# Leaf area index

Subjects: Geography

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Leaf area index (LAI) is an important vegetation parameter.This work provides a introduction of LiDAR technology and the LAI estimation with LiDAR, LAI validation studies, and factors affecting the LAI estimation.

Keywords: LAI ; LiDAR

## 1. Introduction

Leaf area index (LAI) is defined as one half the total green leaf area per unit ground surface area [1]. It is listed as an essential climate variable by the global climate change research community (GCOS) and is a critical variable in processes such as photosynthesis, respiration, and interception [2][3]. The field LAI can be measured using direct sampling or indirect optical methods [4][5][6][7]. With a direct sampling method, the LAI can be directly obtained by harvesting vegetation leaves through the collection of leaf litter or destructive sampling [8]. With an indirect optical method, the LAI is estimated from the canopy gap fraction or transmittance using the Beer–Lambert law. The LAI values obtained from ground measurement are often used as references for remote sensing validation. However, these methods are labor-intensive and time-consuming, and the deployment over large areas is difficult.

The LAI estimations from remote sensing data show the most promise for accurate estimations in large scales. Existing techniques can be divided into two main categories, that is, passive optical remote sensing and active light detection and ranging (LiDAR) remote sensing. Passive optical remote sensing has been widely used to estimate the LAI [9][10][11][12]. Based on both theoretical models and observations, the LAI and vegetation indices (VI) strongly correlate [13]. One major issue in estimating the LAI from the vegetation index calculated from passive optical sensors is the LAI saturation [14][15].

LiDAR is an active remote sensing technology for indirect LAI measurements, which alleviates the saturation problem because of the direct detection of the vertical structure [16]. LiDAR has been applied in many studies for the retrieval of the forest LAI [17][18][19][20][21]. The LAI is estimated from LiDAR data based on the correlation with the gap fraction, which is derived from various laser penetration metrics (LPMs) [22]. The LAI can also be estimated through allometric relationships using forest biophysical parameters derived from LiDAR data such as the canopy height and foliage density [23][24][25]. A few review papers have pointed out that LAI can be effectively estimated from the LiDAR technology [6][7], but further understanding is still required regarding the LAI retrieval methods from different platforms and the basic rationales of the retrieval methods.

## 2. LAI Validation

Different schemes that have been used to validate the LiDAR LAI include direct comparison methods, scaling-up strategies, and the intercomparison of multiple products.

Field measurements, typically limited to a point or very small area, are vital because they are the basis for all validation studies. Based on the direct comparison method, field measurements and the LAI from different LiDAR systems are directly compared. The field LAI obtained from destructive sampling was used to validate the TLS LAI and LVIS LAI; the LAI derived from LiDAR and destructive sampling were in excellent agreement [26]. In addition, the LAI from digital hemispherical photography (DHP) and LAI-2200 are commonly used to validate the LAI from different LiDAR platforms [27][28]. Because of the spatial scale mismatch between field measurements and remote sensing estimation, it is usually difficult to use this method for global validation.

Based on the scaling-up strategy, the field LAI is scaled up via different platforms for the validation with SLS LAI products, thus bridging the scale differences between the field LAI and the LAI derived from SLS. The TLS provides an additional indirect ground-based technique to estimate the LAI. The LAI derived from TLS can be used as field measurement [29][30][31]. The LAI can be validated using scaling-up strategy at multiple spatial scales through LiDAR remote sensing [32]. First, the ground-based (DHP, LAI-2200, TLS) LAI is related to aircraft observations of the LAI. Then, the ALS observations of the LAI are used to validate the LAI derived from SLS tracks that intersect the aircraft coverage. The upscaling validation method has been widely used in the remote sensing community [33]. However, this method may be affected by several factors. First, ground LAI derived from photos, TLS, and LAI sensors may be inconsistent among themselves. Second, errors are introduced by the scale mismatch between ground field data and ALS. Third, different data sources are based on varying spatial footprints and viewing geometries, which may complicate LAI validation.

Multiple products can be compared to determine the relative quality of land products. The intercomparison method has been used as a proxy to assess the temporal and spatial consistency. The LiDAR-derived LAI values are aggregated to the resolution of the passive satellite LAI products to evaluate all LAI data. The GLOBCARBON [19] and MODIS [34] LAI products have been used to compare with the LiDAR-derived LAI map. The registration between LiDAR and the satellite LAI maps is important because misregistration could severely bias the pixel-by-pixel comparison.

Current validation studies are mostly performed at local scales. The results indicate a significant correlation between airborne LiDAR and the field-derived LAI at the plot scale in a tropical forest, with R2 = 0.58 and RMSE = 1.36 [35], and a moderate agreement (R2 = 0.63, RMSE = 1.36) between LVIS and the field-derived LAI at tower footprint scales in tropical rainforest [18]. Based on a large-scale validation method, R2 and RMSE values of 0.69 and 0.33 were obtained between the LVIS LAI and GLAS LAI at GLAS tracks in the Sierra National Forest [32]. The LiDAR-derived LAI was evaluated using the MODIS LAI product, yielding R2 and RMSE values of 0.86 and 0.76 in mixed coniferous forest [34]. However, the LAIs derived from ALS or SLS still lack sufficient ground validation and intercomparison validation using existing global LAI products generated from passive optical sensors. The LiDAR also has the capability to provide the LAI vertical profile, from site [18] to regional and continental [36] scales. Due to the lack of ground-measured data on the LAI vertical profile of the forest, the LAI vertical distribution map has not been completely validated. Existing validation work is mainly based on limited site or observation tower data [36].

## 3. Future Prospects

The major advantage of LiDAR technology is its capability to characterize the vertical vegetation structure at different heights [15]. LiDAR-derived LAIs have been used in the validation of the passive satellite LAI products [33]. We expect the use of LiDAR LAI will increase with the growing availability of high-quality LAI data derived from LiDAR. Different LiDAR data provided by the different lidar systems have been used to estimate LAI. However, there is no universal LiDAR metric for LAI estimation; therefore, the selection of proper LiDAR metrics is crucial for LAI estimation. More field measurements and novel LiDAR metrics are necessary for improved LAI estimation in the future.

The ALS observations act as a validation link between field and satellite data [37]. However, the relatively high cost of ALS flight mission has significantly limited its applications. As an alternative platform for ALS, the unmanned aerial vehicle (UAV) costs less but can provide denser points. Therefore, UAV provides an effective platform for LAI estimation [38] and acts as a validation link between field and satellite data [21]. The TLS provides an additional indirect ground-based technique to estimate the LAI [39][30][31]. However, TLS data acquisition is highly time-consuming and labor-intensive. A new backpack LiDAR system was developed for efficient and accurate forest inventory applications, and the derived LAD fits well with the TLS estimates (R2 > 0.92, RMSE = 0.01 m2/m3) [40]. A backpack LiDAR system may provide an alternative platform for TLS data acquisition.

The increasing availability of LiDAR data will greatly enhance the LAI estimation. Fusion of multiple LiDAR data from different systems, platforms, and temporal observations is also a continued research direction [14].

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