Influence of Fusing Lidar and Multispectral Imagery on Remotely Sensed Estimates of Stand Density and Mean Tree Height in a Managed Loblolly Pine Plantation

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ABSTRACT. Stereo aerial photography has long been used to measure tree density and height photogrammetrically. Recent attempts have been made to locate and measure trees automatically in high-resolution digital imagery. This study used small-footprint lidar (1.057 µm, 1 mrad divergence, 0.67 m footprint) and high-resolution (0.61 m) multispectral (550, 675, 700, and 800 nm) data sets to estimate stem counts and tree heights in 15-yr-old loblolly pine stands. A data fusion process was used to combine the datasets. Tree identification accuracy and mean height estimation derived from the separate and fused data sets were compared against field data.

Tree identification was more accurate using spectral data (78.6% and 92.4%) than lidar data (64.7% and 87.3%) within the two planting densities, respectively. The fused dataset improved accuracy of tree identification over the single-dataset approaches (83.5% and 94.8%). Plot-level mean height of lidar-located trees provided the best estimates of mean field height (average difference = 0.15 m). Missed trees for all methods were shorter than mean field height by up to 3.03 m (fused data). These results indicate fusion of spectral and lidar data will likely improve estimates of mean tree height and stem density. Increased lidar posting density is identified as a key factor to improve tree recognition and measurement. For. Sci. 49(3):457–466.

Key Words: Inventory, sensor fusion, ALTMS, infrared.

STAND DENSITY and tree heights are common variables measured during most forest inventories. Both are related to stand condition and development and are key for obtaining estimates of canopy structure, mean stem diameter, and standing timber volume. While stem density and tree height are easily measured from the ground, acquiring these and other field measurements is both expensive and time consuming. In addition, repeated measurements, often taken by different crews and under different conditions, are potentially prone to errors and inherent variability (Omule 1980, McRoberts et al. 1994).

An alternate method for obtaining estimates of stem density and mean stand height is through aerial photogrammetry (Spurr 1948, p. 209–242). With adequate spatial resolution, accurate estimates of stem density can be obtained. Estimates of tree heights from stereo photographs, however, require that both individual treetops and open ground be visible. This very often does not occur within intensively managed pine plantations.

Considerable effort has been put into utilizing remotely sensed data to augment or improve current inventory practices (Leckie 1990, Holmgren and Thuresson 1998, Spurr 1948).
Methods

Study Area and Field Data

Our study utilized a 15-yr-old loblolly pine spacing trial located on Mississippi State University’s Starr Memorial Forest in east-central Mississippi (33°16'N, 88°52'W). The study included four replicates of two planting spacings: 2.4 m × 2.4 m (high density) and 3.0 m × 3.0 m (low density). Current density in the high- and low-density plots averaged 1,234 and 803 trees/ha, respectively. Each spacing block within each replicate contained eight 12.2 m × 12.2 m measurement plots. Measurements from the eight plots were aggregated for analysis. Planting on exact spacing provided information on the location of every live tree within each plot. These stands represent a relatively simple system (single species, even age, known original planting spacing). For typical forest inventory applications, a simple in situ sample of tree height, diameter, etc., may suffice, but our goal was to develop and test a new set of inventory tools with hopes of extrapolating the results to other, more complex stand structures. All trees on each measurement plot were measured following the 1999 growing season for diameter at breast height (1.37 m), total tree height, height to base of live crown, and crown radius in the four cardinal directions. Field data were linked to a GIS layer identifying the precise location of each tree.

Lidar Data

Aerial scanning small-footprint lidar data were acquired on October 5, 1999 using the Airborne Lidar Topographic Mapping System (ALTMS) flown by TerraPoint LLC (Houston, TX). Data were collected from an altitude of 610 m with a maximum off nadir scan angle of 20°, creating a data swath width of approximately 396 m. The laser system operated at a wavelength of 1.057 µm with a 1 mrad divergence resulting in a 0.67 m footprint on the ground. TerraPoint reported the horizontal accuracy of the data to be 0.67 m. Vertical accuracy was better than 0.43 m. This pulsed system provided an on-the-ground posting density of 1.0 to 1.5 m. The ALTMS collected up to four returns per outgoing pulse.

Tree Identification.—Data from the first recorded return from each lidar pulse were interpolated using ERDAS Imagine 8.4 (ERDAS, Inc., Atlanta, GA) to create a canopy surface layer. The nonlinear rubber sheeting interpolation algorithm was used with an output pixel size 0.1524 m. We chose nonlinear rubber sheeting over linear rubber sheeting based on the quality of the lidar data set and the form of the trees being studied. The data provided by the ALTMS had consistent along- and across-track posting densities, resulting in a fairly regular grid of lidar points. With a regular grid of points and the conical form of the loblolly crowns, the nonlinear interpolation algorithm resulted in a smoother, more realistic appearing canopy surface than the linear interpolation algorithm provided in ERDAS.

Loblolly pine trees grown in regularly spaced plantations typically have fairly conical and symmetrical crowns. The row spacing and canopy symmetry is clearly evident from the three-dimensional depiction of the interpolated lidar surface (Figure 1). A focal search function was used to identify the location of individual trees assuming the pixel associated with the peak of a tree would be higher than neighboring pixels within the lidar canopy surface. A pixel was deemed a crown peak if it was higher than all neighboring pixels within a 1.219 m radius. This radius was chosen so that if the window was centered on a tree peak, only one tree would should fall within that window, given the minimum field planted spacing of 1.52 × 1.52 m.
Ground Layer Identification.—A ground elevation layer is required to compute tree height from lidar data. While no consensus currently exists on the optimal method to derive a ground layer from lidar data, many procedures include statistical filtering to remove data points not originating from the ground (Kraus and Pfeifer 1998, Petzold et al. 1999, Axelsson 1999, Hyypa and Inkinen 1999). Filtering is repeated until a final ground surface is completed. Our study utilized this type of an approach. The initial data set included the last recorded lidar return from each emitted pulse. In open areas such as canopy gaps or adjacent lanes, or occasionally in very dense canopy, only a single return was recorded. Most pulses striking the canopy contained between two and four returns. For each pulse, the lowest return was extracted and used to interpolate a preliminary ground surface layer utilizing the linear rubber sheeting algorithm with the same pixel size as the canopy surface layer (Figure 2a). A 0.607 m filter window was passed over the interpolated data layer, retaining the value in the center pixel if it was within 0.01 m of the minimum value within the window. All retained pixel values were interpolated again into a new ground surface layer. The procedure was repeated until the resulting surface did not appreciably change from the previous iteration. In the case of this data set, three iterations were determined to be acceptable for the final ground surface layer (Figure 2b).

Multispectral Data

Multispectral data consisting of four spectral channels (550 nm, 675 nm, 700 nm, and 840 nm) were collected by Spectral Visions (Stennis Space Center, MS) over the study site on September 7, 1999 (Figure 3). The size of the charged couple device (CCD) array of the system was 1,320 pixels by 1,028 pixels. Data were collected from 1,067 m above ground level, yielding a 0.58 m (resampled to 0.61 m) pixel size at nadir. Each image covered approximately 765 m by 596 m.

Tree Identification.—Identifying individual trees within the spectral data was accomplished using an approach similar to that used with the lidar data. Healthy conifers strongly reflect near-infrared (NIR) energy. Reflectance of NIR radiation is high from healthy vegetation with high exposure to sunlight; therefore, within the canopy surface, tree peaks generally have higher NIR reflectance values than locations on the shoulders or edges of the crowns. A 1.219 m radius filter was passed over the spectral data. The center pixel was considered a tree peak if its NIR value was higher than its neighbors within the window.

Fusion of Data Sources for Tree Identification

It was deemed inappropriate to directly fuse unitless digital values representing NIR reflectance in the spectral imagery with elevation values (height measurement units in meters) in the lidar data, because the two values had no relation to each other. Therefore, prior to fusing the two data sources, we created a common metric for the values in each data set. A focal search window was passed across each data layer to assign the center pixel in each window to a percentile value corresponding to the proportion of pixels within each window containing values lower than the value of the center pixel. A 3.048 m radius window was used for the spectral data and 1.219 m radius window for the lidar data. The search radius was increased for the spectral data set to increase the number of pixels examined for percentile computation. A 1.219 m radius in the spectral data would have resulted in a window with only 2-pixel radius window. The resulting files were combined by multiplication to yield a final fused layer with a pixel size of 0.1524 m corresponding to the pixel size of the interpolated lidar data layer (Figure 4). A focal window was passed across the fused data layer to locate peak values assumed to represent treetops.
Derivation of Tree Height

Tree heights cannot be extracted directly from single view spectral data; therefore, estimated tree heights for all three tree identification approaches were derived from the lidar data. The only difference among the three data sets was the number and location of identified tree peaks. The interpolated lidar data layer and the fused data layer both had the same interpolated raster cell size. The resolution of the spectral data layer, however, was four times lower than the other two layers. The lidar pixel with the highest value falling within the area encompassed by the spectrally identified tree peaks was therefore assumed to be the location of the tree.
Figure 4. Spectral and lidar data sets were fused to create a new data set shown above (same area as Figure 3). Pixels with higher fused values (near infrared reflectance and lidar height) than their neighbors appear brighter. Individual tree crowns can be distinguished as clusters of bright pixels in both density stands.

Figure 4 peak. Tree heights for each tree identification approach were calculated by subtracting the pixel elevation value of the lidar ground layer from the pixel elevation value of the lidar canopy surface layer at each of the identified tree peak locations. Because the exact pixel identified as the location of a tree peak can vary between the approaches, it is possible for a single tree correctly identified by all three approaches to have three different values for estimated tree height.

Statistical Analyses

Analysis of variance approaches (SAS, proc mixed procedure) were performed to determine if the percentage of trees correctly identified in the remotely sensed data sets differed from each other (by spacing, by identification method, and interaction of spacing and method) as well as from the actual number of trees identified in the field. The relative accuracy of the three approaches was also compared across the two stand densities (t-tests). In addition, the percent of trees incorrectly identified by each approach was compared (t-tests). These are identified trees that do not correspond with a live tree identified in the field. The average estimated height of identified trees per replicate (N = 4) was compared to the average field measured height values to determine if mean height estimates differed significantly between tree identification approach (t-tests). Mean height estimates from each technique were also compared to each other (t-tests). We chose to perform our statistical analyses at the replicate level, as compared to single-plot or single-tree level. A summary table of single-tree statistics is presented. Each of the eight plots within each replicate consisted of a different genetic family. If we analyzed the data at the plot level, we would have to consider an additional interaction factor (genetics), which was not our purpose. Analysis at the single tree level could be performed as well, and some single tree level statistics are reported, but interpretation of their significance is confounded somewhat by the extremely large sample size and degrees of freedom. Our single-tree analyses may result in statistical significance, but may not have great biological or practical significance. The significance levels were set at alpha equal to 0.05.

Results

Tree Identification

The three tree identification approaches differed significantly (P < 0.001) in their ability to correctly identify live trees (Table 1). Accuracy of live tree identification also differed significantly (P < 0.001) between the two stand densities (Table 1). In the low-density plots (3.048 m initial spacing), live tree identification ranged from 87.27% (lidar) to 94.84% (fused). The high density plots (2.438 m initial spacing) overall had lower tree identification accuracy ranging from 64.67% (lidar) to 83.50% (fused). None of the three identification approaches in either spacing correctly identified living trees with 100% accuracy.

All three tree identification approaches incorrectly identified some trees that were recorded as dead in the field (commission errors). Commission errors reported in Table 1 were computed as the number of trees identified in the lidar, spectral or fused data, but dead in the field divided by the total number of live trees identified by each approach.
number of field identified dead trees. Although the spectral
data approach appears to have the lowest commission error
rate, the rates for all three approaches were not statistically
different from each other. All were statistically different from
zero ($P < 0.0001$). The commission error rate did differ
significantly between the two densities ($P = 0.0459$). The
inclusion of committed trees in the tree counts artificially
inflates the apparent identification accuracy. However, even
when the committed trees were included, in only one case
was the derived stem count statistically equal to the field
count. The fused method in the low density stands identified
385 trees compared to 382 known field trees (100.8%).

**Tree Height**

The difference between field measured mean tree height
and average estimated height of correctly identified trees was
significantly different for all three approaches ($P < 0.0001$)
except for lidar estimated tree heights in high density stands
(Table 2). All three methods underestimated mean tree height.
The average estimated height for lidar identified trees was
closest to field measured height among the three approaches
in both spacings (Table 2). The lidar approach underestimated
mean height by an average of 0.15 m and 0.38 m in the
high and low density plots, respectively. The fused data
approach underestimated height by 0.42 m and 0.50 m, and
the spectral approach underestimated by 0.58 m and 0.70 m
in the high and low density plots, respectively. The field
measured mean tree height for both spacings was not statisti-
cally different ($P = 0.2036$).

Failure to correctly identify all trees influenced the calcula-
tion of mean tree height. The majority of trees missed
(omitted) in all three approaches was shorter than average
(Table 2). The average height of the trees missed by lidar was
1.02 m shorter in the high-density plots and 1.93 m shorter in
the low density plots than the average field measured height.
The trees missed by the spectral method were 1.56 m and 2.41
m shorter, while the average height of the trees missed by the
fused method was 1.91 m and 3.03 m shorter than the average
field measured height, respectively.

The incorrect identification of trees that did not exist in the
field (commission errors) also influenced estimates of aver-
age tree height. The estimated height of committed trees
ranged from 1.11 to 1.77 m shorter than the average field
measured height in the high-density plots and from 2.33 to
2.68 m shorter than the average field measured height in
the low-density plots. The inclusion of the committed trees,
while artificially increasing the apparent accuracy of tree
identification, reduced the accuracy of height estimation in
all three approaches.

### Table 2. Summary statistics of mean tree heights per replicate ($N = 4$) using lidar, spectral, and fused data sets. All values reported are height in meters.

<table>
<thead>
<tr>
<th></th>
<th>High density (2.4 m spacing)</th>
<th>Low density (3.0 m spacing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field measured trees (height m)</td>
<td>17.40</td>
<td>17.32</td>
</tr>
<tr>
<td>Total identified trees</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lidar</td>
<td>17.21a</td>
<td>16.82c</td>
</tr>
<tr>
<td>Spectral</td>
<td>16.81b</td>
<td>16.52d</td>
</tr>
<tr>
<td>Fused</td>
<td>16.96b</td>
<td>16.69d</td>
</tr>
<tr>
<td>Correctly identified trees</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lidar</td>
<td>17.25e*</td>
<td>16.94g</td>
</tr>
<tr>
<td>Spectral</td>
<td>16.82f</td>
<td>16.62gh</td>
</tr>
<tr>
<td>Fused</td>
<td>16.98f</td>
<td>16.82g</td>
</tr>
<tr>
<td>Committed trees</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lidar</td>
<td>16.04</td>
<td>14.88</td>
</tr>
<tr>
<td>Spectral</td>
<td>15.63</td>
<td>14.64</td>
</tr>
<tr>
<td>Fused</td>
<td>16.29</td>
<td>14.99</td>
</tr>
<tr>
<td>Omitted trees</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lidar</td>
<td>16.38</td>
<td>15.39</td>
</tr>
<tr>
<td>Spectral</td>
<td>15.84</td>
<td>14.91</td>
</tr>
<tr>
<td>Fused</td>
<td>15.49</td>
<td>14.29</td>
</tr>
</tbody>
</table>

**NOTE:** Means followed by the same letter are not significantly different. * indicates no difference from field mean height.
We were primarily interested in stand/replicate level analyses, but we also performed a brief tree-by-tree analysis of tree heights (Table 3). All comparisons of tree height were significantly different ($P < 0.001$). The greatest mean difference (1.00 m) was for the spectrally located trees in the high-density plots, while the lowest difference (0.68 m) was in the low-density plots for the lidar and fused data sets.

**Discussion**

Relatively few studies have tried to use remote sensing tools to estimate stem density through identification of individual trees. The accuracy of the approaches used in our study, ranging from 65 to 94%, compares favorably to these other studies. Gougeon (1995) used spectral imagery with 31 cm pixel size to identify individual trees within these other studies. Gougeon (1995) used spectral imagery from 65 to 94%, compares favorably to the approaches used in our study, ranging from 65 to 94%, compares favorably to these other studies. Gougeon (1997) also examined 49-yr-old Douglas-fir ($Pseudotsuga menziesii$) ranging in density from 650 to 1,750 stem/ha, producing stem density estimates with an average error rate of 37% using 60 cm spectral imagery. Gougeon and Leckie (1999) used 30 cm imagery to estimate density in 3- to 10-yr-old jack pine ($Pinus banksiana$) and Scots pine ($Pinus sylvestris$) with an average error rate of 21%.

Very few studies have attempted to estimate stem density using lidar data. Young et al. 2000 estimated density in 9- to 16-yr-old loblolly pine plantations. Density estimates ranged from 5% underestimation to 12% overestimation, with an average absolute error of 5%. Subsequent examination of their data showed more missing trees than the apparent accuracy would suggest, but this was offset by probable commission errors.

Estimating stem counts from remotely sensed data, including lidar, is certainly not new. However, our study was unique in that the precise location of every tree in the field was known. This allowed us to investigate not simply the apparent ability of each approach to identify trees, but also to evaluate errors of omission and commission. Previous studies using remotely sensed data have compared field measured stem density to derived stem density without knowing whether the identified trees actually existed. As found in this study, some identified using remotely sensed data do not exist in the field, and thus artificially raise identification accuracy. In one case in our study, the lidar data set identified more trees than actually existed in the field.

We identified several potential causes of commission errors. Many committed trees, classified as dead in the field, were still standing and contained sufficient material to generate a lidar return, and thus could have been identified as a live tree. Another potential source of commission error was noncrop trees invading a space where a pine tree had died. It is also possible that trees adjacent to canopy gaps have branches that extend far enough into the gap to be identified as separate trees. Although all trees were measured in the field, it was not noted if dead trees were missing or still standing, thus representing possible lidar targets. Future field inventories will include this notation, thus allowing us to separate standing dead targets from missing trees. We believe that standing dead trees were the primary source of commission errors in our study. This is supported by the fact that the approach using only spectral data had the lowest rate of commission errors. A standing dead tree, even with dead needles attached, will have lower NIR reflectance than a live tree; thus it would not be indicated as a tree peak in the spectral data.

Tree count accuracy was higher in the low-density stands than the high density stands. This is likely due to the posting density of the lidar data and the resolution of the spectral data. The nominal posting density of the lidar data was approximately $1.3 \text{ m}$ (0.77 hits/m$^2$). In a fully closed canopy with a 3.0 m $\times$ 3.0 m spacing, the average crown cross-sectional projection area would be approximately 7.30 m$^2$. Thus, each crown would receive an average of 5–6 lidar hits at our posting density. Average crown projection area (target area) decreases to 4.70 m$^2$ at a 2.4 m $\times$ 2.4 m spacing, resulting in approximately 3–4 lidar hits per crown. With fewer lidar hits per crown it becomes more difficult to obtain an accurate representation of the canopy surface.

Within our study area, but not included in this analysis, are pine stands planted at 1.52 m spacing. At our posting density, the identified trees actually existed. As found in this study, the lidar data set identified more trees than actually existed in the field.

### Table 3. Tree-by-tree summary statistics for height estimation of trees from remotely sensed data compared to field measurements. Statistics are derived from field height minus estimated height in meters, except for $N$ (sample size). Negative minimum values indicate an over estimation in height by the remotely sensed data.

<table>
<thead>
<tr>
<th>Identification method</th>
<th>$\mu$</th>
<th>$\sigma$</th>
<th>Min</th>
<th>Max</th>
<th>$N$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>High density</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lidar</td>
<td>0.70</td>
<td>0.67</td>
<td>−1.76</td>
<td>3.82</td>
<td>380</td>
</tr>
<tr>
<td>Spectral</td>
<td>1.00</td>
<td>0.76</td>
<td>−1.45</td>
<td>5.28</td>
<td>461</td>
</tr>
<tr>
<td>Fused</td>
<td>0.79</td>
<td>0.71</td>
<td>−1.76</td>
<td>5.01</td>
<td>490</td>
</tr>
<tr>
<td><strong>Low density</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lidar</td>
<td>0.68</td>
<td>0.71</td>
<td>−2.20</td>
<td>4.83</td>
<td>333</td>
</tr>
<tr>
<td>Spectral</td>
<td>0.91</td>
<td>0.78</td>
<td>−2.19</td>
<td>4.83</td>
<td>352</td>
</tr>
<tr>
<td>Fused</td>
<td>0.68</td>
<td>0.74</td>
<td>−2.20</td>
<td>4.83</td>
<td>362</td>
</tr>
<tr>
<td><strong>All trees</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lidar</td>
<td>0.69</td>
<td>0.69</td>
<td>−2.20</td>
<td>4.83</td>
<td>713</td>
</tr>
<tr>
<td>Spectral</td>
<td>0.96</td>
<td>0.77</td>
<td>−2.19</td>
<td>5.28</td>
<td>813</td>
</tr>
<tr>
<td>Fused</td>
<td>0.75</td>
<td>0.72</td>
<td>−2.20</td>
<td>5.01</td>
<td>852</td>
</tr>
</tbody>
</table>
this spacing would result in an average of 1-2 lidar hits per tree. A high proportion of trees in these very high density stands would be missed entirely or only receive a single hit, and therefore would not show up as peaks in an interpolated canopy surface. The same type of phenomenon occurs with the spectral data. The number of spectral pixels imaging a single crown depends on the size of the crown and the pixel size. As tree density increases, the crown cross-sectional area decreases, thus presenting less of a target for the spectral sensor. Other authors have suggested using a variable sized focal search window to locate trees within remotely sensed imagery (Wulder et al. 2000, Popescu et al. in press). The distance to be searched may be based on tree height, slope break, or range to sill. We are currently developing models that use relative stem density to set the variable focal search window distance.

Tree count accuracy for all three approaches at both densities differed significantly from 100%. However, the lidar approach consistently resulted in lower accuracy than the spectral and the fused approaches for our specific data. Therefore, if an estimate of stem density was all that was needed, it likely would be better to use spectral imagery given similar resolution data sets. Higher density lidar data should also increase accuracy of estimated stem density. Rarely, however, is stem density the only information of interest. Information on tree heights is often desired and, while generally not obtainable in an efficient manner from spectral imagery, heights can be obtained from lidar data.

Mean tree height estimates from all three identification approaches were less than field measured mean tree height. This is consistent with other studies that have used lidar to estimate mean stand height (Naesset 1997, Hyypää and Inkinen 1999, Young 2000). Lidar is a point-sampling tool that records height at discrete locations. Tree tops present relatively small targets, thus very few lidar returns actually emanate from the highest point on a tree. The peaks identified in the interpolated lidar canopy surface generally represent a point on the side of a crown and, therefore, underestimate the true height of the tree. ERDAS provides two interpolation algorithms, nonlinear and linear rubber sheeting. While the nonlinear rubber sheeting interpolation algorithm in ERDAS often tends to slightly overshoot the high points, the resulting tree height estimates still tend to be lower than actual tree height. The algorithm that most accurately represents a surface depends on lidar posting density, spatial arrangement of lidar points on the surface, shape of target, and interpolated pixel size among other factors. To provide reassurance that they were not substantially different, the nonlinear and linear interpolation algorithms were used on our lidar data to generate canopy surfaces that were then compared to each other. The mean difference was 0.005 m with a standard deviation of 0.202 m, indicating very low height discrepancies between the two interpolation algorithms. All located trees in the two interpolated surfaces were within 0.1 m of each other in height. Other software packages may offer more interpolation algorithms, which may result in different canopy surfaces. Very often, the differences in interpolated surfaces will be minimal, but it is possible that there will be spurious observations in the final surface if an inappropriate algorithm is used. More studies are needed in this area.

The accuracy of mean height estimates obtained in our study are better than reported in some other studies. Naesset (1997) used a lidar data set with a density of between 0.09 and 0.13 posts/m² to estimate mean stand height in Norway spruce and Scots pine. Initial underestimates were between 4.1 m and 5.5 m. Weighting the lidar return heights reduced the underestimation to 2.1 m to 3.6 m. Young et al. (2000) used lidar (approximately 1.4 posts/m²) to estimate heights of individually identified trees in 9- to 16-year-old loblolly pine stands. They underestimated mean stand height by an average of 1.8 m., ranging from 0 to –4.0 m. Hyypää and Inkinen (1999) found that lidar-derived height estimates of 89 individual trees (Norway spruce and Scots pine) were generally within 1.0 m; and reported that lidar derived mean height for 41 stands was generally overestimated with a 2.3 m (13.6%) standard error. They attributed the overestimation to missing many of the shorter-than-average trees. However, the stands had also undergone two growing seasons between the time of field measurement and when the lidar data were collected.

The largest underestimation of mean tree height in our study was 0.70 m, obtained with the spectral data approach in the low-density stands. The average underestimation of mean tree height across all three approaches and both spacings was 0.45 m (0.077 m standard error). It should again be noted that tree heights in all three approaches were derived from the lidar data. Mean tree heights varied due to differences in the location and number of identified trees among the three approaches. While the three approaches often identified the same tree, the assumed location of the crown peak varied.

Live trees missed by the three methods ranged from 1.02–3.03 m shorter than the average height of correctly identified trees (mean 1.98, standard deviation 0.69 m). Shorter trees tend to have less crown projection area, resulting in a smaller target. The crown area visible to lidar may be further obscured by taller neighboring trees when “viewed” from high off-nadir scan angles. Improvements in tree identification accuracy between the three approaches were generally gained through improvements in identifying smaller than average trees. This, however, further reduced estimates of mean tree height. Ironically, the more accurate approaches for identifying trees were the least accurate at estimating mean tree height.

The major factor limiting the ability of lidar to identify trees in our data set was posting density. Given a constant posting density, the probability of a crown receiving a lidar strike decreases as crown cross-sectional area deceases. Without an adequate number of lidar canopy returns, an accurate canopy surface layer cannot be generated. The number of returns per tree crown needed to accurately portray the canopy surface is not known at this time, but in general higher density lidar posting should result in more accurate canopy characterization. Lidar posting density can be increased through lower altitude flights, slower flight speeds, higher laser pulse rates and narrower scan angles. The issue of posting density versus stand density is a statistical sampling issue needing additional investigation.
Another issue needing further study relates to variability between individual lidar flight lines. We collected multiple overlapping and orthogonal flight lines intending to combine them to artificially increase the lidar posting density. Independent positional accuracy within each flight line ultimately prevented us from combining flight lines. However, we found that when individual flight lines were interpolated separately, there was considerable discrepancy in the accuracy of tree identification. Evans et al. (2001) suggest that this may be due to imposing a regular sampling interval of lidar posts upon a regular planting grid. Lidar pulses from one flight line may trace a path directly over the tops of crowns yielding an accurate representation of canopy structure, while returns from another flight line may follow a path falling between individual crowns. The data reported here were from what appeared to be the best flight line (out of eight flight lines that covered any portion of the study area), and thus represent a probable best-case scenario for tree identification and height estimation given the conditions of our stands and the density of our lidar data.

The fusion of spectral data with lidar data shows promise for improving assessment of basic stand structural attributes from remotely sensed data. The data fusion process used in this study could be improved, however. Geographic registration errors between the spectral and lidar data could be reduced through the orthorectification of the spectral data using the lidar canopy surface as an elevation model. A large contribution of the spectral data not considered in this study may be in the reduction of commission errors. Spectral data may also be used to classify the species of interest (e.g., live pine) and remove dead and noncrop trees from consideration. Another issue to be considered is the different spatial resolutions of the two data sets. There are three options that could be performed with the different spatial resolutions: (1) keep them as they are, (2) sample to the coarsest resolution, or (3) sample to the finest resolution. For this study we wanted to avoid resampling issues, therefore we stayed with the current resolution of the data sets. This could yield potential problems in that one spectral pixel was equal to 16 lidar canopy surface pixels. It is important that the data being used is capable of detecting the target of interest. As stated earlier, the lidar data is unlikely to strike the exact tree top, thus we often underestimate tree height. The spectral data will image the individual tree top, but if it is too spatially coarse, it may not be able to distinguish the top from its surroundings.

Perhaps the largest improvement in individual tree identification and height estimation could result from increasing lidar posting density. An accurate depiction of the canopy surface is needed to identify tree location and height. Products derived from the canopy surface map (texture, slope, surface curvature) may also have potential to aid in tree identification and classification (Fox et al. 1985, Peddle and Franklin 1991, Peddle and Duguay 1995). As lidar sensor technology continues to improve, posting densities will increase. This will ultimately increase the utility of lidar as a tool for forest assessment.

**Literature Cited**


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