Track Forest Biomass Dynamics and Carbon Flux using Multitemporal Airborne Lidar Remote Sensing

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Introduction

Forests are intricately tied to us. They supply timber, shelter wildlife, sustain biodiversity, support tourism, shape culture, purify water, conserve soil, store carbon, and regulate climate. Consequences of forest changes therefore can be enormous, highlighting the necessity of developing effective tools to measure forest statuses and changes.

Of current technologies for remotely mapping terrestrial environments, lidar features prominently for its superior ability to acquire 3D ecosystem structure. Since its advent, lidar has been acclaimed as a breakthrough revolutionizing the field of vegetation remote sensing (Zhao et al., 2015). It maneuvers a pulsed time-of-flight laser to resolve 3D canopy structures rapidly and precisely *(Fig. 1)*, offering ways to derive forest characteristics across scales with accuracies unattainable by its conventional counterparts

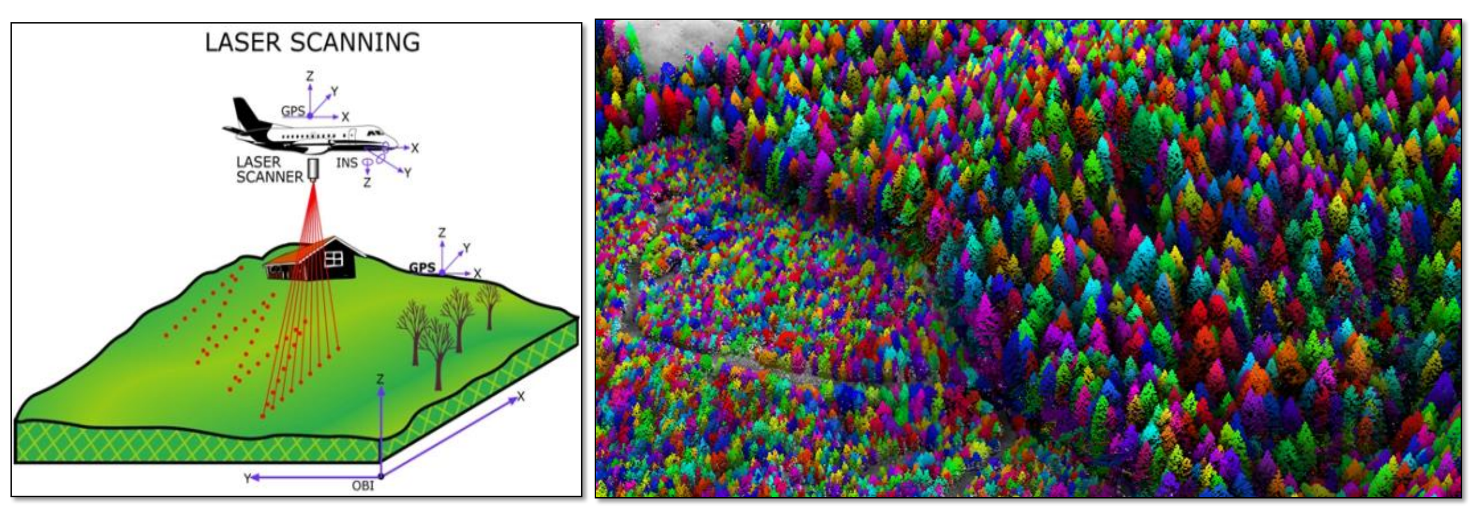

Figure 1. Principle of airborne laser scanning and its use to map forest vertical structures at fine scales over space

Aims

This study aims to assess the utility of multitemporal lidar for tracking forest dynamics and tackle practical difficulties limiting the use of historical repeat lidar data for vegetation analysis. The overall goal is to determine the degree to which multitemporal lidar can be used to derive changes in forest characteristics at both individual tree and grid levels. A particular emphasis is on evaluating and improving lidar-based methods to monitor biomass dynamics over time, especially if lacking ancillary ground data to calibrate models at a given time.

Methods

Our study area is a 20km2 forested landscape near the Aberfoyle village in Scotland, UK (Fig. 2). Part of the area falls within Queen Elizabeth Forest Park. Four airborne lidar datasets were collected for the study area over a ten-years span using Optech's ALTM sensors in 2002, 2006, 2008, and 2012, respectively. Field inventory data were first collected in 2002 on twelve 50mx50m plots and then again in 2006 on the same plots. Multiple tree parameters are tallied, including height, crown width, and dbh.

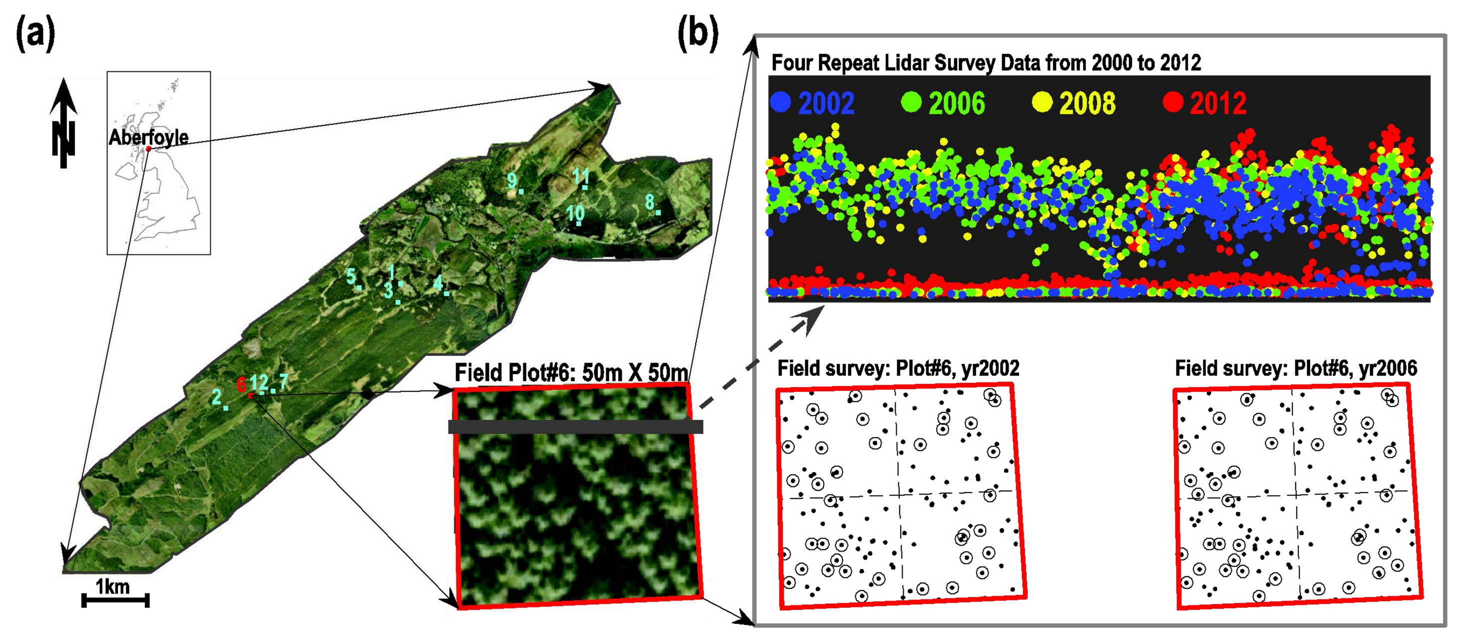

Figure 2. (a) Study area and (b) availability of field and lidar data. Twelve 50mX50m field plots, as labeled from 1 to 12, were surveyed in both 2002 and 2006. Four repeat lidar surveys were flown in 2002, 2006, 2008, and 2012, respectively, capturing forest changes over time.

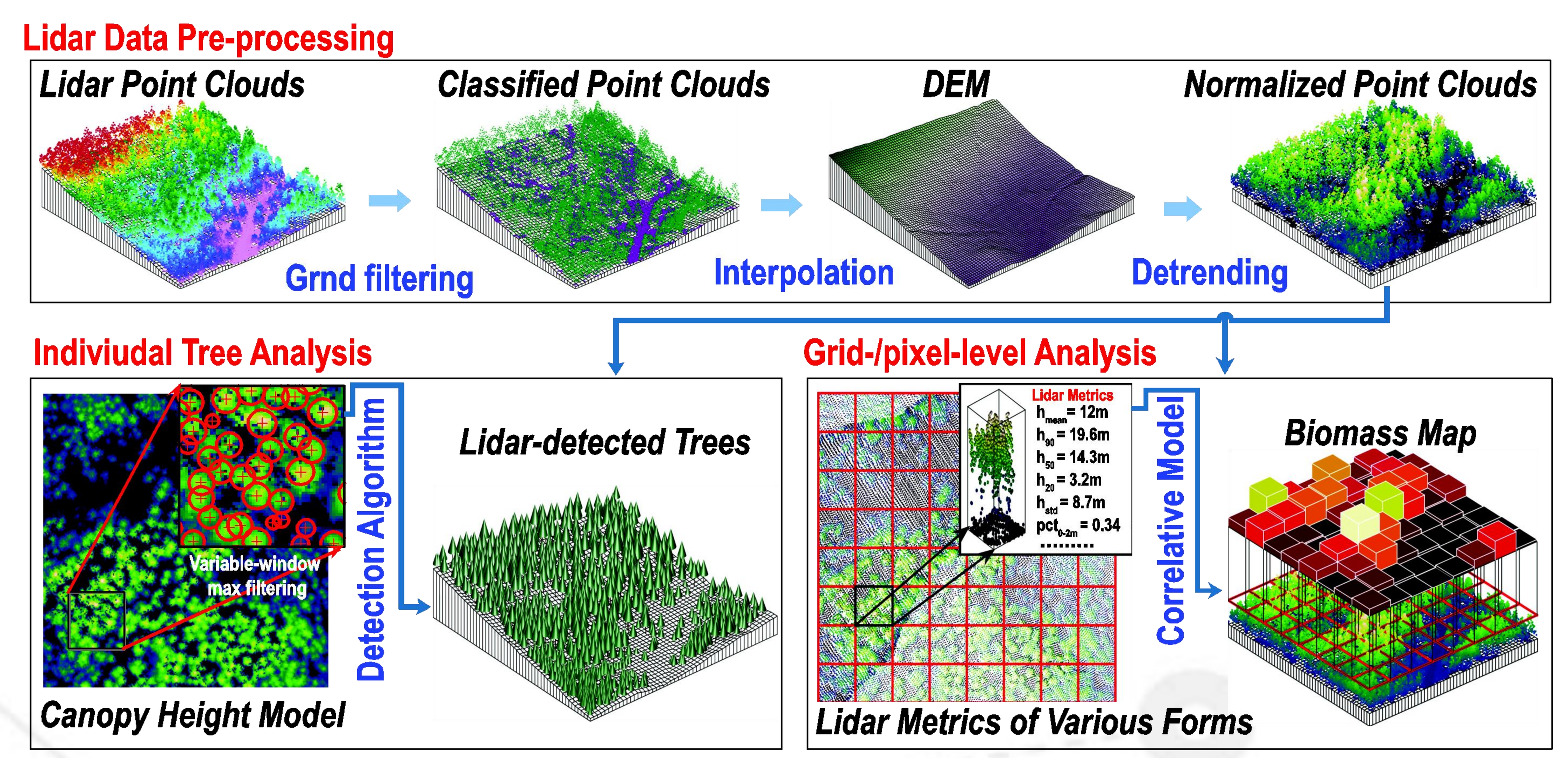

Figure 3. A lidar-based framework to derive forest parameters at two contrasting analysis unit levels: Single tree vs. grid. Raw 3D point clouds were first filtered and detrended to obtain terrain and canopy. Then, detrended point clouds were rasterized into canopy height model for individual tree delineation using a customized variable-window filtering algorithm and were also gridded into a set of lidar metrics to estimate canopy parameters (e.g., biomass) at chosen spatial resolutions via correlative modeling.

We combined the lidar and field data to derive forest parameters for each of the four lidar surveys and examine their temporal changes. Our methodological framework includes a series of data analyses, algorithms, and correlative modeling that vary in nature and complexity (Fig. 3). For individual tree analysis, we implemented a variable-window filtering algorithm to delineate trees. On grid levels, we computed various lidar metrics, classified spatialtemporal patterns of forest changes, and evaluated multiple modeling strategies to estimate biomass and its change.

Results & Conclusions

Changes in forest height were measured well by lidar across the landscape and over time (Fig.4). Lidar also captured forest vertical structural changes from natural growth or known disturbances (Fig. 5).

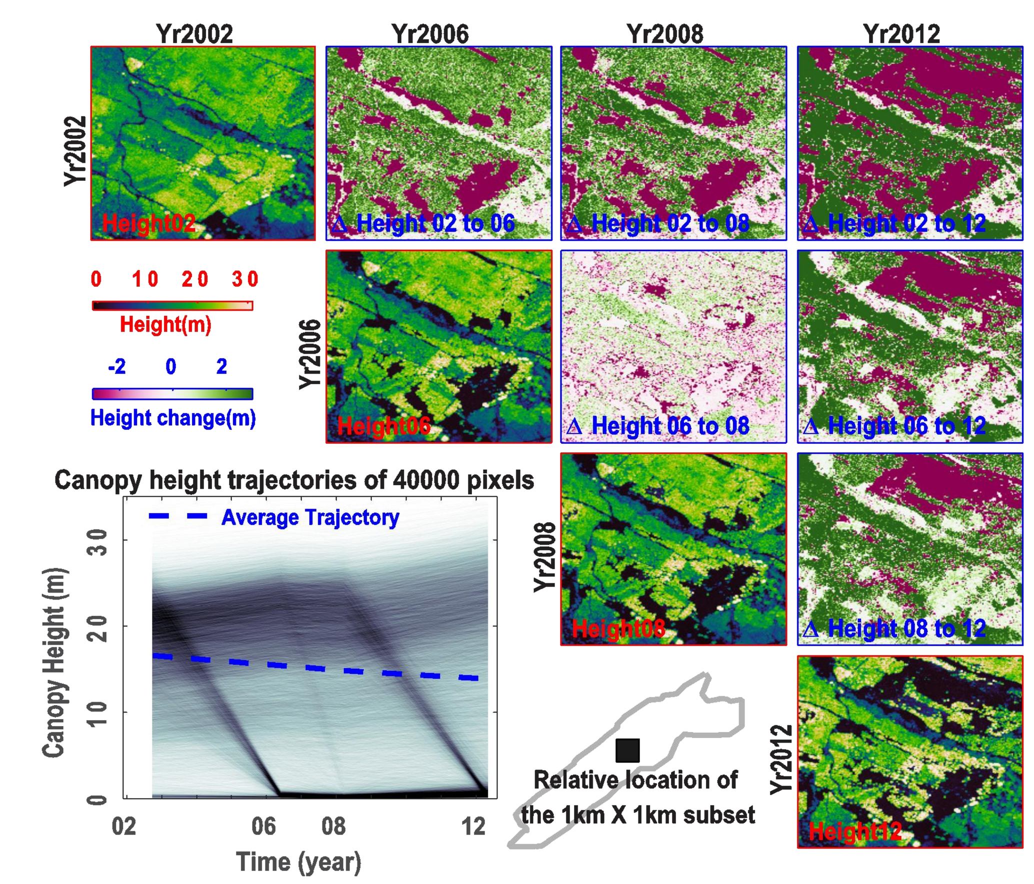

Figure 4. Changes in lidar-derived forest canopy height for a 1kmx1km subregion at a 5 m grid resolution through 2002-2012. The four diagonal images refer to canopy height for the four data years whereas the images on the upper triangle refer to height differences between any two of the four years. On the lower left, the density plot depicts the assemblage of trajectories for the 4000 pixels of the subregion.

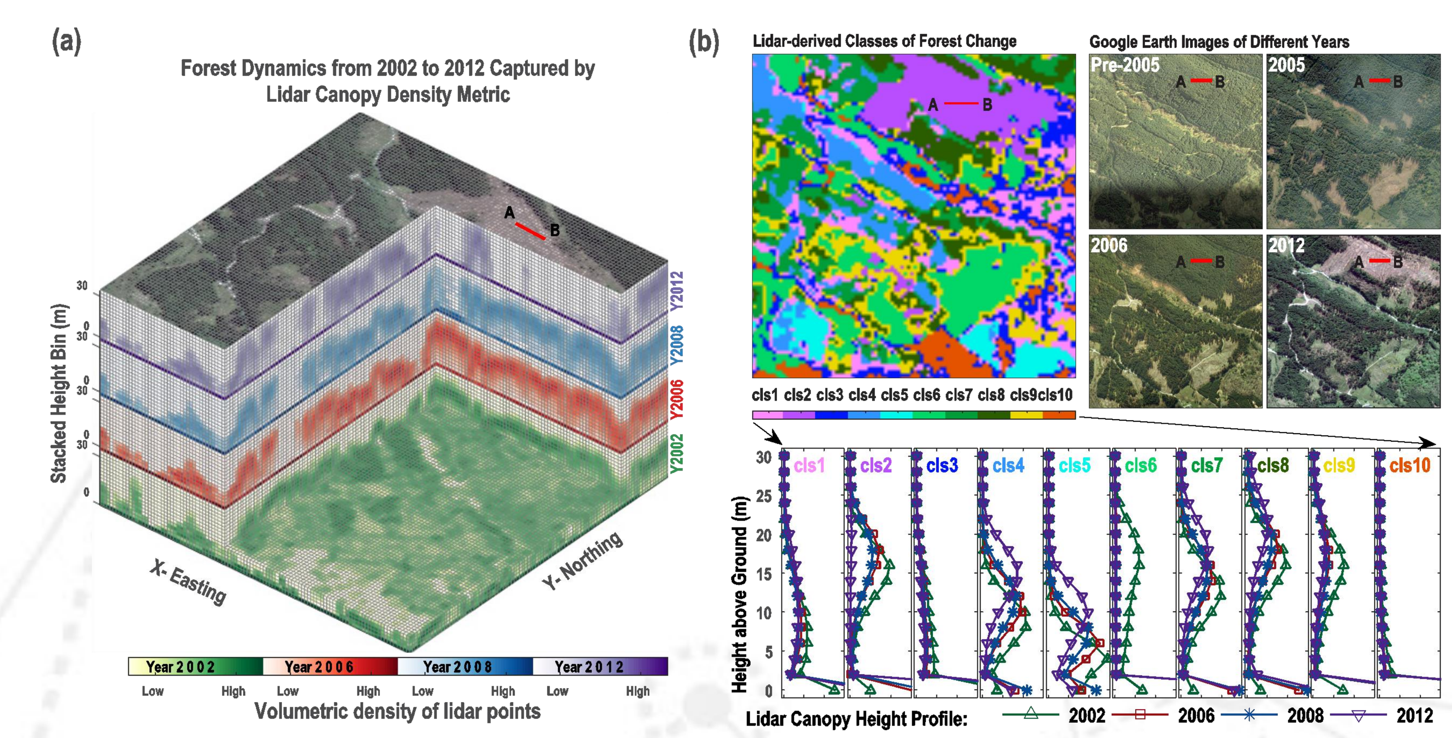

Figure 5. Forest structure changes over time on the 1kmx1km region of Fig. 4. (a) A 3D volumetric view of lidar canopy height profiles stacked vertically for the four years. Darker colors denote higher lidar point densities, namely more plant materials. (b) The stacked 3D height-bin data in (a) were classified into ten forest change classes (top), which show distinct canopy height profiles (bottom*)*

Lidar boasts the best technology for mapping 3D vegetation structure. The utility of mutitemporal lidar for ecological and environmental monitoring is enormous and is expected to be further augmented through the integration of satellite time-series data. We envision an ever-increasing role of lidar in supporting research and management activities, such as those concerning carbon sciences, forest degradation, biodiversity conservation, and land-use.

Bibliography

Zhao, Kaiguang, et al. "Terrestrial lidar remote sensing of forests: Maximum likelihood estimates of canopy profile, leaf area index, and leaf angle distribution." Agricultural and Forest Meteorology 209 (2015): 100-113.