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An integrated method for validating long-term leaf area index products using global networks of site-based measurements

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ABSTRACT

Long-term ground LAI measurements from the global networks of sites (e.g. FLUXNET) have emerged as a promising data source to validate remotely sensed global LAI product time-series. However, the spatial scale-mismatch issue between site and satellite observations hampers the use of such invaluable ground measurements in validation practice. Here, we propose an approach (Grading and Upscaling of Ground Measurements, GUGM) that integrates a spatial representativeness grading criterion and a spatial upscaling strategy to resolve this scale-mismatch issue and maximize the utility of time-series of site-based LAI measurements. The performance of GUGM was carefully evaluated by comparing this method to both benchmark LAI and other widely used conventional approaches. The uncertainty of three global LAI products (i.e. MODIS, GLASS and GEOV1) was also assessed based on the LAI time-series validation dataset derived from GUGM. Considering all the evaluation results together, this study suggests that the proposed GUGM approach can significantly reduce the uncertainty from spatial scale mismatch and increase the size of the available validation dataset. In particular, the proposed approach outperformed other widely used approaches in these two respects. Furthermore, GUGM was successfully implemented to validate global LAI products in various ways with advantaging frequent time-series validation dataset. The validation results of the global LAI products show that GLASS has the lowest uncertainty, followed by GEOV1 and MODIS for the overall biome types. However, MODIS provides more consistent uncertainties across different years than GLASS and GEOV1. We believe that GUGM enables us to better understand the structure of LAI product uncertainties and their evolution across seasonal or annual contexts. In turn, this method can provide fundamental information for further LAI algorithm improvements and the broad application of LAI product time-series.

1. Introduction

Leaf Area Index (LAI), which is defined as one half of the total green leaf area per unit ground surface area (Chen and Black, 1992), has been widely used to characterize the structure and function of vegetation (Garrigues et al., 2008). As the leaf is the primary interface for the exchange of fluxes of energy, mass (e.g. water, nutrients and CO_2) and momentum between the surface and the planetary boundary layer, LAI is identified as a key parameter in most terrestrial ecosystem models (Bonan, 1995; Liu et al., 1997; Richardson et al., 2012; Sellers et al., 1997). Thus, generating accurate, consistent and continuous long-term global LAI datasets from remote sensing observations has drawn the attention of scientific communities (Myneni et al., 2002; Zhu et al., 2013). Several LAI products based on different combinations of sensors (e.g. MODIS, VEGETATION, MERIS, VIIRS etc.) and algorithms (e.g. using the look-up table generated from radiative transfer models, machine learning etc.) have been developed (Baret et al., 2007; Knyazikhin et al., 1998; Yan et al., 2018) and widely used in a broad range of user communities (e.g. Bi et al., 2015; Samanta et al., 2012; Zhu et al., 2016). Assessing the uncertainties associated with these LAI products through comparisons with independent ground-truth measurements (i.e. direct validation) is pivotal for their proper use in land surface

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models and other applications (Fang et al., 2012; Morisette et al., 2006; Yan et al., 2016).

Direct validation is the most common approach to evaluate products to understand the uncertainties associated with input, pre- or post-processing and inversion algorithms. Many regional field campaigns (e.g. VALERI, BigFoot, SAFARI 2000, etc.) have collected and provided invaluable ground LAI measurements covering a wide range of biome types and spatial variabilities (Morisette et al., 2006). In the Committee on Earth Observation Satellites (CEOS) hierarchical four-stage validation approach, current global medium-resolution LAI products (250 m–1 km) are considered to be validated at Stage 2 ("Product accuracy is estimated over a significant set of locations and time periods by comparison with reference in situ or other suitable reference data.") after a tremendous effort from scientific communities (Camacho et al., 2013; Yan et al., 2016). However, most previous studies were limited to evaluate the temporal performance of the LAI products due to limited resources for collecting time-series of ground LAI via recursive field campaigns (Claverie et al., 2013). This restriction is critical because assessing the temporal performance of these products enables us to better understand the structure of the uncertainties and their evolution across seasonal or annual contexts (Barr et al., 2004; Weiss et al., 2007) and consequently reach the upper validation stage (Stage 3). To improve the temporal assessment capability, the global network of sites (e.g. FLUXNET), which enables to obtain continuous time-series of ground LAI measurements (hereafter, $LAI_{site\text{-}TS}$) using onboard instruments or recursive data collection (Baldocchi et al., 2001), emerges as a promising data source for validation (Xu et al., 2016). However, the spatial scale mismatch restricts the utilization of LAI measurements from these networks as the LAI is conventionally measured within an area of tens of meters around a site. The scale issue usually introduces undesired errors in the validation of remote sensing products because the spatially heterogeneous land surface results in incomparability between observations from sites and satellites (Yang et al., 2006b). Therefore, using $LAI_{site\text{-}TS}$ to validate time-series of LAI products remains a challenge that should be addressed for broader application of long-term global LAI products.

Currently, two approaches are available to remedy the scale issue in utilizing $LAI_{site\text{-}TS}$: (1) the "bottom-up" method and (2) the spatial representativeness evaluation method (Fensholt et al., 2004; Morisette et al., 2006). The "bottom-up" method proposed by the CEOS Land Product Validation (LPV) subgroup is designed to link the ground measured LAI to the remotely sensed LAI through a rigorous upscaling procedure (Tan et al., 2005). This method first employs a two-stage sampling strategy: (a) capture the variability across the extent of a site based on multiple elementary sampling units (ESUs), and (b) capture the variability within pixels of the high spatial resolution image (HSI) by repeating measurements within each ESU. Then, a transfer function is established based on the ground LAI and the spectral measurements from the HSI to generate an LAI reference map (hereafter, LAI_{HSI}). Finally, the generated LAI_{HSI} map is spatially aggregated to retrieve scale-matched LAI (hereafter, $LAI_{HSI\text{-}AGG}$) for direct comparison (Morisette et al., 2006). The "bottom-up" approach is effective for both homogeneous and heterogeneous landscapes because it employs a sufficient number ($20-100$) of ESUs to represent regions with different spatial heterogeneities and obtain a robust transfer function between LAI and spectral characteristics. However, this method is unsuitable for most of sites where LAI measurements were repeated throughout years (e.g. FLUXNET sites) because of poor spatial sampling. Note that the "bottom-up" approach may also be unsuccessful if the HSI is unavailable because of unexpected conditions (e.g. the cloud effect and the temporal mismatch due to the satellite local passing time). The second approach is based on the evaluation of the spatial representativeness of $LAI_{site\text{-}TS}$ (Xu et al., 2016). This method determines whether the LAI measurements are spatially representative for the product pixel by quantitatively considering the point-to-pixel comparability and within-pixel heterogeneity. Quantifying the reliability of ground observations is advantageous because this approach can reduce potential errors from point-to-pixel inconsistency. In particular, time-series validation practice can greatly benefit from this approach because it can consider changing spatial heterogeneity within the product pixel grid over time due to variation in vegetation growth at different growth stages (Ding et al., 2014). However, the stand-alone implementation of this approach yields only a few valid (i.e. high representativeness) $LAI_{site\text{-}TS}$ dataset from networks that can accurately represent the product pixels. Consequently, this limit in implementing the stand-alone second approach hinders the ability to assess the temporal performance of the product. Therefore, an additional processing (i.e. upscaling) is required to use less representative measurements to derive the time-series validation dataset.

Here, we propose an integrated approach, namely, the Grading and Upscaling of Ground Measurements (GUGM), which reconciles the *pros* and *cons* of the above two approaches. The GUGM is expected to be more suitable for $LAI_{site\text{-}TS}$ than the current methods, i.e. the "bottom-up" method and the spatial representativeness evaluation method, in two respects: (1) reducing the uncertainty of the upscaled LAI dataset, and (2) increasing the size of the available LAI dataset. This paper aims to (a) provide a full description of the GUGM, (b) evaluate the performance of the GUGM compared to that of conventional approaches, and (c) implement the proposed approach on three global LAI products: MODIS, GLASS and GEOV1. The paper is organized as follows. Section 2 describes the framework of the GUGM method. Section 3 introduces the data and detailed methods in this study. Section 4 provides the results and discussion for the evaluation of GUGM and the application of GUGM for the three global LAI products. Finally, Section 5 provides concluding remarks on this study.

2. Framework of the GUGM method

The proposed GUGM method mainly includes two sequential processes, i.e. spatial representativeness grading and spatial upscaling. GUGM first ingests $LAI_{site\text{-}TS}$, the reflectance of the HSI and a land cover map as inputs, and then generates a LAI validation dataset (hereafter, $LAI_{site\text{-}HSI}$), which is directly comparable to LAI products with minimizing potential scale effects. Note that $LAI_{site\text{-}HSI}$ is generated by using the combination of $LAI_{site\text{-}TS}$ and $LAI_{HSI\text{-}AGG}$ at a given spatial resolution. The framework of GUGM is shown in Fig. 1 and a detailed description of each step is provided below.

2.1. Spatial representativeness grading

The method presented by Xu et al. (2016) uses three indicators to evaluate the spatial representativeness of $LAI_{site\text{-}TS}$: Dominant Vegetation Type Percent (*DVTP*), Relative Absolute Error (*RAE*) and Coefficient of Sill (*CS*). These indicators are calculated based on the HSI. The *DVTP* is defined as the percent of the area covered by the vegetation type which was observed at the LAI field site. It indicates whether the site-observed vegetation type is the same as the dominant vegetation type in the product pixel grid. The *RAE* quantifies the point-to-pixel consistency by calculating the absolute difference between the $LAI_{site\text{-}TS}$ and $LAI_{HSI\text{-}AGG}$, and then dividing by $LAI_{HSI\text{-}AGG}$ in the product pixel grid. The *CS*, defined as the ratio of the square root of the sill value from a fitted variogram function to $LAI_{HSI\text{-}AGG}$, describes the spatial heterogeneity caused by different vegetation densities within a pixel grid. To adequately compute a variogram, we secured sufficient pair samples (e.g. 4160 and 860 for minimum and maximum lag distance within 1-km area, respectively). To grade the spatial representativeness of the measurements, the proper selection of the thresholds for *DVTP*, *RAE*, and *CS* is critical. For the sake of brevity, a detailed description of the threshold selection for the three indicators is not provided here (see Section 2 of Xu et al. (2016) for the details). Based on the established rules, the spatial representativeness of $LAI_{site\text{-}TS}$ in the product pixel grid is divided into five levels (Levels 0–4), as shown in Table 1. Level 0