Laser scanning in modelling changes in vegetation – added value for existing data sets

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Abstract

Airborne laser scanning (ALS) has already successfully been used for applications of detailed vegetation mapping because of its capability to produce accurate information on vegetation and ground surfaces simultaneously. ALS data are also collected for urban planning purposes whereas mobile laser scanning (MLS) has been of interest in research of river dynamics. The main objective was to investigate the applicability of laser scanning in applications for vegetation monitoring required in continuously changing environment. This paper presents a method for updating existing and producing new tree attributes in heterogeneous urban recreational forests, mapping and monitoring changes in riverine vegetation, and mapping areas with wind disturbance and producing a continuous probability surface of wind predisposition to identify areas that are most likely to experience wind damage. In the future, several organizations in Finland will acquire ALS data for various purposes increasing the temporal resolution of the data. Therefore, the developed applications for tree-attribute update, monitoring riverine vegetation, and producing model to detect areas vulnerable to wind disturbance, could increase the utilization of 3D data sets as well as increase the value of the data.

Keywords: Forest inventory, forest mensuration, LiDAR, remote sensing, mapping, monitoring.

1 Introduction

For managing natural resources properly, detailed and up-to-date information is required. Vegetation plays an important role in urban planning, hindering erosion in riverine environments, and providing various ecosystem services from managed and natural forests. Laser scanning has already operationally been applied in mapping forest resources in Nordic countries. In addition, there is an interest in research in applying airborne laser scanning (ALS) in change detection e.g. [7, 12, 16). In riverine environments, mobile laser scanning (MLS) has been studied in detecting changes of river banks e.g. [4, 15]. In green, urban environments, changes in individual tree-level is necessary, especially related to growth and required management activities whereas knowledge on vegetation changes in riverine environment can improve flood risk modelling. Wind has been the main cause for losses in forest yield values, therefore more understanding from drivers of wind damage disturbance is needed.

This paper presents development of methods for urban tree-attribute update, change detection in riverine environment, and identifying areas vulnerable to wind-induced damage with data sets that were originally collected for other purposes (urban planning, modelling river dynamics, and developing nation-wide elevation model).

2 Materials and methods

The study included data from tree different study areas: a 2.7 ha in total of recreational urban park of Seurasaari in Helsinki, Finland, a reach of 3.5 km of Pulmanki Riveri on border of Norway in northern Finland, and a 173 km^2 of managed boreal forests near Huittinen in southwest of Finland. From Seurasaari field reference included diameter-at-breast-height (dbh) from 389 trees. Aerial images from Pulmanki and Huittinen were applied as reference data.

ALS data were applied in detecting individual tree crowns in Seurasaari whereas open access ALS data were applied in mapping wind damage for Huittinen. Multi-temporal MLS data were acquired for Pulmanki in late summer of 2009, 2010, 2011, and 2012.

In generating digital terrain model (DTM) from ALS and MLS data sets, a method developed by Axelsson [1] was used. DTM was applied in normalizing digital surface models (DSMs) for Seurasaari and Huittinen, and MLS point clouds for Pulmanki. Sample unit for Seurasaari was individual tree crowns whereas a 2 m x 2 m grid was applied in Pulmanki, and 16 m x 16 m grid for Huittinen. Metrics from ALS or MLs point clouds were extracted for sample units, and variables for predictions were selected based on their importance (Seurasaari), biological relevance (Pulmanki), or statistical significance (Huittinen).

2.1 Multisource single-tree inventory in updating urban tree attributes

For updating urban tree attributes, a method called multisource single-tree inventory (MS-STI) was tested. In MS-STI an existing tree map and ALS data were combined to avoid leaving trees undetected which is one of the challenges of techniques in individual tree detection. Terrestrial laser scanning (TLS) data were used in identifying trees: tree trunks were detected and their location was recorded manually from TLS point clouds.

Tree crown segments were derived from canopy height model (CHM) and they were linked to TLS-based tree map. Metrics above 0.5 m threshold describing height distribution of CHM (e.g. max, min, standard deviation, height percentiles) were extracted for each crown segment and the most important metrics were selected based on non-parametric random-forest technique where importance is based on classification trees and their accuracy. The random forest was iterated by a step-wise looping procedure to remove the least important candidate variable at each iteration until there was only a single predictor variable. Root-mean-square errors (RMSEs) were calculated for each combination of predictor variables and analyzed before the final modeling. In addition, random forest was also applied in searching for nearest neighbours for estimation of tree attributes. Neighbours are defined based on their probability of ending in the same terminal node in all developed 1200 regression trees. Estimation of dbh was based on selection of one to five neighbours. Accuracy of the estimations was assessed based on RMSE and bias.

2.2 Area-based approach in detecting changes in riverine vegetation

Visual interpretation of aerial images were used in classifying vegetation in Pulmanki for grid cells of 230 for testing and 212 for training. A common woodland classification was applied in determining whether the vegetation class for a training and testing cells was bare ground (no vegetation), field layer (comprised of grasses, ferns, or other low growing shrubs), shrub layer (small trees or larger shrubs), or canopy layer (dominant tree canopy).

Area-based approach is a method where statistical dependency between target and predictor variables are defined [11]. Metrics describing vegetation height and density (i.e. mean height, 95th percentile height, and standard deviation of height) were selected. Random forest was applied in predicting vegetation class to the entire study area. Model based on 2012 MLS data was applied in predicting vegetation classes also for 2009, 2010, and 2011.

A separate testing set of 212 cells was selected to evaluate the accuracy of the classification for 2012 data. To assess whether differences in MLS data acquisition parameters affected the results, a random sample of unchanged cells (n = 27) was chosen.

2.3 Logistic regression in mapping wind damage risk

A sample of 430 cells of 16 m by 16 m were visually determined from aerial images as damaged (n = 196) or undamaged (n = 234) as a ground truth for wind damage mapping. Predictor variables related to topography and elevation were derived from DTM (e.g. mean elevation, slope, and aspect) whereas predictors describing height and density of forest canopy were derived from CHM (e.g. minimum, maximum, mean, and standard deviation) to be applied in logistic regression. Openly available tree species information based on multisource national forest inventory (NFI) was also employed.

Logistic regression was used to develop two separate models: one with ALS-based predictors only (LR_{ALS}) and the other one including also information about tree species in addition to variables derived from ALS ($LR_{ALS+NFI}$). This way it was possible to see how the information about tree species affects the results, because different tree species have different tolerance on wind damage [13]. Stepwise selection procedure with both forward and backward elimination was applied in selecting the final predictor variables. The final models were used for developing a continuous probability surface to map areas with high risk for suffering of wind damage.

3 Results and discussion

3.1 Updating urban tree attributes

Based on calculated relative RMSE for every metrics combination, the prediction accuracy was not too sensitive to the quantity of used metrics (the maximum difference in RMSE% was 8.8 percentage points).

Although conditions were very heterogeneous in urban, recreational park, the results were relatively reliable: the relative RMSE varied between 19.9% and 22.7% including a relative bias from -0.4% to -2.3% with various number of neighbors (Table 1). Comparing other studies where individual trees are used as sample units is not straightforward, as many of the studies have been conducted in managed forests. However, the dbh estimates from this study are similar to the earlier results e.g. [6, 9, 10, 14, 17]. In addition, tree height and crown size were possible to estimate and they could be included in tree registers applied for city planning (e.g. identifying trees interfering lamp posts -> pruning, removing trees that are hazardous for citizens).

Table 1. Dbh estimates based on random-forest technique with various numbers of neighbors.

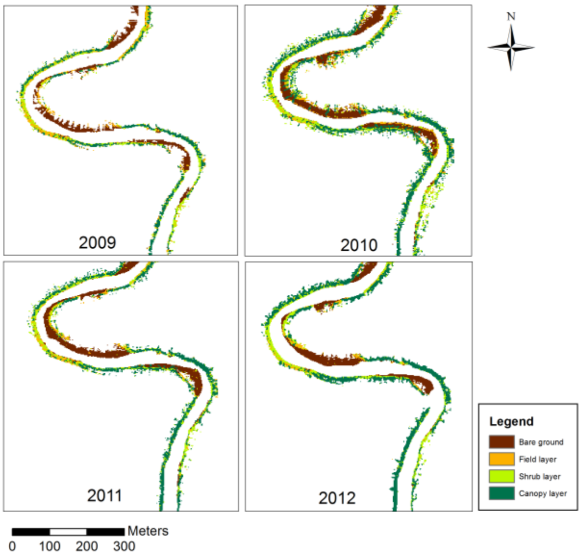
Number of neighbors	Bias, cm	Bias, %	RMSE, cm	RMSE, %
1	0,01	-0,36	5,78	19,91
2	-0,16	-0,53	6,39	21,32
3	-0,31	-0,95	6,85	22,49
4	-0,61	-1,72	6,85	22,45
5	-0,84	-2,31	6,97	22,71

3.2 Monitoring vegetation changes

Mean values of selected metrics (mean height, 95th percentile height, and standard deviation of height) were statistically different between four vegetation classes, in other words they could be applied in differencing vegetation (Figure 1). Overall accuracy of 72.6% was obtained with separate test set. Bare ground and canopy layer were classified most accurately (79.5% and 100.00%, respectively) whereas classification accuracy for field and shrub layers were lower (35.0% and 45.2%, respectively). Random sample of unchanged cells confirmed that different acquisition parameters among years did not affect selected metrics and results obtained with data from 2012 can be expected to be similar for other years, as well as for change detection accuracy.

ALS has been applied in mapping riverine vegetation [2, 18] with better classification accuracy: Farid et al. [2] reported 78% accuracy for classifying three age classes of riparian vegetation and Zlinsky et al. [18] gained overall accuracy of 82.5% for wetland vegetation classification. However, both of these studies required substantial field data whereas MLS data was possible to use with reference from aerial images.

Figure 1: Example of vegetation maps produced for River Pulmanki for years 2009, 2010, 2011, and 2012.

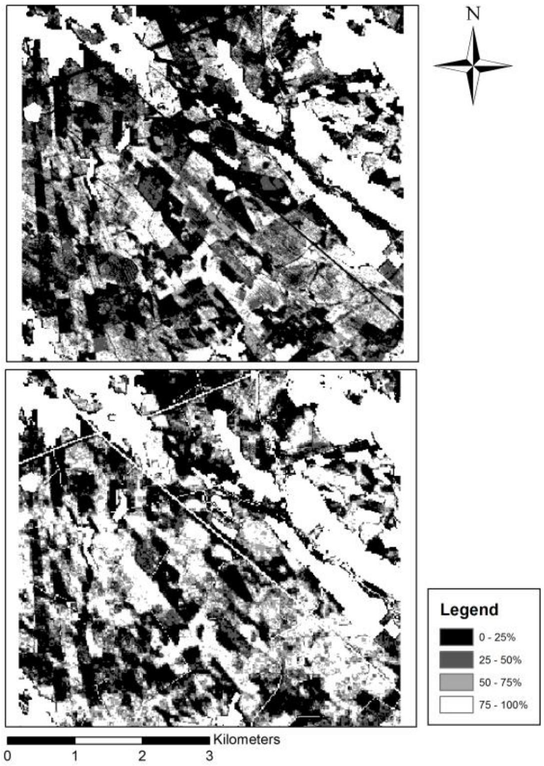


3.3 Wind damage risk modelling

From sample cells with wind damage, 94.4% were dominated by either Scots pine or Norway spruce and those sample cells also had higher mean and maximum values of CHM. Therefore, mature conifer stands are more susceptible to wind damage. Mean elevation and mean value of CHM (with adjacent cells included) were most significant predictors ($p<0.001$) for LR_{ALS}. In addition to these two, mean volume of pine and spruce per hectare were included in $LR_{ALS+NFI}$ when information from multisource NFI was included. Prediction accuracy increased from 73% with LR_{ALS} to 81% with $LR_{ALS+NFI}$.

With the two models it was possible to produce a continuous probability surface for identifying areas with high probability of experiencing wind damage (Figure 2). ALS data provide information about vegetation height and density as well as topography and elevation which have been used to describe susceptibility to wind damage [3, 8, 5, 13].

Figure 2: Example of maps indicating areas liable to wind damage.



4 Conclusions

The paper presented methods developed with data collected for purposes of urban planning, river dynamic modelling, and improving Finnish elevation model. The results demonstrated the other applications for these data sets, in other words they can be used in updating urban tree attributes, monitoring vegetation changes in riverine environment, and mapping wind damage risk for forest areas. Especially openly accessible data sets are increasing which creates pressure for developing different applications for them and this paper contributed for this emerging field.

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