Concepts and Techniques for Large-Scale Mapping of Urban Vegetation Using Mobile Mapping Point Clouds and Deep Learning

Josafat-Mattias Burmeister[1], Rico Richter[2], Jürgen Döllner[3]

[1]University of Potsdam, Digital Engineering Faculty/Germany · burmeister@uni-potsdam.de
[2]University of Potsdam, Digital Engineering Faculty/Germany
[3]University of Potsdam/Hasso Plattner Institute/Germany

Abstract: In urban environments, roadside vegetation provides important ecosystem services. Reliable and up-to-date information on urban vegetation is therefore needed as a basis for sustainable urban design and regular tasks such as vegetation maintenance. Mobile laser scanning (MLS), i. e., the use of vehicle-mounted laser scanners, offers strong potential for capturing 3D point clouds of road environments on a large scale at a low cost. In this paper, the potential and challenges of using MLS for vegetation mapping are discussed. To lay a foundation for MLS-based inventories of roadside vegetation, a concept for the automatic detection and analysis of vegetation in MLS point clouds using deep learning is presented. The proposed workflow covers vegetation detection and classification, delineation of individual trees, and estimation of tree attributes. In a case study, an initial implementation of the workflow is tested using MLS datasets from two German cities and the results are evaluated through visual inspection. It is demonstrated that the proposed deep-learning approach is able to detect and classify vegetation in MLS point clouds of complex urban road scenes. When delineating individual trees, accurate results are obtained for solitary trees and trees with little canopy overlap, while the delineation of trees with strongly overlapping canopies needs further improvement in some cases. The results indicate that geometric tree attributes such as tree height and trunk diameter can be accurately estimated from MLS point clouds if the accuracy of the preceding processing steps is sufficiently high.

Keywords: Vegetation mapping, tree inventory, mobile mapping, deep learning, LiDAR

1 Introduction

In urban environments, roadside vegetation provides important ecosystem services, including sequestering carbon, mitigating air pollution, regulating microclimate, providing habitat, and promoting human well-being (SÄUMEL et al. 2016). Urban trees also help mitigate the effects of climate change through local cooling and stormwater absorption (PATAKI et al. 2021). Therefore, maintaining and expanding roadside vegetation is essential for sustainable urban development. Reliable and up-to-date information on urban vegetation is needed to guide the design of urban green spaces toward the provision of ecosystem services (ELDERBROCK et al. 2020) and to develop appropriate green space management programs (SCHIPPERIJN et al. 2005). Many municipalities, especially in North America and Europe, therefore, conduct inventories of public green spaces. These inventories often focus on surveying individual trees, i. e., mapping the location of individual trees, and collecting tree attributes such as tree species, height, and trunk diameter (MA et al. 2021). Since manual vegetation inventories are costly and time-consuming, the use of LiDAR systems (Light Detection and Ranging) for automated or semi-automated vegetation mapping has become an important research topic. These systems capture the environment in the form of high-resolution 3D point clouds and can be used with various acquisition platforms. The acquisition can be categorized as terres-

Journal of Digital Landscape Architecture, 8-2023, pp. 451-462. © Wichmann Verlag, VDE VERLAG GMBH · Berlin · Offenbach. ISBN 978-3-87907-740-3, ISSN 2367-4253, e-ISSN 2511-624X, doi:10.14627/537740048.

trial laser scanning (TLS) with tripod-mounted laser scanners, personal laser scanning (PLS) with handheld or backpack-mounted laser scanners, mobile laser scanning (MLS) with vehicle-mounted laser scanners, unmanned aerial vehicle-borne laser scanning (UAV-LS), and airborne laser scanning (ALS). Compared to TLS, PLS, and UAV-LS, the use of vehicle-mounted laser scanners significantly reduces the acquisition effort, while providing 3D point clouds with higher resolution and fewer occlusions than ALS. Because of these characteristics, MLS is a well-suited technology for the large-scale mapping of roadside vegetation and thus could become a complement or alternative to conventional vegetation surveys. Compared to conventional field surveys, MLS-based vegetation mapping would reduce labor and cost, while providing a richer, three-dimensional representation of vegetation. To realize the potential of MLS for vegetation mapping, an automated approach is needed to derive semantic information about vegetation from raw 3D point clouds. To lay a foundation for building such a system, this paper presents a general concept for the automatic detection and analysis of vegetation in MLS point clouds. In contrast to previous work, the proposed workflow builds on a modern deep-learning approach for 3D point cloud segmentation. In a case study, an initial implementation of the proposed workflow is tested on MLS datasets from two cities and first results are provided.

2 Potential of MLS-Based Vegetation Inventory

Compared to conventional field surveys, MLS-based vegetation inventories would provide several advantages: First, the labor and cost of vegetation surveys would be reduced, allowing larger areas to be mapped and vegetation inventories to be updated more frequently (e. g., quarterly to cover all seasons). Second, capturing vegetation in the form of 3D point clouds would provide additional and more detailed data on urban vegetation. For example, shrubs and hedges could be mapped, which are not recorded in most conventional vegetation surveys despite their ecological value and aesthetic impact. Furthermore, conventional tree inventories usually only capture a limited number of tree attributes (ÖSTBERG et al. 2013). Using 3D point clouds, additional geometric tree attributes such as trunk orientation or crown volume could be captured (HERRERO-HUERTA et al. 2018). 3D point clouds could even be used to model the entire branching structure of trees (DU et al. 2019). Overall, the data collected in MLS-based vegetation inventories could be used to build comprehensive tree information models, as proposed by SHU et al. (2022). Such information models would address the information needs of a wide range of stakeholders, including city officials, arborists, ecologists, and landscape architects. For landscape architects, information derived from MLS-based vegetation inventories could be particularly useful for the following applications: (1) At the beginning of the design process, more detailed plant models could be created to enable a more accurate representation and analysis of existing vegetation. While generic plant models have been commonly used to visualize vegetation (OEHLKE et al. 2015), plant models derived from 3D point clouds could be used to create more realistic visualizations of vegetation. Moreover, plant models derived from 3D point clouds could also be used to estimate the ecosystem services and disservices provided by existing vegetation. For example, the shading provided by trees could be modeled, or the carbon storage and oxygen release potential of vegetation could be estimated (SCHOLZ et al. 2018). (2) Conducting MLS-based vegetation surveys on a regular basis could also provide ground truth data for building and validating simulation models of plant growth (WHITE et al. 2022). More accurate simulation of plant growth would support decisions between different planting regimes in the design of green spaces. (3) Once a certain planting regime has been established, MLS could be used to continuously monitor the green space (e. g., growth and condition). In this way, design decisions could be evaluated, and vegetation maintenance measures could be planned and aligned with the design goals.

3 Challenges in MLS-Based Vegetation Inventory

While MLS offers significant potential for the large-scale mapping of roadside vegetation, several challenging data characteristics must be considered when developing systems to automatically process MLS point clouds for vegetation mapping:

Large data volume: MLS produces large amounts of data with hundreds of points per square meter. To be able to process MLS point clouds of large road segments or entire city districts, all processing steps must be automated and implemented efficiently. This requires algorithms that allow parallel processing with modern multicore systems or graphics cards.

Varying point density: The point density of MLS point clouds depends on the scanner type, the acquisition speed, and the distance to the scanner trajectory. Systems for processing MLS point clouds must therefore be robust to varying point densities.

Occlusions: In MLS point clouds, vegetation may be completely or partially occluded by other objects. The algorithms for detecting and analyzing vegetation in MLS point clouds must therefore be able to cope with incomplete data, i. e., 3D point clouds that cover only a part of the surface.

Limited per-point attributes: Most LiDAR systems provide the 3D coordinates and reflection intensity for each scanned point. More advanced systems can capture additional attributes such as surface color (e. g., from panoramic images), temperature, or humidity. To support a wide range of scanner types, however, algorithms for vegetation detection and analysis should only rely on point coordinates and reflection intensity as input attributes.

Integration of multi-temporal MLS data: Approaches for storing and processing multi-temporal MLS data are needed to enable continuous vegetation monitoring. Since inaccuracies can occur in the georeferencing of MLS point clouds, techniques for co-registering 3D point clouds from different acquisition runs are needed. In addition, approaches are needed to increase the coverage and merge redundant information from MLS point clouds acquired at different times and to identify areas that have changed between acquisition runs.

4 A Concept for the Detection and Analysis of Vegetation in MLS Point Clouds Using Deep Learning

In the following, a concept for the automatic detection and analysis of vegetation in MLS point clouds is presented. The proposed workflow is divided into three steps: (1) In the first step, deep-learning models are used to extract vegetation points from raw MLS point clouds and classify them into different vegetation types. (2) In the second step, the tree points detected by a deep-learning model are segmented into individual trees. (3) Using the point clouds of individual trees, tree attributes such as tree height and trunk diameter are derived.

4.1 Detection and Classification of Vegetation

Besides vegetation, urban MLS point clouds contain a variety of other objects such as city furniture, vehicles, and buildings. An automated approach is required to segment 3D point clouds of such complex scenes into vegetation points and non-vegetation points. In addition, different vegetation types, such as low vegetation and trees, need to be distinguished.

4.1.1 Related Work

While the present work aims to detect both low vegetation and trees, most previous work has focused on tree detection in MLS point clouds. To segment urban MLS point clouds into tree points and non-tree points, many works use either rule-based approaches (HAO et al. 2022, HUI et al. 2022) or statistical machine learning approaches (WEINMANN et al. 2017, CHEN et al. 2019). While rule-based approaches are usually not able to detect other vegetation types than trees and are often very dataset-specific, statistical machine learning approaches often lack the capability to combine geometric features of different spatial scales. The recent work of CHEN et al. (2021) is among the first to use a deep-learning approach for vegetation detection in urban MLS point clouds. However, the PointNLM architecture proposed in their work is trained on hand-crafted geometric features of supervoxels and does not yet exploit the full potential of recent deep-learning architectures for 3D point cloud segmentation.

4.1.2 Methodology

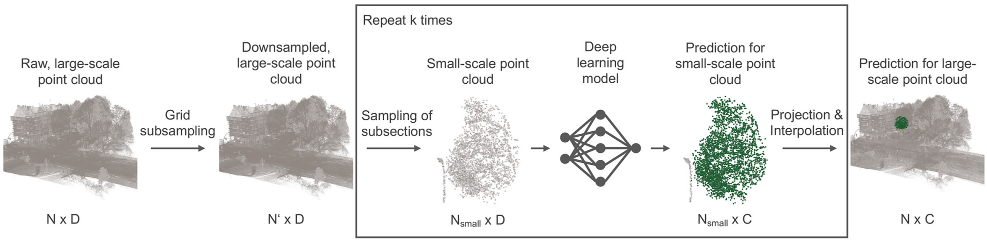

Fig. 1: Overview of the deep-learning approach used in this work (C = number of semantic classes, D = number of point attributes, N = number of points in large-scale point cloud, N' = number of points in downsampled, large-scale point cloud, N_{small} = number of points in small-scale point cloud).

In general, deep-learning architectures for processing 3D point clouds can be divided into architectures that operate on intermediate representations of point clouds such as 2D images or 3D voxel grids, and architectures that process point clouds directly (BELLO et al. 2020). Our workflow is built upon architectures that process 3D point clouds without intermediate representations. These architectures usually are more efficient than architectures that use intermediate representations and are designed to self-learn geometric features at different spatial scales. Recent examples of such architectures include KP-FCNN (THOMAS et al. 2019), a fully convolutional neural network (FCNN) based on a kernel-point (KP) convolution, and

RandLA-Net (HU et al. 2020), "an efficient and lightweight neural architecture to directly infer per-point semantics for large-scale point clouds" based on random sampling (Rand) and local feature aggregation (LA). In our implementation, the KP-FCNN Rigid architecture is used. Different variants of this architecture exist, targeting different processing tasks such as classification or semantic segmentation of 3D point clouds. In this work, the detection of vegetation in MLS point clouds and its classification into different vegetation types are modeled as a single semantic segmentation task. To this end, models are trained to distinguish the following classes:

Low vegetation includes all types of low vegetation, e. g., shrubs, hedges, and potted plants.

Tree trunk includes tree trunks, defined as the segment ranging from the base of a trunk to the first branching.

Tree branch includes the main branches of a tree that are not covered by foliage.

Tree crown includes tree foliage and the branches and twigs covered by it.

Other includes all non-vegetation points, e. g., ground, buildings, and city furniture.

This classification scheme is more fine-grained than the classification schemes used in previous studies. Segmenting trees into trunk, branch, and crown areas provides additional semantic information that can be used to delineate individual trees and estimate certain tree attributes. However, the proposed classification scheme also requires more detailed ground truth annotations to train deep-learning models, which increases the annotation effort.

Since large-scale MLS point clouds usually contain millions of points, they cannot be processed as a whole by deep-learning models. Therefore, our workflow includes two preprocessing steps to prepare raw MLS point clouds for processing by deep-learning models (Figure 1). First, the resolution of the large-scale point clouds is reduced by grid subsampling. Subsequently, small subsections of fixed size (4 m radius, 4096 points) are sampled from the downsampled large-scale point clouds. These small-scale point clouds are processed by the deep-learning model. The model predictions are mapped to the large-scale point clouds and are interpolated for points that were not covered by the small-scale point clouds.

4.2 Delineation of Individual Trees

The deep-learning approach described in the previous section performs point-wise segmentation, where each point is assigned to a semantic class. However, for points that are classified as tree points, the deep-learning approach does not provide information about which individual tree a point belongs to. Therefore, an additional processing step is required to segment the tree points identified by a deep-learning model into individual trees. Especially in areas with high tree density and overlapping tree canopies, delineating individual trees can be a challenging task.

4.2.1 Related Work

In previous work, different algorithms have been proposed to delineate neighboring trees with overlapping crowns, including graph-based approaches (ZHONG et al. 2017), clustering approaches (LI et al. 2021), and region growing approaches (LI et al. 2016). Some of these approaches rely on the correct detection of tree trunks and are therefore not robust to occlusions and misclassifications of tree trunks. Additionally, many algorithms for delineating individual trees are based on voxel representations of 3D point clouds, which limits their accuracy.

4.2.2 Methodology

To improve robustness to incomplete data and achieve more accurate segmentation of overlapping tree canopies, we propose a multi-step approach to delineate individual trees. The proposed approach is inspired by several previous works (WU et al. 2013, ZHONG et al. 2017, XU et al. 2020, YANG et al. 2020) and consists of the following steps:

1) **Identification of tree locations:** In the first step, the locations of individual trees are identified. To improve robustness against incomplete data, tree trunks, main branches, as well as treetops are considered for identifying tree locations. To identify tree locations based on tree trunks and main branches, trunk and branch points identified by the deep-learning approach are clustered using the DBSCAN algorithm (ESTER et al. 1996). Adjacent clusters with similar growth direction are merged and the midpoints of the remaining clusters are used as approximate tree locations. To identify tree locations based on crown tops, a 2D canopy height model is constructed and searched for local maxima. The positions of local maxima whose distance from the already found tree locations is above a threshold are added to the set of tree locations.

2) **Coarse delineation of individual trees:** The tree locations obtained in the previous step are used to determine the coarse boundaries of the individual trees and to identify regions with overlapping tree canopies. Different algorithms can be used for this purpose, e. g., 2D Voronoi segmentation can be performed (ZHONG et al. 2017), or a canopy height model can be constructed and segmented using the 2D marker-controlled Watershed algorithm (KORNILOV & SAFONOV 2018). For the implementation in this work, a combination of both algorithms is used.

3) **Refined delineation of overlapping tree canopies:** If the coarse tree delineation indicates that two trees are close to each other, their canopies may overlap. In such cases, the segmentation of the tree canopy is refined. Different approaches can be used to delineate trees with overlapping canopies, including graph-based approaches, clustering approaches, or region growing approaches. Our workflow uses a region growing approach since it reflects the natural growth direction of trees and allows the delineation of trees with different shapes. Specifically, we implement a custom, density-based region growing algorithm that is inspired by the DBSCAN algorithm (ESTER et al. 1996). In this algorithm, for each tree to be processed, a set of seed points is selected (i. e., points that belong to the tree with a high degree of certainty). In an iterative process, neighbor points of the seed points are assigned to the respective tree, if they have not yet been assigned to another tree. Neighbor points that satisfy the core point criterion as defined in the DBSCAN algorithm (ESTER et al. 1996) become seed points themselves. To ensure that neighboring trees grow evenly, points are sorted according to their distance from the crown boundary determined during coarse tree delineation and processed in that order.

4) **Removal of implausible trees:** In the final processing step, trees with implausible shape or size are discarded. Specifically, trees with few points and trees whose height is below a threshold are filtered out.

4.3 Estimation of Tree Attributes

After obtaining point clouds representing individual trees, different tree attributes can be estimated. Most existing studies focus on the estimation of geometric tree attributes (HERRERO-HUERTA et al. 2018, WU et al. 2013, XU et al. 2020), while few authors also derive non-geometric attributes such as tree species or vitality (WU et al. 2018, CHEN et al. 2019). Since 3D point clouds are particularly suitable for deriving geometric tree attributes, we also focus on these attributes. However, algorithms for estimating non-geometric tree attributes such as tree species, carbon storage capacity, or oxygen release potential may be integrated into the workflow in the future. For the estimation of the attributes tree location (WU et al. 2013), tree height, trunk direction, crown width (HERRERO-HUERTA et al. 2018), trunk diameter at breast height (CHEN et al. 2019), and crown volume (LI et al. 2020), we adopt the approaches used in previous work. Other tree attributes, namely under-branch height, and crown base height, can directly be derived from the deep-learning-based segmentation of trees into trunk, branches, and crown.

5 Case Study

A test application was implemented to demonstrate the potential of the concept presented in this paper. MLS point clouds collected in the cities of Essen, Germany, and Hamburg, Germany, were used to evaluate the test application. The point clouds were acquired using Trimble MX8 scanners in the leaf-on season. We manually annotated the point clouds and split them into a training set, a validation set, and a test set. In the following, some preliminary results for the test set are shown.

Figure 2 shows exemplary results of the deep-learning-based vegetation detection and classification. As can be seen there, large portions of the vegetation are segmented correctly. However, several smaller segmentation errors can be identified: In multiple cases, low vegetation and tree crowns are confused. In addition, some pole-like objects are misclassified as trees. There are also a few cases in which tree trunks are missed by the deep-learning model.

Results of the delineation of individual trees are shown in Figure 3. While solitary trees and adjacent trees with little canopy overlap are correctly delineated in most cases, the results for the delineation of trees with strongly overlapping canopies are mixed. Trees whose crown has a large extent are over-segmented in several cases, and some parts of tree crowns with low point density are missed by the region growing algorithm.

Figure 4 shows some results of the estimation of tree attributes. As can be seen there, accurate estimates of geometric tree attributes are obtained if the accuracy of the preceding processing steps is sufficiently high. When large parts of a tree are missed during tree segmentation, attributes such as tree height, crown width, and crown volume are often underestimated. In cases where multiple trees are recognized as a single tree, the crown width and crown volume are often overestimated.

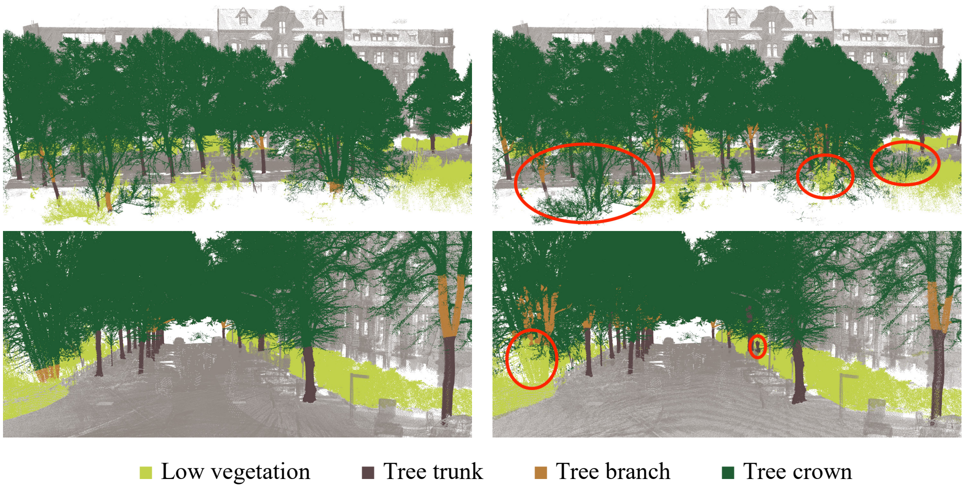

Fig. 2: Results of deep-learning-based vegetation detection and classification for a point cloud from the test set that was acquired in Hamburg, Germany. The images on the left show the ground truth annotation and the images on the right show the prediction. Some areas with classification errors are outlined in red.

Fig. 3: Results of delineating individual trees in a point cloud from the test set that was acquired in Essen, Germany. The image on the left shows the ground truth annotation and the image on the right shows the result of the algorithmic delineation of individual trees. Points belonging to the same tree are shown in the same color.

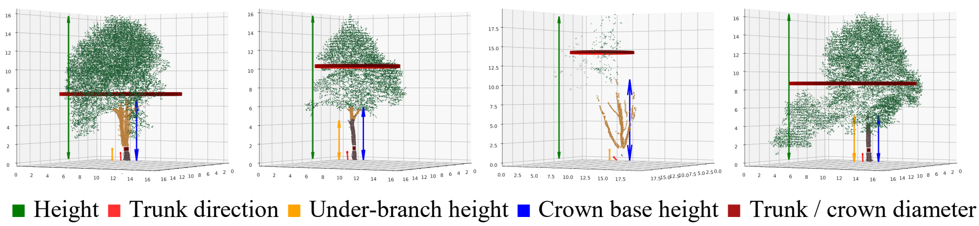

Fig. 4: Example results of the estimation of tree attributes

6 Discussion and Conclusion

In this work, a concept for the automatic detection and analysis of vegetation in MLS point clouds has been presented. The implementation of the concept produced promising results for representative MLS point clouds from two cities. However, to approach the accuracy of manual vegetation mapping, the method needs to be further improved. Since the accuracy of vegetation detection and classification affects the accuracy of the following processing steps, further improvement of the deep-learning approach for vegetation detection and classification would be of major benefit. Despite this need for improvement, the preliminary results of this work suggest that the proposed deep-learning approach can detect and classify vegetation in complex street scenes that would be difficult to model using rule-based approaches. However, this comes at a price: The training of deep-learning models requires extensive annotated training data and high computing power of graphics hardware. To improve the practicality of the approach, techniques to reduce the labeling effort (e. g., active learning or transfer learning) and improve model speed (e. g., model pruning) could be incorporated into the workflow.

While the test application presented in this paper was limited to capturing geometric tree attributes, it would be desirable to derive even richer tree information models to cover a broader range of use cases. For example, detailed models of tree branching structures could be derived from 3D point clouds to enable estimation of aboveground biomass and carbon storage capacity, as well as realistic vegetation visualization. Furthermore, it would be useful to integrate approaches for processing multi-temporal MLS data into the workflow. In this way, point clouds representing vegetation in leaf-on and leaf-off conditions could be combined. Capturing vegetation in leaf-off conditions would avoid the occlusion of woody components by foliage and thus facilitate the acquisition of woody biomass and the delineation of individual trees. In addition, approaches for predicting non-geometric tree attributes such as tree species and tree vitality could also be integrated into the workflow, e. g., by combining 3D point clouds with spectral data from panoramic images or aerial photographs.

Since MLS is a cost-effective method to survey very large areas, the present work focused on vegetation mapping using MLS. However, MLS is only suitable for capturing vegetation in the proximity of drivable roads, while PLS or UAV-LS are more suitable for mapping vegetation in parks or private gardens. To provide a complete mapping of urban vegetation, the concept presented in this work should be transferred to other LiDAR platforms. Since PLS point clouds have similar characteristics to MLS point clouds and a generic deep-learning approach is used in this work, transferring the approach to PLS point clouds should be possible with little effort.

Building on the concept presented in this paper, a data processing tool could be developed for large-scale and cost-effective urban vegetation mapping. Such a tool would enable continuous monitoring of urban vegetation and thus provide a basis for sustainable design and maintenance of urban green spaces. In particular, it would enhance the study of ecosystem services provided by urban vegetation and could thus help to guide the design of urban green spaces towards the provision of ecosystem services.

Acknowledgments

We thank the anonymous reviewers for their valuable feedback as well as *AllTerra Deutschland GmbH* and the *Department for Geoinformation, Surveying and Cadastre* of the City of Essen for providing mobile mapping data. This work was partially funded through grants by the BMDV (*TWIN4ROAD*, 19F2210) and the BMBF (*AI research group FFS-AI*, 01IS22062 and *TreeDigitalTwins*, 033L305).

References

BELLO, S. A., YU, S., WANG, C., ADAM, J. M. & LI, J. (2020), Review: Deep Learning on 3D Point Clouds. Remote Sensing, 12 (11), 1729. doi:10.3390/rs12111729.

CHEN, Y., WANG, S., LI, J., MA, L., WU, R., LUO, Z. & WANG, C. (2019), Rapid Urban Roadside Tree Inventory Using a Mobile Laser Scanning System. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12 (9), 3690-3700. doi:10.1109/JSTARS.2019.2929546.

CHEN, Y., WU, R., YANG, C. & LIN, Y. (2021), Urban vegetation segmentation using terrestrial LiDAR point clouds based on point non-local means network. International Journal of Applied Earth Observation and Geoinformation, 105, 102580. doi:10.1016/j.jag.2021.102580.

DU, S., LINDENBERGH, R., LEDOUX, H., STOTER, J. & NAN, J. (2019), AdTree: Accurate, Detailed, and Automatic Modelling of Laser-Scanned Trees. Remote Sensing, 11 (18), 2074. doi:10.3390/rs11182074.

ELDERBROCK, E., ENRIGHT, C., LYNCH, K. A. & REMPEL, A. R. (2020), A Guide to Public Green Space Planning for Urban Ecosystem Services. Land, 9 (10), 391. doi:10.3390/land9100391.

ESTER, M., KRIEGEL, H.-P., SANDER, J. & XU, X. (1996), A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In: SIMOUDIS, E., HAN, J. & FAYYAD, U. (Eds.), Proceedings of the Second International Conference on Knowledge Discovery and Data Mining. AAAI Press, Portland, 226-231. https://www.aaai.org/Papers/KDD/1996/KDD96-037.pdf (11.05.2022).

HAO, W., ZUO, Z. & LIANG, W. (2022), Structure-Based Street Tree Extraction from Mobile Laser Scanning Point Clouds. In: The 5th International Conference on Image and Graphics Processing, ICIGP '22. ACM, New York, 373-379. doi:10.1145/3512388.3512443.

HERRERO-HUERTA, M., LINDENBERGH, R. & RODRÍGUEZ-GONZÁLVEZ, P. (2018), Automatic tree parameter extraction by a Mobile LiDAR System in an urban context. PloS ONE, 13 (4), e0196004. doi:10.1371/journal.pone.0196004.

HU, Q., YANG, B., XIE, L., ROSA, S., GUO, Y., WANG, Z., TRIGONI, N. & MARKHAM, A. (2020), RandLA-Net: Efficient Semantic Segmentation of Large-Scale Point Clouds. In: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR '20. IEEE, Los Alamitos, 11105-11114. doi:10.1109/CVPR42600.2020.01112.

HUI, Z., LI, Z., JIN, S., LIU, B. & LI, D. (2022), Street Tree Extraction and Segmentation from Mobile LiDAR Point Clouds Based on Spatial Geometric Features of Object Primitives. Forests, 13 (8), 1245. doi:10.3390/f13081245.

KORNILOV, A. S. & SAFONOV, I. V. (2018), An Overview of Watershed Algorithm Implementations in Open Source Libraries. Journal of Imaging, 4 (10), 123. doi:10.3390/jimaging4100123.

LI, J., CHENG, X., WU, Z. & GUO, W. (2021), An Over-Segmentation-Based Uphill Clustering Method for Individual Trees Extraction in Urban Street Areas From MLS Data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 2206-2221. doi:10.1109/JSTARS.2021.3051653.

LI, L., LI, D., ZHU, H. & LI, Y. (2016), A dual growing method for the automatic extraction of individual trees from mobile laser scanning data. ISPRS Journal of Photogrammetry and Remote Sensing, 120, 37-52. doi:10.1016/j.isprsjprs.2016.07.009.

LI, Y. Q., LIU, H. Y., LIU, Y. K., ZHAO, S. B., LI, P. P. & XIAO, W. (2020), Street Tree Information Extraction and Dynamics Analysis From Mobile LiDAR Point Cloud. In: PAPARODITIS, N., MALLET, C., LAFARGE, F., REMONDINO, F., TOSCHI, I. & FUSE, T. (Eds.), XXIV ISPRS Congress, Commission II. Copernicus Publications, Göttingen, 271-277. doi:10.5194/isprs-archives-XLIII-B2-2020-271-2020.

MA, B., HAUER, R. J., ÖSTBERG, J., KOESER, A. K., WEI, H. & XU, C. (2021), A global basis of urban tree inventories: What comes first the inventory or the program. Urban Forestry & Urban Greening, 60, 127087. doi:10.1016/j.ufug.2021.127087.

OEHLKE, C., RICHTER, R. & DÖLLNER, J. (2015), Automatic Detection and Large-Scale Visualization of Trees for Digital Landscapes and City Models Based on 3D Point Clouds. In: BUHMANN, E., ERVIN, S. M. & PIETSCH, M. (Eds.), Peer Reviewed Proceedings of Digital Landscape Architecture 2015 at Anhalt University of Applied Sciences, DLA '15. Wichmann, Berlin/Offenbach, 151-159.

ÖSTBERG, J., DELSHAMMAR, T., WISTRÖM, B. & NIELSEN, A. B. (2013), Grading of Parameters for Urban Tree Inventories by City Officials, Arborists, and Academics Using the Delphi Method. Environmental Management, 51 (3), 694-708. doi:10.1007/s00267-012-9973-8.

PATAKI, D. E., ALBERTI, M., CADENASSO, M. L., FELSON, A. J., MCDONNELL, M. J., PINCETL, S., POUYAT, R. V., SETÄLÄ, H. & WHITLOW, T. H. (2021), The Benefits and Limits of Urban Tree Planting for Environmental and Human Health. Frontiers in Ecology and Evolution, 9, 1-9. doi:10.3389/fevo.2021.603757.

SÄUMEL, I., WEBER, F. & KOWARIK, I. (2016), Toward livable and healthy urban streets: Roadside vegetation provides ecosystem services where people live and move. Environmental Science & Policy, 62, 24-33. doi:10.1016/j.envsci.2015.11.012.

SCHIPPERIJN, J., PILLMANN, W., TYRVÄINEN, L., MÄKINEN, K. & O'SULLIVAN R. (2005), Information for Urban Forest Planning and Management. In: KONIJNENDIJK, C., NILSSON, K., RANDRUP, T. & SCHIPPERIJN, J. (Eds.), Urban Forests and Trees. Springer, Berlin/ Heidelberg, 399-417. doi:10.1007/3-540-27684-X_15.

SCHOLZ, T., HOF, A. & SCHMITT, T. (2018), Cooling Effects and Regulating Ecosystem Services Provided by Urban Trees – Novel Analysis Approaches Using Urban Tree Cadastre Data. Sustainability, 10 (3), 712. doi:10.3390/SU10030712.

SHU, Q., RÖTZER, T., DETTER, A. & LUDWIG, F. (2022), Tree Information Modeling: A Data Exchange Platform for Tree Design and Management. Forests, 13 (11), 1955. doi:10.3390/f13111955.

THOMAS, H., QI, C. R., DESCHAUD, J.-E., MARCOTEGUI, B., GOULETTE, F. & GUIBAS, L. (2019), KPConv: Flexible and Deformable Convolution for Point Clouds. In: 2019 IEEE/CVF International Conference on Computer Vision, ICCV '19. IEEE, Los Alamitos, 6410-6419. doi:10.1109/ICCV.2019.00651.

WEINMANN, M., WEINMANN, M., MALLET, C. & BRÉDIF, M. (2017), A Classification-Segmentation Framework for the Detection of Individual Trees in Dense MMS Point Cloud Data Acquired in Urban Areas. Remote Sensing, 9 (3), 277. doi:10.3390/rs9030277.

WHITE, M. G., HAEUSLER, M. H. & ZEUNERT, J. (2022), Simulation and Visualisation of Plant Growth Using a Functional-structural Model. Journal of Digital Landscape Architecture, 7-2022, 191-199. doi:10.14627/537724019.

WU, B., YU, B., YUE, W., SHU, S., TAN. W., HU, C., HUANG, Y., WU, J. & LIU, H. (2013), A Voxel-Based Method for Automated Identification and Morphological Parameters Estimation of Individual Street Trees from Mobile Laser Scanning Data. Remote Sensing, 5 (2), 584-611. doi:10.3390/rs5020584.

WU, J., YAO, W. & POLEWSKI, P. (2018), Mapping Individual Tree Species and Vitality along Urban Road Corridors with LiDAR and Imaging Sensors: Point Density versus View Perspective. Remote Sensing, 10 (9), 1403. doi:10.3390/rs10091403.

XU, S., SUN, X., YUN, J. & WANG, H. (2020), A New Clustering-Based Framework to the Stem Estimation and Growth Fitting of Street Trees From Mobile Laser Scanning Data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 3240-3250. doi:10.1109/JSTARS.2020.3001978.

YANG, J., KANG, Z., CHENG, S., YANG, Z. & AKWENSI, P. H. (2020), An Individual Tree Segmentation Method Based on Watershed Algorithm and Three-Dimensional Spatial Distribution Analysis From Airborne LiDAR Point Clouds. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 1055-1067. doi:10.1109/JSTARS.2020.2979369.

ZHONG, L., CHENG, L., XU, H., WU, Y., CHEN, Y. & LI, M. (2017), Segmentation of Individual Trees From TLS and MLS Data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10 (2), 774-787. doi:10.1109/JSTARS.2016.2565519.