COMPARISON OF LIDAR-DERIVED DATA AND HIGH RESOLUTION TRUE COLOR IMAGERY FOR EXTRACTING URBAN FOREST COVER

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Abstract.—Remote sensing has many applications in forestry. Light detection and ranging (LiDAR) and high resolution aerial photography have been investigated as means to extract forest data, such as biomass, timber volume, stand dynamics, and gap characteristics. LiDAR return intensity data are often overlooked as a source of input raster data for thematic map creation. We utilized LiDAR intensity and elevation difference models from a recent Morgantown, WV, collection to extract land cover data in an urban setting. The LiDAR-derived data were used as an input in user-assisted feature extraction to classify forest cover. The results were compared against land cover extracted from high resolution, recent, true color, leaf-off imagery. We compared thematic map results against ground sample points collected using realtime kinematic (RTK) global positioning system (GPS) surveys and to manual photograph interpretation. This research supports the conclusion that imagery is a superior input for user-assisted feature extraction of land cover data within the software tool utilized; however, there is merit in including LiDAR-derived variables in the analysis.

INTRODUCTION

Light detection and ranging (LiDAR) is an active remote sensing technology that utilizes near-infrared light pulses, differential GPS, and inertial measurements to accurately map objects and surfaces along the earth. The technology is often utilized from an aerial platform to create elevation and topographic models of the Earth's surface (Lillesand et al. 2008). It has many applications in forestry research due to the high spatial resolution and accuracy of the data and also the ability to collect multiple returns for a single laser pulse, which allows for the analysis of the vertical structure of forested areas (Wynne 2006). Forestry inventory attributes and canopy metrics such as canopy height, basal area, volume, crown diameter, and stem density have been derived from LiDAR data (Magnussen et al. 2010, Næsset 2009, Popescu et al. 2003). Also, the classification of individual tree species has been pursued (Brandtberg 2007, Ørka et al. 2009).

LiDAR intensity is a measure of the strength of the return pulse, and this measurement is correlated with surface material (Lillesand et al. 2008). However, prior research by Lin and Mills (2010) has shown that return intensity is influenced by many variables including footprint size, scan angle, return number, and range distance. LiDAR return intensity has not been as heavily explored for its usefulness in forestry and land cover mapping due to the difficulty of radiometric calibration (Flood 2001, Kaasalainen et al. 2005). Brennan and Webster (2006) explored the use of LiDAR-derived parameters, including intensity, for land cover mapping using image object segmentation and rule-based classification and obtained individual class accuracies averaging 94 percent.

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The purpose of this work was to compare LiDAR-derived data, LiDAR all return intensity and elevation difference models, and high resolution aerial imagery as inputs for user-assisted feature extraction of land cover with the software tool Feature Analyst (Visual Learning Systems, Missoula, MT). Land cover was differentiated in an urban setting and results were compared. The following land cover classes were of interest: barren/developed/impervious, grass, water, deciduous tees, and coniferous trees. We investigated whether forested land cover could be differentiated from other land cover types in an urban environment using feature extraction if only LiDAR data are available but no high-resolution imagery. The LiDAR-derived data were utilized in a raster format.

User-assisted feature extraction uses user-defined knowledge, as training data, to recognize and classify target features in an image (Visual Learning Systems 2002). Feature Analyst uses machine-learning algorithms and techniques as object recognition to automate feature-recognition from imagery (Visual Learning Systems 2002). Unlike supervised classification techniques, feature extraction classifies an image using more than just the digital number (DN) or spectral information contained by each pixel. Spatial context information such as spatial association, size, shape, texture, pattern, and shadow are considered (Opitz 2003). Studies have shown that feature extraction or object-based algorithms are more effective and accurate at extracting information from high resolution imagery than traditional image classification methods, such as supervised classification, because additional image characteristics are considered such as spatial context (Friedl and Brodley 1997, Harvey et al. 2002, Hong and Zhang 2006, Kaiser et al. 2004).

Feature extraction takes into account the spatial context that is available in high resolution data. We hypothesized that the textural information available in LiDAR-derived data could be utilized to differentiate forested land cover from other land cover types. As Figure 1 demonstrates, forested areas often show more texture and variability of LiDAR intensity values than more homogenous surfaces, such as pavement or grass.

STUDY AREA

This study was conducted in Morgantown, WV, within a 5.3 km^2 area near the Evansdale Campus of West Virginia University (Fig. 2). This area was selected because LiDAR and high resolution aerial imagery were available and a wide variety of land cover types are present.

METHODS

LiDAR Data

LiDAR data were collected on November 12, 2008, at an altitude of 3,500 ft (1066 m) above ground level (AGL) from an aircraft platform. An ALTM 3100 sensor was utilized at a pulse rate of 100 kHz, a half scan angle of 18 degrees, and a scan frequency of 30 Hz. Up to four returns were recorded per laser pulse. This was a leaf-off collection.

Imagery Data

True color imagery was flown during leaf-off conditions in March of 2010 at a cell size of 6 inches. This imagery was made available by the Monongalia County Commission. Visual inspection of the imagery showed that it was well color balanced and precisely orthorectified.

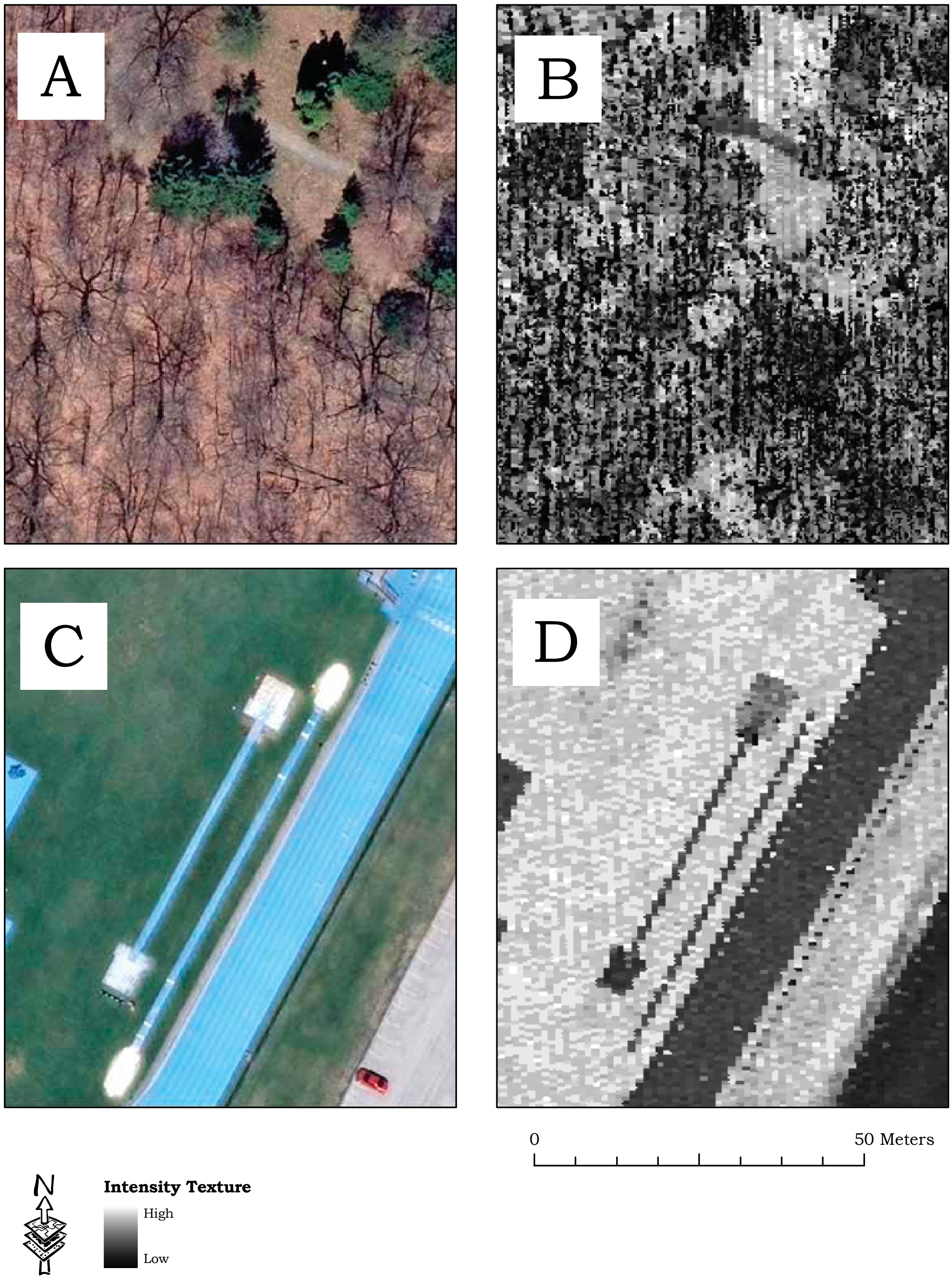

Figure 1.—Comparison of LiDAR intensity texture in forested (A and B) and nonforested (C and D) areas (1 ft cell size intensity models and 6 inch cell size imagery).

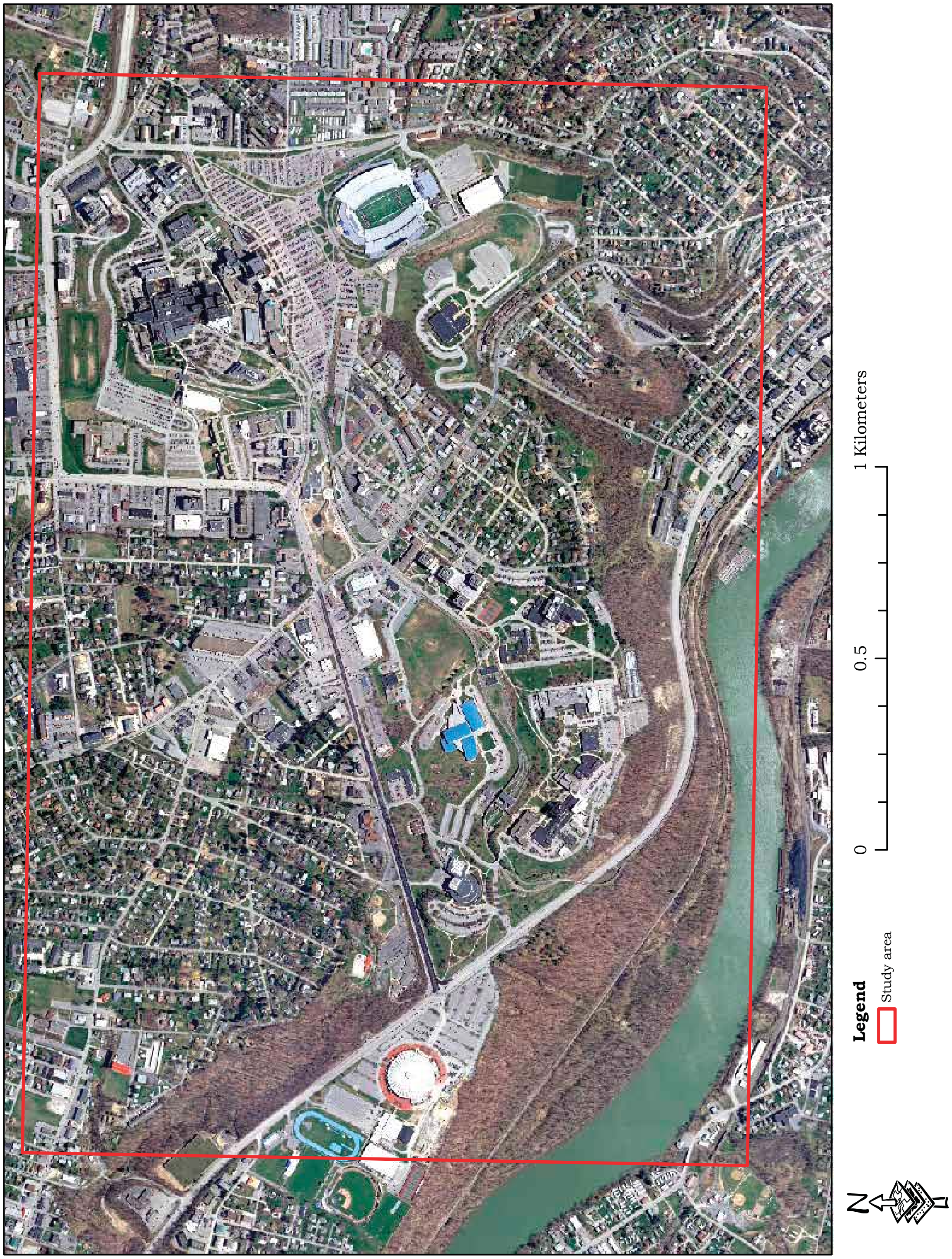

Figure 2.—Study area in Morgantown,WV.

Data Preparation

Raster grids were created from the LiDAR point data. The data were converted to multipoint shapefiles within ArcMap using the 3D Analyst Extension. Point data were then interpolated to raster grids using inverse distance weighting (IDW). Grids with a cell size of 1 ft were created for all returns and ground returns to create a digital elevation model and a digital surface model. The ground model was subtracted from the all returns model to obtain an elevation difference model for the study area.

Table 1.—Training data for land cover classes

Class	Number of training polygons	Total area
Water	60	73,505 m^2
Grass	80	12,774 m^2
Deciduous trees	55	22,923 m^2
Coniferous trees	53	1,472 m^2
Barren/Developed/Impervious	264	59,201 m^2

Table 2.—Feature Analyst parameters used

Parameter	Imagery	LiDAR-Derived	All
Classification method	Multi-class	Multi-class	Multi-class
Output format	Raster	Raster	Raster
Wall-to-wall classification	Applied	Applied	Applied
Resampling factor	2	1	1
Histogram stretch	Applied	Applied	Applied
Input presentation	Manhattan (7)	Manhattan (9)	Manhattan (5)
Find rotated instances of features	Applied	Applied	Applied
Learning algorithm	Approach 1	Approach 1	Approach 1
Aggregate areas	80	80	80

Elevation differences between the surfaces were most commonly a result of vegetation and manmade structures. An intensity grid was created from the all returns data at the same resolution using the same methodology.

Training Data

Training data for the land cover classes of interest were created by manual interpretation of the imagery and LiDAR-derived raster grids as polygons within ArcMap; as a result, land cover training data were created by visual interpretation of the input raster grids. Training data were collected throughout the study area in order to take into account class variability. Table 1 describes the training data collected. Due to variability, the most training data were collected for the barren/developed/impervious class. Separate training data were collected for conifers and deciduous trees. The same training data was used for each feature extraction performed so as not to induce variability or bias between the runs.

Feature Extraction

Three separate feature extractions were performed using the following raster data:

1) True color imagery
2) LiDAR-derived variables (all return intensity and elevation difference)
3) All three inputs

This was conducted so that comparisons could be made between thematic map results obtained from only the imagery, only the LiDAR-derived variables, and a combination of the two. User-assisted feature extraction was performed within ERDAS IMAGINE® using the software tool Feature Analyst by Visual Learning Systems. This software tool has many user defined parameters as described in Table 2.

The only parameters changed between runs were the resampling factor and the pattern width of the input presentation. The resampling factor was set at 2 for the image only result so that a 1 ft cell size output would be obtained to match the cell size of the other results. The input presentation determines the shape and size of the search window used to gather spatial context information for each pixel. Feature Analyst records the spectral information for all pixels within the pattern to define the characteristics of the land cover class. Within Feature Analyst, the number of bands multiplied by the number of pixels within the search window cannot exceed 100 (Visual Learning Systems 2002). For each run we used the maximum pattern width allowable for the Manhattan pattern to make the most use of the spatial context information in the imagery and the LiDAR-derived variables.

We defined the parameters based on results obtained in previous research, suggestions from the software user's manual, and professional judgment. Although it is possible to conduct further processing within Feature Analyst to enhance the results, we decided to compare initial outputs so as not to induce variability and bias between the runs; as a result, the final accuracies obtained here should not be considered a representation of the optimal use of the software. All results were thematic map raster grids with a 1 ft cell size.

Error Assessment

Two error assessments were performed. First, 10,000 random points were selected using Hawth's Tools, an extension for Arc Map. The thematic map class for each run was determined at each point. A 200-point subset of these points was then randomly selected for validation. We then manually interpreted the land cover class at the point locations by comparison to the true color imagery.

Second, 140 ground points were collected in the study area representing thematic categories using Pacific Crest realtime kinematic (RTK) survey equipment. The horizontal precision of these points averaged 0.03 m (3 cm). These points were then compared to the thematic map results. It should be noted that these points do not represent a rigorous random sample. They were collected to conduct a relative comparison of the mapping results and should not be considered a measure of true accuracy.

RESULTS AND DISCUSSION

Thematic map results are provided in Figures 3 through 5. By visual inspection, several observations can be made regarding the products. First, two problems associated with image classification at this spatial scale are shadowing and relief displacement of above ground objects, such as trees. In the imagery alone result, we observed that tree shadows were often classified as part of the tree, potentially overestimating the tree extents. Building shadows were often classified as coniferous trees. We generally found that the inclusion of the LiDAR-derived parameters help to reduce this type of error. An example is shown in Figure 6 in which a water tower shadow was classified as coniferous trees in the image only result but was more correctly classified in the result utilizing all variables. Relief displacement is a problem in aerial imagery, but is not a problem in the LiDAR data. This displacement distorts the true location and spatial extent of a tree crown. There were also classification errors associated with roofs, which contain spectral variability by color and texture. Generally, LiDAR data enhanced roof and building classification.

Figure 3.—Land cover result for imagery alone.

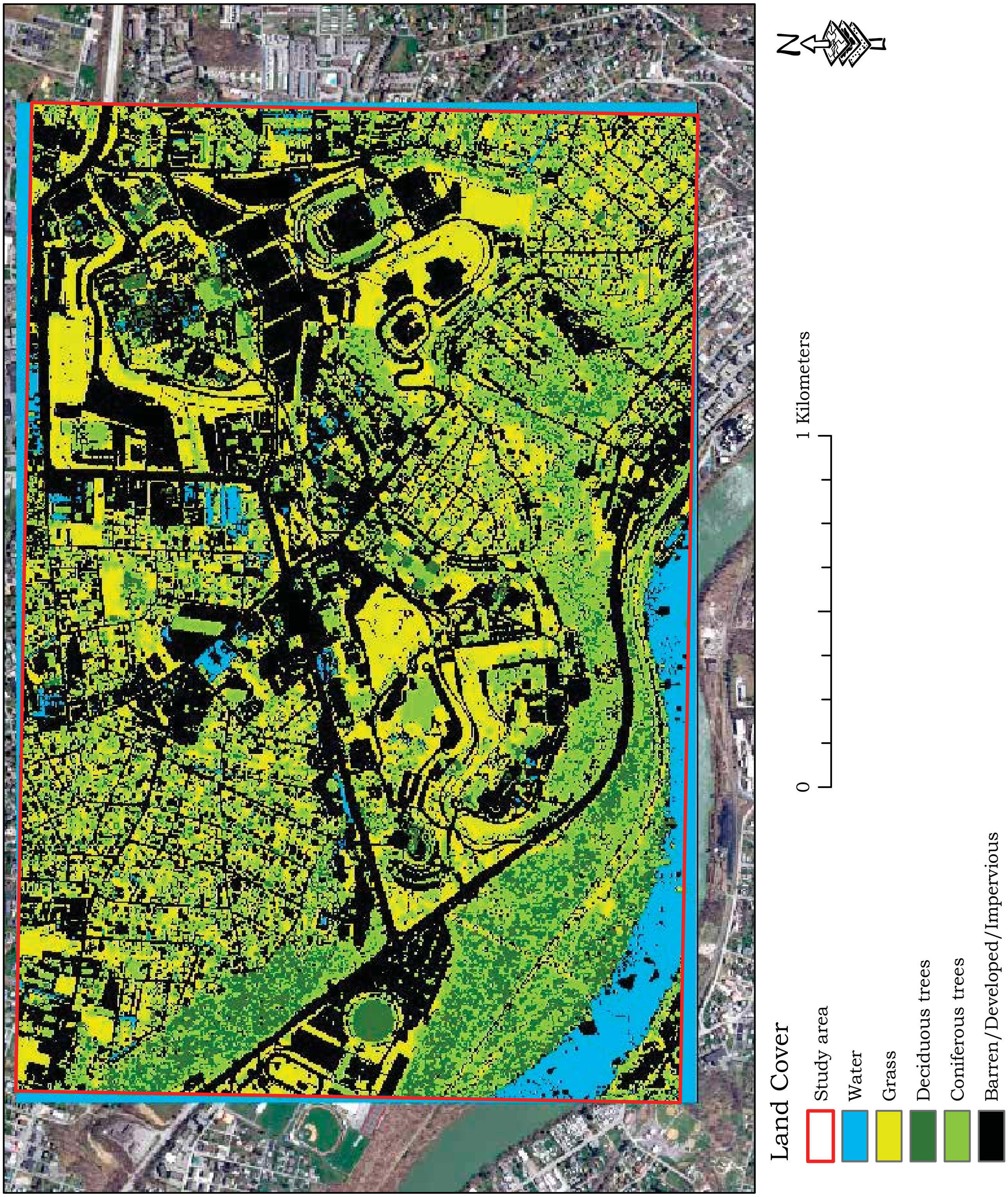

Figure 4.—Land cover result for LiDAR-derived variables alone.

Figure 5.—Land cover result for all variables.

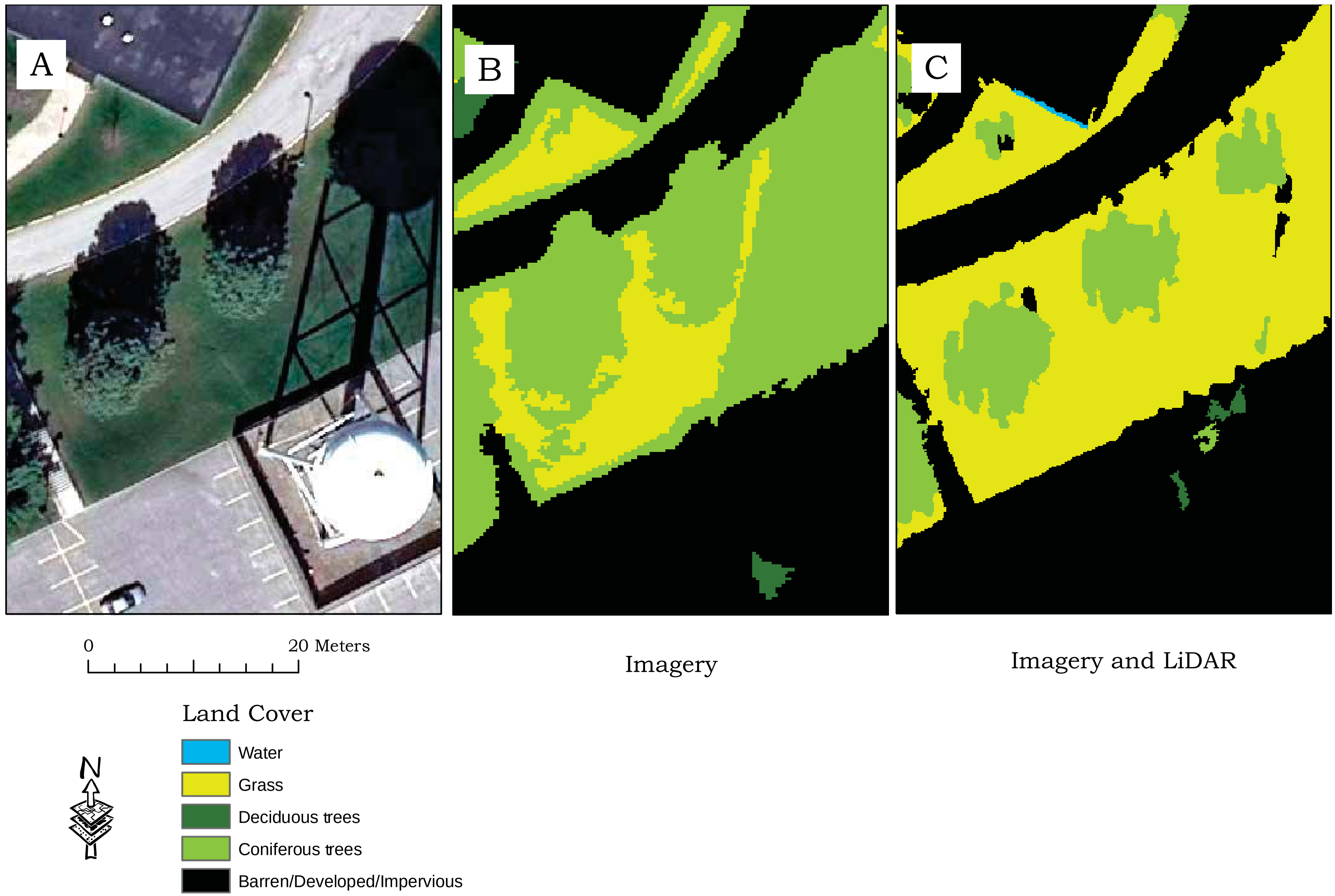

Figure 6.—Comparison of shadow classification. Land cover in shadows was more correcty classified when utilizing LiDAR-derived data along with the imagery. With only imagery, land cover in shadows was commonly incorrectly classified as coniferous trees.

LiDAR-derived data poorly separated deciduous and coniferous trees as shown in Figure 7. It should be noted that leaf-off LiDAR data were utilized, and leaf-on data were not assessed. Leaf-on data may allow for more separation between these forest types; however, that was not explored. Based on visual inspection, coniferous and deciduous trees were more accurately differentiated from imagery than LiDAR-derived parameters. This may be a result of intensity, elevation difference, and intensity spatial texture being similar for both categories. In leaf-off imagery, deciduous and coniferous trees are spectrally different. These forest types proved to be more separable using image spectral bands than LiDAR intensity and elevation difference within the software tool utilized.

Error matrixes for the classifications are provided in Tables 3 through 6. Thematic map accuracy was compared at randomly selected point locations based on manual photograph interpretation. These error matrixes suggest that the classification relying on LiDAR-derived variables alone was least accurate. Confusion between coniferous and deciduous trees was common. The matrixes and K_{hat} coefficients of agreement do not suggest a significant increase in accuracy when LiDAR-derived parameters are included with the imagery.

Error assessment relative to the ground surveyed points showed a relative increase in accuracy if both imagery and LiDAR-derived parameters were utilized as described in Table 6. Deciduous and coniferous forests were not differentiated in this assessment due to the inability to accurately sample coniferous trees with the RTK equipment. This assessment suggests that omission error, or the misclassification of tree pixels as other land cover types, was the dominant error source.

If the error matrix for the LiDAR-derived data only (Table 4) is recalculated so that error between coniferous and deciduous forest is not considered but rather a single forest class, an increase in both the user's and producer's accuracy for the forest class is observed (Table 7). If a binary forest raster is desired within an urban or developed landscape, it may be appropriate to utilize only LiDAR-derived variables in a feature extraction environment; however, if coniferous and deciduous trees are to be differentiated, imagery may be necessary.

Table 3.—Error matrix with imagery utilized

		Reference data					
		Water	Grass	Deciduous	Coniferous	Barren	User's accuracy
Classification	Water	9	0	0	0	0	100%
	Grass	0	25	0	2	1	93%
	Deciduous	0	6	39	0	10	71%
	Coniferous	1	8	0	7	2	39%
	Barren	0	1	0	0	89	99%
	Producer's accuracy	90%	62%	100%	78%	87%	Overall: 85% K_{hat}: 77%

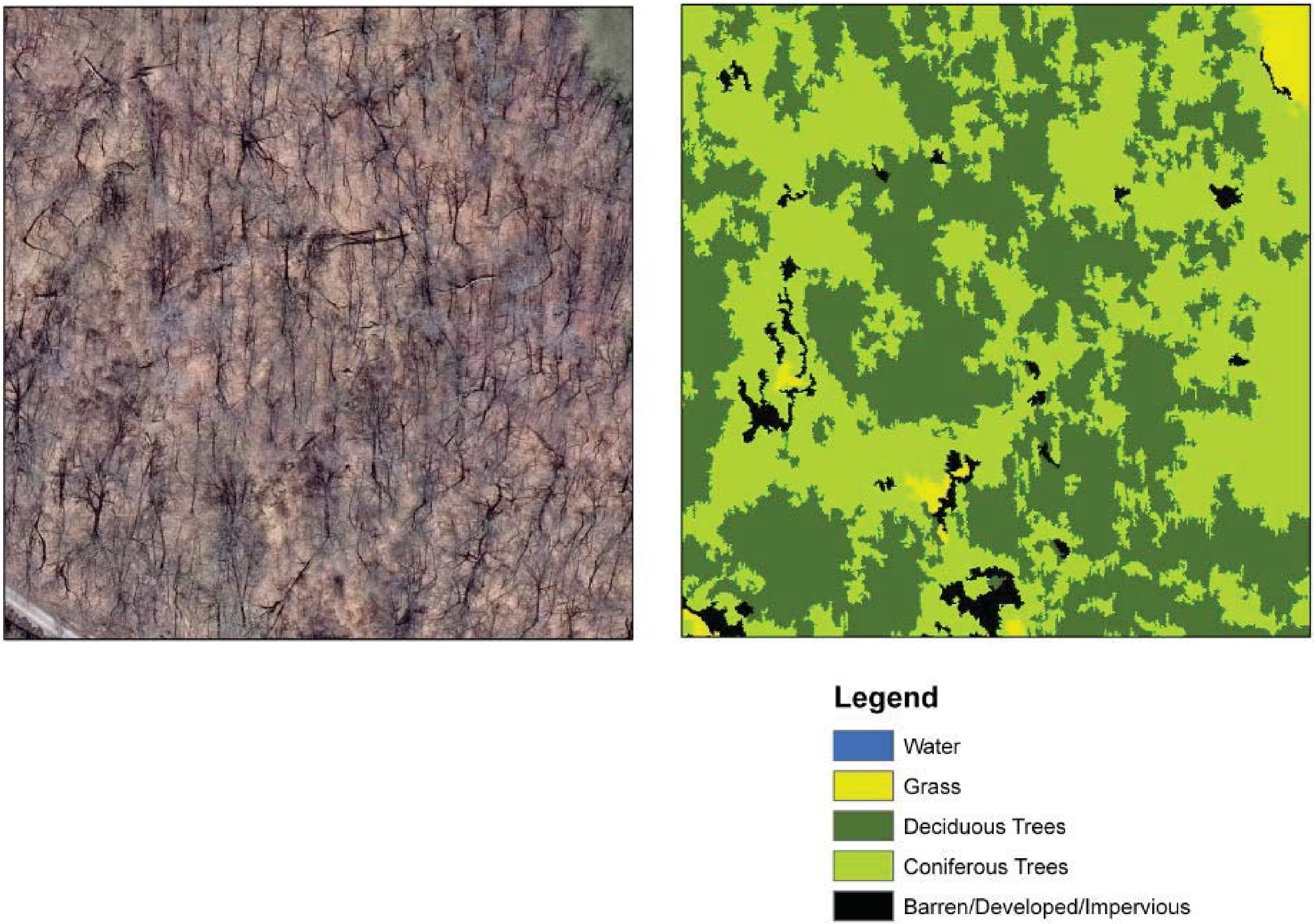

Figure 7.—Example of forest misclassification. Coniferous and deciduous trees were confused when only LiDAR-derived data were utilized.

Table 4.—Error matrix with LiDAR-derived data utilized

		Reference data					
		Water	Grass	Deciduous	Coniferous	Barren	User's accuracy
Classification	Water	7	0	0	0	2	78%
	Grass	0	33	4	0	6	77%
	Deciduous	0	0	10	0	6	63%
	Coniferous	0	4	23	9	12	19%
	Barren	3	3	2	0	76	90%
	Producer's accuracy	70%	83%	26%	100%	75%	Overall: 68% K_{hat}: 54%

Table 5.—Error matrix with all data utilized

		Reference data					
		Water	Grass	Deciduous	Coniferous	Barren	User's accuracy
Classification	Water	9	0	0	0	0	100%
	Grass	0	29	0	0	0	100%
	Deciduous	0	1	33	1	8	77%
	Coniferous	1	5	5	8	4	35%
	Barren	0	5	1	0	90	94%
	Producer's accuracy	90%	73%	85%	89%	88%	Overall: 85% K_{hat}: 77%

Table 6.—Error relative to sampled ground points

	Imagery	LiDAR-derived	All
Forest comission error	10%	0%	0%
Forest omission error	14%	25%	9%
Overall accuracy	93%	91%	97%

Table 7.—Error matrix with LiDAR-derived data utilized and tree type not differentiated

		Reference data				
		Water	Grass	Forest	Barren	User's accuracy
Classification	Water	7	0	0	2	78%
	Grass	0	33	4	6	77%
	Forest	0	4	42	18	65%
	Barren	3	3	2	76	90%
	Producer's Accuracy	70%	83%	88%	75%	Overall: 79% K_{hat}: 68%

CONCLUSIONS

Although there was not a significant increase in map accuracy when LiDAR-derived variables, such as elevation difference and all returns intensity, were considered, there was merit in including the data. For example, inclusion of LiDAR-derived variables, based on visual inspection, reduced the negative influence of shadows and relief displacement on thematic map results. However, differentiation of deciduous and coniferous forest was significantly improved by the inclusion of leaf-off imagery in the analysis. If the desired product was a binary result to differentiate forest from nonforest, it may be appropriate to utilize only LiDAR-derived data. It should be noted that the results of this analysis only apply to the software tool in question. Other processes may allow for more accurate land cover mapping, such as the methods suggested by Brennan and Webster (2006). We simply compared initial outputs using variable data inputs; as a result, it may be possible to increase thematic map accuracy by implementing additional processing available in the software.

Future research should attempt thematic map creation from LiDAR intensity data and other derived products using other software tools and processes. Also, the inclusion of additional LiDAR parameters, such as the number of multiple returns in a given area, should be explored for their usefulness in creating thematic maps. Later echoes may help isolate deciduous trees in leaf-off data. Although this work supports the importance of imagery in thematic map creation, LiDAR data may help to increase thematic map accuracy when high resolution land cover is required.

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LITERATURE CITED

Brandtberg, T. 2007. **Classifying individual tree species under leaf-off and leaf-on conditions using airborne LiDAR.** ISPRS Journal of Photogrammetry and Remote Sensing. 61: 325-340.

Brennan, R.; Webster, T.L. 2006. **Object-oriented land cover classification of LiDAR-derived surfaces.** Canadian Journal of Remote Sensing. 32(2): 162-172.

Flood, M. 2001. **LiDAR activities and research priorities in the commercial sector.** International Archives of Photogrammetry and Remote Sensing. 34(3/W4): 3-7.

Friedl, M.A.; Brodley, C.E. 1997. **Decision tree classification of land cover from remotely sensed data.** Remote Sensing of Environment. 61: 399-409.

Harvey, N.R.; Theiler, J.; Brumby, S.P.; Perkins, S.; Szymanski, J.J.; Bloch, J.J.; Porter, R.B.; Galassi, M.; Young, A.C. 2002. **Comparison of GENIE and conventional supervised classifiers for multispectral image feature extraction.** IEEE Transactions on Geoscience and Remote Sensing. 40(2): 393-404.

Hong, G.; Zhang, Y. 2006. **Object-based change detection in high resolution image.** In: Proceedings of the ASPRS 2006 annual conference; 2006 May 1-5; Reno, NV. Bethesda, MD: American Society for Photogrammetry and Remote Sensing. [Unpaginated CD-ROM].

Kaasalainen, S.; Ahokas, E.; Hyyppa, J.; Suomalainen, J. 2005. **Study of surface brightness from backscattered laser intensity: calibration of laser data.** IEEE Geoscience and Remote Sensing Letters. 2: 255-259.

Kaiser, J.V., Jr.; Stow, D.A.; Cao, L. 2004. **Evaluation of remote sensing techniques for mapping transborder trails.** Photogrammetric Engineering and Remote Sensing. 70(12): 1441-1447.

Lillesand, T.M.; Kiefer, R.W.; Chipman, J.W. 2008. **Remote sensing and image interpretation,** sixth edition. Hoboken, NJ: John Wiley and Sons. 756 p.

Lin, Y.; Mills, J.P. 2010. **Factors influencing pulse width of small footprint, full waveform airborne laser scanning data.** Photogrammetric Engineering and Remote Sensing. (76): 49-59.

Magnussen, S.; Næsset, E.; Gobakken, T. 2010. **Reliability of LiDAR derived predictors of forest inventory attributes: a case study with Norway spruce**. Remote Sensing of Envvironment. 114: 700-712.

Næsset, E. 2009. **Effects of different sensors, flying altitudes, and pulse repetition frequencies on forest canopy metrics and biophysical stand properties from small-footprint airborne laser data.** Remote Sensing of Environment. 113: 148-159.

Opitz, D. 2003. **An automated change detection system for specific features.** In: Proceedings of the International ESRI user conference, 2003 July 7-11; San Diego, CA. Redlands, CA: Environmental Systems Research Institute. [Unpaginated CD-ROM]. Available at http://proceedings.esri.com/library/userconf/proc03/p0417.pdf.

Ørka, H.O.; Næsset, E.; Bollandsås, O.L. 2009. **Classifying species of individual trees by intensity and structure features derived from airborne laser scanner data.** Remote Sensing of Environment. 113: 1163-1174.

Popescu, S.C.; Wynne, R.H.; Nelson, R.F. 2003. **Measuring individual tree crown diameters with LiDAR and assessing its influence on estimating forest volume and biomass.** Canadian Journal of Remote Sensing. 29(5): 564-577.

Visual Learning Systems. 2002. **User manual, feature analyst 4.2 for ERDAS Imagine.** Missoula, MT: Visual Learning Systems.

Wynne, R.H. 2006. **LiDAR remote sensing of forest resources as the scale of management.** Photogrammetric Engineering and Remote Sensing. 72(12): 1310-1314.