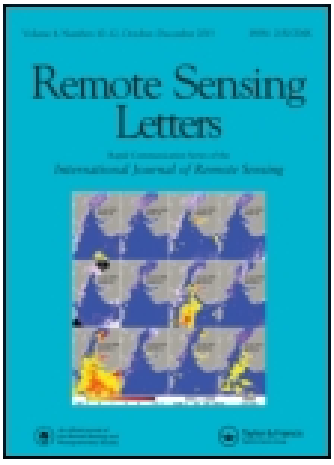

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Estimation of forest stand diameter class using airborne lidar and field data

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In this study, a method for estimating the stand diameter at breast height (DBH) classes in a South Korea forest using airborne lidar and field data was proposed. First, a digital surface model (DSM) and digital terrain model (DTM) were generated from the lidar data that have a point density of 4.3 points/m^2, then a tree canopy model (TCM) was created by subtracting the DTM from the DSM. The tree height and crown diameter were estimated from the rasterized TCM using local maximum points, minimum points and a circle fitting algorithm. Individual tree heights and crown diameters were converted into DBH using the allometric equations obtained from the field survey data. We calculated the proportion of the total number of individual trees belonging to each DBH class in each stand to determine the stand DBH class according to the standard guidelines. More than 60% of the stand DBH classes were correctly estimated by the proposed method, and their area occupied over 80% of the total forest area. The proposed method generated more accurate results compared to the digital forest type map provided by the government.

1. Introduction

As interest in sustainable enterprises, biomass and eco-friendly projects increases, forest management, forest planning and optimum afforestation are becoming key policy priorities. Various types of forest information are needed to address these priorities (Leckie et al. 2003; Wulder et al. 2004; Larsen et al. 2011; Chang et al. 2011). Many countries have been providing forest information to users in the form of forest type maps, which are based on forest attributes acquired through methods such as field surveys and interpretation of remotely sensed data (Pekkarinen, Reithmaier, and Strobl 2009; Yim et al. 2010; Kempeneers et al. 2011). The main forest information included in a forest type map is forest types, species, age classes, diameter at breast height (DBH) classes, crown density and tree height.

The most frequently used method of constructing a forest inventory is a field survey with plot sampling (Korhonen et al. 2006; Paletto and Tosi 2009). However, the field survey method is labour-intensive, expensive and time-consuming (Chang et al. 2011). Furthermore, the results of a forest survey are influenced by the experience of the experts involved (Ma, Hart, and Redmond 2001; Fiala, Garman, and Gray 2006, Korhonen et al. 2006). For these reasons, many researchers have studied means of obtaining forest information through remotely sensed data such as satellite images, aerial photographs

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and airborne light detection and ranging (lidar) data. The remote sensing technique is known to be appropriate for surveying large and inaccessible forest areas that are difficult to approach (Chang et al. 2011; Larsen et al. 2011).

Previous studies on forest information extraction using low or medium spatial resolution images have estimated the forest attributes such as forest cover, heights, ages, crown closure and leaf area index (Salvador and Pons 1998; Franklin et al. 2003; Hanset et al. 2000; Butusov 2003). Other studies used high spatial resolution satellite images and texture measures for segmentation and classification (Kayitakire, Hamel, and Defourny 2006; Pekkarinen, Reithmaier, and Strobl 2009; Chang et al. 2011). Dalponte, Bruzzone, and Gianelle (2008) analysed the joint effect of hyperspectral and lidar data for classifying complex forest areas.

The lidar system, which can directly generate 3D point cloud data, also has been applied to extract forest information in previous studies. The lidar system is an active sensor that measures time interval between outgoing laser pulses and the laser pulses reflected from the ground or objects on the ground, and the range measurements are combined with location (from GPS) and attitude (from IMU) of the lidar sensor to generate 3D coordinates (x, y, z) of corresponding objects. Lidar is appropriate for studying forested regions because it has a multi-return characteristic that can penetrate through vegetation and it can record laser returns both from vegetation and from the ground (Chang et al. 2012, 2013). Previous studies focused on estimating forest characteristics such as species, tree heights and biomass using airborne lidar data (Chang et al. 2012; Kim et al. 2012). Lidar data also have been used to delineate individual trees and to estimate their attributes at tree levels (Persson, Holmegren, and Soerman 2002; Popescu and Wynne 2004; Chen et al. 2006; Koch, Heyder, and Weinacker 2006; Vaughn, Moskal, and Turnblom 2012; Chang et al. 2013). Persson, Holmegren, and Soerman (2002) estimated the position, height and crown diameter of individual trees, and their proposed algorithm was validated with field measurements; 71% of all trees were correctly detected. The height and crown diameter of the detected trees were estimated with a root mean square error of 0.63 and 0.61 m, respectively. Popescu and Wynne (2004) determined tree heights and crown diameters by applying local filters with variable size windows. Circular windows provided better results for conifer trees, while square windows produced a better model fit for deciduous trees. Chen et al. (2006) and Koch, Heyder, and Weinacker (2006) proposed modified watershed segmentation for detecting individual tree crowns because the general watershed algorithm caused overestimation or underestimation according to the topographies or parameters. Vaughn, Moskal, and Turnblom (2012) used discrete return and full-waveform lidar data to detect individual tree species, while Chang et al. (2013) used only discrete return lidar data for identifying individual tree crowns; in these studies, the detection accuracies of the individual tree species and crowns were 85% and 77%, respectively.

Although various types of forest information have been investigated in previous studies, DBH is the most representative characteristic of a tree and DBH measurements are collected in most field survey. It is also known as an important factor for estimating the forest product, biomass and stand volume. In a forest type map or National Forest Inventory, the DBH classes of the forest stands are determined by a plot-based field survey. However, estimating DBH using optical remote sensing data is challenging because tree stems are usually invisible to the optical sensors due to high canopy cover. Although the plot level DBH can be estimated from the tree height using allometric equations (Koch, Heyder, and Weinacker 2006; Chang et al. 2013), the allometric equations are mostly derived from the forest attributes of stand units from dominant

trees, and various errors in tree heights, DBH and age classes are inevitable in the plot level DBH estimation. Nevertheless, there have been few studies that aimed to estimate stand level information using the information collected at the individual tree level.

To tackle these issues, we propose a novel method for estimating DBH class of each stand based on the individual tree attributes estimated from airborne lidar data and field survey data. The DBH of individual tree was estimated using the tree attributes extracted from lidar data, and lidar-derived attributes and the field survey data were used to develop localized models to estimate DBH from the lidar attributes. The results were analysed and compared with the reference data generated through the field survey.

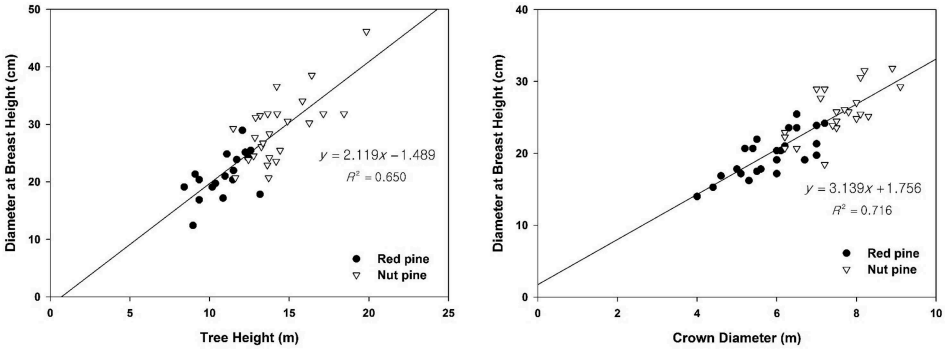
2. Study area and field data collection

The study area is located in Cheonan, central South Korea, at 36° 46′ N and 127° 13′ E, and it consists of several land cover types such as forest, building, artificial covers, grass and water. Although the forest in the study site is a mixed forest comprised of several species of trees, it is dominated by conifers such as red pine (*Pinus densiflora*) and nut pine (*Pinus koraiensis*). The forest in the study site is complex, dense, unplanted and unmanaged. These factors are typical characteristics of forests in South Korea, which makes it challenging to acquire stand level tree attributes. The airborne lidar data used in this study were acquired at an altitude of 1300 m by an Optech Airborne Laser Terrain Mapper (ALTM) 3070 (Optech, Ontario, Canada) on 1 September 2009, and aerial photographs were also collected simultaneously (Figure 1). The point density of the lidar data is approximately 4.3 points/m^2, including the first-return and the last return (Chang et al. 2013).

Detailed field survey data were collected on April 2011. Tree heights, DBH and the crown diameter were measured in the sampling of rectangle plots. Although there is a time discrepancy between the lidar acquisition and field survey, there was slight forest change from 2009 to 2012. We did not consider the growth of the trees because the effects of the

(*a*) (*b*)

Figure 1. Images from the study area (N 36° 46′, E 127° 13′) of (*a*) aerial photographs and (*b*) a tree canopy model (TCM) generated from lidar data. The overlapped red lines indicate the stand boundary of the digital forest type map. The data coverage is 750 m × 750 m.



(*a*) (*b*)

Figure 2. Scatter plots of field data with a linear regression line: (*a*) tree height vs. DBH (43 trees); (*b*) crown diameter vs. DBH (47 trees).

forest change were negligible based on the forest conditions and climate of the study site. The plot size was determined based on the topographic conditions and forest understory. The position of individual tree was measured using a handheld GPS. Trees that have visible tree tops were surveyed using a total station, which can measure a position of object with sub-centimetre accuracy, and tree heights were calculated from these measurements. The DBH and the crown diameter were measured with tape measures, assuming that the tree stems and crowns are circular. A total of 47 trees were measured in six plots. Figure 2 shows the scatter plot and the linear regression line between the DBH, crown diameter and tree height derived from the field survey data. The heights and DBHs of 43 individual trees (18 red pines and 25 nut pines) were measured, and the crown diameters and DBHs were measured for 50 trees (25 red pines and 25 nut pines). Figure 2 indicates that red pine and nut pine have similar relationships between the DBH, crown diameter and tree height. The coefficient of determination, R^2, was 0.65 and 0.72; thus, the correlation between the tree height, DBH and crown diameter is fairly high. These localized regression models were then used to convert the tree height and crown diameter estimated from lidar data into DBH. In addition, to evaluate the accuracy of the DBH class estimation, the stand DBH class was also measured with the field survey.

There were 27 forest stands in the study area, and the average size of the stands was 7673.39 m^2. The stand DBH class of each forest stand was classified into three levels in the forest type map: small DBH tree (more than 50% of trees with DBHs of 6–16 cm), medium DBH tree (more than 50% of trees with DBHs of 18–28 cm) and large DBH tree (more than 50% of trees with DBHs larger than 30 cm). This standard classification was published by the Korea Forest Research Institute (KFRI).

3. Methodology

Our method is based on the following assumption: 'The stand DBH class can be accurately estimated if the individual tree DBH is accurately extracted'. Therefore, the proposed algorithm consists of three major steps: (1) preprocessing the lidar data; (2) extracting the individual tree attributes; and (3) estimating the stand DBH class. The preprocessing and estimation of individual tree attributes steps are extended from our previous study (Chang et al. 2013). All processes except the point pre-classification and

the interpolation process were implemented using Matlab (MathWorks, Natick, MA, USA).

In the first step, digital surface model (DSM), digital terrain model (DTM) and tree canopy model (TCM) were generated from the lidar data. The DSM is the height model derived using the first-return reflection points on the object's surface. The DTM is the height model of the ground surface from which the objects are removed, and it can be generated with last-return points. The TCM was created by subtracting the DTM from the DSM (Popescu and Wynne 2004; Chang et al. 2013). In this study, the point-based data were converted into raster data for the efficient processing of the lidar data. When generating a DSM, the highest value of the first-return points within a pixel was used to minimize errors related to the interpolation (Alexander 2009). The DTM was generated by inverse distance weighting in ArcGIS 9.3 (Esri, Redlands, CA, USA) based on irregularly distributed ground points that were pre-classified by Terra Scan (Terrasolid Corporation, Helsinki, Finland). The spatial resolution of the DSM, DTM and TCM was set to 0.5 m.

Individual tree attributes, such as tree height and crown diameter, were extracted from the rasterized TCM using local maximum and minimum points. A 7 × 7 fixed circular window and a 3 × 3 fixed square window were used as the local maximum and local minimum filters, respectively. The tree height and centre point can be obtained from the local maximum points. The local minimum points are located in the valleys between individual trees. The four local minimum points nearest the central point of the individual tree were extracted. The most appropriate circles were fitted as tree crowns. The final individual tree crowns were identified after eliminating the errors, such as overlaps and circles that were too close (Chang et al. 2013).

Because the DBH cannot be measured directly from aerial remote sensing data, the DBH of individual trees was indirectly estimated from field survey data and individual tree attributes of lidar data. The tree height and crown diameter were set as independent variables, and the DBH was set as a dependent variable. In this study, the following two equations were adopted for estimating the DBH.

$$\mathrm{DBH} = 2.1194 \times (\text{tree height}) - 1.4980 \tag{1}$$

$$\mathrm{DBH} = 3.1389 \times (\text{crown diameter}) + 1.756 \tag{2}$$

where the DBH is in centimetres and the tree height and crown diameter are in metres. Equations (1) and (2) were derived by the scatter plots and linear regressions using the field survey data (Figure 2). The tree height and crown diameter of individual trees extracted from the lidar data were used for estimating the DBH. The crown diameter and tree height of individual trees were converted to DBH using Equations (1) and (2); then, the converted DBHs were separately analysed according to the equations for estimating the stand DBH class.

The stand DBH class was estimated by using the proportion of individual trees in each stand that belong to each class. The stand boundary was extracted from the 1:5000 digital forest type map because trees that are outside of the stand boundary are not considered forest. The aforementioned KFRI standard in Section 2 was adopted to determine the stand DBH class. If no single DBH class comprises 50% or more of the individual trees, then the DBH class with the highest proportion of trees was determined as the stand DBH class. The accuracy assessment of the DBH class map was calculated by using the reference map generated from the field survey. Because all of the stands in the study

site have different areas, the number of stands that correspond to the field survey data and their areas were determined.

4. Results and discussion

In this study, tree heights and crown diameters estimated from lidar data were converted into DBH based on the localized regression models: Equations (1) and (2). Figure 3 shows the scatter plot and correlation between the field-measured DBH and estimated DBH based on these models. We selected 21 individual trees and presented the correlation between field-measured DBH and the estimated DBH from the tree height based model (Equation 1) in Figure 3(*a*). Tree tops of the selected trees were distinguishable in the field, and the results indicated that both the field measurements and the estimated DBH showed strong linear relationship. Figure 3(*b*) illustrates the correlation between field measured DBH and estimated DBH from the crown diameter-based model (Equation 2), and 37 trees were selected in this analysis. The R^2 for the regression lines in Figures 3(*a*) and 2(*b*) were 0.68 and 0.60, and the slope of the regression lines were 1.844 and 1.663, respectively. Although the tree heights-based model (Figure 3(*a*)) yielded higher R^2 value compared to the crown diameter-based model, the crown diameter-based model resulted in smaller and closer to 1 slope value.

Figure 3 indicates that our model underestimates DBH when the DBH was over 30 cm. The underestimation may result from several factors including (1) errors in the estimated tree height and crown diameter from the lidar system; (2) misidentified local maximum and minimum locations; and (3) heterogeneous tree shapes and the forest environment (Hyyppä et al. 2008). Tree heights can be underestimated when the laser did not precisely hit tree tops because of the low point density; thus, the incorrect local maximum location was extracted. Crown diameters are variable and complex according to the forest environment, such as tree density and management. These factors affect the crown size. The large canopy cover overlapped around smaller trees and led to an underestimation of the crown diameter, i.e., the local minimum points were extracted

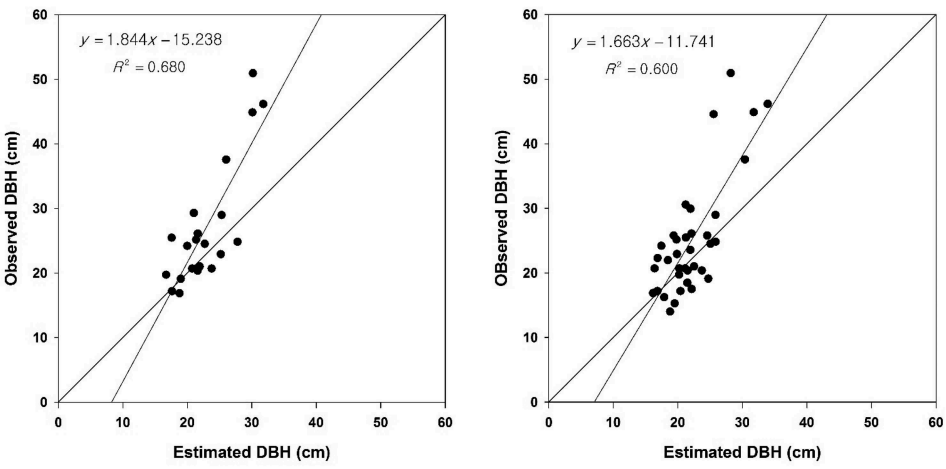


Figure 3. Field measures versus lidar estimates with linear regression line: (*a*) DBH obtained using Equation (1) using tree heights; (*b*) DBH obtained using Equation (2) using crown diameters.

from the middle of canopy boundary rather than the edge of the tree crown. In addition, our crown diameter measurements are based on the circular shape assumption, which is not satisfied especially when forests are unmanaged as is our study area. Although the DBH was underestimated when DBH is larger than 30 cm, the stand DBH classes were rather accurately estimated because the threshold for separating the medium and large classes was 30 cm. For ideal conditions, such as high point density data and a well-managed forest, the proposed method could produce better results without DBH under-estimation. However, lidar data would still have been acquired with low point density, and there are diverse conditions, such as mixed, unmanaged and complex forests. Therefore, the proposed method is useful for estimating the attributes of forest stands. Additional study would be needed when the different standard is adopted for determining DBH classes.

The stand DBH class map was generated using the estimated DBH of the individual trees. Figure 4 shows the stand DBH class map of the field survey data for the reference, the result obtained based on the tree-height based model, the result obtained based on the crown diameter-based model, and the 1:5000 digital forest type map. In the study area, the medium tree class was widely distributed, while the small and large tree classes were also

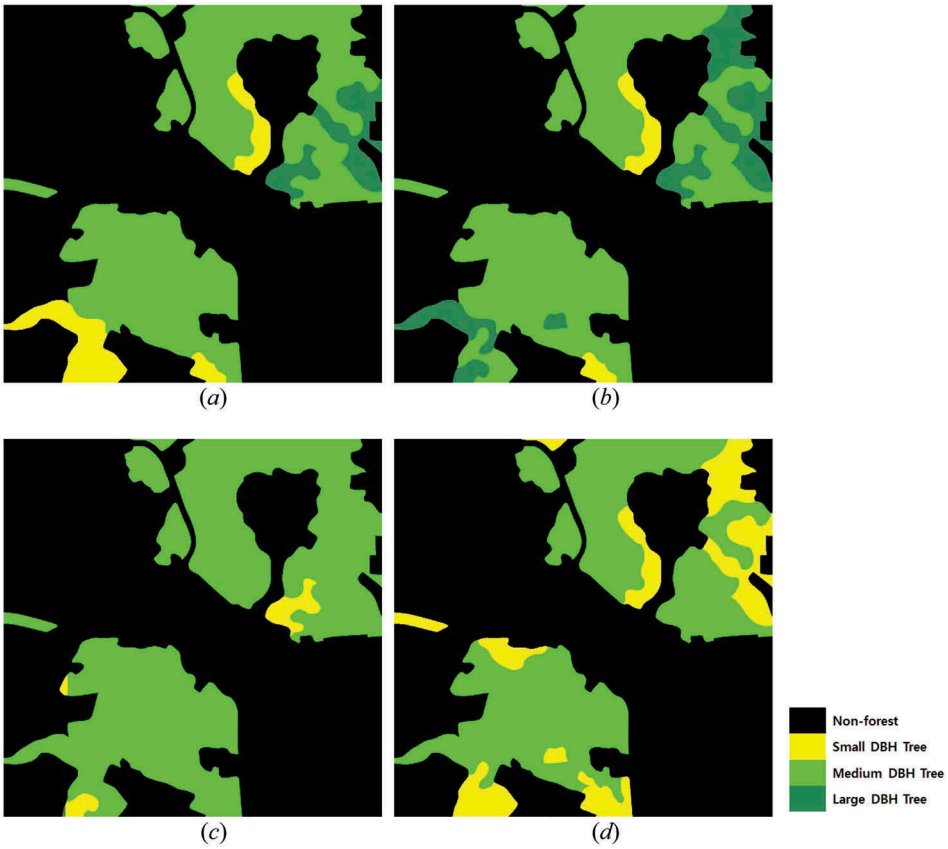


Figure 4. DBH class map based on forest stand: (*a*) reference map by field survey; (*b*) result by Equation (1); (*c*) result of Equation (2); (*d*) DBH classes derived from 1:5000 digital forest type map.

Table 1. The accuracy assessment of DBH class map.

Method of estimating DBH class	Stand accuracy (%)	Area accuracy (%)	Kappa coefficient
Estimated by Equation (1)	70.37 (19 stands)	87.22	0.49
Estimated by Equation (2)	62.96 (17 stands)	80.10	0.13
Digital forest type map	59.26 (16 stands)	77.13	0.25

apparent. Although the DBH class was incorrectly estimated in some stands, the result obtained based on the tree height-based model was the most accurate (Figure 4(*b*)). For the results based on the crown diameter-based model, most of the stands were classified as the medium DBH class (Figure 4(*c*)). There were also errors in the DBH classes of the digital forest type map provided by KFRI (Figure 4(*d*)) because the standard forest type map is generated with crown diameters that were measured in aerial photographs. Although the digital forest type map in the study area was produced the same year as the lidar data were acquired, errors occurred. In all cases, the small and large DBH classes had more misclassifications than the medium DBH class. In particular, the estimations of the DBH class with crown diameters (Equation (2)) exhibited significant misclassifications in the small and large DBH classes, while the results of Equation (1) and KFRI mainly had errors in the large DBH class. The misclassification errors were caused by the variation in the tree heights and crown diameters due to the forest conditions and the individual tree attributes.

Table 1 shows the result of the quantitative accuracy assessment. The result determined using Equation (1) had the highest accuracy; 19 stands were matched correctly over 87% of the total forest area. The kappa coefficient was 0.49 or moderate agreement (Jensen 2004). In the result determined using Equation (2), 17 stands were correctly estimated with a kappa coefficient of 0.13; these stands occupied approximately 80% of the total forest area. Using the field survey data in the DBH class map of the digital forest type map, 16 stands over 77% of the area were correctly matched, with a kappa coefficient of 0.25. Although the stand DBH class in the study area was mainly composed of the medium DBH level and kappa coefficient of the result of Equation (2) was lower than that of the digital forest type map, the accuracy of the DBH class map provided by the digital forest type map was the lowest. The method using the tree heights was more accurate than the methods using the crown diameter.

The results demonstrated that the highest performance of the proposed method was achieved when the individual tree heights were used. Since the crown diameter was more variable than the tree height (Chang et al. 2013), more errors occurred in the stand DBH class estimations. Although the coverage of the study area was limited, the stand DBH class of the digital forest map contained errors.

5. Conclusion

This study proposed methods for estimating stand DBH class using airborne lidar data and field survey data. Individual tree information, such as tree height and crown diameter, was extracted from lidar data. The tree heights and crown diameters were converted into DBH by using the relational equation obtained from the field survey data. The ratio of the DBH class of individual trees in each stand produced accurate stand DBH classes, although the study area was an unplanted and unmanaged forest. When tree heights were used, 70.37%

of the stands were correctly estimated over 87.22% of the total forest area. In case of crown diameters, 62.96% of the stands and 80.10% of the stand area were correctly matched to the reference map. Some errors occurred due to the influence of the relational equation, the forest conditions and the stand boundary. However, this study verified that stand DBH classes can be estimated from airborne lidar and field survey data.

Future works will include further investigation of individual tree detection errors, which are influenced by several factors including forest conditions, quality of field surveys and point density of lidar data. The proposed method can be potentially improved through the use of various field surveys, high point density lidar data and additional information on forest conditions related to tree growth such as tree species and tree density. Furthermore, adaptation of different standard of classes and the underestimation issues will be addressed.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Alexander, C. 2009. "Delineating Tree Crowns from Airborne Laser Scanning Point Cloud Data Using Delaunay Triangulation." *International Journal of Remote Sensing* 30: 3843–3848. doi:10.1080/01431160902842318.

Butusov, O. B. 2003. "Textural Classification of Forest Types from Landsat 7 Imagery." *Mapping Sciences & Remote Sensing* 40: 91–104. doi:10.2747/0749-3878.40.2.91.

Chang, A., Y. Eo, S. Kim, Y. Kim, and Y. Kim. 2011. "Canopy-Cover Thematic-Map Generation for Military Map Products Using Remote Sensing Data in Inaccessible Areas." *Landscape and Ecological Engineering* 7: 263–274. doi:10.1007/s11355-010-0132-1.

Chang, A., Y. Eo, Y. Kim, and Y. Kim. 2013. "Identification of Individual Tree Crowns from Lidar Data Using a Circle Fitting Algorithm with Local Maxima and Minima Filtering." *Remote Sensing Letters* 4: 29–37. doi:10.1080/2150704X.2012.684362.

Chang, A., Y. Kim, Y. Kim, and Y. Eo. 2012. "Estimation of Individual Tree Biomass from Airborne Lidar Data Using Tree Height and Crown Diameter." *Disaster Advances* 5: 360–365.

Chen, Q., D. Baldocchi, P. Gong, and M. Kelly. 2006. "Isolating Individual Trees in a Savanna Woodland Using Small Footprint LiDAR Data." *Photogrammetric Engineering & Remote Sensing* 72: 923–932. doi:10.14358/PERS.72.8.923.

Dalponte, M., L. Bruzzone, and D. Gianelle. 2008. "Fusion of Hyperspectral and LiDAR Remote Sensing Data for Classification of Complex Forest Areas." *IEEE Transactions on Geoscience and Remote Sensing* 46: 1416–1427. doi:10.1109/TGRS.2008.916480.

Fiala, A. C. S., S. L. Garman, and A. N. Gray. 2006. "Comparison of Five Canopy Cover Estimation Techniques in the Western Oregon Cascades." *Forest Ecology and Management* 232: 188–197. doi:10.1016/j.foreco.2006.05.069.

Franklin, S. E., R. J. Hall, L. Smith, and G. R. Gerylo. 2003. "Discrimination of Conifer Height, Age and Crown Closure Classes Using Landsat-5 TM Imagery in the Canadian Northwest Territories." *International Journal of Remote Sensing* 24: 1823–1834. doi:10.1080/01431160210144589.

Hanset, M. C., R. S. Defries, J. R. G. Townshend, and R. Sohlbefg. 2000. "Global Land Cover Classification at 1 Km Spatial Resolution Using a Classification Tree Approach." *International Journal of Remote Sensing* 21: 1311–1364.

Hyyppä, J., H. Hyyppä, D. Leckie, F. Gougeon, X. Yu, and M. Maltamo. 2008. "Review of Methods of Small-Footprint Airborne Laser Scanning for Extracting Forest Inventory Data in Boreal Forests." *International Journal of Remote Sensing* 29: 1339–1366. doi:10.1080/01431160701736489.

Jensen, J. R. 2004. *Introductory Digital Image Processing: A Remote Sensing Perspective*. New Jersey: Prentice Hall.

Kayitakire, F., C. Hamel, and P. Defourny. 2006. "Retrieving Forest Structure Variables Based on Image Texture Analysis and IKONOS-2 Imagery." *Remote Sensing of Environment* 102: 390–401. doi:10.1016/j.rse.2006.02.022.

Kempeneers, P., F. Sedano, L. Seebach, P. L. Strobl, and J. San-Miguel-Ayanz. 2011. "Data Fusion of Different Spatial Resolution Remote Sensing Images Applied to Forest-Type Mapping." *IEEE Transactions on Geoscience and Remote Sensing* 49: 4977–4986. doi:10.1109/TGRS.2011.2158548.

Kim, Y., A. Chang, Y. Kim, J. Song, and C. Kim. 2012. "Estimation of Forest Biomass from Airborne Lidar Data as Measures against Global Warming – Individual Tree Unit and Forest Stand Unit." *Disaster Advances* 5: 295–299.

Koch, B., U. Heyder, and H. Weinacker. 2006. "Detection of Individual Tree Crowns in Airborne Lidar Data." *Photogrammetric Engineering & Remote Sensing* 72: 357–363. doi:10.14358/PERS.72.4.357.

Korhonen, L., K. T. Korhonen, M. Rautiainen, and P. Stenberg. 2006. "Estimation of Forest Canopy Cover: A Comparison of Field Measurement Techniques." *Silva Fennica* 40: 577–588. doi:10.14214/sf.315.

Larsen, M., M. Eriksson, X. Descombes, G. Perrin, T. Brandtberg, and F. A. Gougeon. 2011. "Comparison of Six Individual Tree Crown Detection Algorithms Evaluated under Varying Forest Conditions." *International Journal of Remote Sensing* 32: 5827–5852. doi:10.1080/01431161.2010.507790.

Leckie, D., F. Gougeon, N. Walsworth, and D. Paradine. 2003. "Stand Delineation and Composition Estimation Using Semi-Automated Individual Tree Crown Analysis." *Remote Sensing of Environment* 85: 355–369. doi:10.1016/S0034-4257(03)00013-0.

Ma, Z., M. M. Hart, and R. L. Redmond. 2001. "Mapping Vegetation across Large Geographic Areas: Integration of Remote Sensing and GIS to Classify Multisource Data." *Photogrammetric Engineering and Remote Sensing* 67: 295–307.

Paletto, A., and V. Tosi. 2009. "Forest Canopy Cover and Canopy Closure: Comparison of Assessment Techniques." *European Journal of Forest Research* 128: 265–272. doi:10.1007/s10342-009-0262-x.

Pekkarinen, A., L. Reithmaier, and P. Strobl. 2009. "Pan-European Forest/Non-Forest Mapping with Landsat ETM+ and CORINE Land Cover 2000 Data." *ISPRS Journal of Photogrammetry and Remote Sensing* 64: 171–183. doi:10.1016/j.isprsjprs.2008.09.004.

Persson, A., J. Holmegren, and U. Soerman. 2002. "Detecting and Measuring Individual Trees Using an Airborne Laser Scanner." *Photogrammetric Engineering and Remote Sensing* 68: 925–932.

Popescu, S. C., and R. H. Wynne. 2004. "Seeing the Trees in the Forest: Using Lidar and Multispectral Data Fusion with Local Filtering and Variable Window Size for Estimating Tree Height." *Photogrammetric Engineering & Remote Sensing* 70: 589–604. doi:10.14358/PERS.70.5.589.

Salvador, R., and X. Pons. 1998. "On the Reliability of Landsat TM for Estimating Forest Variables by Regression Techniques: A Methodological Analysis." *IEEE Transactions on Geoscience and Remote Sensing* 36: 1888–1897. doi:10.1109/36.729360.

Vaughn, N. R., L. M. Moskal, and E. C. Turnblom. 2012. "Tree Species Detection Accuracies Using Discrete Point Lidar and Airborne Waveform Lidar." *Remote Sensing* 4: 377–403. doi:10.3390/rs4020377.

Wulder, M. A., J. C. White, K. O. Niemann, and T. Nelson. 2004. "Comparison of Airborne and Satellite High Spatial Resolution Data for the Identification of Individual Trees with Local Maxima Filtering." *International Journal of Remote Sensing* 25: 2225–2232. doi:10.1080/0143116031000165925 2.

Yim, J. S., C. Kleinn, H. K. Cho, and M. Y. Shin. 2010. "Integration of Digital Satellite Data and Forest Inventory Data for Forest Cover Mapping in Korea." *Forest Science and Technology* 6: 87–96. doi:10.1080/21580103.2010.9671976.