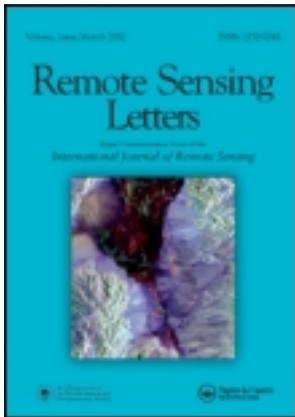


This article was downloaded by: [National Forest Service Library]

On: 13 June 2012, At: 06:36

Publisher: Taylor & Francis

Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK



## Remote Sensing Letters

Publication details, including instructions for authors and subscription information:

<http://www.tandfonline.com/loi/trsl20>

### Estimating plot-level tree structure in a deciduous forest by combining allometric equations, spatial wavelet analysis and airborne LiDAR

Steven R. Garrity<sup>a</sup>, Kevin Meyer<sup>a</sup>, Kyle D. Maurer<sup>a</sup>, Brady Hardiman<sup>b</sup> & Gil Bohrer<sup>a</sup>

<sup>a</sup> Department of Civil, Environmental, and Geodetic Engineering, Ohio State University, Columbus, OH, 43210, USA

<sup>b</sup> Department of Evolution, Ecology, and Organismal Biology, Ohio State University, Columbus, OH, 43210, USA

Available online: 27 Sep 2011

To cite this article: Steven R. Garrity, Kevin Meyer, Kyle D. Maurer, Brady Hardiman & Gil Bohrer (2012): Estimating plot-level tree structure in a deciduous forest by combining allometric equations, spatial wavelet analysis and airborne LiDAR, Remote Sensing Letters, 3:5, 443-451

To link to this article: <http://dx.doi.org/10.1080/01431161.2011.618814>

PLEASE SCROLL DOWN FOR ARTICLE

Full terms and conditions of use: <http://www.tandfonline.com/page/terms-and-conditions>

This article may be used for research, teaching, and private study purposes. Any substantial or systematic reproduction, redistribution, reselling, loan, sub-licensing, systematic supply, or distribution in any form to anyone is expressly forbidden.

The publisher does not give any warranty express or implied or make any representation that the contents will be complete or accurate or up to date. The accuracy of any instructions, formulae, and drug doses should be independently verified with primary sources. The publisher shall not be liable for any loss, actions, claims, proceedings, demand, or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.

## Estimating plot-level tree structure in a deciduous forest by combining allometric equations, spatial wavelet analysis and airborne LiDAR

STEVEN R. GARRITY\*<sup>†</sup>, KEVIN MEYER<sup>†</sup>, KYLE D. MAURER<sup>†</sup>, BRADY HARDIMAN<sup>‡</sup> and GIL BOHRER<sup>†</sup>

<sup>†</sup>Department of Civil, Environmental, and Geodetic Engineering, Ohio State University, Columbus, OH 43210, USA

<sup>‡</sup>Department of Evolution, Ecology, and Organismal Biology, Ohio State University, Columbus, OH 43210, USA

(Received 13 June 2011; in final form 25 August 2011)

Object-oriented classification methods are increasingly used to derive plant-level structural information from high-resolution remotely sensed data from plant canopies. However, many automated, object-based classification approaches perform poorly in deciduous forests compared with coniferous forests. Here, we test the performance of the automated spatial wavelet analysis (SWA) algorithm for estimating plot-level canopy structure characteristics from a light detection and ranging (LiDAR) data set obtained from a northern mixed deciduous forest. Plot-level SWA-derived and co-located ground-based measurements of tree diameter at breast height (DBH) were linearly correlated when canopy cover was low (correlation coefficient ( $r$ ) = 0.80) or moderate ( $r$  = 0.68), but were statistically unrelated when canopy cover was high. SWA-estimated crown diameters were not significantly correlated with allometrically based estimates of crown diameter. Our results show that, when combined with allometric equations, SWA can be useful for estimating deciduous forest structure information from LiDAR in forests with low to moderate (<175% projected canopy area/ground area) levels of canopy cover.

### 1. Introduction

Plant canopy structure is a critical component of vegetated ecosystems because of its role in determining many ecosystem functions (Lefsky *et al.* 2002, Bohrer *et al.* 2009, Shugart *et al.* 2010, Hardiman *et al.* 2011). Many forest structure attributes can be obtained from relating allometric equations to height measurements and, therefore, efforts to remotely quantify spatially explicit canopy structure have been aided by advancements of three-dimensional light detection and ranging (LiDAR) techniques and the proliferation of LiDAR-derived data (e.g. Nelson *et al.* 1984, Dubayah and Drake 2000, Lefsky *et al.* 2002, Lim *et al.* 2003, van Leeuwen and Nieuwenhuis 2010, Yu *et al.* 2011). As the spatial resolutions of remotely sensed imagery and LiDAR have increased, so too have object-based approaches to data classification, which have facilitated the detection of individual vegetation objects (e.g. Falkowski *et al.*

---

\*Corresponding author. Email: sgarrity@lanl.gov. Now at: International, Space and Response Division, Los Alamos National Laboratory, Los Alamos, NM 87545, USA.

2006, Koch *et al.* 2006, Strand *et al.* 2006, Laliberte *et al.* 2007, Smith *et al.* 2008, Zhang *et al.* 2010). The combination of increasing spatial resolutions, availability of three-dimensional data sets and increasing focus on identification of individual vegetation objects have increased our ability to characterize detailed vegetation structure information at the ecosystem level and beyond.

The application of object-based classification algorithms for detecting and delineating trees in LiDAR data has been particularly successful in coniferous forests (e.g. Popescu and Wynne 2004, Falkowski *et al.* 2006, 2008, Koch *et al.* 2006, Yu *et al.* 2011). However, detecting trees within deciduous forests has proven to be more difficult (e.g. Popescu and Wynne 2004, Popescu *et al.* 2004, Anderson *et al.* 2006, Koch *et al.* 2006). This is likely because, within partly or fully closed deciduous canopies, there is a high level of crown overlap (Koch *et al.* 2006) and potentially because the tops of many deciduous crowns are relatively flat and irregularly shaped, making the detection of local maxima and crown boundaries difficult.

The objective of our study is to test the capability of spatial wavelet analysis (SWA) to detect deciduous trees within an airborne LiDAR data set. SWA has been used to identify conifer trees in LiDAR data with relatively high accuracy, even when stand density and canopy cover are very high (Falkowski *et al.* 2008), suggesting that it may be effective for detecting deciduous trees within continuous canopies. This is the first time that SWA has been tested for estimating tree structure information in a deciduous forest. We evaluate the performance of SWA by comparing LiDAR- and ground-based measurements using plot-level censuses and observed allometric relationships of plot-level deciduous tree structure. We also compare SWA results with the performance of TreeVaW (Kini and Popescu 2004), a software package that uses the variable filtering window method described by Popescu and Wynne (2004). The variable filtering window method has been reasonably successful for identifying tree- and plot-level deciduous forest structural characteristics using LiDAR data (Popescu *et al.* 2002, Popescu and Wynne 2004, Antonarakis *et al.* 2008), and thus provides a suitable method for comparison with SWA performance.

## 2. Materials and methods

### 2.1 Study area

This study was conducted in a northern mixed deciduous forest at the University of Michigan Biological Station (UMBS) located in the northern portion of Michigan's lower peninsula (45° 33'35" N, 84° 42'49" W, 230 m elevation). Dominant land cover types within the study area include mixed forest and deciduous broadleaf forest. Overstorey tree species consists of (in the order of decreasing abundance) *Populus grandidentata* Michx. (bigtooth aspen), *Acer rubrum* L. (red maple), *Populus tremuloides* Michx. (quaking aspen), *Betula papyrifera* Marsh. (paper birch), *Quercus rubra* L. (red oak), *Fagus grandifolia* Ehrh. (American beech) and *Pinus strobes* L. (eastern white pine). The mean canopy height is roughly 18 m and the mean annual peak leaf area index (LAI) is approximately 3.8 m<sup>2</sup>/m<sup>2</sup>. The mean stand density is 1012 stems/ha (281 stems/ha for trees with diameter at breast height (DBH) >20 cm).

### 2.2 Field survey

Measurements of DBH were acquired for all trees within sixty 16 m radius plots and one 60 m radius plot between June and August 2010. The 16 m radius plots were

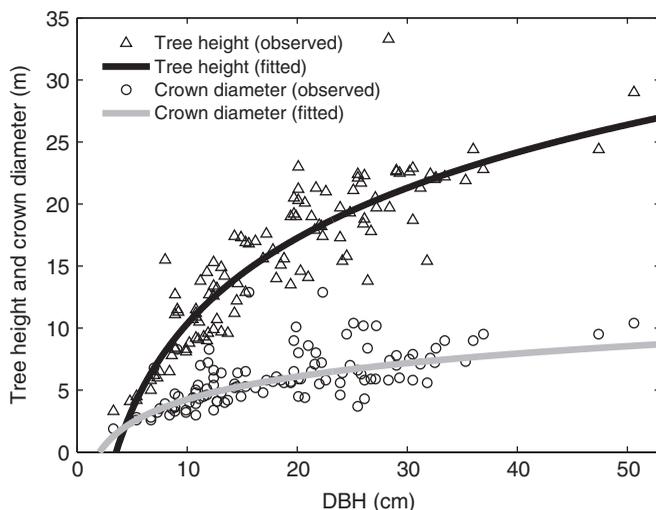


Figure 1. Allometric relationships between DBH and tree height (triangles and solid black line) and crown diameter (open circles and grey line). Data were obtained from three species in the UMBS forest. Tree height =  $9.97 \times \log(\text{DBH}) - 12.61$ . Crown diameter =  $2.67 \times \log(\text{DBH}) - 1.90$ .

arranged in seven transects radiating to the west (from  $225^\circ$  to  $15^\circ$ ) from the 60 m radius plot at  $20^\circ$  intervals (Schmid *et al.* 2003). Along each transect, plots were located using 100 m spacing between plot centres. Allometric relationships relating DBH to height and crown diameter were calculated using observations from 112 trees (35 bigtooth aspen, 38 red maple and 39 eastern white pine) with DBH greater than 3 cm randomly sampled from within the 60 m radius plot (figure 1). Tree height was trigonometrically determined using the angle of inclination to tree stem apex, which was measured with a digital protractor (Mitutoyo, Aurora, IL, USA) located at a fixed distance from the tree stem. Crown diameter was determined by measuring, on the ground, the visually estimated greatest distance spanning the tree's crown.

### 2.3 LiDAR acquisition and processing

LiDAR data were acquired in September 2009 for a  $40 \text{ km}^2$  area of the UMBS forest. LiDAR acquisition was performed by the National Center for Airborne Laser Mapping (NCALM) using a Gemini ALTM<sup>®</sup> laser scanner (Optech Inc., West Henrietta, NY, USA) mounted on a fixed-wing aircraft flying at approximately 600 m above ground level. The sensor acquired data with a pulse rate frequency of 125 kHz and a scan frequency of 40 Hz. The data were collected in 35 flight lines with 366 m swath width and 50% overlap, producing an average point density of 9.5 points/m<sup>2</sup>. Ground-based global positioning system (GPS) check points ( $n = 1023$ ) that were collected during the flight were compared with the nearest neighbour LiDAR shot and returned an average difference of 0.05 m with SD of 0.07 m.

NCALM deliverables included a point cloud of laser returns and a digital elevation model (DEM) with 1 m spatial resolution created from ground returns. The point cloud was binned to the same grid as the DEM, and the highest return in each bin was registered. The field of highest returns was subtracted from the DEM to produce

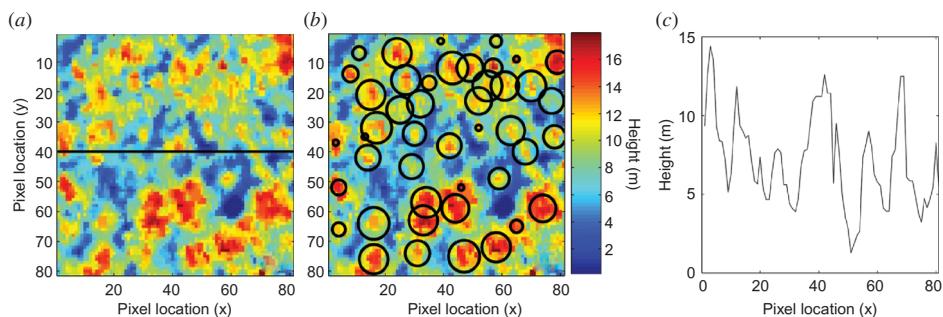


Figure 2. (a) Subset image of LiDAR-derived CHM. (b) CHM with SWA-detected trees is outlined in black circles. (c) Vertical profile of CHM taken from the row of pixels is denoted by the black line in (a).

the canopy height model (CHM). The CHM was further filtered so that canopy height values above the set minimum or maximum possible height (0 and 50 m) were replaced with the minimum or maximum value. There were less than 0.1% of the pixels that met this criterion. A  $3 \times 3$  median filter was applied to the CHM to reduce within-crown height variability while still maintaining contrast at crown boundaries (Lillesand *et al.* 2004, Coggins *et al.* 2008). Figure 2(a) illustrates a subset of the resulting CHM within the UMBS forest.

#### 2.4 Spatial wavelet analysis

The automated object-oriented SWA algorithm (Strand *et al.* 2006) was used to automatically detect the location and crown diameter of individual trees within the CHM (figure 2(a)). Similar to previous studies that used SWA for detecting vegetation objects in imagery (Strand *et al.* 2006, Garrity *et al.* 2008, Smith *et al.* 2008) and LiDAR (Falkowski *et al.* 2006, 2008), we used a two-dimensional Mexican hat wavelet mother function. SWA works by convolving a series of increasingly larger wavelets, each with an identical form as the mother function, with the CHM using a dilation scale ranging from 2 to 12 m and a step size of 0.25 m. SWA output consisted of the spatial coordinates ( $x$ ,  $y$ ) within the CHM of identified crown centre locations accompanied by the optimal dilation scale. The optimal dilation scale of each detected tree corresponds with the crown diameter and is identified by goodness-of-fit scores between wavelet dilation size and image object size (figure 2(b)). Additional details of the SWA algorithm are described by Falkowski *et al.* (2006) and Strand *et al.* (2006).

#### 2.5 Data analysis

Geographic coordinates from the centre of each field survey plot were used to locate plots within the CHM. The CHM was split into sixty  $30 \text{ m} \times 30 \text{ m}$  subsets and one  $120 \text{ m} \times 120 \text{ m}$  subset, where each subset was geographically co-located with a plot. The SWA algorithm was applied to each subset to automatically detect the location of crown centres and crown diameters. At the location of each detected crown centre, height was obtained from the CHM and converted to DBH using the allometric relationship developed for the UMBS forest (see figure 1). The mean allometrically

derived DBH was calculated for each plot. Similarly, the TreeVaW software was used to automatically identify individual tree heights within the entire CHM. Subsets of the TreeVaW output were extracted from co-located plot areas. Mean plot-level DBH was allometrically calculated from the TreeVaW-estimated tree heights within each plot.

For each plot surveyed during the field campaign, the mean DBH from trees having a measured DBH greater than or equal to the 75th percentile was calculated. The 75th percentile was used in an effort to only include the top of canopy crowns for comparisons with SWA- and TreeVaW-detected trees because sub-canopy trees cannot be detected using a CHM. Mean crown diameter in each plot was obtained from the observed allometric equation (figure 1) using the measured DBH of canopy trees. Mean plot-level crown diameters were only compared with SWA-estimated diameters. TreeVaW uses a user-defined allometric equation to calculate crown diameter from each detected tree height, making comparison of performance for estimating DBH and crown diameter redundant.

Field-based canopy cover was calculated by dividing the sum of total crown area of each plot, which was allometrically calculated from field-measured DBH, by the ground area of each plot. The estimates of plot canopy cover were used to divide the plots into three canopy coverage classes: low ( $<125\%$  cover), moderate ( $\geq 125\%$  and  $<175\%$  cover) and high ( $\geq 175\%$  cover). Linear regression was used to evaluate the relationship between SWA- and field-derived means of plot DBH and crown diameter, and between TreeVaW- and field-derived means of DBH for all plots within each canopy cover class.

### 3. Results and discussion

Plot-level means of SWA-derived DBH and field-measured DBH were linearly correlated when all data were pooled (correlation coefficient ( $r$ ) = 0.54, significance ( $p$ )  $< 0.01$ , root mean squared error (RMSE) = 3.35 cm). This relationship improved in areas where canopy cover was low ( $r = 0.80$ ,  $p < 0.01$ , RMSE = 2.12 cm) or moderate ( $r = 0.68$ ,  $p < 0.01$ , RMSE = 2.79 cm) (figure 3(a) and 3(b)). However, the relationship between SWA and field DBH was not statistically significant when canopy cover was high ( $r = 0.05$ ,  $p = 0.86$ ) (figure 3(c)). TreeVaW-derived DBH was not statistically correlated with field-measured DBH regardless of canopy cover class. SWA-estimated mean diameters were uncorrelated with DBH-based estimates of mean crown diameters (figure 3(d)–3(f)).

There were two areas where SWA performed poorly: estimating DBH in high canopy cover ( $>175\%$ ) and estimating crown diameter. Similar declines of SWA and other object-based performance have been reported in other ecosystems where canopy coverage is high (Strand *et al.* 2006, Falkowski *et al.* 2008, Garrity *et al.* 2008). In this study, decreased performance of SWA in high canopy cover conditions was likely due to crown overlap and prevalence of subdominant trees, which makes differentiation between trees difficult and increases the likelihood of omission or crown merging (Koch *et al.* 2006). Furthermore, SWA-based estimates of DBH relied on height information from LiDAR data so that any uncertainty in the CHM or in the allometric relationship between height and DBH would have decreased the goodness-of-fit in the correlation with field estimates.

Lack of significant correlation between SWA and field measures of crown size may have been, in part, due to the shape of the allometric relationships between DBH and crown diameter. SWA estimates crown diameter directly from the CHM, whereas

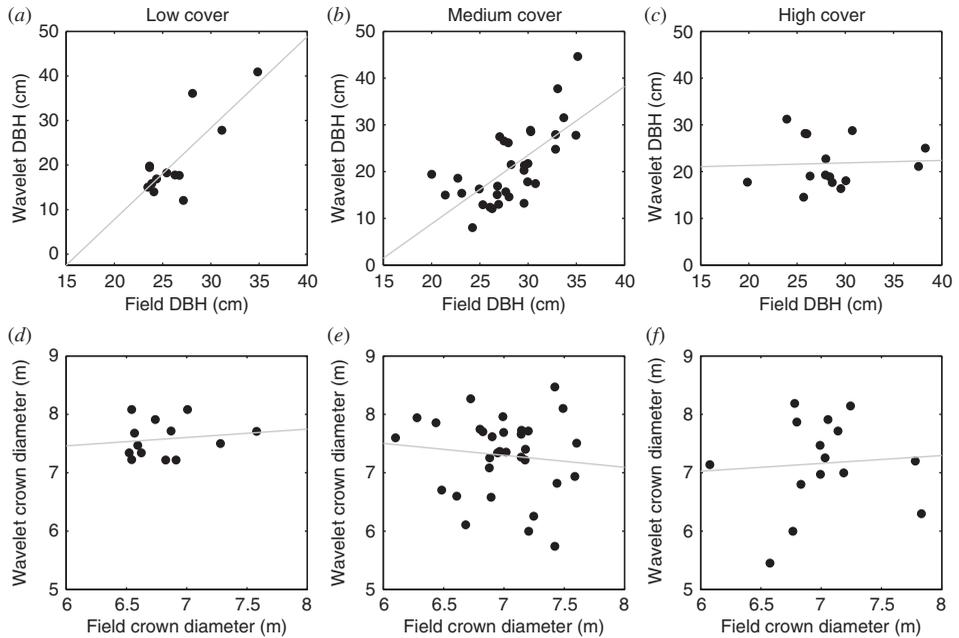


Figure 3. (a–c) SWA-estimated mean DBH versus field-measured mean DBH. (d–f) SWA-estimated mean crown diameter versus field-estimated mean crown diameter. (a) and (d) are for canopy cover <125%, (b) and (e) are for canopy cover  $\geq 125%$  and <175% and (c) and (f) are for canopy cover  $\geq 175%$ . Note that field-estimated crown diameter was calculated by applying the allometric relationship shown in figure 1 to DBH measurements.

field-based estimates of crown diameter rely on the allometric relationship with DBH. Low sensitivity between crown diameter and DBH greater than approximately 10 cm (i.e. flatness of the crown diameter model in figure 1 above a DBH of 10 cm) leads to large uncertainty in crown diameter for large DBH observations. Lack of correlation between SWA and field crown diameters may have also been affected by crown shape. The Mexican hat wavelet function is used by the SWA algorithm to detect regularly shaped circular objects. Crown shape irregularities likely result in under- and over-estimation of crown size. Overall, these issues make it difficult to determine whether crown diameters from SWA or inferred from field measurements of DBH are more representative of the actual crown dimension.

#### 4. Conclusions

Many potential applications will benefit from improved individual tree crown detection in broadleaf forests. Combined with allometric equations, remotely sensed tree structure information can supplement forest inventory data over large areas (e.g. Wulder *et al.* 2008) and provide data for dynamic vegetation, atmospheric or hydrodynamic models that resolve the ecosystem with a tree-level or sub-canopy level of representation for the vegetation (e.g. Bohrer *et al.* 2005, 2009, Medvigy *et al.* 2009), for large-scale estimates of standing biomass and carbon storage in forests (Asner *et al.* 2010) and for prediction of fuel properties and fire risks in hardwood forests (Skowronski *et al.* 2007). It can also provide data about the spatial statistics of the

structure and tree distribution of forest patches, which can be used for the construction of virtual canopies for numerical studies of forest function (Bohrer *et al.* 2007).

Our results show that SWA performs relatively well for estimating tree structural information in deciduous forests relative to previous studies that used the image segmentation approach (e.g. Anderson *et al.* 2006, Koch *et al.* 2006) or the variable filter window approach tested in this study. Particularly in low to moderately dense plots, with up to 175% cover, SWA is a useful tool for extracting plot-level DBH information from LiDAR-derived tree heights. Although SWA-estimated crown diameters were not related to field measurements, future applications can leverage on allometric equations relating DBH to crown size and other structural information.

### Acknowledgements

The authors acknowledge Christoph Vogel and Peter Curtis for their assistance with collecting and providing access to the field survey data. This work was in part supported by a Biosphere-Atmosphere Research and Training (BART) summer REU fellowship from the UMBS to Meyer. Maurer was funded by a National Science Foundation (NSF) Integrative Graduate Education and Research Traineeship (IGERT) fellowship (NSF grant DGE-0504552) awarded by the BART program. LiDAR data were provided through an NSF–NCALM graduate seed award to Hardiman. The field survey was funded by the US Department of Energy’s Office of Science (BER) through the Midwestern Regional Center of the National Institute for Global Environmental Change (NIGEC) under Cooperative Agreement DE-FC03-90ER610100, and the Midwestern Regional Center of the National Institute for Climatic Change Research (NICCR) at Michigan Technological University, under Award DE-FC02-06ER64158. Bohrer and Garrity were funded in part by NSF grant DEB-0911461, the US Department of Agriculture–National Institute for Food & Agriculture (NIFA) – Air Quality grant CSREES-OHOR–2009–04566 and by the USDA–Forest Service Northern Research Station, East Lansing, MI, Joint Research Venture 10–JV–11242302–013. Any opinions, findings and conclusions or recommendations expressed in this article are those of the authors and do not necessarily reflect the views of the NSF.

### References

- ANDERSON, J., MARTIN, M.E., SMITH, M.-L., DUBAYAH, R.O., HOFTON, M.A., HYDE, P., PETERSON, B.E., BLAIR, J.B. and KNOX, R.G., 2006, The use of waveform lidar to measure northern temperate mixed conifer and deciduous forest structure in New Hampshire. *Remote Sensing of Environment*, **105**, pp. 248–261.
- ANTONARAKIS, A.S., RICHARDS, K.S., BRASINGTON, J., BITHELL, M. and MULLER, E., 2008, Retrieval of vegetative fluid resistance terms for rigid stems using airborne lidar. *Journal of Geophysical Research*, **113**, G02S07, doi:10.1029/2007JG000543.
- ASNER, G.P., POWELL, G.V.N., MASCARO, J., KNAPP, D.E., CLARK, J.K., JACOBSON, J., KENNEDY-BOWDOIN, T., BALAJI, A., PAEZ-ACOSTA, G., VICTORIA, E., SECADA, L., VALQUI, M. and HUGHES, R.F., 2010, High-resolution forest carbon stocks and emissions in the Amazon. *Proceedings of the National Academy of Sciences of the United States of America*, **107**, pp. 16738–16742.
- BOHRER, G., KATUL, G.G., WALKO, R.L. and AVISSAR, R., 2009, Exploring the effects of microscale structural heterogeneity of forest canopies using large-eddy simulations. *Boundary Layer Meteorology*, **132**, pp. 351–382.

- BOHRER, G., MOURAD, H., LAURSEN, T.A., DREWRY, D., AVISSAR, R., POGGI, D., OREN, R. and KATUL, G.G., 2005, Finite-element tree crown hydrodynamics model (FETCH) using porous media flow within branching elements – a new representation of tree hydrodynamics. *Water Resources Research*, **41**, W11404, doi:10.1029/2005WR004181.
- BOHRER, G., WOLOSIN, M., BRADY, R. and AVISSAR, R., 2007, A Virtual Canopy Generator (V-CaGe) for modeling complex heterogeneous forest canopies at high resolution. *Tellus Series B-Chemical and Physical Meteorology*, **59B**, pp. 566–576.
- COGGINS, S., COOPS, N.C. and WULDER, M.A., 2008, Initialization of an insect infestation spread model using tree structure and spatial characteristics derived from high spatial resolution digital aerial imagery. *Canadian Journal of Remote Sensing*, **34**, pp. 485–502.
- DUBAYAH, R.O. and DRAKE, J.B., 2000, Lidar remote sensing for forestry. *Journal of Forestry*, **98**, pp. 44–52.
- FALKOWSKI, M.J., SMITH, A.M.S., GESSLER, P.E., HUDAK, A.T., VIERLING, L.A. and EVANS, J.S., 2008, The influence of conifer forest canopy cover on the accuracy of two individual tree measurement algorithms using lidar data. *Canadian Journal of Remote Sensing*, **34**, pp. S338–S350.
- FALKOWSKI, M.J., SMITH, A.M.S., HUDAK, A.T., GESSLER, P.E., VIERLING, L.A. and CROOKSTON, N.L., 2006, Automated estimation of individual conifer tree height and crown diameter via two-dimensional spatial wavelet analysis of lidar data. *Canadian Journal of Remote Sensing*, **32**, pp. 153–161.
- GARRITY, S.R., VIERLING, L.A., SMITH, A.M.S., FALKOWSKI, M.J. and HANN, D.B., 2008, Automated detection of shrub location, crown area, and cover using spatial wavelet analysis and aerial photography. *Canadian Journal of Remote Sensing*, **34**, pp. S376–S384.
- HARDIMAN, B., BOHRER, G., GOUGH, C., VOGEL, C. and CURTIS, P., 2011, The role of canopy structural complexity in wood net primary production of a maturing northern deciduous forest. *Ecology*, **92**, pp. 1818–1827.
- KINI, A. and POPESCU, S.C., 2004, TreeVaW: a versatile tool for analyzing forest canopy LIDAR data: a preview with an eye towards future. In *ASPRS 2004 Fall Conference*, 12–16 September, Kansas City, MO (Bethesda, MD: American Society of Photogrammetry and Remote Sensing).
- KOCH, B., HEYDER, U. and WEINACKER, H., 2006, Detection of individual tree crowns in airborne lidar data. *Photogrammetric Engineering & Remote Sensing*, **72**, pp. 357–363.
- LALIBERTE, A.S., FREDRICKSON, E.L. and RANGO, A., 2007, Combining decision trees with hierarchical object-oriented image analysis for mapping arid rangelands. *Photogrammetric Engineering & Remote Sensing*, **73**, pp. 197–207.
- LEFSKY, M.A., COHEN, W.B., PARKER, G.G. and HARDING, D.J., 2002, Lidar remote sensing for ecosystem studies. *Bioscience*, **52**, pp. 19–30.
- LILLESAND, T.M., KIEFER, R.W. and CHIPMAN, J.W., 2004, *Remote Sensing and Image Interpretation*, 5th ed., 763 pp. (New York: Wiley).
- LIM, K., TREITZ, P., WULDER, M., ST-ONGE, B. and FLOOD, M., 2003, LiDAR remote sensing of forest structure. *Progress in Physical Geography*, **27**, pp. 88–106.
- MEDVIGY, D., WOFSY, S.C., MUNGER, J.W., HOLLINGER, D.Y. and MOORCROFT, P.R., 2009, Mechanistic scaling of ecosystem function and dynamics in space and time: the Ecosystem Demography model version 2. *Journal of Geophysical Research-Biogeosciences*, **114**, G01002, doi:10.1029/2008JG000812.
- NELSON, R., KRABILL, W. and MACLEAN, G., 1984, Determining forest canopy characteristics using airborne laser data. *Remote Sensing of Environment*, **15**, pp. 201–212.
- POPESCU, S.C. and WYNNE, R.H., 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**, pp. 589–604.

- POPESCU, S.C., WYNNE, R.H. and NELSON, R.F., 2002, Estimating plot-level tree heights with lidar: local filtering with a canopy-height based variable window size. *Computers and Electronics in Agriculture*, **37**, pp. 71–95.
- POPESCU, S.C., WYNNE, R.H. and SCRIVANI, J.A., 2004, Fusion of small-footprint lidar and multispectral data to estimate plot-level volume and biomass in deciduous and pine forests in Virginia, USA. *Forest Science*, **50**, pp. 551–565.
- SCHMID, H.P., SU, H.B., VOGEL, C.S. and CURTIS, P.S., 2003, Ecosystem-atmosphere exchange of carbon dioxide over a mixed hardwood forest in northern lower Michigan. *Journal of Geophysical Research-Atmospheres*, **108**, 4417, doi:10.1029/2002JD003011.
- SHUGART, H.H., SAATCHI, S. and HALL, F.G., 2010, Importance of structure and its measurement in quantifying function of forest ecosystems. *Journal of Geophysical Research*, **115**, G00E13, doi:10.1029/2009JG000993.
- SKOWRONSKI, N., CLARK, K., NELSON, R., HOM, J. and PATTERSON, M., 2007, Remotely sensed measurements of forest structure and fuel loads in the Pinelands of New Jersey. *Remote Sensing of Environment*, **108**, pp. 123–129.
- SMITH, A.M.S., STRAND, E.K., STEELE, C.M., HANN, D.B., GARRITY, S.R., FALKOWSKI, M.J. and EVANS, J.S., 2008, Production of vegetation spatial-structure maps by per-object analysis of juniper encroachment in multitemporal aerial photographs. *Canadian Journal of Remote Sensing*, **34**, pp. S268–S285.
- STRAND, E.K., SMITH, A.M.S., BUNTING, S.C., VIERLING, L.A., HANN, D.B. and GESSLER, P.E., 2006, Wavelet estimation of plant spatial patterns in multi-temporal aerial photography. *International Journal of Remote Sensing*, **27**, pp. 2049–2054.
- VAN LEEUWEN, M. and NIEUWENHUIS, M., 2010, Retrieval of forest structural parameters using LiDAR remote sensing. *European Journal of Forest Research*, **129**, pp. 749–770.
- WULDER, M.A., WHITE, J.C., COOPS, N.C. and BUTSON, C.R., 2008, Multi-temporal analysis of high spatial resolution imagery for disturbance monitoring. *Remote Sensing of Environment*, **112**, pp. 2729–2740.
- YU, X., HYYPPÄ, J., VASTARANTA, M., HOLOPAINEN, M. and VIITALA, R., 2011, Predicting individual tree attributes from airborne laser point clouds based on the random forests technique. *ISPRS Journal of Photogrammetry and Remote Sensing*, **66**, pp. 28–37.
- ZHANG, X.Y., FENG, X.Z. and JIANG, H., 2010, Object-oriented method for urban vegetation mapping using IKONOS imagery. *International Journal of Remote Sensing*, **31**, pp. 177–196.