Extraction of forest structural parameters based on the intensity information of high-density airborne light detection and ranging

Chunxiang Cao
Yunfei Bao
Wei Chen
Yongfeng Dang
Lin Li
Rong Tian
Guanghe Li

Extraction of forest structural parameters based on the intensity information of high-density airborne light detection and ranging

Chunxiang Cao,[a] Yunfei Bao,[a,b] Wei Chen,[a,b] Yongfeng Dang,[c] Lin Li,[d] Rong Tian,[a,b] and Guanghe Li[e]

[a]Institute of Remote Sensing Applications of Chinese Academy of Sciences,
State Key Laboratory of Remote Sensing Science, PO Box 9718-13, Datun Road,
Chaoyang District, 100101, Beijing, China
cao413@irsa.ac.cn

[b]Graduate University of Chinese Academy of Sciences, No. 19, Yuquan Road,
Shijingshan District, 100049, Beijing, China

[c]State Forestry Administration, No. 18, Hepingli East Street, Dongcheng District, 100714,
Beijing, China

[d]China Agricultural University, College of Information and Electrical Engineering, Computer
Science and Technology, No. 17, Tsinghua East Road, Haidian District, 100083, Beijing, China

[e]Beijing University of Technology, No. 100, Pingle Park, Chaoyang District, 100124,
Beijing, China

Abstract. The quantitative description of forest canopy structure is significant for the investigation of a forest, which serves as an important component of the terrestrial ecosystem. Light detection and ranging (LIDAR), as a new technical means that can acquire high-precision vertical information, plays a crucial role in forest monitoring and management. Choosing Dayekou forest experimental area in the Heihe watershed as a study area, we separated the ground points from the vegetation points using the skewness-change algorithm based on the intensity information from airborne LIDAR data. After that, digital terrain model (DTM) and digital surface model (DSM) were generated, respectively, based on which the canopy height model (CHM) was acquired. Finally, using the variational window, the local maximum filter method was used to extract individual tree heights and crown widths from CHM. The determination coefficients of tree heights and crown widths were 0.8568 and 0.3923, respectively. The validation results indicated that the tree heights could be effectively extracted from intensity information of airborne LIDAR, while the accuracy of extracted crown widths needed to be improved. In the future work, aerial photos and other high-resolution images would be combined to improve the accuracy. © 2012 Society of Photo-Optical Instrumentation Engineers (SPIE). [DOI: 10.1117/1.JRS.6.063533]

1 Introduction

Forest serves as an important component of the land surface ecosystem as well as terrestrial biosphere, thus playing a crucial role in the global and regional carbon cycle.[1] Forest canopy structures determine the transmittance of sunlight in the canopy and are able to affect the major physiological processes of vegetation (such as photosynthesis, transpiration, nitrogen cycle, and so on) as well as the energy exchange and circulation between vegetation and atmosphere.[2,3] Additionally, the forest canopy structures are also significant for the forest vegetation net primary productivity.[4] Consequently, the quantitative description of forest canopy structure is significant for the investigation and management of forest resources and can further contribute

to the assessment of aboveground biomass, hence benefits more accurate estimation of forest carbon sinks. Thus it could provide strong support for the study of carbon cycle.

As the light detection and ranging (LIDAR) technology rapidly develops and gradually matures, it has been a novel remote sensing means applied in various fields including photogramming, mapping, ocean observations, atmospheric monitoring, forest survey as well as military fields and so on. As a new technical technology, which can acquire high-precision vertical information, LIDAR plays an important role in the forest structural parameters extraction and forest resource management. In these areas, there have already been quite a lot of successful cases from international researchers showing the successful applications of LIDAR data.[2,3,5–9]

Quick access to information of surface coverings through LIDAR is beneficial to reduce the workload of the field measurements in traditional forest inventory, as well as to extend the scope of the forest survey. Besides, based on LIDAR technology, the extracted high-precision forest parameters including heights, crown widths, vegetation fractional cover as well as leaf area index (LAI) can serve as modeling input variables to improve the accuracy of the biomass estimation. But until now, there is little research about the extraction of forest parameters using LIDAR data, especially based on its intensity information in mountain areas, which still needs further study.[5,10,11]

During the latest studies, two main methods are used to extract forest heights and crown widths based on airborne LIDAR point cloud data: one is to establish regression relationships between field-measured tree heights, crown widths, and partially extracted average canopy height, along with canopy height variance as well as other statistical characteristics from LIDAR point cloud data;[12–14] the other is to extract heights, crown widths, and other parameters using canopy height model (CHM) from LIDAR data.[15–20] The second method is mainly applied in the modeling studies using high-resolution optical imagery, with basic assumptions as follows:[4]

1. The treetop generally has a performance of the bulge;
2. The crown's projection on the ground can be approximated by a regular geometric shape, with mostly circular approximation in latest work;
3. The center of treetops should have a higher "value" than the crown edges, which performed as higher brightness in the high-resolution images.

Based on the assumptions, many algorithms have been developed for the extraction of forest structural parameters from CHM, which mainly include local maximum filter method,[18,19,21] watershed algorithm,[22] and some other new ones.[20]

In our study, we proposed to extract the forest structural parameters using the intensity information of airborne LIDAR data. First, we chose Dayekou forest hydrology experimental area in the Heihe watershed as study area and separated the ground points from the vegetation points using the skewness-change algorithm based on the intensity information from airborne LIDAR data. After the separation, digital terrain model (DTM) and digital surface model (DSM) were generated, respectively, and then the CHM of the study area was calculated. Finally, the local maximum filter method was used to extract individual tree heights and crown widths from CHM using the variational window. The validation was conducted using field-measured parameters. The determination coefficients of tree heights and crown widths were 0.8568 and 0.3923, respectively. It indicated that the tree heights could be effectively extracted based on intensity information of airborne LIDAR, while the extraction accuracy of crown widths still needed to be improved. In the future studies, we would try to combine aerial photos or other high-resolution optical images and even radar data to improve the accuracy.

2 Study Area and Data

2.1 Study Area

The study area of Dayekou forest hydrology experimental area is located in the Qilian Mountain area, with geographic coordinates ranging from N38°29′ to 38°35′ in latitude and from E100°12′ to 100°20′ in longitude within Gansu province, western China (Fig. 1). The elevation varies from
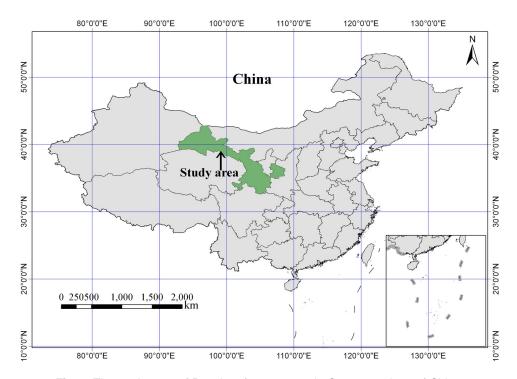
Fig. 1 The study area of Dayekou forest center in Gansu province of China.

2500 to 3800 m above the sea level. This area has a typical temperate continental mountainous climate. In winter, when the atmospheric circulation is controlled by the Mongolia anticyclone, the climate appears to be cold and dry, with little precipitation. But when the atmospheric circulation is controlled by the continental cyclone in summer, the diurnal difference of temperature is dramatic. There is large difference of precipitation between summer and winter, and annual precipitation mainly takes place in summer. Influenced by the climate and terrain, the prevalent vegetation types are mountainous pastures and forests. The dominant vegetation types include *Picea crassifolia*, Sabina przewalski, and grassland. Vegetation density varies with terrain, soil, water, and climate factors. In this study, the coniferous tree species of *Picea crassifolia* was selected as a target.

2.2 *LIDAR Data Acquisition*

An airborne laser scanning flight was carried out over the study area in June 2008. The airborne laser scanning system used is LiteMapper-5600 developed by the German company IGI. It is the first batch of commercial airborne LIDAR terrain mapping systems using waveform digitization. Its laser scanner is RIEGL LMS-Q560, the sensor specifications of which are shown in Table 1.

The flight was conducted with a nominal height of 700 to 800 m over ground, leading to a pulse density of 0.36 to 1.6 points per square meter. To increase the pulse density, repetitive flights with the same height above ground were carried out over the sample study area. The flights in the sample plot were five times more than those in other areas, so the pulse density was increased to 2 to 7 points per square meter. Additionally, as the laser scanner records a waveform data, multiple returns need to be sampled. The site of the LIDAR data was shown in Fig. 2. The data used in this study was the high-density airborne LIDAR data covering the blue area.

2.3 *Field Measurement Data*

During the field survey, we selected a large sample plot of 100×100 m in an area with slope less than 20 deg. In order to ensure the accurate position of our plots, we located them with DGPS stations within the open space of standing forest. As shown in Fig. 3, there are six red points

Table 1 Specifications of RIEGL LMS-Q560.

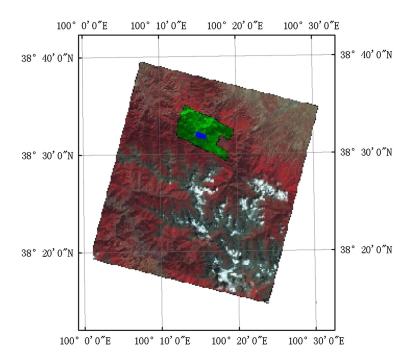| Specifications	Values
Max. Measurement range	1800 m
Measurement accuracy	20 mm
Max. pulse repetition frequency	200 kHz
Multiple target separation within single shot	0.6 m
Laser wavelength	1550 nm
Return pulse width resolution	0.15 m
Scan speed	10–160 scans/s
Scan angle accuracy	001 deg
Laser beam divergence	0.5 m rad

Fig. 2 The site of the LIDAR data. The green shows the low-density LIDAR point data area; the blue denotes the high-density LIDAR point data area.

representing six DGPS measurement datum points, two of which are in the interior of the large plot, while the other four are in the external area. Besides, we still used the mobile stations to determine the accurate positions of all the trees. As the communications between datum points and mobile stations were accomplished via satellite signal transduction, it was not necessary to "see" all trees from these DGPS points. For the convenience of field measurement of each timber and their statistics, we had subdivided the large plot into 16 small subplots. The 16 small squares in Fig. 3 represented the 16 subplots with a size of 25 m × 25 m, which were numbered from 1 to 16.

Based on the subdivision, the large plot was separated into 16 subplots, and there were 1,456 trees in all subplots in total. The structural parameters of each individual tree, including the height, crown width as well as diameter at the breast height (DBH), and height under the branch, were measured using an altimeter rod, a tape measure, a ribbon tape, and so on. The geographic position of each individual tree also was measured using the stations of TOPCON GTS-602 and TOPCON GPT-7002.
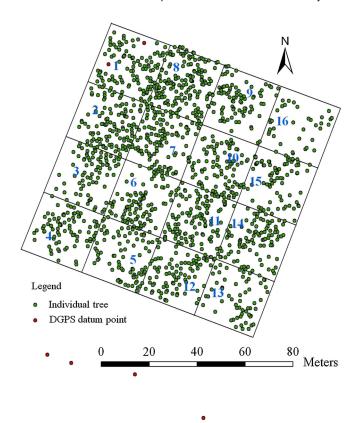
Fig. 3 Field measurements of individual trees and their spatial distribution.

3 Methods and Results

3.1 *Generation of CHM*

The LIDAR intensity represents the reflectance characteristics of the surface in the near-infrared spectra between wavelengths of 800 and 1550 nm. The ratio of received to transmitted laser energy thus increases with the increase of reflectivity of the target and decreases with the decreasing distance between sensor and target. In a forested area, there are differences between vegetation and ground soil in both reflectivity and height. LIDAR intensity is also an important information source, which can be exploited in forest characterization. In this study, we separate the ground points from the vegetation points using the skewness-change algorithm based on the intensity information of the high-density LIDAR data.[2]

In the skewness-change algorithm, the changes of statistical characteristics of skewness have been used. Based on the central limit theorem, naturally measured samples will follow a normal distribution. The object points may disturb the normal distribution. The statistical results of LIDAR intensity from several different area samples have been used to prove it. In our study area, the distribution of LIDAR intensity could be considered as a combination of two normal distributions. The skewness and kurtosis of this distribution are two characteristics, which are used in statistical analyses to describe the distribution of LIDAR points based on its intensity. Based on the change curves of skewness and kurtosis, the vegetation points are separated from ground points. The method, which makes use of intensity of laser scanner data, is especially applicable in steep and forested areas.

The ground points separated from LIDAR points using skewness change algorithm still include a few aboveground points, which are indicated as noise. After removing the noise, DTM as well as fractional vegetation cover are generated, respectively, according to whether or not pulses have their first echo on the ground. First, a triangulated irregular network (TIN) is constructed for the ground point based on a Delaunay triangulation of its elevation data. Then a rectangular grid of pixels is extracted from each TIN using linear interpolation
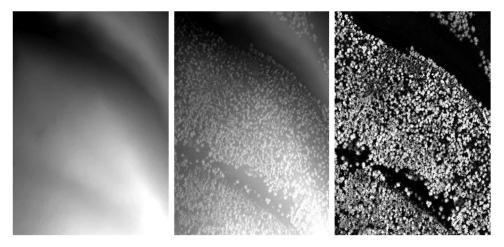
Fig. 4 The DTM (left), DSM (mid), and CHM (right) of the study area.

with a constant sampling interval of one meter. Finally, the raster DTM of one-square-meter spatial resolution is generated.

Then the DSM is obtained through filtering out the uppermost echoes and then the CHM is acquired from Eq. (1). Figure 4 shows the DTM, DSM, and CHM of the study area with a spatial resolution of 1 m, respectively.

$$CHM = DSM - DTM \tag{1}$$

3.2 Determination of Variational Window

Before the extraction of tree heights and crown widths from CHM, we should first determine the detection window, including its shape and size. When Kini and Popescu[23] extracted an individual tree's structural parameters using local maximum filter algorithm, a variational window was used. Its size was determined according to the relationship between tree heights and crown widths, which were influenced by the species (deciduous or coniferous forest). As there is only one kind of tree (*Picea crassifolia*) in our sample plot, we only need to determine one kind of relationship between tree height and crown width. According to the structural parameters of 1,456 trees, we established a linear relationship between the heights and crown widths, which was shown as Eq. (2) and in Fig. 5. In Eq. (2), D_{crown} is the crown width, and H_{tree} is the tree height. The R square of the relationship is 0.6103, which meets the requirement of accuracy for variational window determination. Based on this relationship, we could determine the size of window; however, its shape is still uncertain. In most previous studies, it was set as square. Considering that the crown projection is circular no matter what is the shape of crown itself, we finally select the circular window,[23] which is more appropriate for the extraction in our study.
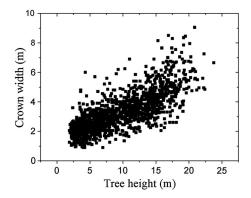

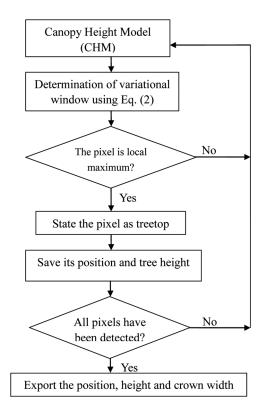**Fig. 5** Regression relationship between tree heights and crown widths from field measurements.

Fig. 6 Flow chart of the local maximum filter algorithm for locating trees and measuring height and crown width.[18]

$$D_{\text{crown}} = 0.2041 H_{\text{tree}} + 1.3457 (R^2 = 0.6103) \qquad (2)$$

3.3 Extraction of Structural Parameters

Finally, based on the variational window, the local maximum filter algorithm was performed to extract individual tree heights and crown widths from the CHM.[16] The flow chart of this algorithm was shown in Fig. 6. The extraction result was partly shown in Fig. 7 in which the green cross marks indicated the tree locations with a base map of CHM. The right one showed the corresponding aerial photo.

4 Discussion and Conclusion

4.1 Discussion

After extracting the heights and crown widths of individual trees, we performed the validation using field-measured values. The validation results are shown in Figs. 8 to 10. Figure 8 shows the validation result of tree heights. From it we could find that the determination coefficient (R^2) between extracted heights and measured values was up to 0.8568, which indicated the efficiency of height extraction.

From Fig. 8, we could find that the extracted heights were among 8 to 20 m while the field-measured values were between 4 and 25 m. Comparing the minimum height, we concluded that some of the lower trees cannot be effectively extracted using the method in this paper. It probably resulted because the lower and younger trees had been covered by higher and lusher surrounding trees and thus could not be detected by airborne LIDAR. It also accounted for that the number of extracted trees from CHM was less than that from field measurements. At the same time, by comparing the maximum height, we were aware that a few of the highest treetops had also not been detected. The reason may lie in that LIDAR-laser points didn't really hit the apex of the crown. Although there were some undetected trees, in all stands, more than 51.5% of all trees had been detected, and the percentage was larger than 70% in most areas. So the airborne LIDAR
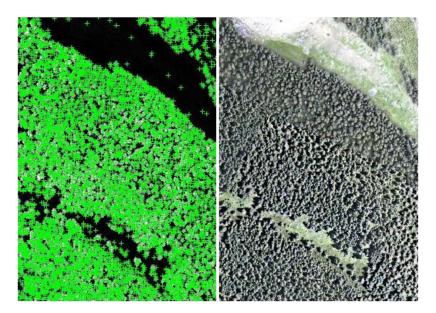
Fig. 7 Tree locations of individual trees from local maximum filter (left) and its corresponding aerial photo (right).
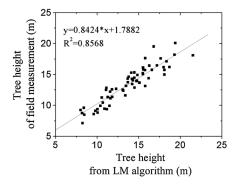

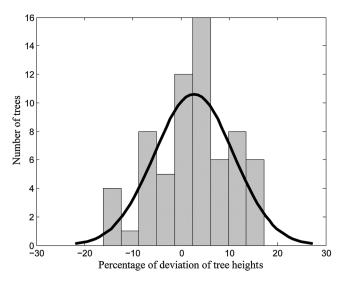**Fig. 8** Comparison of tree heights from Local Maximum (LM) algorithm and field measurements.

Fig. 9 The histogram of deviation of the tree heights between measured and extracted values.
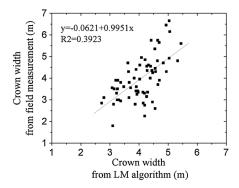
Fig. 10 Comparison of crown widths from LM algorithm and field measurements.

technology was indeed effective and efficient in the extraction of tree heights. In order to adequately demonstrate this point, we made the histogram of deviation of the tree heights between measured and extracted values, which is shown in Fig. 9. From this figure, we found that the deviation followed normal distribution, which indicated the reliability and efficiency of our extraction method.

Figure 10 shows the extraction precision of tree crown widths. The determination coefficient (R^2) for tree crown widths was only 0.3923, which needed to be improved. The points in Fig. 10 also appeared dispersed. It may be due to the crown's edge being susceptible to the crown of surrounding trees when the texture feature was used to extract the crown width in the local maximum filter algorithm. So new algorithms should be developed using airborne LIDAR data. In the future studies, aerial photos and other high-resolution optical images and even radar data could be combined to improve the extraction accuracy. Now we are attempting to combine LIDAR data with high-resolution aerial image to detect the crown's edge more effectively.

4.2 Conclusion

As LIDAR has been a novel remote-sensing means applied to obtain accurate vertical information, it has been quickly developed. In this paper, we first generated the CHM using the skewness-change algorithm based on the intensity information of high-density airborne LIDAR data and then determined the shape and size of the variational window using relationship from field-measured structural parameters, finally extracted the tree locations as well as tree heights, and crown widths using local maximum filter algorithm. But there was a little deviation between some of the extracted and measured locations, so we only validated the extraction precision for the trees whose extracted location was close to the measured position. The validation was performed based on the field-measured structural parameters.

The experiments in our work provided a useful exploration in the extraction of an individual tree's structural parameters using airborne LIDAR data. The results showed that the airborne LIDAR data was significantly effective in the extraction of tree heights while it seemed disappointing in extracting the crown widths. On one hand, it verified that the LIDAR data have more advantages in obtaining vertical information than acquiring horizontal information; on the other hand, it also indicated that new algorithms should be developed and other aerial photos or radar data could be introduced to improve the application effect.

Acknowledgments

References

1. S. Hense et al., "Global biomass mapping for an improved understanding of the CO_2 balance—the Earth observation mission carbon 3-D," *Rem. Sens. Environ.* **94**(1), 94–104 (2005), http://dx.doi.org/10.1016/j.rse.2004.09.006.

2. Y. F. Bao et al., "Synchronous estimation of DTM and fractional vegetation cover in forested area from airborne LIDAR height and intensity data," *Sci. China Ser. E Technical Science* **51**(Suppl. II), 176–187 (2008), http://dx.doi.org/10.1007/s11431-008-6018-x.

3. C. X. Cao et al., "Retrieval of forest canopy attributes based on geometric-optical model using airborne LIDAR and optical remote sensing data," *Int. J. Rem. Sens.* **33**(3), 692–709 (2012), http://dx.doi.org/10.1080/01431161.2011.577830.

4. H. B. Huang, "The forest structural parameter extraction using LIDAR," Doctoral thesis, Institute of Remote Sensing Applications, Chinese Academy of Sciences, Beijing (2008).

5. M. A. Lefsky et al., "Surface LIDAR remote sensing of basal area and biomass in deciduous forests of Eastern Maryland, USA," *Rem. Sens. Environ.* **67**(1), 83–98 (1999), http://dx.doi.org/10.1016/S0034-4257(98)00071-6.

6. F. Morsdorf et al., "The potential of discrete return, small footprint airborne laser scanning data for vegetation density estimation," in *The International Archives of the Photogrammetric, Remote Sensing and Spatial Information Sciences*, Vol. 36, pp. 198–203 (2005).

7. D. L. B. Jupp et al., "Estimating forest LAI profiles and structural parameters using a ground based laser called 'Echidna®,'" *Tree Physiol.* **29**(1), 171–181 (2009), http://dx.doi.org/10.1093/treephys/tpn022.

8. M. Hollaus et al., "Accuracy of large-scale canopy heights derived from LIDAR data under operational constraints in a complex alpine environment," *ISPRS J. Photogramm.* **60**(5), 323–338 (2006), http://dx.doi.org/10.1016/j.isprsjprs.2006.05.002.

9. Z. Fu et al., "Estimation of forest canopy leaf area index using MODIS, MISR, and LIDAR observations," *J. Appl. Rem. Sens.* **5**(1), 053530 (2011), http://dx.doi.org/10.1117/1.3594171.

10. K. L. Lucas, G. T. Raber, and G. A. Carter, "Estimating vascular plant species richness on Horn Island, Mississippi using small-footprint airborne LIDAR," *J. Appl. Rem. Sens.* **4**(1), 043545 (2010), http://dx.doi.org/10.1117/1.3501119.

11. Y. F. Bao, "Study on methods of forest parameters extraction from multi-source remote sensing data," Doctoral thesis, Institute of Remote Sensing Applications, Chinese Academy of Sciences, Beijing (2009).

12. A. T. Hudak et al., "Regression modeling and mapping of coniferous forest basal area and tree density from discrete-return LIDAR and multispectral satellite data," *Can. J. Rem. Sens.* **32**(2), 126–138 (2006), http://dx.doi.org/10.5589/m06-007.

13. M. Maltamo et al., "Identifying and quantifying structural characteristics of heterogeneous boreal forests using laser scanner data," *Forest Ecol. Manag.* **216**(1–3), 41–50 (2005), http://dx.doi.org/10.1016/j.foreco.2005.05.034.

14. S. D. Roberts et al., "Estimating individual tree leaf area in loblolly pine plantations using LIDAR-derived measurements of height and crown dimensions," *Forest Ecol. Manag.* **213**(1–3), 54–70 (2005), http://dx.doi.org/10.1016/j.foreco.2005.03.025.

15. S. Koukoulas and G. A. Blackburn, "Mapping individual tree location, height and species in broadleaved deciduous forest using airborne LIDAR and multispectral remotely sensed data," *Int. J. Rem. Sens.* **26**(3), 431–455 (2005), http://dx.doi.org/10.1080/0143116042000298289.

16. R. Loos and O. Niemann, "Identification of individual trees and canopy shapes using LIDAR data for fire management," in *The IEEE International Symposium on Geoscience and Remote Sensing (IGARSS)*, pp. 3755–3757, IEEE Geoscience and Remote Sensing Society, Denver, Colorado (2006).

17. J. Pitkänen et al., "Adaptive methods for individual tree detection on airborne laser based canopy height model," in *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. 36, pp. 187–191 (2004).
18. S. C. Popescu, R. H. Wynne, and R. E. Nelson, "Estimating plot-level tree heights with LIDAR: local filtering with a canopy-height based variable window," *Comput. Electron. Agr.* **37**(1–3), 71–95 (2002), http://dx.doi.org/10.1016/S0168-1699(02)00121-7.
19. S. C. Popescu, R. H. Wynner, and R. E. Nelson, "Measuring individual tree crown diameter with LIDAR and assessing its influence on estimating forest volume and biomass," *Can. J. Rem. Sens.* **29**(5), 564–577 (2003), http://dx.doi.org/10.5589/m03-027.
20. Q. W. Liu et al., "Extracting height and crown of individual tree using airborne LIDAR data," *J. Beijing For. Univ.* **30**(1), 83–89 (2008).
21. M. Wulder, K. O. Niemann, and D. G. Goodenough, "Local maximum filtering for the extraction of tree locations and basal area from high spatial resolution imagery," *Rem. Sens. Environ.* **73**(1), 103–114 (2000), http://dx.doi.org/10.1016/S0034-4257(00)00101-2.
22. R. Chen et al., "Topographical changes revealed by high-resolution airborne LIDAR data: the 1999 Tsaoling landslide induced by the Chi-Chi earthquake," *Eng. Geol.* **88**(3–4), 160–172 (2006), http://dx.doi.org/10.1016/j.enggeo.2006.09.008.
23. A. Kini and S. C. Popescu, "TreeVaW: a versatile tool for analyzing forest canopy LIDAR data: a preview with an eye towards future," in *ASPRS Fall Conf.*, American Congress on Surveying and Mapping and American Society for Photogrammetry and Remote Sensing, Kansas City (2004).

Chunxiang Cao is a scientist from the Institute of Remote Sensing Applications, Chinese Academy of Sciences in Beijing, China. She mainly focuses on the new cross-disciplinary of remote sensing based diagnose of environment health. It includes forest remote sensing, quantitative remote sensing inversion of ecological environmental parameters as well as public health research using spatial information technology. Until now, she has published more than 90 peer-reviewed papers, more than 30 of which are SCI indexed. She is on the editorial board of the journal of *Positioning* and serves the reviewer of many journals including *Science in China, International Journal of Remote Sensing* etc. Now she is also the executive director of Center for Applications of Spatial Information Technologies in Public Health and would like to deepen and widen the research associated with environment health based on remote sensing.

Yunfei Bao graduates from the Institute of Remote Sensing Applications, Chinese Academy of Sciences, and mainly focuses on the research of forest parameters extraction from multi-source remote sensing data. He is now working in Beijing Institute of Space Mechanics and Electricity.

Wei Chen gets his master degree in the State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing Applications, Chinese Academy of Sciences. Now he is a PhD student of Biosphere Informatics Laboratory, Department of Social Informatics, Graduate School of Informatics, Kyoto University. His research mainly focuses on forest remote sensing and environmental informatics, including the retrieval of forest parameters (VFC, LAI, biomass etc.), ecological recovery after forest ecosystems disturbance and so on. By now, he has published more than 10 peer-reviewed papers, 6 of which are accomplished as first author. He is now studying the forest in the Greater Hinggan Mountain area of China.

Yongfeng Dang is a senior engineer from the Institute of Forest Inventory and Planning, Chinese State Forestry Administration, China. He is mainly engaged in forest resource monitoring and evaluation, which includes the National Forest Inventory (NFI), the remote sensing monitoring of the national forestry ecological projects, the protection of the national forest land use planning, as well as remote sensing monitoring of national forest resources. He has published more than 6 books as one of editors, and issued more than 21 papers in his work fields.

Lin Li works as associate professor of Computer Science and Technology Department, College of Information and Electrical Engineering at China Agriculture University(CAU), China. She obtained her PhD from China Agriculture University (CAU). Her current research interest includes software engineering(SE), software automation(SA), bioinformatics, etc. Until now, she has published more than 40 peer-reviewed papers.

Rong Tian graduated from School of Remote Sensing and Information Engineering, Wuhan University in 2010. Now she is a master student of Institute of Remote Sensing Applications, Chinese Academy of Sciences. Her research mainly focuses on assessment of wetland ecosystem and the applications of remote sensing in wetland research. By now, she has published about 7 peer-reviewed papers, 2 of which are accomplished as first author. She is now studying the Water-Level-Fluctuation Zone (WLFZ) in the Three Georges Area.

Guanghe Li a fourth grade student from Beijing University of Technology, majoring in Industrial Design. He worked at Beijing Dondu design corporation from October 2009 to October 2010. He designed VI for Beijing Jian Yuan Tian Di environmental protection technology company and Beijing Narpuli automation technology company. He has published 2 SCI indexed papers in International Journal of Remote Sensing and Canadian Journal of Remote Sensing.