Estimation of LAI, fPAR and AGB based on data from Landsat 8 and LiDAR at the Calhoun CZO

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Background

Remote sensing of Leaf Area Index (LAI) and the fraction of absorbed Photosynthetically Active Radiation (fPAR) by the foliar canopy form the basis for monitoring vegetation health and productivity over vast land areas. LAI (defined as hemisurface area of leaves per unit of horizontal ground surface area, m^2/m^2) and fPAR have direct impact on radiative transfer of plant canopies and they belong to a group of Essential Climate Variables (GCOS 2012). Information on the Above Ground Biomass (AGB) is especially of interest for operational forest management and planning. In this study data from Landsat 8 and LiDAR (Light Detection And Ranging) were used to estimate LAI, fPAR and AGB in the Calhoun Critical Zone Observatory (CZO) area. At present it is not clear which vegetation indices are best in estimating temperate forest fPAR and LAI in Calhoun research site. Nor is it known how much AGB is contained by these forests. The aims of this study were to find out: 1) Which vegetation indices are best correlated with LAI and fPAR at the peak growing season? 2) How good are LiDAR derived metrics in estimating forest canopy gap fraction and LAI, and 3) which LiDAR metrics are the most important in estimating AGB in Calhoun forests?

Materials & methods

Study area is located at the Calhoun CZO in South Carolina (-81.69W, 34.60N) and belongs to temperate forest zone (**Fig. 1.**). Most of the measurements were conducted during summer 2014. The total number of studied forest plots was 34. Plots were dominated by Loblolly pine (*Pinus taeda*) and different hardwood species (total of 27 hardwoods species, e.g. *Quercus, Liriodendron, Liquidambar* and *Carya*). The plot centers were located using GPS receiver with ±4-5m accuracy. For each plot, all trees within a 15m radius from the plot center were measured. In addition, ground-based estimates of effective LAI (LAIe) and canopy gap fraction were measured using LAI-2000-instrument. Canopy gap fraction describes the vertical cover fraction of a tree canopy. LAIe is calculated based on Beer-Lamberts law and measured directional gap fraction readings. Optically measured estimates of LAIe underestimate the 'true' LAI due to shoot-level clumping (e.g. Stenberg et al. 1994) and thus a correction was applied for pine dominated stands (Thérézien et al. 2007). Above ground biomass was estimated using general equations for pine and mixed hardwoods (Jenkins et al., 2004). Ground-based fPAR was modeled as described by Majasalmi et al. (2015).

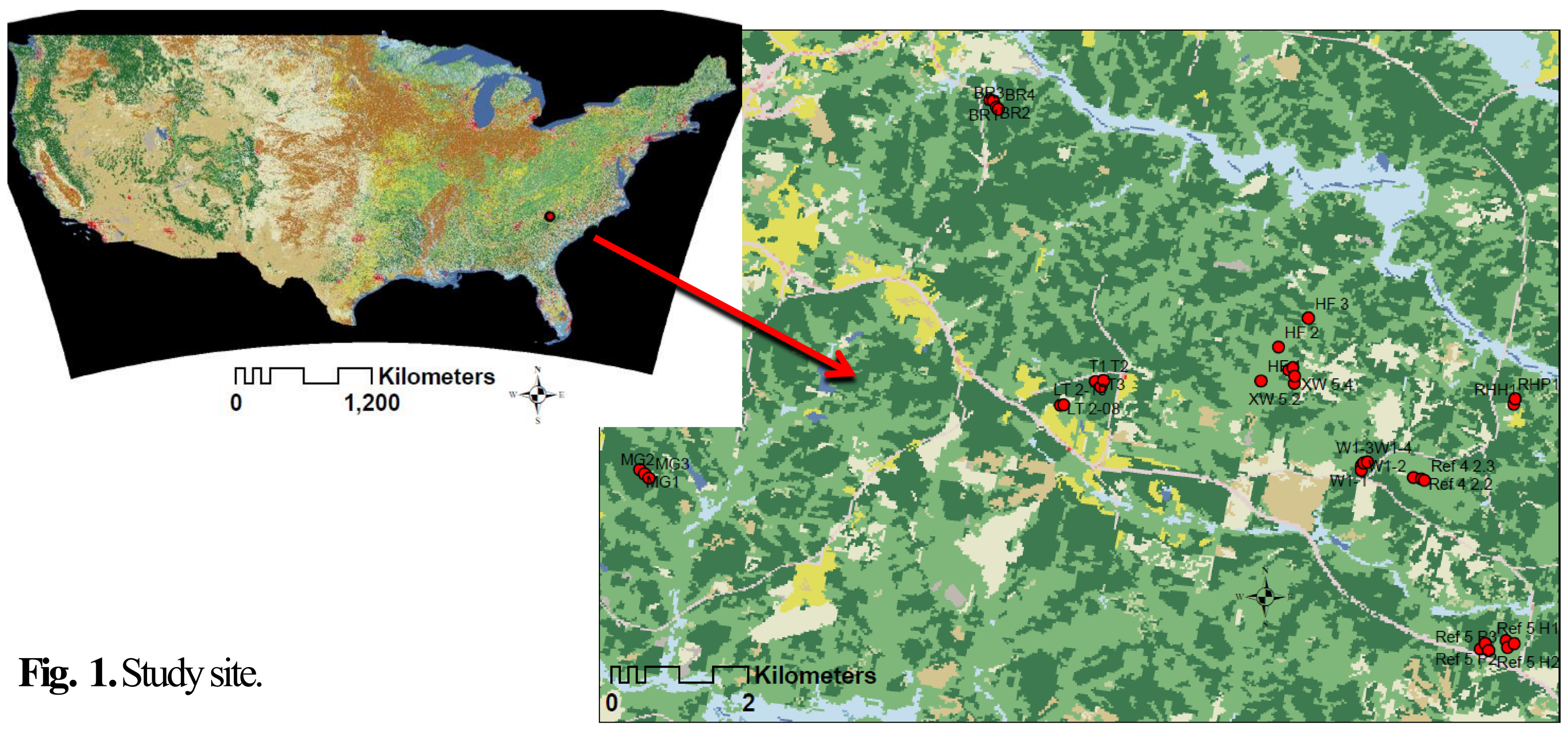

Fig. 1. Study site.

Remote sensing data contained both data from Landsat 8 and LiDAR. Landsat images were used on Day Of Years (DOYs) 208 and 240, because those correspond with field measurements and with the LiDAR data acquisition (DOYs 218 and 219). Landsat surface reflectance values and LiDAR features were extracted to forest plots using a circle with a 15m radius. Satellite-based estimates of LAI and fPAR (PAR wavelenght region: 400-700nm) were obtained using Vegetation Indices (VIs). VIs are often based on measurements on red (640-670nm) and Near-Infrared (NIR, 850-880nm) wavelenghts, because healthy green vegetation has typically strong absorbtion in red and high reflection in NIR wavelenghts. To estimate forest LAI and fPAR, we tested over 20 vegetation indices derived from Landsat data. Data from LiDAR was used to retrieve structural properties of forest canopies (LAI, canopy gap fraction and AGB), because 3D point clouds are effective in characterizing the geometry of forests. LiDAR data processing were made using LAStools software. Processing included removal of noise and pulses arriving at angles larger than 15°. Returns above 1.37m height threshold were classified as canopy hits. The canopy height metrics were calculated using all returns. Stepwise regression was used to create the LiDAR-based AGB model. LiDAR-based canopy gap fraction and LAI were calculated as explained by Korhonen and Morsdorf (2014).

Results

In estimating LAI, the best satellite-based VI at the peak growing season was Enhanced Vegetation Index (EVI,=(NIR-red)/(NIR+6*red-7.5*blue+1), where NIR, red and blue refer to different Landsat 8 bands). The correlation was slightly higher between LAI and EVI (r=0.75) than between fPAR and EVI (r=0.63) (**Fig. 2.**). However, on DOY 240 Normalized Difference Vegetation Index (NDVI,=(NIR-red)/(NIR+red)) was found effective in separating hardwood and pine spp. dominated stands. The correlations between LAI and NDVI (H: r=0.63, P: r=0.74) were similar to those observed between fPAR and NDVI (H: r=0.86, P: r=0.64).

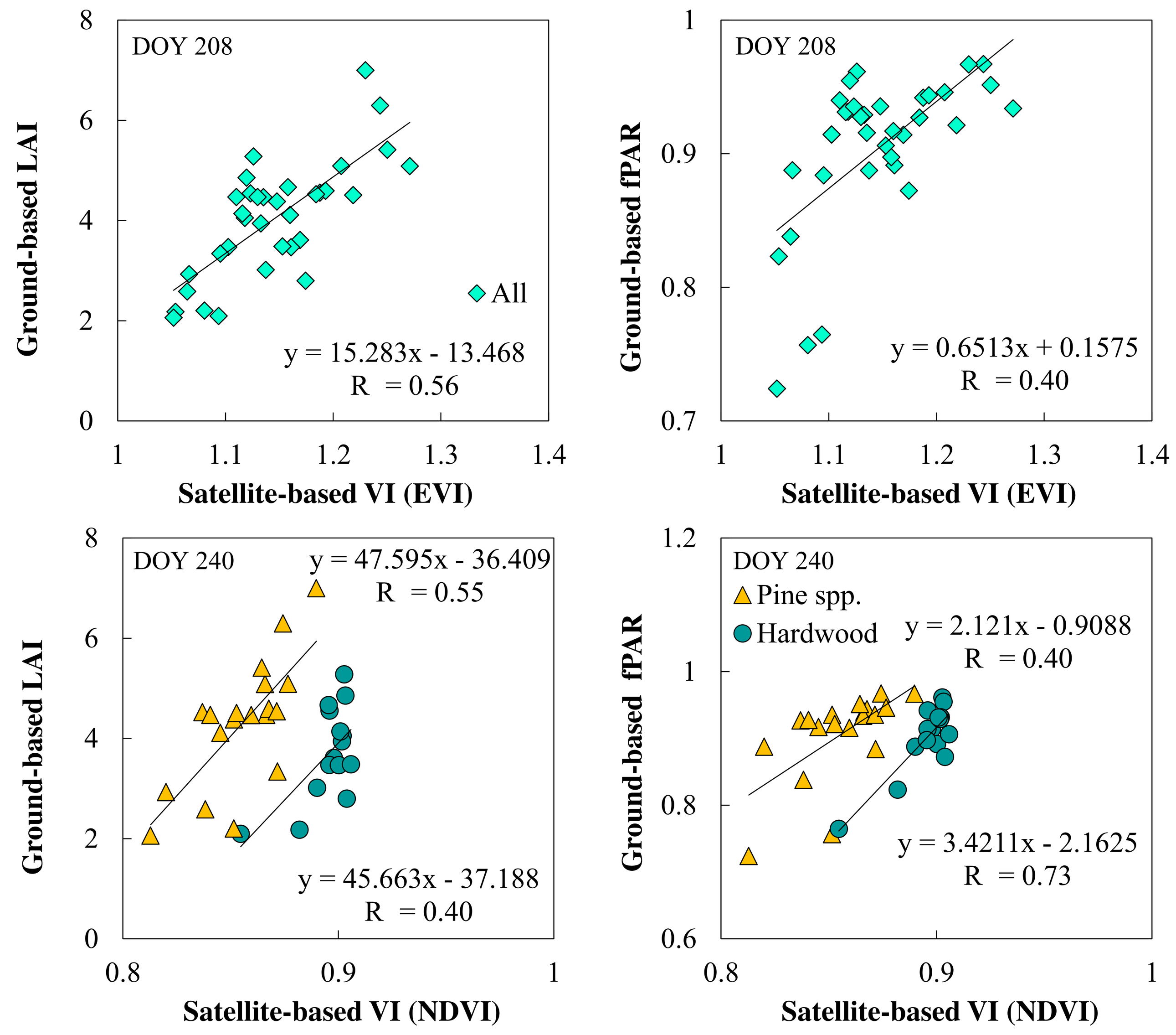

Fig. 2. Comparisons of satellite-based and ground-based estimates of LAI and fPAR.

Results showed that LiDAR derived metrics were effective in estimating forest canopy gap fraction (r=0.74) and LAIe (r=0.75, LAIe=2.4*(-ln(ACI))*ACI, where ACI is ratio between canopy returns and all returns, and 2.4 describes slighly vertical canopy structure) (**Fig. 3**.). The differences were larger between LiDAR-based and ground-based gap fraction estimates than between LiDAR-based and ground-based LAIe estimates. LAIe is calculated by integrating over upper hemisphere, and thus less prone to location related errors compared to nearly vertical canopy gap fraction. The highest correlations were obtained between modeled AGB using Jenkins (2004) allometric biomass equations and LiDAR metrics. The intercept between LiDAR-based AGB and ground-based AGB was close to zero and the slope close to one. The AGB estimates ranged from 45 to 320 Mg/ha.

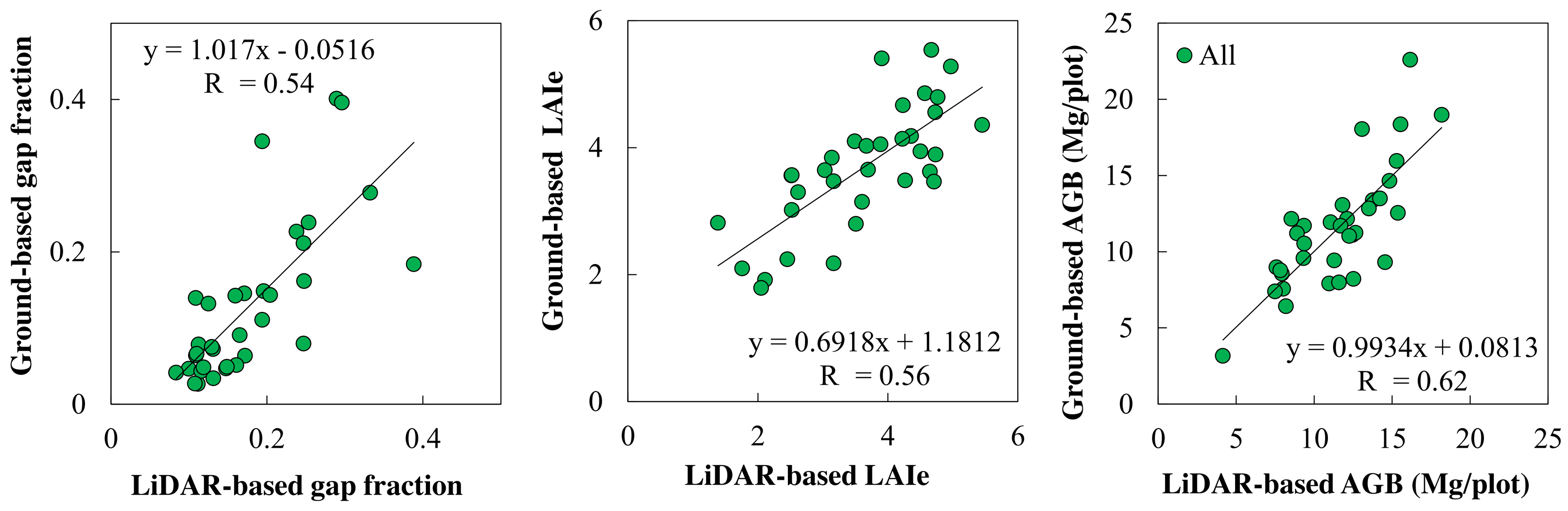

Fig. 3. Comparisons of LiDAR-based and ground-based estimates of gap fraction, LAIe (=direct output of the LAI-2000 instrument) and AGB.

<u>Note, the results shown in this presentation are preliminary!</u>

Conclusions

- EVI is among the best vegetation indices in estimating forest canopy LAI and fPAR at the peak-season (~DOY 208) at the Calhoun CZO. NDVI may effectively separate stands dominated by pine species from those by hardwood.
- LiDAR-based estimates of canopy gap fraction and LAI showed good agreement with field measured values.
- The best LiDAR features to estimate forest AGB were the average height of all returns (avg_h), First echo Cover Index (FCI, see Korhonen and Morsdorf, 2014) and Digital Elevation Model (DEM) (R^2=0.96, Std.Err.=2.52):
  0.479*avg_h + 14.153*FCI - 0.067*DEM

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General: Remote sensing data may be obtained using passive or active sensor systems. Passive remote sensing is based on measuring solar radition that is reflected by land surfaces. Active sensor systems sent beams of coherent radiation at specific wavelenghts and data is obtained based on time it takes a beam to travel to the target and back to receiver. Both remote sensing systems are sensitive to different vegetation properties, and thus neither is 'optimal' for all applications. For example, optical satellite images are well suited for monitoring phenology or health of vegetation, but to estimate structure or AGB active systems are more effective. The selection of the remote sensing technique depends also on the extent which should be covered using remotely sensed data; for regional analysis (<few thousand km^2) active systems may be used, but to cover larger land areas (e.g. continents) and for ongoing monitoring optical satellite data is more economical option.