Agricultural and Forest Meteorology 252 (2018) 231–240

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Variability and bias in active and passive ground-based measurements of effective plant, wood and leaf area index

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A R T I C L E I N F O

Keywords:
Sensor comparison
Leaf area index
Terrestrial LiDAR
Hemispherical photography
LAI-2200
Validation

A B S T R A C T

In situ leaf area index (LAI) measurements are essential to validate widely-used large-area or global LAI products derived, indirectly, from satellite observations. Here, we compare three common and emerging ground-based sensors for rapid LAI characterisation of large areas, namely digital hemispherical photography (DHP), two versions of a widely-used commercial LAI sensor (LiCOR LAI-2000 and 2200), and terrestrial laser scanning (TLS). The comparison is conducted during leaf-on and leaf-off conditions at an unprecedented sample size in a deciduous woodland canopy. The deviation between estimates of these three ground-based instruments yields differences greater than the 5% threshold goal set by the World Meteorological Organization. The variance at sample level is reduced when aggregated to plot scale (1 ha) or site scale (6 ha). TLS shows the lowest relative standard deviation in both leaf-on (11.78%) and leaf-off (13.02%) conditions. Whereas the relative standard deviation of effective plant area index (ePAI) derived from DHP relates closely to TLS in leaf-on conditions, it is as large as 28.14–29.74% for effective wood area index (eWAI) values in leaf-off conditions depending on the thresholding technique that was used. ePAI values of TLS and LAI-2x00 agree best in leaf-on conditions with a concordance correlation coefficient (CCC) of 0.796. In leaf-off conditions, eWAI values derived from DHP with Ridler and Calvard thresholding agrees best with TLS. Sample size analysis using Monte Carlo bootstrapping shows that TLS requires the fewest samples to achieve a precision better than 5% for the mean ± standard deviation. We therefore support earlier studies that suggest that TLS measurements are preferential to measurements from instruments that are dependent on specific illumination conditions. A key issue with validation of indirect estimates of LAI is that the true values are not known. Since we cannot know the true values of LAI, we cannot quantify the accuracy of the measurements. Our radiative transfer simulations show that ePAI estimates are, on average, 27% higher than eLAI estimates. Linear regression indicated a linear relationship between eLAI and ePAI–eWAI (R^2 = 0.87), with an intercept of 0.552 and suggests that caution is required when using LAI estimates.

1. Introduction

Leaf area index (LAI) is an essential climate variable (ECV) that describes the amount of leaf material in an ecosystem (Nemani et al., 2003; Asner et al., 2003; Disney et al., 2016). LAI is commonly used as a measurement of forest structure and its temporal patterns are used to monitor how biological cycles are connected and correspond to climate change (Polgar and Primack, 2011; White et al., 2009; Bequet et al., 2011; Calders et al., 2015b). To be useful for climate modelling, full end-to-end traceability and assessment of the uncertainty of the process from sensor measurement through to the generation of the ECV product and the resulting time-series is needed (Dowell et al., 2013). Space-borne estimates of LAI are essential to provide a greater spatial and temporal coverage compared to in situ estimates, but the retrieval process is more complex due to the mixed contributions of leaves, other tree elements, understorey vegetation and soil to the measured radiation flux. We require knowledge of the measurement uncertainty and the uncertainty of the derived ECV and its time-series. It is critical to

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https://doi.org/10.1016/j.agrformet.2018.01.029
Received 25 September 2017; Received in revised form 8 January 2018; Accepted 20 January 2018
0168-1923/

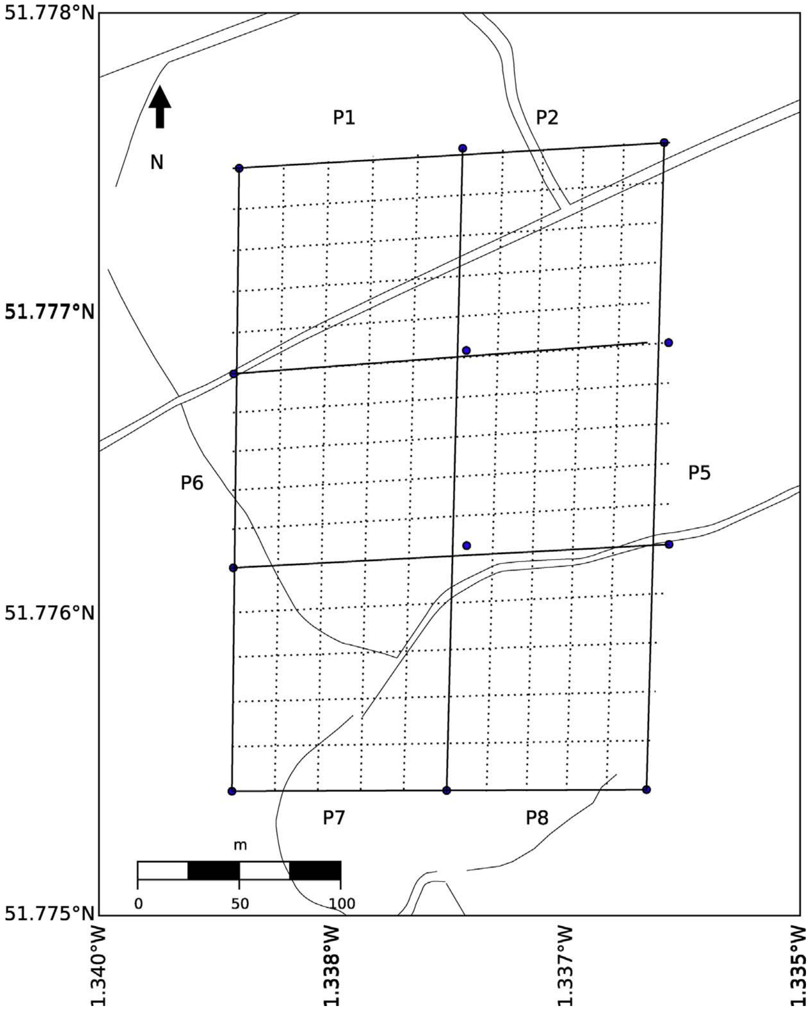

Fig. 1. The location of the 6 plots (1 ha) within the wider 6 ha study area. Figure modified from Origo et al. (2017).

benchmark the different (global) space-derived LAI products and compare these against in situ measurements to ensure their accuracy and reliability. The Global Climate Observing System (GCOS) specified the target requirements for LAI products to be a maximum of 15% uncertainty and 10% stability (the maximum acceptable change in systematic error per decade) (GCOS, 2016), with some target requirements being as low as 5% (WMO, 2012). WMO (2012) listed different breakthrough and threshold requirements depending on the application area of LAI products.

In situ observations are key for the validation of these global spaceborne LAI products. However, comparison of different in situ sensors demonstrated a level of variability typically above these targeted GCOS requirements (Ryu et al., 2010b; Woodgate et al., 2015b). These ground-based sensors measure light transmission and are therefore sensitive to all plant constituents (not just leaves), and plant area index (PAI) is therefore a more correct term. Ground-based sensors can essentially only measure PAI or WAI in deciduous forests, whereas LAI is the key input parameter for models related to climate, agricultural meteorology or hydrology (WMO, 2012). For clarity, within this paper we interpret LAI, PAI and WAI for broadleaved woody species as follows:

- **LAI** is half of the green leaf area per unit of horizontal ground surface area (Chen and Black, 1992).
- **PAI** is half of the surface area of all above-ground vegetation matter per unit of horizontal ground surface area.
- **WAI** is half of the surface area of all above-ground woody matter per unit of horizontal ground surface area.

Two of the most widely-used 2D ground-based passive instruments are digital hemispherical photography, DHP (Origo et al., 2017; Woodgate et al., 2015b) and the LAI-2000 or LAI-2200 (hereafter referred to as LAI-2x00) (Ryu et al., 2010a,b). Methodological errors can occur at any stage during data acquisition and analysis (Jonckheere et al., 2004). Measurement protocols for these instruments require specific light conditions and levelling, while analysis protocols generally involve image thresholding (DHP) and/or linking below and above canopy measurements to derive canopy gap fraction (LAI-2x00).

More recently, 3D terrestrial LiDAR (light detection and ranging) instruments are being used to estimate PAI and to quantify forest structure (Jupp et al., 2009; Calders et al., 2014; Vaccari et al., 2013; Cuni-Sanchez et al., 2016). Terrestrial LiDAR, also called terrestrial laser scanning (TLS), is an active remote sensing technique that accurately measures distances by transmitting laser pulses and analysing the returned energy as a function of distance or time (Newnham et al., 2015; Calders et al., 2015). TLS measurements are insensitive to light conditions and inclination sensors provide accurate instrument levelling information (Woodgate et al., 2015b).

This paper presents a direct comparison of effective PAI and WAI from three different sensors (DHP, LAI-2x00 and TLS) at the scale of medium-resolution satellite-products. Study areas in other comparisons of this sort are generally small, which hinders their ability to produce reliable comparison statistics that are representative of the wider vegetated area. For example, the number of sample points per study area in Woodgate et al. (2015b) ranged from 4 to 72, with a maximum plot area of 0.5 ha and only a few sample plots had coincident measurements of all three sensors. Ryu et al. (2010b) used a large study area,