. In most cases, vineyard inventories are created via examination of satellite or aerial imagery of varying spatial and spectral resolutions (Hall et al. 2002).

Delineating vineyard and non-vineyard land uses has proven challenging because of the spatial pattern and structure of the crop and its dependency on the spatial resolution of the imagery. Grapevines are most often trained on trellises, which create a discontinuous surface of analysis made up of vine rows and spaces between vine rows known as inter-row spaces. Thus, using low- or medium (i.e. 10–30 m)-resolution imagery is problematic because image pixels represent both classes of ground cover (Trollier et al. 1989). On the other hand, high-spatial-resolution imagery provides pixels that represent the vine row, the inter-row space or mixed pixels that can be
Automatically excluded (Hall and Louis 2009). In the same light, spectral resolution can also be a problem. Traditional image-processing methods have implemented the red and near-infrared spectral bands to characterize the grapevine leaf canopy for vineyard parcel delineation, vine row delineation and crop health assessments (Hall et al. 2002, Wassenaar et al. 2002, Da Costa et al. 2007, Cunha et al. 2010). In particular, vineyard delineation methodologies have been based exclusively on the spectral characteristics of the vegetation canopy to perform unsupervised and supervised classifications (Trolier et al. 1989, Gong et al. 2003), textural recognition (Da Costa et al. 2007) and spatial transformations including Fourier and wavelet analyses (Wassenaar et al. 2002, Delenne et al. 2008, Delenne et al. 2010, Lefebvre et al. 2010) and Gabor filters (Rabatel et al. 2008). The suite of methods developed to accurately locate and assess vineyards attests to the overall difficulty of this type of research.

Given the challenges associated with accurate identification of vineyard land use and parcel delineation, alternative methods are sought that attempt to mitigate the difficulties associated with both spatial and spectral considerations, as well as phenological characteristics of vineyard crops. Alternative remote-sensing data sets, such as lidar, provide an additional third dimension of information for the analysis of terrain and vegetation structure (x, y and z). A suite of research has focused on lidar-based prediction of vegetation characteristics and structure (Lefsky et al. 2002, Zimble et al. 2003, Mundt et al. 2006, Coops et al. 2007, Jensen et al. 2008, Hopkinson and Chasmer 2009), and most studies related to lidar-based vegetation feature extraction or inventory are focused on forest ecosystems (Leckie et al. 2003, Popescu et al. 2003, Koukoulas and Blackburn 2005, Borolot 2006, Lin et al. 2011) or urban environments (Haala and Brenner 1999), though Jang et al. (2008) employed airborne lidar for inventory of orchard trees. At present, few studies have used lidar data sets, airborne or terrestrial, to analyse grapevines or vineyards. Terrestrial lidar scanning has created useful three-dimensional models of grapevine vegetation (Rosell Polo et al. 2009) as well as characterized grapevine trunk biomass (Keightley and Bawden 2010). Although terrestrial lidar data have proven useful in studying specific grapevines over designated periods of time, the data thus far have not aided in characterizing the vineyard as a whole or in inventoruing parcels over a larger viticultural area. Bailly et al. (2008) used airborne lidar within a vineyard landscape but focused on demarcating drainage networks, not addressing the delineation of vineyard parcels. In this study, we examined the capacity of moderate post-spacing (1.4 m) airborne lidar data to capture bare earth (inter-row spaces) and canopy (vine canopy and trellis structure) features for extracting and classifying vineyard land use and parcel boundaries based on vine row spatial structure and pattern.

2. **Materials**

2.1 **Study area**

The Texas Hill Country American Viticultural Area (THCAV A) was recognized in 1991. The THCAV A is located in south-central Texas, west of Austin and north of San Antonio (see figure 1). This AV A contains 22 wineries, encompasses parts of 22 counties and covers an area of over 38 000 km². Three specific study sites with wineries and associated vineyards were selected within the THCAV A for our analysis: Driftwood Estate Winery (Driftwood), Texas Hills Vineyard (Texas Hills) and Spicewood Vineyards (Spicewood). The vineyards at the study sites were established in the mid-to late-1990s. These study sites were chosen because they are all located within the
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Figure 1. The study area, which falls into the THCA-V in south-central Texas. Also note the three study sites that are included in the analysis: Driftwood Estate Vineyards/Winery in Hays County, Texas Hills Vineyard in Blanco County and Spicewood Vineyards in Blanco County. The lidar coverage area is shown in light grey (urban area is shown in dark grey).

lidar acquisition region discussed in the next section. Each of these wineries has several vineyard parcels of differing size, shape, vine row orientation and grape varietals. Driftwood is located in Hays County, southwest of Austin, and has approximately 5.5 ha of vineyard area. Texas Hills and Spicewood are located in Blanco County, west of Austin, and have approximately 8 and 6.5 ha of grapevines, respectively. These vineyards are outlined in red within the study tiles shown in figure 2. The vineyards at Driftwood can be found in the northwest quadrant of figure 2(a). The Texas Hills vineyard parcels are centrally located in the analysis tile in figure 2(b). The vineyards at Spicewood are located on the central-eastern edge of figure 2(c).

2.2 Data

The lidar data were acquired between spring and early summer of 2006 using an Optech 2050 airborne system. The data acquisition was part of a larger initiative to provide Federal Emergency Management Agency (FEMA)-compliant elevation data for specific areas within the larger Capital Area Council of Governments (CAPCOG) in central Texas. Acquisitions were designed to provide a relatively high-density data set of mass points suitable for development of contours...
Figure 2. Three natural-colour tiles that serve as the lidar areas of analysis. Each tile covers an area of approximately 2.6 km$^2$. The vineyard parcels in each image are outlined in red. (a) Driftwood, (b) Texas Hills and (c) Spicewood.

required for hydraulic/hydrological model development, flood mitigation assessment and environmental impact analysis.

The multiple-return data sets were acquired in the UTM Zone 14N NAD 83 and NAVD 88 coordinate system. The point cloud density of the lidar data was 0.33 points/m$^2$. Three tiles of lidar returns (LAS file format) were included in the analyses of the three vineyard and surrounding areas, as shown in figure 2. Each tile covers an area of approximately 2.60 km$^2$ (1.50 km east to west by 1.75 km north to south). The extent of the analysis matches the image tiles provided in figure 2.

Visualization of raw lidar data is a powerful tool for the examination of vineyard areas (figure 3). Lidar returns within the point cloud with light tone have relatively high elevation and most likely represent vegetation, while points with dark tone exhibit low elevation attributes and represent bare earth or low ground cover. The vine rows
Figure 3. Three-dimensional visualizations of the raw lidar point cloud at the three study sites. The tallest vegetation is shown in white, bare earth in dark grey and intermediate vegetation in between. Vineyard pattern and orientation is immediately recognizable in the raw data before processing. (a) Driftwood, (b) Texas Hills and (c) Spicewood.

are easily distinguishable from all of the other surrounding land-use types (trees, bare earth and other types of low vegetation). In most cases, the orientation of the vine rows may also be directly observed. Driftwood, for example, has vine rows oriented in
two different directions. The Driftwood visualization (figure 3(a)) shows a tree in the middle of a vineyard parcel, which is confirmed in aerial imagery. Some vineyards are clearer than others in regard to their shape and structure. For instance, the intricate shape of the Texas Hills vineyard pictured in figure 3(b) is much less apparent than those shown at Driftwood or Spicewood (see figures 3(a) and (c)).

3. Methods

3.1 Lidar processing and surface creation

The lidar data were processed using the Fusion software package provided by the Remote Sensing Applications Center of the United States Department of Agriculture (Salt Lake City, Utah, USA). The Fusion package contains point cloud-filtering algorithms for processing LAS files, visualization capabilities as well as other analysis and export tools. Three surfaces resulted from the raw lidar data set: digital terrain model (DTM), digital surface model (DSM) and normalized digital surface model (nDSM). To create the DTM surface, Fusion’s GroundFilter algorithm (Kraus and Pfeifer 1998) removes lidar returns that represent features above the ground surface. The DTM surface was interpolated at a spatial resolution of 0.6 m to coincide with the relatively small width of vine rows (i.e. approximately 2 feet). Though the DTM resolution is less than the nominal post spacing of the raw lidar, this higher spatial resolution is preferred to separate the pixels representing vine row heights from those representing the inter-row space heights (Hall et al. 2002). The DSM represents all non-ground features. The nDSM surface is created by subtracting the DTM surface from the DSM surface and represents the relative elevation of surface features from ground level. Thus, vine row cells have height values equalling that of the top, or near the top, of the vine row structure above 1 m and inter-row spaces contain values at or near zero representing the ground or very near ground. All three study tiles were processed in the same manner with equivalent spatial resolutions.

3.2 Surface classification

To accurately classify the vine parcels, a focal statistics moving window analysis of height range was employed to differentiate vines from other low-lying vegetation features. The focal statistics function acts upon every pixel of a raster by assigning the central pixel the value of the amalgamated neighbourhood pixels. In the case of vineyards, the height range of surrounding pixels is useful because vine rows have a constant height due to the trellis structure. This constant height can be found by subtracting the ground values from the values of the top of the vine canopy and/or trellis structure. The output is a new surface, the focal statistics of the nDSM surface (nDSMFOCAL), calculated by equation (1):

\[ \text{nDSM}_{\text{FOCAL}} = \text{nDSM}_{\text{MAX}} - \text{nDSM}_{\text{MIN}}, \]  

where \( \text{nDSM}_{\text{MAX}} \) and \( \text{nDSM}_{\text{MIN}} \) refer to the maximum and minimum raster values for a specified window size (e.g. 12 \times 12). To determine which neighbourhood size window best suited the needs of the analysis, a series of windows were passed over the data set (see § 4.2 and figure 5).
nDSM_{FOCAL} was used as the single input to an unsupervised classification using the Iterative Self-Organizing Data Analysis Technique (ISODATA). The ISODATA algorithm was parameterized to identify a maximum of six clusters with the purpose of organizing the focal statistics output. The uniform nature of the vineyard height surface following the focal statistics function places all of the vineyard parcels and some similar vegetation areas (contiguous pixels of the same height) throughout the tile into a distinct vineyard class. Following a raster-to-vector transformation, the vineyard class was then assessed for accuracy.

### 3.3 Accuracy assessment

Vineyard parcels were manually digitized based on coincident natural-colour imagery acquired through CAPCOG. This high-spatial-resolution (45 cm) imagery thus became the comparative reference information for the study. Accordingly, the digitized parcels were compared with the LiDAR-based classification results to compare the level of agreement between the two products. The digitized vineyard parcels shown in figure 2 served as the basis for accuracy assessment. The accuracy assessment consisted of calculating the ratio between the total area of manually digitized and LiDAR-based classification products. Two accuracy measures were calculated: (1) the accuracy of the vineyard area is separated from the non-vineyard area and (2) the accuracy of the classified vineyard parcels compared to the digitized parcels. For the first assessment, the resulting percentages represent the amount of total area, both vineyard and non-vineyard, correctly classified by the lidar-based methodology. For the second assessment, the resulting percentages represent the amount of area of the classified vineyards that matches the vineyard area of the digitized vineyards. The results of the first accuracy assessment are presented in contingency tables, while the results of the second assessment are discussed.

### 4. Results

#### 4.1 Point cloud-filtering and the resulting lidar surfaces

The point cloud filters and the resulting DTM, DSM and nDSM surfaces provide detailed elevation information at each of the study sites. The DSM and nDSM surfaces, in particular, capture vegetation heights of all types of vegetation including low vegetation like grapevines. The resulting nDSM surfaces for each of the three study sites are shown in figures 4(a)–(c) in their entirety. Additionally, the vineyard parcels within each of the study tiles are shown in greater detail in figures 4(d)–(f). The surface represents vegetation heights in a two-dimensional surface rather than the three-dimensional visualization as shown in figure 3. Much like in figure 3, the tallest trees and vegetation throughout the study sites are shown in white, while the bare earth is denoted in black. The vine rows become apparent in the nDSM because rows of lighter shades represent the vines and darker shades represent the inter-row spaces. These pixels of uniform heights fall into line with one another, giving away the location of the vine row structure. In this case, much like with the visualizations of figure 3, the orientation of the vine rows becomes obvious. The vine row and inter-row space differentiation is strong at Driftwood, Spicewood and most of Texas Hills except in the northwest corner of the southern vine parcel there. The vine rows might be less apparent in this area because of the spacing of the lidar returns in that particular area or due to error associated with the point cloud-filtering algorithms. Otherwise,
Figure 4. The nDSM surfaces in entirety ((a)–(c)) and of selected vineyard parcels ((d)–(f)). White areas are tall vegetation, while black areas are very low-lying vegetation or bare earth. The vine row pattern is apparent in (d)–(f), which represent vineyard parcels extracted from the nDSM. (a) and (d) Driftwood, (b) and (e) Texas Hills and (c) and (f) Spicewood.

the nDSM provides a reliable height surface that properly characterizes the vineyard landscape and can be derived with a focal statistics operation to extract the vineyard parcels.
4.2 Focal statistics and surface classification

Based on the focal statistics output images, we selected a 12 × 12 neighbourhood (see figure 5). Smaller neighbourhood analyses like those in figures 5(a) and (b) did not adequately fill vineyard parcels and left undesirable patches of space. On the other hand, larger neighbourhoods smoothed the surface excessively, not producing acceptable parcel boundaries (see figure 5(d)). The 12 × 12 window (see figure 5(c)), therefore, was able to both fill the parcel area and provide accurate parcel boundaries.

Figure 6 represents the results of the focal statistics analyses of the nDSMs in their entirety (nDSM_{FOCAL}). The difference between the nDSM and nDSM_{FOCAL} surfaces relates to the smoothing nature that the focal statistics creates. Using this geospatial technique, areas of relatively tall vegetation become more unified as pixel values increase in similarity. The vineyard pixels become uniform through the focal statistics because the range is being assigned, or rather the difference between the highest and lowest cells in the focal window. In the case of vineyard cells, the value should be the difference between the tallest vine structure and the lowest cells of inter-row space. Therefore, nearly all the vineyard pixels gain values of the vine row heights. After the focal statistics filter, almost all the vineyard pixels have the same height value. The

![Figure 5](image-url)  
Figure 5. A comparison of differing focal statistics analysis windows of vineyard parcels at Spicewood (inverted greyscale). The 12 × 12 pixel window provides the most desirable parcel delineation results because it fills the parcels and accurately demarks the boundaries. (a) 4 × 4, (b) 8 × 8, (c) 12 × 12 and (d) 16 × 16.
Figure 6. Focal statistics results ((a)–(c)) for the three study tiles – a 12 × 12 cell summary assigning a range (highest–lowest) value to the central cell. The vineyard cells have values of 1–2 m, representing the height of the vines and trellising system. Specific vineyard areas are also shown with an inverted greyscale ((d)–(f)). (a) and (d) Driftwood, (b) and (e) Texas Hills and (c) and (f) Spicewood.

Vineyard areas in each of the three sample sites become more apparent than was previously possible with only the nDSM surface (see figure 4). All of the vineyard parcels in each of the study tiles have a similar grey colour, representing the ground-to-vine heights. The focal statistics provides a more generalized surface by which the entire vineyard parcels can easily be delineated via a simple unsupervised classification.
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Figure 7. Unsupervised classification results of the focal statistics summary surfaces. The vineyard class is shown in the light grey tone. Other areas with similar vegetation heights fall into the vineyard class. The vineyard parcels are the only features covering significant, uniform areas within the classification. (a) Driftwood, (b) Texas Hills and (c) Spicewood.

The focal statistics surface classification results are provided in figure 7. Six clusters (classes) of vegetation heights were created based on the differing heights: one class represents vineyards, while the rest represent non-vineyards (see figure 7). By way of visual interpretation, parcel square and rectangular shapes are easily distinguishable from all of the other vegetative features in the study areas. The tree within the smallest vine parcel at Driftwood (figure 7(a)) was automatically excluded from the vineyard class. In this case, the lidar-based method proved more accurate in terms of vine location because the tree location was not easily recognizable in the aerial imagery.

4.3 Product evaluation and accuracy assessment

Vineyard parcels identified and extracted from the classification of nDSM$_{FOCAL}$ were compared with the manually digitized parcels for comparison and accuracy assessment. Visual comparison of the lidar-based vineyard classification and the digitized parcels indicates a high level of agreement between the two methods (see figure 8).
For our quantitative assessment, the Driftwood tile is 98.15% accurate compared to the digitized parcel boundary (see table 1). This percentage represents the total of the correct vineyard and non-vineyard area within the analysis tile (the sum of correctly classified areas shown in bold in tables 1–3). Likewise, Texas Hills and Spicewood have similarly high accuracies, 97.55% and 96.96%, respectively (see tables 2 and 3). The mean accuracy of correctly classified vineyard area for all three vineyard sites was 97.55%. In terms of parcel delineation, the predicted results remain highly accurate (see figure 7). Driftwood results in an accuracy of 90.17%, Texas Hills, 90.62%, and Spicewood, 85.58%. Mean accuracy for all three study sites was 88.79%. In either case,
Table 2. Comparison matrix of predicted versus digitized vineyard and non-vineyard areas for the Texas Hills study site.

<table>
<thead>
<tr>
<th>Classified</th>
<th>Digitized</th>
<th>Vineyard (No. of pixels %)</th>
<th>Non-vineyard (No. of pixels %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vineyard</td>
<td>220 913 (23.66%)</td>
<td>14 596 (1.56%)</td>
<td></td>
</tr>
<tr>
<td>Non-vineyard</td>
<td>8 264 (0.89%)</td>
<td>689 829 (73.89%)</td>
<td></td>
</tr>
<tr>
<td>Total: 933 602 (100%)</td>
<td></td>
<td>97.55% correctly classified</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Comparison matrix of predicted versus digitized vineyard and non-vineyard areas for the Spicewood study site.

<table>
<thead>
<tr>
<th>Classified</th>
<th>Digitized</th>
<th>Vineyard (No. of pixels %)</th>
<th>Non-vineyard (No. of pixels %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vineyard</td>
<td>168 378 (18.06%)</td>
<td>20 366 (2.18%)</td>
<td></td>
</tr>
<tr>
<td>Non-vineyard</td>
<td>8 002 (0.86%)</td>
<td>735 721 (78.90%)</td>
<td></td>
</tr>
<tr>
<td>Total: 932 467 (100%)</td>
<td></td>
<td>96.96% correctly classified</td>
<td></td>
</tr>
</tbody>
</table>

the proposed lidar vineyard delineation methodology is accurate across three different study areas within the THCAVA.

5. Discussion

5.1 Factors influencing accurate vineyard classification

The proposed method does not differentiate between the vineyard parcels that are spaced at or near the same distance as the individual vine rows are spaced from one another. For instance, the Spicewood parcel delineations are the least accurate of the three study sites because the method had trouble differentiating separate vine parcels in close proximity to one another, as can be found in the northern parcels. These close-proximity parcels, shown in figure 8(c), are found in the Spicewood tile more so than in either of the other two tiles. These four vineyard parcels were classified as one large one. Likewise, at the Driftwood study site in figure 8(a), the rectangular southeast parcels had the same result.

Also, in nearly all cases, the lidar-based classification product extends beyond the area of the digitized parcels derived from the NAIP imagery. This relates back to the large size of the focal statistics smoothing window. A smaller window would have more accurate edges, but would have more holes within the parcel. The 12 × 12 moving window best compromises these issues. Taking into account the entire tile of the analysis, the vineyard and non-vineyard areas show a high level of agreement. In terms of the accuracy of the digitized image parcels, the study might have also benefited from in situ parcel boundary data collected using a high-accuracy GPS receiver.
Beyond the high level of accuracy the proposed methodology has shown, an unexpected advantage was realized in regard to the identification of a tree within a vineyard parcel at Driftwood. The lidar-derived vineyard parcels found inconsistencies that even the digitized vineyard parcels did not account for (i.e. a tree in the middle of the square-shaped, north-westernmost Driftwood vineyard parcel). This attests to the value of height-based data provided by lidar.

5.2 Factors influencing the application of the proposed methodology to additional viticultural areas

The primary weakness of this new method relates to its overall cost. Airborne lidar data are relatively expensive to acquire. Therefore, if this method is to be adopted, a substantial amount of funding may be necessary to acquire or purchase data. In this case, the lidar data were provided free of charge by CAPCOG. Nonetheless, lidar data are becoming increasingly available as local, state and governmental agencies add the sensor data to their growing list of geospatial inventories. Looking further, when national or international lidar data become available, this methodology can be used and tested over a number of study areas and AVAs in the USA and elsewhere across the globe. At that point, researchers can start addressing questions such as minimum lidar post density, footprint and scan angle considerations.

Another consideration in such an analysis is the size of the moving window. In a different viticultural area, the size of the moving window may vary depending on the geometry of the vine rows, most importantly the spacing, and the resolution of the DSM. Therefore, a 12 × 12 analysis window may not be ideal in all cases.

5.3 Extended application in viticulture and other crops

Beyond the scope of viticulture, the application of this methodology to crops exhibiting similar spatial patterns and structures is of interest. This lidar-based methodology may suit delineating orchards and other crops with inherent spatial and height-based patterns. Within the scope of viticulture, many other research areas can be addressed with lidar data. For parcel or vine row delineation, fusing high-spatial-resolution aerial or satellite imagery with lidar elevation surfaces (nDSM or otherwise) has been shown to improve the accuracy of image classifications (Huang et al. 2011). Stacking height-based information with spectral characteristics may prove to be the best method by which particular ground features can be delineated. In terms of visualization, colour values from aerial/satellite imagery or image indices can be attached to the lidar point cloud to convey the spectral characteristics that lidar lacks, and this addresses the third dimension that imagery lacks. For instance, attaching an NDVI colour value like Hall et al. (2003) to the point cloud could create a three-dimensional model of grapevine vegetation vigour. This could prove very useful for vineyard managers and other decision-makers who address the variability of grapevine canopy vigour in the field.

6. Conclusion

A new remote-sensing method for identifying vineyard land uses has been proposed that uses topographic and vegetation height information derived from airborne lidar scanner data in place of satellite or aerial imagery. This lidar-based methodology is advantageous because it does not rely on the spectral characteristics of
the grapevine canopy, which has proven difficult (Trolier et al. 1989). Instead, the height characteristics of the vine/trellis rows are compared with that of the bare earth, resulting in a textured surface for classification. Consequently, the results at three study sites in the THCA VA indicate that airborne lidar data can accurately predict vineyard parcel locations in all cases, with border accuracy greater than 85% for the vineyard-only class and greater than 96% for the vineyard/non-vineyard results. Overall, the results of our study suggest that lidar data can be used to correctly identify vineyard parcels as well as height-based discrepancies within vineyard parcels that are less likely to be found in phenologically dependent imagery.

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