

# Urban tree health assessment using airborne hyperspectral and LiDAR imagery

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## ABSTRACT

Urban trees provide valuable ecosystem services but are at the same time under continuous pressure due to unfavorable site conditions. In order to better protect and manage our natural capital, urban green managers require frequent and detailed information on tree health at the city wide scale. In this paper we developed a workflow to monitor tree defoliation and discoloration of broadleaved trees in Brussels, Belgium, through the combined use of airborne hyperspectral and LiDAR data. Individual trees were delineated using an object-based tree detection and segmentation algorithm primarily based on LiDAR data with an average accuracy of 91%. We constructed Partial Least Squares Regression (PLSR) models to derive tree chlorophyll content (RMSE = 2.8  $\mu\text{g}/\text{cm}^2$ ;  $R^2 = 0.77$ ) and Leaf Area Index (LAI; RMSE = 0.5;  $R^2 = 0.66$ ) from the average canopy spectrum. Existing spectral indices were found to perform significantly worse (RMSE > 7  $\mu\text{g}/\text{cm}^2$  and > 1.5 respectively), mainly due to contamination of tree spectra by neighboring background materials. In the absence of local calibration data, the applicability of PLSR to other areas, sensors and tree species might be limited. Therefore, we identified the best performing/least sensitive spectral indices and proposed a simple pixel selection procedure to reduce disturbing background effects. For LAI, laser penetration metrics derived from LiDAR data attained comparable accuracies as PLSR and were suggested instead. Detection of healthy and unhealthy trees based on remotely sensed tree properties matched reasonably well with a more traditional visual tree assessment (93% and 71% respectively). If combined with early tree stress detection methods, the proposed methodology would constitute a solid basis for future urban tree health monitoring programs.

## 1. Introduction

Urban trees and forests are known to provide a wide range of ecosystem services (e.g. cooling, air filtering, water interception, recreation), thereby significantly improving the quality of life for urban residents (Bolund and Hunhammar, 1999; Salmond et al., 2016). At the same time, urban trees are under continuous pressure due to several factors that negatively affect their health (Berrang et al., 1985). Compared to the surrounding rural areas, urban environments are characterized by high peak temperatures (Cregg and Dix, 2001), high concentrations of air pollution and poor soil conditions due to human activities. Urban soils typically contain high amounts of inert construction materials, pollutants and de-icing salts, are characterized by high bulk densities and poor soil structure due to soil compaction and hence support little biological activity, in turn leading to low organic matter content (Czerniawska-Kusza et al., 2004; Day and Bassuk, 1994; Scharenbroch et al., 2005). All these factors increase the risk of nutrient and water stress, in turn deteriorating a tree's metabolism and growth

and decreasing its ability to provide ecosystem services. Particularly low available rooting space due to soil compaction has been found to negatively affect urban tree condition (Day and Bassuk, 1994; Sanders and Grabosky, 2014; Scharenbroch et al., 2017). In addition, poor site conditions increase the risk of infestation by insects and diseases (Cregg and Dix, 2001). Severe tree health issues may eventually lead to tree stability loss, in turn threatening public safety (Lonsdale, 1999). Given their high value to society and the high pressure they are experiencing, urban trees should be carefully managed, including prevention, restoration and replacement of dead or diseased trees. To facilitate this, professional green managers ideally require frequent, reliable and spatially-explicit information on the health status of all trees under their care. Traditionally, tree health is monitored using the visual tree assessment (VTA) method (Mattheck and Breloer, 1994), applied in-situ by trained tree experts. Although this method has already been successfully used in many cities (Fink, 2009), it is affected by a certain degree of subjectivity, provides mostly qualitative information and is limited in spatial extent and temporal frequency to time and labor

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constraints of tree experts. Remote sensing technology has the potential to deliver quantitative, spatially continuous information covering entire cities at once and can be easily replicated through time.

Tree health research employing remote sensing data has been dominated by forestry studies linking vegetation indices like NDVI (Normalized Difference Vegetation Index; Rouse et al., 1973), mostly derived from multispectral satellite data, to different tree health aspects like defoliation (Royle and Lathrop, 1997; Wang et al., 2010). Aside from estimating vegetation abundance and cover (Van De Voorde et al., 2008), the potential of this coarse (10–30 m) multispectral data for urban vegetation studies is limited by the high abundance of mixed pixels in urban scenes compared to more uniform forest ecosystems. The presence of background materials within a pixel negatively affects the calculation of vegetation indices (Somers et al., 2009b; van Beek et al., 2015). Researchers have therefore turned to color infrared imagery, sacrificing spectral detail in favor of fine spatial resolution (< 1 m), for urban tree health mapping (Sari and Kushardono, 2016; Xiao and McPherson, 2005). Such imagery however only provides general measures of greenness (such as NDVI), typically sensitive to multiple vegetation characteristics at once (e.g. chlorophyll content and biomass), and hence enable us to locate problematic trees but without identifying the underlying causes. Different types of stress trigger different physiological reactions in trees (Günthardt-Goerg and Vollenweider, 2007), which are eventually expressed visually either via leaf loss (drought, frost, insect damage) or via changes in leaf color (nutrient stress, diseases). Both variables (defoliation and discoloration) are often used in conjunction as tree health indicators (Lakatos et al., 2014; Stone et al., 2000) and can, from a remote sensing perspective, objectively be estimated by respectively determining Leaf Area Index (LAI) and chlorophyll content. Airborne hyperspectral data provides the spectral detail required to derive these individual tree characteristics (e.g. Delalieux et al., 2008; Delegido et al., 2014). Its lower spatial resolution (typically 2–4 m) can be compensated through fusion with airborne LiDAR data, providing highly detailed structural information. The added value of the LiDAR component for urban tree health assessment lies in its potential to estimate LAI (Alonzo et al., 2015; Klingberg et al., 2017; Morsdorf et al., 2006; Oshio et al., 2015) and to delineate individual tree objects in a highly accurate way (Alonzo et al., 2014; Zhao et al., 2017; Zhen et al., 2016).

The main objective of this study was to develop a workflow to assess urban tree health in a quick and cost-effective way using a combination of airborne hyperspectral and LiDAR data as an alternative to the currently established VTA approach. Our workflow comprised three steps: (1) detailed detection and delineation (segmentation) of individual trees using airborne LiDAR data, (2) determination of chlorophyll content and LAI of each individual tree from airborne hyperspectral and LiDAR data and (3) integration of these two variables into an objective tree health indicator. In this paper, an unhealthy tree is defined as a tree featuring a decreased metabolism, visually expressed by significant defoliation and/or leaf discoloration when compared to other trees from the same species. The approach was tested on a set of trees in the city of Brussels, Belgium. For the extraction of tree properties from hyperspectral data we compared the performance of spectral indices (a biophysically based approach) versus Partial Least Squares Regression (PLSR; a regression approach relying on local calibration data). PLSR was preferred here over other machine learning approaches as it is widely recognized as one of the standardized approaches to retrieve canopy biochemistry from hyperspectral data, uses the entire spectrum to predict the variable of interest and results in a set of meaningful and easily interpretable regression coefficients allowing to identify the most important spectral zones with regard to this variable (Asner et al., 2011; Martin et al., 2008; Meerdink et al., 2016; Singh et al., 2015; Townsend et al., 2003). Many different spectral indices have already been developed to derive chlorophyll content (e.g. Dash and Curran, 2004; Daughtry et al., 2000; Gitelson et al., 2003; Sims and Gamon, 2002) and to a lesser extent LAI (Delalieux et al., 2008). With the exception of the

NAOC index (Delegido et al., 2014), all of these indices were designed for relatively homogeneous forest canopies or plantations. An important objective of this study was, therefore, to test which of the existing indices can be safely applied to the complex urban environment, with its high abundance of man-made materials. We additionally tested a strategy to minimize background effects by gradually eliminating contaminated or non-pure tree pixels from the analysis. Although many studies exist on deriving individual tree properties from remote sensing data, to our knowledge this study was the first attempt to integrate these properties into an objective health indicator specifically for urban trees.

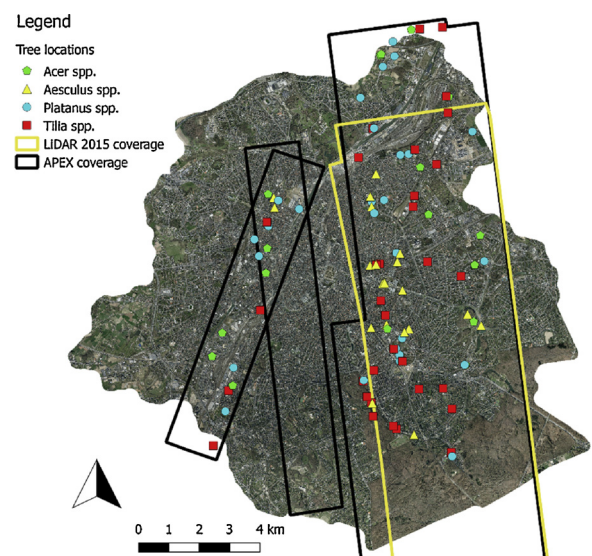
## 2. Data

### 2.1. Airborne hyperspectral data

On June, 30 2015 a hyperspectral image was acquired over the city of Brussels, Belgium using the Airborne Prism Experiment (APEX) sensor mounted in an airplane. The flight took place around solar noon at an altitude of 3600 m above sea level. APEX records the spectral response in 285 spectral bands within the 412–2431 nm range, of which 218 were retained for analysis after removal of atmospheric absorption bands (412–450 nm, 1340–1500 nm, 1760–2020 nm, 2350–2431 nm). Image pre-processing was done using an automated processing chain at the Flemish Institute for Technological Research (Biesemans et al., 2007), consisting of geometric correction via direct georeferencing (Vreys et al., 2016), projection in the Belgian Lambert 72 coordinate system and atmospheric correction using a MODTRAN4 radiative transfer model (Berk et al., 1999; Sterckx et al., 2016). The resulting image had a spatial resolution of 2 m and mainly covered the Eastern part of the Brussels capital area (Fig. 1), comprising a wide range of urban structure types (i.e. dense and sparse residential, commercial and urban green zones).

### 2.2. Airborne LiDAR data and derived surface models

The eastern part of our study area was covered by an airborne LiDAR dataset collected in Summer 2015 by Aerodata Surveys Nederland BV (yellow rectangle in Fig. 1) with an average point density of 15 points/m<sup>2</sup>. For the remainder of the study area not covered by the



**Fig. 1.** Location of urban trees used in this study within the Brussels Capital Region, Belgium, and in relation to the coverage of the APEX hyperspectral dataset (black rectangles), LiDAR 2015 (yellow rectangle) and LiDAR 2012 datasets (entire region). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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