**A Methodology for Validating Decametric Resolution Synoptic Satellite Leaf Area Index and fAPAR Products**

November 13, 2025

Fernandes, Brown, Nickeson, Niro, Tang + all others in alphabetical order

**Document Change Record**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Iss.** | **Rev.** | **Date** | **Reason** | **Comments** |
| 0 | 0 | October 24, 2025 | Initial draft | Draft outline for CEOS review |
| 0 | 1 | November 13, 2025 | CEOS draft | Draft outline for external review |

# Abstract

## Context

Leaf Area Index (LAI) and the Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) are biophysical indicators that, respectively, quantify terrestrial vegetation density and potential gross primary productivity. Synoptic (>1000km x 1000km).

LAI and FAPAR products at spatial resolution <=250m and temporal resolution <=10d are required by the United National Global Climate Observing System (GCOS). These requirements can be generally satisfied using algorithms applied to decametric resolution optical and radar satellite data fundamental data records.

Conformity to thematic quality requirements by GCOS and other users must also be addressed through validation. . The Committee of Earth Observation systems requires validation using matchups that are globally representative and ideally using in-situ fiducial reference measurements.

## Survey

Current validation methods quantify thematic quality rely on estimates derived from limited matchups of product and reference measurements that are not global representative of product measurement conditions. Matchups using reference estimates, derived by combing in-situ reference measurements, have been used to improve representativeness but the additional uncertainty of matchups on validation estimates is generally ignored. The majority of studies report validation results aggregated over all matchups rather than, as required by GCOS and CEOS, conditional on the measured LAI or FAPAR.

## This Study

1. A method for quantifying the uncertainty, apparent bias and apparent accuracy of decametric resolution LAI and FAPAR satellite products with synoptic extent is presented that:
2. Estimates the probability validation statistics are representative of product measurements.
3. Quantifies the impact of addititional uncertainty when using fiducial reference estimates on validation statistics.
4. Determines the conformity of product measurements to user requirements

## Findings

1. Representativeness:
2. Impact of FRE:
3. Conformity:

# Introduction

## Problem Statement

**Leaf area index** (LAI) and the **fraction of absorbed photosynthetically active radiation** (FAPAR) measure, respectively, the density and potential gross primary productivity of terrestrial vegetation (Watson, 1947; Monteith 1972; WMO, 2022).

LAI and FAPAR (hereafter LAI/FAPAR) are essential agriculture, biodiversity and climate variables required for systematic monitoring of vegetation status and trends (Navarro et al., 2017; GEOGLAM 2022; United Nations, 2022; FAO, 2025; WMO, 2025).

**Satellite fundamental data records** (FDRs)from **optical imagers**, **synthetic aperture radar** (SAR) imagers and **Light detection and ranging** (LIDAR) instruments, serve as inputs to algorithms that generate LAI/FAPAR **products** at **synoptic** (>1000km length scales) extents (Fernandes et al., 2014; Campos-Taberner et al., 2017; CEOS, 2018; Fang et al., 2019; Dubayah et al., 2020).

The Committee of Earth Observation Satellites (CEOS) has been tasked by the United Nations (UN) with developing validation protocols and good practices to validate synoptic satellite LAI/FAPAR products with respect to UNGlobal Climate Observing System (GCOS) user requirements (CEOS, 2018).

CEOS last published a good practice document for validation of synoptic LAI products with **spatial resolution** >=250m in 2014 (Fernandes et al., 2014). Subsequent validation studies that have applied both CEOS methods and new methods for validating LAI/FAPAR products (Camacho et al, 2018a,b; Xu et al., 2018a,b; Fang et al., 2019a,b; Fuster et al., 2020; Brown et al., 2020; Ma and Liang, 2022; Ma et al., 2022; Cao et al., 2023; Camacho et al., 2024; Brown et al., 2021; Fernandes et al., 2023; Fernandes et al., 2024; Djamai et al., 2025) . There have also been new insights into the use of metrological methods for validation in general and, specifically, for testing the conformity of products to user requirements (Widlowski, 2015; Origo et al., 2020; Brown et al., 2021; Camacho et al., 2024; Lanconelli et al., 2024). Current GCOS baseline user requirements can only be satisfied by data products or algorithms capable of on-demand production (hereafter ‘products’) at decametric or finer spatial resolution (WMO, 2025).

## Goal

The goal of this paper is to provide a methodology for validation of decametric resolution synoptic LAI/FAPAR products for GCOS requirements that addresses research gaps in current good practice documents and validation studies.

## Terminology

For clarity, terms in bold are defined by internationally accepted standards from the Joint Committee for Guides in Metrology (JGCM, 2021), the United Nations ([UNTERM](https://unterm.un.org/unterm2/en/)) or CEOS ([CEOS | Committee on Earth Observation Satellites](https://ceos.org/)).

## 1.4 User Requirements

### 1.4.1 What is a specification?

A user requirement **specification** is a document that defines:

1. **measurands,** the particular quantity subject to measurement (e.g. LAI\FAPAR),
2. required **parameters**, quantitative characteristics of product measurements (), associated with these measurements including statistical and deterministic quantities (e.g. the LAI or FAPAR uncertainty)
3. and **tolerance limits**, values of the measurand that separate intervals of permissible values from intervals of non-permissible value, e.g. threshold levels for LAI or FAPAR uncertainty

### 1.4.2 Current Specifications

LAI/FAPAR product user requirements are available from satellite operators (European Space Agency, 2007; European Space Agency, 2010; Dubayah et al. 2020), meteorological services (Camacho et al., 2018a), and GCOS (WMO, 2025 ).

### GCOS Requirements

This method validates GCOS requirements as they represent a broad range of users and because this study is led by the Committee of Earth Observing Systems (CEOS) that has been tasked by the UN to validate satellite products for GCOS (WMO, 2022).

#### Measurands

User requirements are evaluated with respect to **measurands** defined by GCOS (Table 1), endorsed by the WMO (GCOS, 2025), and under review by CEOS (Fernandes et al., 2024a,b). These definitions are applied based on the product name: a product named “LAI” or “FAPAR” is validated with respect to that measurand irrespective of known or stated deviations due to sensor or algorithm limitations. Products with different names can also be validated as an estimator for a measurand notwithstanding prior knowledge of systematic differences. For example, Global Ecosystems Dynamics Instrument (GEDI) L2B Canopy Cover and Vertical Profile Metrics Data Global Footprint Level V002 product (Dubayah et al. 2021) includes **plant area index** (PAI), defined as half the surface area of plants area per horizontal ground area. PAI is not a GCOS user requirement, but it is likely that product users will apply PAI products as proxies of LAI.

Table 1. GCOS definition of LAI/FAPAR measurands (WMO, 2025) with conditions specified by CEOS (Fernandes et al., 2024a,b)

|  |  |  |
| --- | --- | --- |
| **Measurand** | Leaf Area Index | Fraction of Absorbed Photosynthetically  Active Radiation |
| **Abbreviation** | LAI | FAPAR |
| **SI Symbol** | None | None |
| **SI Units1** | 1 | 1 |
| **Definition** | half the total green leaf area per unit horizontal ground area | the fraction of incoming solar radiation in the 400–700 nm spectral range that is absorbed by green elements of plants for photosynthesis |
| **Exclusions** | non vascular organs (miss, bryophytes, green stems). Green leaves below the ground or water surface. | Plants below the ground or water surface. |
| **Conditions** | Definition of “green” | Definition of “green” and “effectively”  Incoming solar radiation field. Adjectives include:  Direct: direct solar illumination  Diffuse: isotropic over lower hemisphere downwelling solar radiation  Ambient: ambient downwelling solar radiation field |

*1The System International dimensions of LAI and FAPAR units is “1” and are omitted (Thompson and Taylor, 2008).*

GCOS LAI and FAPAR measurands are ambiguous in that they use the condition “green” without definition. The proposed CEOS definition of “green” based on the International Commission of Illumination ([CIE | International Commission on Illumination / CIE, Comission internationale de l'Eclairage / Internationale Beleuchtungskommission | CIE](https://cie.co.at/)) is used in this paper (Fernandes et al., 2024a). The FAPAR measurand is also ambiguous in that it does not define the term ‘‘effectively intercepted”. The proposed CEO definition of ‘effectively intercepted’ as “intercepted by plant organs capable of photosynthesis” (Fernandes et al., 2024b).

#### Tolerance Limits

**Tolerance limits,** are limiting values for requirements for a measurand to test compliance of products with user requirements.

GCOS specifies three types of tolerance limits for user requirements: **threshold**, the minimum requirement that must be met , **breakthrough**, an intermediate level indicating a significant improvement in applicability, and **goal** , the ideal requirement. The least restrictive level is assumed in cases where a level is not specified.

GCOS tolerance limits are provided for (Table 2, WMO, 2025):

“1. **Spatial Resolution** - horizontal and vertical (if needed).

2. **Temporal resolution** (or frequency) – the frequency of observations e.g. hourly, daily or annual.

3. **Measurement Uncertainty (uncertainty)** – the parameter, associated with the result of a measurement, that characterizes the dispersion of the values that could reasonably be attributed to the measurand (GUM)1. It includes all contributions to the uncertainty, expressed in units of 2 standard deviations, unless stated otherwise.

4. **Stability** – The change in bias over time. Stability is quoted per decade.

5. **Timeliness** - The time expectation for accessibility and availability of data.”

Table 2. GCOS threshold, breakthrough, and goal user requirements for LAI/FAPAR products.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Requirement** | **Units** | **LAI** | | | **FAPAR** | | |
| threshold | breakthrough | goal | threshold | breakthrough | goal |
| Horizontal  Resolution | m | 250 | 100 | 10 | 250 | 250 | 10 |
| Temporal  Resolution | d | 10 | 10 | 1 | 10 | 10 | 1 |
| Timeliness | d | 10 | 5 | 1 | 10 | 5 | 1 |
| Relative Standard Uncertainty | % | 10 | 10 | 5 | 5 | 5 | 2.5 |
| Minimum Standard Uncertainty | 1 | 0.05 | 0.05 | 0.025 | 0.025 | 0.025 | 0.0125 |
| Stability | %/year | 0.6 | 0.6 | 0.3 | 0.3 | 0.3 | 0.1 |

##### Timeliness

Timeliness requirements can be satisfied with sufficient computing resources assuming the current access to input FDRs with latency of <1d continues. Timeliness is not assessed here as these factors are not well defined for current decametric LAI/FAPAR products and are likely to change.

##### Spatial Resolution

The spatial resolution defines the spatial extent of the product **minimum mapping unit** (MMU). Spatial resolution is not defined by GCOS. The CEOS definition “The highest magnification of the sensor at the ground surface.” (CEOS WGCV glossary of terms)in not a SI quantity. The WMO definition as the “distance between independent measurements or grid points” corresponds to the spatial sampling resolution and not the spatial support of measurements ([UNTERM](https://unterm.un.org/unterm2/en/)). Here “spatial resolution” if defined as “the median distance of secants passing through the centroid of the product mapping unit projected on the local horizontal datum”. This definition is both a SI quantity and returns the expected result of the width of square mapping units such as product pixels from optical imagers and the diameter of circular mapping units of LIDAR instruments.

For brevity, products derived from FDRs with spatial resolutions coarser than 100m (Supplementary Material S1), are not including in this method although we later discuss how they can be validated using outputs from this method..

Validation reports confirming that input FDRs satisfy decametric spatial resolution, ideally following CEOS (CEOS, 2025) or International Society for Photogrammetry and Remote Sensing (xx) methods, must be cited. Currently, only products derived from passive optical FDRs and the GEDI FDRs meet baseline spatial resolution requirements with synoptic spatial coverage (Table 3).

Table 3. . Decametric resolution synoptic LAI and FAPAR products and algorithms available for on-demand production.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Product** | Boston University Landsat | Kang et al.  Landsat | SL2P Europe | SL2P-CCRS Canada | GROUNDED EO | HiGlass | GEDI |
| **ECV** | LAI | LAI | LAI | LAI, FAPAR | LAI, FAPAR | LAI, FAPAR | LAI |
| **FDRs** | Landsat xx | Landsat xx | S2 | S2 | S2 | Landsat 8/9  S2 | GEDI |
| **Spatial Extent** | CONUS | CONUS | EU, Global JECAM | CAN, US NEON,EU ICOS, AU TERN | US NEON,EU ICOS, AU TERN | China | Global sampling |
| **Temporal Extent** |  |  |  | 2019- |  | 2018-2023 |  |
| **Spatial Resolution** | 30m | 30m | 10m | 20m | 20m | 20m | xx |
| **Temporal Resolution** | Peak season | Peak season | Peak Season | Monthly | Variable | 5d |  |
| **Timeliness** | No repeat | No repeat | xx | Annual update | No repeat | No repeat | xx |
| **Validation Status** | Stage 2 | Stage 3 | Stage 1 | Stage 3 | Stage 3 | Stage 2 | Stage xx |
| **Product Reference** | Ganguly | Kang | Weiss and Baret, 2020 | Fernandes et al., 2021 | Brown et al., 2025 | Ma et al., 2025 | Dubyah et al. xx |
| **Validation References** | xx | xx | xx | xx | xx | Ma et al., 2025 | xx |
| **Access** | On request | xx | xx | Geo.ca | On request | F | xx |

##### 1.4.3.2.3 Temporal Resolution

Temporal resolution defines the temporal extent of the product MMU. GCOS threshold requirements indicate a temporal resolution of 10d for LAI/FAPAR products. CEOS defines geophysical **product levels** thatconstraint temporal resolution (Table 4, CEOS, 2008): Level 2 requires a one-to-one correspondence between products and a FDR measurement while Level 3 and 4 allow for a many to one correspondence . For example, a Level 2 LAI/FAPAR product may have a temporal resolution spanning a few minutes, a Level 3 daily composite will have a temporal resolution of 1d, a Level 4 monthly gap filled estimate a temporal resolution of 30d.

This method only considers level 2 and level 3 products as there are currently no Level 4 synoptic decametric resolution LAI/FAPAR products (Table 3).. Level 3 or 4 LAI/FAPAR products have the potential to meet threshold spatial and temporal resolution requirements. For example, the number of monthly clear sky observations from the Harmonized Landsat Sentinel-2 FDRs ranging from ~3 at the Equator to >20 at 75°N (Ju et al., 2025). However, this method does not validate temporal resolution requirements due to limited access to long term products.

Table 4. CEOS Geophysical Product levels.

|  |  |
| --- | --- |
| **Level** | **Definition** |
| 2 | Derived geophysical parameters (e.g. sea surface temperature, leaf area index) at the same resolution and location as Level 1B source data. |
| 3 | Data or retrieved geophysical parameters which have been spatially and/or temporally re-sampled (i.e. derived from Level 1 or 2 products), usually with some completeness and consistency. Such re-sampling may include averaging and compositing |
| 4 | Model output or results from analyses of lower level data (i.e., variables that are not directly measured by the instruments, but are derived from these measurements; could be derived from multiple instrument measurements). |

##### 1.4.3.2.4 Thematic Quality

**Thematic quality** corresponds to tolerance limits for conformity assessments of product measurements within a set of MMUs, .

The set of MMUs depends on the CEOS Validation Stage (Table 5). Stage 1 and 2 Validation can be satisfied if the MMUs only correspond to **assessment units** (AU), defined as mapping units where are compared to reference measurements ). Stage 3 and 4 Validation requires AUs representing synoptic product measurements **error** **conditions** (hereafter conditions, ) comprised of **influence quantities**, such as environmental, sensor and algorithm characteristics, that affects the result of the measurement.

Table 5. CEOS land product validation stages.

|  |  |
| --- | --- |
| Stage | Description |
| 0 | No validation. Product accuracy has not been assessed. Product considered beta. |
| 1 | Product accuracy is assessed from a small (typically < 30) set of locations and time periods by comparison with in situ or other suitable reference data. |
| 2 | Product accuracy is estimated over a significant (typically > 30) set of locations and time periods by comparison with reference in situ or other suitable reference data. Spatial and temporal consistency of the product, and its consistency with similar products, has been evaluated over globally representative locations and time periods. Results are published in the peer-reviewed literature. |
| 3 | Uncertainties in the product and its associated structure are well quantified over a significant (typically > 30) set of locations and time periods representing global conditions by comparison with reference in situ or other suitable reference data. Validation procedures follow community-agreed-upon good practices. Spatial and temporal consistency of the product, and its consistency with similar products, has been evaluated over globally representative locations and time periods. Results are published in the peer-reviewed literature. |
| 4 | Validation results for stage 3 are systematically updated when new product versions are released or as the interannual time series expands. When appropriate for the product, uncertainties in the product are quantified using fiducial reference measurements (FRM) over a global network of sites and time periods (if available). |

GCOS specifies tolerance limits for LAI/FAPAR uncertainty, relative uncertainty and stability. These quantities require estimation of the systematic component of LAI/FAPAR error (bias). Accuracy is also estimated since it is included in other user requirement specifications. Additionally CEOS Stage 4 validation requires that uncertainty is quantified using fiducial reference measurements that, in addition to other characteristics, must be collected in-situ (Goryl et al., 2023).

The Joint Committee for Guides in Metrology (JGCM, JGCM 2008, JGCM 2012, JGCM 2020, JGCM 2021 ) guidance documents are used here for thematic quality assessment as these have been endorsed by CEOS and GCOS.

###### Uncertainty

**Uncertainty** () is a “parameter, associated with the result of a measurement, that characterizes the dispersion of the values that correspond to a measurand”. (JGCM, 2021; GCOS, 2025). Further, with r respect to the measurement, “the expectation or expected value of the error arising from a systematic effect is zero. ” (JGCM, 2008) This implies that the bias in the must be corrected prior to using it to estimate if it is significant in size relative to the required accuracy of the measurement. The **standard uncertainty** ( is “the uncertainty of the result of a measurement expressed as a standard deviation” and the relative standard uncertainty (is defined as .

###### Stability

**Stability** () is “the change in bias over time. Stability is quoted per decade” (WMO, 2025). GCOS associates with a product MMU but does not specify the temporal interval for estimating bias.

Bias

**Bias** () is “the mean error of measurement that would result from an infinite number of measurements of the same measurand carried out underrepeatability conditions minus a true value of the measurand” (JGCM, 2008) . **Repeatability conditions** are conditions of the measurement where the agreement between successive measurements of the same measurand have low relative dispersion.

The true value of the LAI/FAPAR ( ) is only known for non-vegetated conditions. Subsequently, the **error of indication** (), defined as , cannot be quantified in an unbiased manner barring exceptional circumstances, such as MMUs with zero vegetation. Here, is estimated by the apparent error of indication (, hereafter **apparent error**) , defined as , where is an unbiased reference measurement whose uncertainty is much smaller than, and is estimated by the apparent bias () defined as “the expected value of for a repeatability condition”.

###### Maximum Permissible Error (MPE)

GCOS does not place requirements on theMaximum Permissible Error () of a measurement, defined as the maximum that meets requirements. However, users may require an estimate of the dispersion of (labelled here, ) for downstream applications such as land surface models. Here is estimated by the apparent accuracy () defined as “parameter, associated with the result of a measurement, that characterizes the dispersion of for a repeatability condition without prior correction for measurement bias.”

## Validation

### Definition of Validation

**Validation** is the “provision of objective evidence that a given item fulfills specified requirements … where the specified requirements are adequate for an intended use” (JGCM, 2021). Here the specified requirements correspond to GCOS LAI/FAPAR requirements for synoptic products CEOS and the intended use is for modelling and adaptation applications by GCOS users as well as monitoring applications by other UN user groups.

### Types of Validation

Thematic quality can be quantified by **Type A validation**, that perform “statistical analyses of series of observations” or (not “exclusive or” ) by **Type B validation**, “that use other means” (JGCM, 2006). “Type A evaluations of components are obtained from a probability density function (pdf) derived only from an **observed frequency distribution** while Type B evaluations from an assumed probability density function based on the degree of belief that an event will occur probability(JGCM, 2006)”.

#### Type A Validation

Type A estimates parameters given a set of observations of over a finite set of conditions . In this regard, Type A validation alone cannot currently meet CEOS Stage 3 requirements for LAI/FAPAR since corresponds to in-situ reference measurements that are known to not represent global conditions. This is in contrast to validation of man-made measurements such as the length of a ruler where the global conditions that impact the measurement are few, such as ambient temperature, and can both be replicated during in-situ comparisons and known with sufficient apparent accuracy during measurements.

#### Type B Validation

Type B validation associates a prior distribution to validation parameters given a condition. Here we define priors for the condition corresponding to unique land cover and . The prior distribution can come from expert knowledge only or, as performed here, by using expert knowledge. Type B validation could in principle simply apply priors for thematic quality quantities without relying on representative reference measurements. However, to satisfy the CEOS requirement that validation be performed using reference measurements, here the prior is used . to determine the probability that is a member of the same sampling distribution as (hereafter **inclusion probability** , For example, there is a high probability that the conditions of a Type A uncertainty estimate for a specific crop and sensor is representative of a for a measurement over the same crop type by the same sensor. The approach is still a Type B validation since the sampling distribution needs to be specified using expert knowledge. Without a prior, the observations of form a frequency distributions defined as “a summarized grouping of data divided into mutually exclusive classes and the number of occurrences in a class.” and Type A parameters are numbers related to the data . With priors are samples of a probability distribution., defined as :a [function](https://en.wikipedia.org/wiki/Function_(mathematics)) that gives the probabilities of occurrence of possible **events** for an [experiment](https://en.wikipedia.org/wiki/Experiment_(probability_theory)) “ and Type A parameters are now statistics of the probability distribution. Because of the priors, the validation experiment becomes a statistical experiment (Box et al. 2005). Statistical experiments have three components that structure the remained of this study ( Stehman and Czaplewski, 1998, Tyukavina et al. 2025).:

1. The **sampling design** is *“the protocol by which the reference sample units are selected”*.
2. The **response design** contains "all the steps that lead to a decision regarding the agreement between individual RM and products measurements [hereafter, ‘matchups’’]”.
3. The **analysis** specifies the procedures to estimate validation statistics given observed differences at matchups with their associated uncertainties, and report these estimates in a manner that users can determine if products meet requirements with a stated level of confidence.

## Research Questions

LAI/FAPAR validation methods have spent a lot of effort dealing with the need to match reference and product measurements (matchups) over spatial extents coarser than typical in-situ LAI/FAPAR surveys (Fernandes et al. 2003; Garrigues et al., 2008; Camacho et al., 2013; Fang et al., 2013; Fernandes et al. 2014; Weiss et al., 2014; Fang et al. 2019a; Fang et al., 2019b; Brown et al. 2020; Baret et al., 2021; Camacho et al., 2021). This matching problem exists to a lesser extent for decametric products (Brown et al., 2021; Fernandes et al. 2023) but other issues remain: the representativeness of validation statistics based on limited matchups, quantifying the uncertainty associated with estimated errors, and the need to account for RM uncertainty when estimating these statistics, that are only partially addressed in existing validation studies. These issues give rise to research gaps categorized here using the three components of validation experiments.

### Sampling Design

Current validation studies rely on observations of **matchups:** pairs for **assessment units** (AU), that define the spatial and temporal extents of observed . Matchups based onFRM are currently limited to episodic regional spatial samples or longer term samples over limited sites (Figure 1). The geographic and temporal imbalance of matchups suggests that is likely not representative of synoptic conditions.

A map of the world

AI-generated content may be incorrect.

A map of the world

AI-generated content may be incorrect.

A map of the world

AI-generated content may be incorrect.

Figure 1.  (Top) Location and number of grounded EO FRM sites detailed in Appendix A, (Middle) of matchups with S2 products derived using SL2P, (bottom) approximate matchups with GEDI products (probably 40% lower than indicated ).

Most LAI/FAPAR validation studies address this imbalance using a Type B approach by performing Type A validation each unique land cover classes and assuming if the land cover associated with matches the land cover of . In addition to assuming accurate land cover information, this approach is sensitive to the samples for a given land cover class. For example, for Sentinel-2 LAI products from the Simplified Level 2 Prototype Processor (SL2P) algorithm for 42 deciduous broadleaf forest (DBF) AUs within the US National Ecological Observatory Network (Figure 1, NEON) was initially quantified as 1.18 +/-0.03 for 203 matchups (Fernandes et al., 2023), then dropped to 0.94 +/- xx when the number of matchups increased to 500 500 match-ups (Fernandes et al., 2024) and subsequently increased to 1.43 +/-xx when the number of matchups increased to (Brown et al. 2025).

Current good practice attempts to improve Type B validation by performing Type A validation conditional on both land cover and and then assuming if the land cover and of the measurement being validated match (Fernandes et al., 2014). This approach is flawed:

is a function of so estimates of for a specific land cover and may be biased when applied to product measurements,

is only available for reference measurement sites so the approach cannot be applied synoptically without assuming a relationship between and ,

and, even if a relationship between and can be calibrated, for example over reference sites, there are many influence factors besides the LAI/FAPAR measurand, for example soil and canopy optical properties, canopy clumping, leaf angle, and acquisition geometry.

The limitations of current response design raises the first research question:

*Q1* How *can the inclusion probability of mapping units in synoptic LAI/FAPAR products be modelled given available matchups over FRM?*

### Response Design

The response design includes

1. defining the RM measurand and the approach for assessing the uncertainty and apparent bias of (not to be confused with product uncertainty)
2. specifying how is estimated when comparing RM and at a matchup and how the additional uncertainty due to this estimation is quantified.

RM definition has been a source of confusion for many LAI/FAPAR validation studies (Fernandes et al., 2014; Fang et al., 2019). Uncertainty estimates of FRM () can be modelled using combinations of Type A and Type B methods (Brown et al. 2025). These uncertainty estimates can be improved, especially with respect to biases that are also difficult to quantify since they depend on destructive sampling for LAI (Stenberg et al., 1994; Mason et al., 2012; Malone et al., 2002; Demarez, et al., 2008) and digital twins for FAPAR (Lanconelli et al., 2024). Addressing gaps in methods for quantifying FRM uncertainty and apparent bias are outside the scope of this method as FRM require in-situ rather than remote sensing surveys.

The process of determining matchups will generally result in greater uncertainty of the apparent error for a matchup () in comparison to since FRM and product measurements do not exactly match an assessment unit in time and space. The will depend on the matchup method given a set of product measurements for an AU and set of FRM for the same AU :

1. simple average: where the overbar corresponds to a simple average
2. land cover weighted average: where the overbar corresponds to an average weighted by the area of land cover in the AU matching the land cover of each of
3. fiducial reference estimates: where is a **transfer function** that ideally provides an unbiased estimate of given measurements of auxillary variables for the AU. The requirement for unbiasedness is usually satisfied by using regression functions calibrated using a set of that is assumed representative of the AU. Examples of include geostatistical interpolation where corresponds to location and regression estimators where corresponds to multispectral imagery (VALERI, xx).

The bias of FRE estimates of is often *assumed* negligible through the use of robust estimators of the expected value of FRM (Fernandes et al. 2003; Camacho et al., 2024) or regression estimators that account for measurement errors in regressors and response (Fernandes and Leblanc, 2006; Tang et al., xx; Camacho et al., 2024). This assumption is incorrect as there is no such regression estimators that is a prior unbiased although the Thiel-Sen regression estimate is consistent a priori (Fernandes and Leblanc, 2006). Additionally, all regression approaches will be biased the FRM are not representative of the AU. The first two approaches, based only on FRM in an AU, will likely be spatially representative of a <=250m resolution MMU but may not be representative with respect to the time of the matchup. This suggests that FRM should be supplemented by FRE to increase the inclusion probability of validation experiments.

For matchups using only FRM, and can be modelled as the Euclidean sum of the FRM standard uncertainty and the standard error of FRM estimates within the AU (Brown et al., 2021). For matchups using FRE, previous studies have assumed (VALERI, Baret et al., 2021) or used regression confidence intervals rather than prediction intervals (Brown et al., 2020; Camacho yet al. 2024). Both of these approaches will likely underestimate of . This concern is addressed by the second research question:

Q2 How can the additional RM uncertainty and bias due to matchup error be quantified?

### Analysis

1. CEOS Stage 3 validation requires estimates of the probability that a product measurement conforms to tolerance limits for standard uncertainty, relative standard uncertainty and stability
2. Methods for assessing GCOS requirements for stability are outside our scope as the number of locations with long term matchups (Djamai et al. 2025) are currently insufficient to consider a Stage 3 or 4 validation.
3. Conformity to MPE has been previously addressed using a simple acceptance approach, that does not account for matchup uncertainty, but GCOS uncertainty tolerance limits were incorrectly applied (Brown et al. 2021, Fernandes et al., 2023,2024,2025). Confusion with respect to terminology remains within CEOS and the wider scientific literature. For example, a number of CEOS good practice documents use the terms “accuracy” for bias, “precision” for uncertainty, and “uncertainty” Fernandes et al., 2014 ; Doxani et al. 2018). The situation with respect to terms has improved with recent FRM methods (Brown et al. 2021) and with the use of FRM for validation (Brown et al., 2025) and conformity testing (Camacho et al., 2024).
4. Most studies test conformity and report validation parameters from observed matchups conditioned only land cover. This violates the fundamental JGCM assumption that the conditions considered by a Type A estimate are repeatable and representative of the conditions of an arbitrary product measurement. This violation can result in biases in parameter estimates due to sampling effects (see Section 1.4.1) and due to differences in conditions within a land cover class. For example, the of Sentinel-2 LAI estimates from the Simplified Level 2 Prototype Processor for 203 matchups for 74 deciduous broadleaf (DBF) sites in North America was 1.18 +/-0.03 but ranged from 0.02 +/- at reference LAI 1 to 2.6 +/- 0.04 at reference LAI 6 (Fernandes et al., 2023).
5. Current good practice recommends quantifying thematic quality conditional on both land cover and (Fernandes et al., 2014) . This increases the likelihood that conditions for a validation parameter are repeatable but resulting conformity tests apply to the conditions of reference measurement and not conditions of other product measurement . Instead, good practices should require estimating conformity and associated parameters conditioned on land cover and so that validation experiments conducted over limited matchups can be associated with synoptic product estimates. To address the research gap is addressed this study addresses the question:
6. Q3. Analysis: How can conformity to GCOS requirements to , and estimates of be analyzed conditional on land cover and in a manner consistent with assumptions of representativeness and accounting for matchup error.

## 1.7 Scope and Novelty

Section 2 documents the measured and simulated datasets used to demonstrate methods. Section 3 describes methods used to address the research questions. The impact of these methods is assessed in Section 4 by validating available datasets and comparing these results with validation statistics using current validation good practices. The implications and limitations of our findings are discussed in Section 5 together with other approaches that should be considered. Conclusions related to our research questions, to the extent possible, are provided in Section 6.

Limitations to scope xx.

Novelty xx.

# 2.Data Sets

## 2.1 Satellite Data Records

### 2.1.1 S2 L2B reflectance with HLS S30 FMASK and S2 Cloudless for cloud masking

The HLS30 FMASK and S2 cloudless mask will be used only to improve the S2 L2B Sen2cor mask. We will use S2L2B only for brevity (we could use HLS L30 and S30 but beyond scope).

Note – this data will be extracted for all grounded-EO sites and a geographical global sampling for demonstration of product validation. We will also use it to produce FRE for perhaps 2 sites.

### 2.1.2 ESA Global Land Cover at 10m

Note – this is not perfect but will be used to demonstrate methodology.

### 2.1.3 Resolve Ecoregions

Note – this is not perfect but will be used to demonstrate methodology.

## 2.2 Decametric Resolution Products

### 2.2.1 SL2P LAI and FAPAR estimated for a global sample of S2 FDRs and for S2 FDRs over FRM and FRE

This is already extracted for GROUNDED EO for +/-1d of measurements but we will extract for +/-7d as well.

### 2.2.2 GEDI PAI

From Wang et al., 2025 for two NEON sites – will need correction for geolocation.

## 2.3 Matchups with FRM

### 2.3.1 GROUNDED EO Brown et al. 2025.

GROUNDED EO corresponds to xx LAI and xx FAPAR FRM over xx sites spanning xx land cover classes in the US, EU and AU.

(Note – we will need to update FRM uncertainty using consensus error models)

(Note – there are many other datasets but we only want to demonstrate the method and not apply it)

### 2.3.2 GEDI matchups Wang et al. 2025

GEDI PAI matchups with NEON PAI (we will convert to LAI) for all sites.

NEON ALS matchups with NEON PAI (we will convert to LAI) for two sites..



Figure 2. NEON areas with GEDI measurements. From Wang et al. 2025.

## 2.4 Simulated datasets

### 2.4.1 FLIGHT simulations of forests for S2 bands similar to Fernandes et al. 2024.

A radiative transfer (RT) model corresponding to FLIGHT canopy RT model and PROSPECT5 leaf RT model was used to simulate sentinel 2 top of canopy bi=directional reflectance for conditions typical of North American forests (Fernandes et al. 2024). FLIGHT was used as it’s uncertainty is well characterized and falls within the ensemble of reference canopy RT models (Widlowski et al. xx). These simulations were used to verify theoretical aspects of validation experiments.

# 3. Methods

## Sample Design

A sample design is required since a Type B validation, that assigns a prior pdf to observed apparent errors, implies apparent errors are sampled for a set of conditions drawn from a sampling distribution of apparent errors, .

### 3.1.1 Design Based Inference

Design based inference allows the estimation of statistics about a sampling distribution using measurements from samples of the distribution. In design based inference, samples correspond to a **probability sample** selected by a random mechanism such that the probability of observing each condition in the sampling distribution is known and exceeds zero (Stehman and Foody, 2019). For some measurement devices, samples can be drawn in a manner that the sampling distribution includes all conditions of interest, for example a ruler is validated across a range of temperatures in a lab. This strategy is not feasible for LAI/FAPAR product measurements because:

1. is large, it includes many aspects of the environment and sensor,
2. we rarely have access to replicate matchups for each or even each ,
3. and is generally not known.

To address these limitations we define the corresponds to unique values of land cover and since:

1. both land cover and are statistically related to apparent errors,
2. we have sufficient replicate matchups to estimate statistics for such conditions with some degree of confidence,
3. and land cover and are known for each measurement.

However, there will still be other effects, such as canopy clumping, canopy optical properties, soil properties and sensor acquisition geometry, that could result in systematic differences in for each unique land cover and . To address this limitation we censor matchups with low for a given land cover even though censoring will restrict the representativeness of validation statistics.

Censoring requires a prior model of .The dispersion of is skewed due to the nonlinear relationship of FDRs and and truncated because has physical limits ( for LAI for FAPAR) (Figure 3 and Figure 4). As a result, we model as truncated Normal or Cauchy distributions. These distributions was selected as they maximize the Shannon entropy given constraints on the truncated mean and variance, for truncated Normal, or median and median absolute deviation, for truncated Cauchy. Rather than binning residuals for a when estimating the parameters of we used weighted estimates of parameters given a prior pdf for from the product estimate (here we used the SL2P prior):

(1)

(2)

Note weighted median and median absolute deviations were estimated in a similar manner but cannot be written analytically.

A group of colored lines

AI-generated content may be incorrect.

Figure 3. Scatter plots of estimated LAI versus observed residuals over FRM coloured according to cumulative probability of residual conditions on estimated LAI for (left) Truncated Normal and (right) Truncated Cauchy prior distributions. Black circles fall outside 99.7%ile central confidence interval of conditional residuals. Conditional 75%ile (green curve), 50%ile (orange curve) and 25%ile (red curve) are indicated as well.

A group of colored lines

AI-generated content may be incorrect.

Figure 4. Scatter plots of estimated FAPAR versus observed residuals over FRM coloured according to cumulative probability of residual conditions on estimated FAPAR for (left) Truncated Normal and (right) Truncated Cauchy prior distributions. Black circles fall outside 99.7%ile central confidence interval of conditional residuals. Conditional 75%ile (green curve), 50%ile (orange curve) and 25%ile (red curve) are indicated as well.

We censor by discarding matchups where falls outside the k%ile central interval. Such censoring can only be performed explicitly over matchups where both and are available. However, if is a linear function of some that we can observe coincident with any it follows that will be greater than the minimum within the convex hull of of matchups that contain . We use Harmonized Landsat and Sentinel-2 FDRs to estimate since they offer synoptic coverage with high temporal revisit. To increase the likelihood that is a linear function of we use embeddings from the SL2P algorithm for estimating LAI/FAPAR uncertainty. The SL2P algorithm uses shallow neural networks where linear combination of 5 hidden nodes, the embeddings, predict uncertainty given inputs from S2 or Landsat surface reflectance and acquisition geometry. The convex hull of associated with FRM samples corresponding to a minimum is used to censor (Figure 5, Figure 6).

A screenshot of a graph

AI-generated content may be incorrect.

Figure 5. Density plots (blue) of estimated LAI versus estimated LAI residuals based on SL2P (based on PROSAIL) together with samples within the convex hull of FRM matchups with inclusion probability falling within the 68%ile central interval (red) and the 99.7%ile central inverval (yellow).

A screenshot of a graph

AI-generated content may be incorrect.

Figure 6. Density plots (blue) of estimated FAPAR versus estimated FAPAR residuals based on SL2P (based on PROSAIL) together with samples within the convex hull of FRM matchups with within the 68%ile central interval (red) and the 99.7%ile central inverval (yellow). The percentage of simulations included is indicated in the title , with the higher value corresponding to the 99.7%ile interval.

## 3.2 Response Design

The response design includes the specification of FRM, , the method to produce match-ups and modelling matchup uncertainty.

### **3.2.1 FRM**

FRM should ideally:

1. Have documented SI traceability (or conform to appropriate international community standards), utilising instruments that have been characterised using metrological standards.
2. Be statistically independent from the satellite bio-geophysical retrieval process.
3. Be accompanied by an uncertainty budget for all instruments, derived measurements and validation methods.
4. Adhere to community-agreed, published and openly available measurement protocols/procedures and management practices.
5. Be accessible to other researchers allowing independent verification of processing systems.

Here, the Grounded EO FRM data are used. Other FRM data are listed in Supplementary Material S3)

### **3.2.1.1 FRM Bias**

FRM are assumed to be unbiased estimates of LAI and FAPAR measurands. Biases due to ignoring clumping (Figure 2), woody matter (Figure 3, Figure 4) or missing understory measurements (Figure 5, Figure 6) can exceed xx% of LAI and xx% of FAPAR.

#### 3.2.1.1.1 FRM Bias Correction

Regressions are used to fit land cover specific correction factors are fit to measurements and applied to FRM missing these corrections(Supplementary Material S3). The prediction confidence intervals of these regression fits are included in the FRM uncertainty model.

FRM4VEG methods are used to estimate FRM uncertainty (Figure 7).

A graph with a number of words

AI-generated content may be incorrect.

Figure 7. Grounded EO FRM with standard uncertainty.

### **3.2.2 Matchups**

We compare FRM only and FRE approaches for matchups. The FRE approach will include a univariate linear regression and a multivariate linear regression (GPR?).

#### 3.2.2.1 Fiducial Reference Measurements

The Grounded EO approach was used to produce matchups using FRM only.

1. The ESU was modelled as a function of canopy height, in-situ sample design and field of view of each in-situ input measurement.
2. The assessment unit corresponded to set of nominal product measurement footprints that overlap the estimated footprint of the ESU.
3. FRM measurements for the AU were paired with mean corresponding Sentinel-2 product measurements acquired within one day

##### 3.2.2.1.1 Temporal window sensitivity

Do we deal with this?

##### 3.2.2.1.2 Robust estimators of mean

Other studies used a trimmed mean is used minimize the effect of outliers due to poor geolocation or FDR input. The trimming corresponded to discarding the 20% of S2 product measurements with the largest difference to the FRM. (Fernandes et al., 2023)

##### 3.2.2.1.3 Uncertainty

The matchup uncertainty is estimated as the Euclidean sum of the standard error of the mean of products and the FRM uncertainty. NOTE – we are putting the product standard error here and not as part of the product uncertainty since an it should not be attributed to product errors for a single product measurement.

**FRM uncertainty is required for conformity testing and estimating apparent errors.**

Similar to product validation, a combination of Type A uncertainty evaluation and Type B uncertainty evaluation can be used to quantify the FRM uncertainty. Irrespective,

FRM are associated with an elementary sampling unit (ESU) defined as a, usually uninterrupted, interval in space and time.

ESU Measurement Uncertainty Model

Exhaustive destructive measurement can be used to quantify Type A LAI uncertainty although this is rarely performed. As a result the uncertainty of ESU measurements of LAI and FAPAR will rely on a combination of Type A and Type B uncertainty based on a model for uncertainty propagation. This uncertainty model (e.g. Figure 4) consists of components related to sampling and components related to instrumentation that we assume are independent and combine using a Euclidean sum or standard errors (for Type A) and standard deviations (for Type B). Models are required for all measurement approaches (Table 4,Table 5).

*Table 4. LAIFRM Models*

|  |  |  |  |
| --- | --- | --- | --- |
| Name | Instrument | Measurand | Considerations |
| ICOS LAI-2200 | LAI-2200 | LAI | woody correction, understory data, clumping correction |
| GBOV DHP | DHP | LAI | woody correction, understory data, clumping correction |

*Table 5 FAPAR FRM Models*

|  |  |  |  |
| --- | --- | --- | --- |
| Name | Instrument | Measurand | Considerations |
| ICOS-Radiometer | LICOR PAR sensor | Ambient APAR | woody correction, understory data, moss |
| GBOV DHP | DHP | Direct APAR at 10:30am | woody correction, understory data, moss |

A diagram of a black camera

AI-generated content may be incorrect.

Figure 8. FRM4 veg uncertainty model for FIPAR and LAI (the figure will need to be modified to include WAI as input).

#### 3.2.2.2 Fiducial Reference Estimates

In some cases it is desirable to have RM estimated over spatial or temporal extents sufficiently different from the ESUs corresponding to a FRM that the FRM uncertainty may not be applicable.

Such estimates, when associated with an uncertainty traceable to FRM are labelled fiducial reference estimates (FRE).

FRE is then an exercise in modelling estimates of LAI/FAPAR and their uncertainty given FRM and ancillary information such as location, time period, other aspects of condition (Section xx), and remote sensing measurements at a resolution similar or finer that the size of an ESU.

FRE use **predictors** calibrated with FRM paired with regressors based on auxiliary geospatial information

**Linear regression predictors** that offer **prediction confidence intervals** are recommended since these intervals are statistically efficient within the convex hull of regressors.

**Regressors** could include products from other sensors, or airborne or satellite imagery as long as they are independent of the product.

##### 3.2.2.2.1 Univariate Linear Models

In cases where the regression relationship can be assumed univariate linear based on exploratory data analysis or expert knowledge (e.g. a ALS lidar estimate of PAI is likely linearly related to LAI for restricted land cover conditions) the Thiel Sen regression can be used to include measurement error in the regressors.

I propose to use as an example this result from Wang et al. <https://doi.org/10.1016/j.agrformet.2025.110612> where we calibrate an estimate of DHP LAI as a function of ALS PAI or alternatively a NDVI-FAPAR calibration from GroundedEO S2 matchups.

Figure: Example of this over neon site with GEDI PAI.

##### 3.2.2.2.2 Multivariate Linear Models

Multivariate models are required when expert knowledge does not indicate a univariate linear relationship.

###### 3.2.2.2.2.1 Dealing with Regressor Measurement Error

In other cases, the calibration database can be augmented with measurements of which synthetic error is added. If so, the regression confidence interval should be increased ](first approximation is ratio of the square root of augmented measurements to square root of initial measurements).

###### 3.2.2.2.2.2 Feature Selection

It is preferrable to use models that have a low intrinsic dimensionality of input features to maximize the likelihood future measurements of regressors are within the convex hull of the calibration dataset regressors. We test:

* + - 1. LASSO based on a library of vegetation indices
      2. Taking the hidden layer of the SL2P networks for LAI/FAPAR.
      3. Others …

###### 3.2.2.2.2.3 Regression Model

Maybe site specific GPRs since Grounded EO shows it is reasonable.

Figure: Example of this over neon site with S2 LAI and FAPAR.

### 3.2.3 Matchup Uncertainty

Matchups correspond to assessment units (AU) corresponding to intervals in space and time that include either FRM or FRE from ESUs in the AU and product measurements in the AU. For convenience the AU corresponds closely to the target MMU of 100m x 100m.

The uncertainty of residuals over an AU between product and reference estimates is modelled as a function of independent sources:

* Within AU variability. This corresponds to the Euclidean sum of the standard error of PM and RM in the AU across space and time.
* Geolocation error: This corresponds to geolocation uncertainty of the product mapping units (PMU) considered in the match up. Geolocation uncertainty can be assessed by shifting the PMU relative to the AU (Type A) or, for very uniform large regions, can be assumed zero (Type B).
* Temporal mismatch error: This corresponds to the inclusion of PM for which the RM are not representative due to differences in time. The temporal matching error can be quantified by comparing residuals as a function of time interval.

Previous studies have used robust statistics to estimate residuals over an AU as a function of punctual residuals between RM and PM for overlapping ESUs and PMUs contained in the AU. For example, Fernandes et al. (2024) used the a trimmed mean that essentially assumes very large residuals are due to poor temporal or spatial matches. Here we will assess this strategy by comparing residuals for different temporal windows and residuals for small temporal windows but based on modelled AU footprints based on canopy height versus nominal footprints corresponding to the MMU (100m x 100m).

## 3.3 Analysis

The analysis protocol specifies the method for estimating validation statistics.

The analysis protocol specifies the method for estimating validation statistics.

GCOS requires and and for a MMU while the accuracy () is also often of interest. Here, the estimation of and since and is accompanied by estimate of the apparent bias , that may be useful to correct products. Estimation of is not covered partly for brevity and partly due to the limited access to long term RM.

Validation statistics are first estimated using FRM only for product measurement mapping units (PMU) assuming AUs for matchups have similar characteristics as PMUs. Statistics are then also estimated using FRE that cover entire PMUs.

### 3.3.1 FRM Validation for Product Mapping Units

Type B estimates of each quantity condition on land cover and are produced using Type A statistics from response designs assuming a prior for .

Fornormal prior, defining as the set of included FRM for a k%ile central interval (see 3.1) estimates of uncertainty and accuracy conditional on are :

(3)

(4)

where is the FRM measurement standard uncertainty.

The effective number of degrees of freedom, , for containing samples is:

(5)

The +/-1 standard deviation confidence interval of , s estimated as:

(6)

The +/-1 standard deviation confidence interval of , s estimated as:

(7)

For Cauchy prior the weighted standard deviation is undefined. Instead we approximate the weighted standard deviation using where is the weighted median absolute deviation to weigh the ith sample. The factor 1.83 is required to match the central confidence interval corresponding to +/-1 standard deviation for a normal prior. Defining as the set FRM samples with , estimates of uncertainty and accuracy conditional on are :

(8)

The +/-1 standard deviation confidence interval of , is estimated as:

(9)

The +/-1 standard deviation confidence interval of , s estimated as:

(10)

Figure xx shows that the relative confidence intervals are generally very small for n>xx which is the case for conditioning on Land Cover and

In principle one could condition on an arbitrary subset of conditions using a local prior parmeterized using weighted nearest neighbour statistics. This strategy has two issues: i. the confidence intervals of estimated validation statistics will increase due to decreased n and ii. the assumption that we can identify conditions in product measurements using x from some other data now becomes more critical since the convex hull of x for a given inclusion probability is far smaller.

### 3.3.2 Validation for Minimum Mapping Units

Random errors will decrease for products whose product mapping units are smaller than the required minimum mapping unit. The decrease will be proportional to the square root of product measurements in a MMU and inversely proportional to the correlation of product errors within the MMU. In the absence of prior knowledge the correlation will be uniform between 0 and 1 with an expected value of 0.5. For example, for S2 20m products with 100m MMUs we have a reduction factor between 0 and 5 with an expected value of 2.5.

We need to quantify the real error correlations. This can be done by quantifying errors with FRE maps and averaging. We will show an example for one neon site.

Figure 3.2.1 PDF of error correlations for selected neon sites.

Figure 3.2.2. LAI analysis

Uncertainty LAI Accuracy and Bias LAI

A graph of different colored lines

AI-generated content may be incorrect.

Figure 3.2.3 FAPAR Analysis

Uncertainty FAPAR Bias and Accuracy FAPAR

A graph of different colored lines

AI-generated content may be incorrect.

# 4. Results

## 4.1 Inclusion Probabilities

Figure 4.1.1: Global Maps of Typical Inclusion Probability for Peak Season NH and Peak Season SH

## 4.2 Response Design

Figure 4.2.1: FRM Bias components for LAI: a. no clumping, b. no woody area, c. no understory

Figure 4.2.2 : FRM Uncertainty vs LAI, with a) local corrections, b) approximate correction for clumping c) approximate correction for woody area d) approximate correction for understory

Figure 4.2.3 : FRM Uncertainty vs FAPAR, with a) local corrections, b) approximate correction for clumping c) approximate correction for woody area d) approximate correction for understory

Figure 4.2.4: Example of LAI estimation using ALS over NEON site: a) scatter plot of estimated vs predicted LAI with prediction confidence intervals b) image of high resolution predictions with non representative areas masked c) image of predictions at scale of AUs d) image of uncertainty at scale of AUs

Figure 4.2.5: Example of LAI estimation using S2 with Grounded EO GPR over NEON site: a) scatter plot of estimated vs predicted LAI with prediction confidence intervals b) image of high resolution predictions with non representative areas masked c) image of predictions at scale pf AUs d) image of uncertainty at scale of AUs

Figure 4.2.6: Example of FAPAR estimation using S2 with Grounded EO GPR over NEON site: a) scatter plot of estimated vs predicted LAI with prediction confidence intervals b) image of high resolution predictions with non representative areas masked c) image of predictions at scale pf AUs d) image of uncertainty at scale of AUs

## 4.3 Analysis

This will supplement the conditional uncertainty and accuracy figures I have included for now in methods.

For SL2P with S2 FDRs (we can add GEDI but the fact that it will have a lot of bias may mean we don’t make global maps)

Figure 4.3.1 Figure showing estimated change in uncertainty as a function of MMU resolution based on errors over FRE.

Figure 4.3.1 Global map of bias and apparent accuracy for NH and SH peak season for LAI

Figure 4.3.2 Global map of bias and apparent accuracy for NH and SH peak season for FAPAR

Figure 4.3.3 Global map of uncertainty and relative uncertainty for NH and SH peak season for LAI

Figure 4.3.4 Global map of uncertainty and relative uncertainty for NH and SH peak season for FAPAR

Figure 4.3.5 Global map of probability of conforming to GCOS uncertainty for NH and SH peak season for LAI

Figure 4.3.6 Global map of probability of conforming to GCOS uncertainty for NH and SH peak season for FAPAR

# Section 5 Discussion

# Section 6 Conclusion

# Acknowledgements

# References

Brown LA, Camacho F, García-Santos V, Origo N, Fuster B, Morris H, Pastor-Guzman J, Sánchez-Zapero J, Morrone R, Ryder J, et al. Fiducial Reference Measurements for Vegetation Bio-Geophysical Variables: An End-to-End Uncertainty Evaluation Framework. Remote Sensing. 2021; 13(16):3194. <https://doi.org/10.3390/rs13163194>

Brown, L. A., Meier, C., Morris, H., Pastor-Guzman, J., Bai, G., Lerebourg, C., Gobron, N., Lanconelli, C., Clerici, M., & Dash, J. (2020). Evaluation of global leaf area index and fraction of absorbed photosynthetically active radiation products over North America using Copernicus Ground Based Observations for Validation data. *Remote Sensing of Environment, 247,* 111935.

Brown, L., Fernandes, R., Djamai, N., Meier, C., Gobron, N., Morris, H., Canisius, F., Bai, G., Lerebourg, C., Lanconelli, C., Clerici, M., & Dash, J. (2021). Validation of baseline and modified Sentinel-2 Level 2 Prototype Processor leaf area index retrievals over the United States. ISPRS Journal of Photogrammetry and Remote Sensing, 175, 71–87. <https://doi.org/10.1016/j.isprsjprs.2021.02.020>

Brown, L.A., Fernandes, R., Verrelst, J., Morris, H., Djamai, N., Reyez-Muñoz, P., D.Kovács, D., Meier, C. (2025). GROUNDED EO: Data-driven Sentinel-2 LAI and FAPAR retrieval using Gaussian processes trained with extensive fiducial reference measurements, *Remote Sens. Environ.,* [*https://doi.org/10.1016/j.rse.2025.114797*](https://doi.org/10.1016/j.rse.2025.114797)*.*

Camacho F, Martínez-Sánchez E, Brown LA, Morris H, Morrone R, Williams O, Dash J, Origo N, Sánchez-Zapero J, Boccia V. Validation and Conformity Testing of Sentinel-3 Green Instantaneous FAPAR and Canopy Chlorophyll Content Products. *Remote Sensing*. 2024; 16(15):2698. <https://doi.org/10.3390/rs16152698>

Camacho, F., García-Haro, F. J., Sánchez-Zapero, J., & Fuster, B. (201a). The EUMETSAT Satellite Application Facility on Land Surface Analysis: Validation report – MSG/SEVIRI vegetation parameters (VEGA) (Issue 3.1, Reference No. SAF/LAND/UV/VR\_VEGA\_MSG). EUMETSAT.

Camacho, F., García-Haro, F.J., Sánchez-Zapero, J. Fuster, N. (2018b). Validation Report MSG/SEVIRI Vegetation Parameters (VEGA), Ref: SAF/LAND/UV/VR\_VEGA\_MSG Issue: Version 3.1 Updated: 6 March 2018, accessed at <https://nextcloud.lsasvcs.ipma.pt/s/LbAmqBTB3Q2tbQP?dir=/VR-Validation_Report&openfile=true> on September 25, 2025.

Campos-Taberner, M., García-Haro, F. J., Camps-Valls, G., Grau-Muedra, G., Nutini, F., Busetto, L., Katsantonis, D., Stavrakoudis, D., Minakou, C., Gatti, L., Barbieri, M., Holecz, F., Stroppiana, D., & Boschetti, M. (2017). Exploitation of SAR and Optical Sentinel Data to Detect Rice Crop and Estimate Seasonal Dynamics of Leaf Area Index. *Remote Sensing*, *9*(3), 248. <https://doi.org/10.3390/rs9030248>

Cao, S., Li, M., Zhu, Z., Wang, Z., Zha, J., Zhao, W., Duanmu, Z., Chen, J., Zheng, Y., Chen, Y., Myneni, R. B., and Piao, S. (2023). Spatiotemporally consistent global dataset of the GIMMS leaf area index (GIMMS LAI4g) from 1982 to 2020, Earth Syst. Sci. Data, 15, 4877–4899, https://doi.org/10.5194/essd-15-4877-2023.

CEOS, (2008). Committee on Earth Observation Satellites Working Group on Information Systems and Services Interoperability Handbook, Issue 1.1, <http://ceos.org/document_management/Working_Groups/WGISS/Documents/WGISS_CEOS-Interoperability-Handbook_Feb2008.pdf>.

CEOS, 2018. [Space Agency Response to GCOS Implementation Plan, version 2.2.1](https://ceos.org/document_management/Working_Groups/WGClimate/Documents/Space%20Agency%20Response%20to%20GCOS%20IP%20v2.2.1.pdf), © The Joint CEOS/CGMS Working Group on Climate (WGClimate), 2018.

Djamai, N., Fernandes, R., Sun, L., Hong, G., Brown, L., Morris, H., & Dash, J. (2025). On the consistency and stability of vegetation biophysical variables retrievals from Landsat-8/9 and Sentinel-2. ISPRS Journal of Photogrammetry and Remote Sensing, 224, 329–347. <https://doi.org/10.1016/j.isprsjprs.2025.04.006>

Dubayah, R., Blair, J. B., Goetz, S., Fatoyinbo, L., Hansen, M., Healey, S., Hofton, M., Hurtt, G., Kellner, J., Luthcke, S., Armston, J., Tang, H., Duncanson, L., Hancock, S., Jantz, P., Marselis, S., Patterson, P. L., Qi, W., & Silva, C. (2020). The Global Ecosystem Dynamics Investigation: High-resolution laser ranging of the Earth’s forests and topography. Science of Remote Sensing, 1, 100002. <https://doi.org/10.1016/j.srs.2020.100002>

Environ. Sci. Pol., 51, pp. 149-169, <https://doi.org/10.1016/j.envsci.2015.03.018>.

European Space Agency. (2007, February 19). *Sentinel-3 mission requirements document* (Doc. No. EOP-SM/1151/MD-md v2.0). European Space Agency.

European Space Agency. (2010, March). *Copernicus Sentinel-2 mission requirements document* (Document No. EOP-SM/1163/MR-dr, i2r0). [https://www.esa.int/Applications/Observing\_the\_Earth/Earth\_observation\_library/Satellite\_mission\_documents](https://www.esa.int/Applications/Observing_the_Earth/Earth_observation_library/Satellite_mission_documents?utm_source=chatgpt.com)

Fang, H. et al., (2019b). Validation of global moderate resolution leaf area index (LAI) products over croplands in northeastern China. Remote Sens. Environ., 233, 111377.

Fang, H., Baret, F., Plummer, S., & Schaepman-Strub, G. (2019a). An overview of global leaf area index (LAI): Methods, products, validation, and applications. *Reviews of Geophysics*. 57, 739–799. <https://doi.org/10.1029/2018RG000608>

FAO. 2025. Global Forest Resources Assessment 2025. Rome. https://doi.org/10.4060/cd6709en

Fernandes, R., Brown, L., Canisius, F., Dash, J., He, L., Hong, G., Huang, L., Le, N. Q., MacDougall, C., Meier, C., Darko, P. O., Shah, H., Spafford, L., & Sun, L. (2023). Validation of simplified level 2 prototype processor Sentinel-2 fraction of canopy cover, fraction of absorbed photosynthetically active radiation, and leaf area index products over North American forests. Remote Sensing of Environment, 293, Article 113600. <https://doi.org/10.1016/j.rse.2023.113600>

Fernandes, R., Djamai, N., Harvey, K., Hong, G., MacDougall, C., Shah, H., & Sun, L. (2024). Evidence of a bias-variance trade-off when correcting for bias in Sentinel-2 forest LAI retrievals using radiative transfer models. Remote Sensing of Environment, 305, Article 114060. <https://doi.org/10.1016/j.rse.2024.114060>

Fernandes, R., Plummer, S., Nightingale, J., Baret, F., Camacho, F., Fang, H., Garrigues, S., Gobron, N., Lang, M., Lacaze, R., Leblanc, S., Meroni, M., Martinez, B., Nilson, T., Pinty, B., Pisek, J., Sonnentag, O., Verger, A., Welles, J., Weiss, M., Widlowski, J.-L., Schaepman-Strub, G., Roman, M., Nickeson, J., 2014. Global Leaf Area Index Product Validation Good Practices, in: Fernandes, R., Plummer, S., Nightingale, J. (Eds.), Best Practice for Satellite-Derived Land Product Validation. Land Product Validation Subgroup (Committee on Earth Observation Satellites Working Group on Calibration and Validation). <https://doi.org/10.5067/doc/ceoswgcv/lpv/lai.002>

Fernandes, R., Tang, H., and Brown, L. (2024a). Proposed definition of leaf area index by the Committee of Earth Observation Satellites; Geomatics Canada, Open File 86, 7 p. <https://doi.org/10.4095/p9fzmg1djq>

Fernandes, R., Tang, H., and Brown, L. (2024b). Proposed definition of fraction of absorbed photosynthetically active radiation by the Committee of Earth Observation Satellites; Geomatics Canada, Open File 85, ver. 1.0, 6 p. <https://doi.org/10.4095/p3gy844zex>

Fuster, B., Sánchez-Zapero, J., Camacho, F., García-Santos, V., Verger, A., Lacaze, R., Weiss, M., Baret, F., & Smets, B. (2020). Quality Assessment of PROBA-V LAI, fAPAR and fCOVER Collection 300 m Products of Copernicus Global Land Service. *Remote Sensing*, *12*(6), 1017. <https://doi.org/10.3390/rs1206101>

GEOGLAM (2022). Full EAV table | AgVariables. Accessed at <https://agvariables.org/> on August 12, 2025.

Goryl, P., Fox, N., Donlon, C., & Castracane, P. (2023). Fiducial Reference Measurements (FRMs): What Are They? *Remote Sensing*, *15*(20), 5017. <https://doi.org/10.3390/rs15205017>

JGCM (2008). Evaluation of measurement data - Guide to the expression of uncertainty in measurement. JCGM 100:2008(E) – in English. <https://doi.org/10.59161/JCGM100-2008E>

JGCM (2012). The role of measurement uncertainty in conformity assessment. JCGM 106:2012 .<https://doi.org/10.59161/JCGM106-2012>

JGCM, (2021), International vocabulary of metrology—Basic and general concepts and associated terms,4th ed. Joint Committee for Guides in Metrology JCGM-WG2-CD-01. JGCM. (2020). Guide to the expression of uncertainty in measurement — Part 6: Developing and using measurement models. JCGM GUM-6:2020. https://doi.org/10.59161/JCGMGUM-6-2020

Ju, J., Zhou, Q., Freitag, B., Roy, D. P., Zhang, H. K., Sridhar, M., Mandel, J., Arab, S., Schmidt, G., Crawford, C. J., Gascon, F., Strobl, P. A., Masek, J. G., Neigh, C. S. R. (2025). The Harmonized Landsat and Sentinel-2 Version 2.0 Surface Reflectance Dataset. *Remote Sensing of Environment*, *324*, 114723. <https://doi.org/10.1016/j.rse.2025.114723>.

LANCONELLI, C., CAPPUCCI, F., ADAMS, J. and GOBRON, N., Evaluation of in situ FAPAR measurement protocols using 3D radiative transfer simulations, REMOTE SENSING, 16, 23, 2024, p. 4552, MDPI, https://data.europa.eu/doi/10.3390/rs16234552, JRC139442.

Ma, H. and Liang, S. (2022) . Development of the GLASS 250-m leaf area index product (version 6) from MODIS data using the bidirectional LSTM deep learning model Remote Sens. Environ., 273 (2022), Article 112985

Ma, H., Liang, S., Xiong, C., Wang, Q., Jia, A., and Li, B (2022). Global land surface 250 m 8 d fraction of absorbed photosynthetically active radiation (FAPAR) product from 2000 to 2021, Earth Syst. Sci. Data, 14, 5333–5347, https://doi.org/10.5194/essd-14-5333-2022.

Ma, H., Q. Wang, W. Li, Y. Chen, J. Xu, Y. Ma, J. Huang, and S. Liang (2025). The first gap-free 20 m 5-day LAI/FAPAR products over China (2018–2023) from integrated Landsat-8/9 and Sentinel-2 Analysis Ready Data. Remote Sensing of Environment, 331, 115048.DOI: 10.1016/j.rse.2025.115048.

Ma, H., Q. Wang, W. Li, Y. Chen, J. Xu, Y. Ma, J. Huang, and S. Liang (2025). The first gap-free 20 m 5-day LAI/FAPAR products over China (2018–2023) from integrated Landsat-8/9 and Sentinel-2 Analysis Ready Data. Remote Sensing of Environment, 331, 115048.DOI: 10.1016/j.rse.2025.115048.

Monteith, J. L. (1972). Solar Radiation and Productivity in Tropical Ecosystems. *Journal of Applied Ecology*, *9*(3), 747–766. https://doi.org/10.2307/2401901

Navarro, L.M., Fernández, N., Guerra, C., Guralnick, R., Kissling, W.D., Londoño, M.C., et al. (2017). Monitoring biodiversity change through effective global coordination. Curr. Opin. Environ. Sustain., 29, 158–169.

Origo, N., Gorroño, J., Ryder, J., Nightingale, J., & Bialek, A. (2020). Fiducial Reference Measurements for validation of Sentinel-2 and Proba-V surface reflectance products. Remote Sensing of Environment, 241, 111690, <https://doi.org/10.1016/j.rse.2020.111690>.

United Nations (2022). Guidelines on Biophysical Modelling for Ecosystem Accounting. United Nations Department of Economic and Social Affairs, Statistics Division, New York. [Biophysical modelling | System of Environmental Economic Accounting](https://seea.un.org/ecosystem-accounting/biophysical-modelling) accessed at <https://seea.un.org/ecosystem-accounting/biophysical-modelling> on August 12, 2025.

[Wang, Y., Fang, H., Li, Y., Li, S., & Tang, H. (2025). **Validation of the vertical plant area index profile product derived from GEDI over global forest sites.** *Agricultural and Forest Meteorology*, *371*, 110612.](https://www.sciencedirect.com/science/article/abs/pii/S0168192325002321)

[Wang, Y., Fang, H., Li, Y., Li, S., & Tang, H. (2025). **Validation of the vertical plant area index profile product derived from GEDI over global forest sites.** *Agricultural and Forest Meteorology*, *371*, 110612.](https://www.sciencedirect.com/science/article/abs/pii/S0168192325002321)

Watson, D.J. (1947). Comparative physiological studies in the growth of field crops. I. Variation in net assimilation rate and leaf area between species and varieties, and within and between years. *Annals* of Botany, 11, <https://doi.org/10.1093/oxfordjournals.aob.a083148>

Widlowski, J.-L., (2015). Conformity testing of satellite-derived quantitative surface variables

WMO (2022). GCOS Implementation Plan 2022: The Global Observing System for Climate. GCOS-245, GOOS-269, WMO- No. 1299. World Meteorological Organization. https://gcos.wmo.int/en/gcos-implementation-plan-2022

WMO (2025). The 2022 GCOS ECVs Requirements 2022 edition - Updated in 2025, GCOS-245,   
<https://library.wmo.int/idurl/4/58111>.

Xu, B., Li, J., Park, T., Liu, Q., Zeng, Y., Yin, G., Zhao, J., Fan, W., Yang, L., Knyazikhin, Y., & Myneni, R. B. (2018b). An integrated method for validating long-term leaf area index products using global networks of site-based measurements. *Remote Sensing of Environment, 209,* 134–151. <https://doi.org/10.1016/j.rse.2018.02.049>.

Xu, B., Park, T., Yan, K., Chen, C., Zeng, Y., Song, W., Yin, G., Li, J., Liu, Q, Knyazikhin, Y., Myneni, R.B. (2018a). Analysis of Global   LAI/FPAR Products from VIIRS and MODIS Sensors for Spatio-Temporal Consistency and Uncertainty from 2012–2016,   Forests, 2018, 9(2), 73. <http://doi.org/10.3390/f9020073>.

JCGM-100, 2008. Evaluation of Measurement data – Guide to the Expression of Uncertainty in Measurement (GUM 1995 With Minor Corrections), Joint Committee for Guides in Metrology, JCGM 100:2008. Available from <http://www.bipm.org/>

Box, George E. P..  Hunter, J.S., Hunter, W. (2005).**Statistics for experimenters : design, discovery, and innovation**, ., 2nd ed, Wiley, SBN: 978-0-471-71813-0.

WMO, (2025b). [INFCOM-3-d08-1(2)-WIGOS-GUIDE-AND-RWC- ...](https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwjorPGPy8-QAxX5pokEHdEZHckQFnoECBgQAQ&url=https%3A%2F%2Fmeetings.wmo.int%2FINFCOM-3%2FEnglish%2F2.%2520PROVISIONAL%2520REPORT%2520(Approved%2520documents)%2FINFCOM-3-d08-1(2)-WIGOS-GUIDE-AND-RWC-GUIDELINES-UPDATE-approved_en.docx&usg=AOvVaw0aJarYUJ76hFld4HK4cQHB&opi=89978449)

JCGM-106, 2012. Evaluation of Measurement Data – The role of Measurement Uncertainty in Conformity Assessment, JCGM 106:2012. Available from http://www.bipm.org/

WELMEC, 2006. Elements for Deciding the Appropriate Level of Confidence in Regulated Measurements, WELMEC 4.2, European co-operation in legal metrology. http://www. welmec.org/fileadmin/user\_files/publications/4-2.pdf.

Loew, A., et al. (2017), Validation practices for satellite-based Earth observation data across communities, *Rev. Geophys.*, 55, 779–817, doi:[10.1002/2017RG000562](https://doi.org/10.1002/2017RG000562).

Gobron N. et. al. 2008. Uncertainty estimates for the FAPAR operational products derived from MERIS — Impact of   TOA radiance uncertainties and validation with field data, *Remote Sensing of Environment*, Vol. 112, pp   1871&—1883, doi:10.1016/j.rse.2007.09.011.

Stehman, S. V., & Foody, G. M. (2019). Key Issues in Rigorous Accuracy Assessment of Land Cover Products. Remote Sensing of Environment, 231, Article ID: 111199.  
https://doi.org/10.1016/j.rse.2019.05.018

Mason et al., 2012. <https://doi.org/10.1016/j.agrformet.2012.06.013>

Malon et al., 2002. DOI:[10.2134/agronj2002.1012](https://doi.org/10.2134/agronj2002.1012?urlappend=%3Futm_source%3Dresearchgate)

Stenberg et al., 1994. <https://doi.org/10.1093/treephys/14.7-8-9.981>

Demarez, V., Sylvie Duthoit, Frédéric Baret, Marie Weiss, Gérard Dedieu. Estimation of leaf area

and clumping indexes of crops with hemispherical photographs. Agricultural and Forest Meteorology,

2008, 148 (4), pp.644-655. 10.1016/j.agrformet.2007.11.015. ird-00421578

Gower, S.T., Kucharik, C.J. and Norman, J.M. (1999) Direct and Indirect Estimation of Leaf Area Index, fAPAR, and Net Primary Production of Terrestrial Ecosystems. Remote Sensing of Environment, 70, 29-51.  
<http://dx.doi.org/10.1016/S0034-4257(99)00056-5>

Goryl, P., Fox, N., Donlon, C., & Castracane, P. (2023). Fiducial Reference Measurements (FRMs): What Are They? *Remote Sensing*, *15*(20), 5017. https://doi.org/10.3390/rs15205017

**Fang et al. (2013)**[**https://doi.org/10.1002/jgrg.20051**](https://doi.org/10.1002/jgrg.20051)

* **Brown, L.A.; Camacho, F.; García-Santos, V.; et al (2021). Fiducial Reference Measurements for Vegetation Bio-Geophysical Variables: An End-to-End Uncertainty Evaluation Framework. Remote Sens, 13, 3194.**
* **Camacho, F.; Fuster, B.; Li, W.; et al. (2021). Crop specific algorithms trained over ground measurements provide the best performance for GAI and fAPAR estimates from Landsat-8 observations. Remote Sens. Environ, 260, 112453.**

Frédéric Baret, Marie Weiss, Denis Allard, Sébastien Garrigues, Marc Leroy, et al.. VALERI: a

network of sites and a methodology for the validation of medium spatial resolution land satellite

products. 2021. hal-03221068

* Weiss et al., (2014). On Line Validation Exercise (OLIVE): A Web Based Service for the Validation of Medium Resolution Land Products. Application to FAPAR Products. Remote Sens, 6, 4190-4216

Cao, S., Li, M., Zhu, Z., Wang, Z., Zha, J., Zhao, W., Duanmu, Z., Chen, J., Zheng, Y., Chen, Y., Myneni, R. B., and Piao, S.: Spatiotemporally consistent global dataset of the GIMMS leaf area index (GIMMS LAI4g) from 1982 to 2020, Earth Syst. Sci. Data, 15, 4877–4899, https://doi.org/10.5194/essd-15-4877-2023, 2023.

Fernandes, R., Tang, H., and Brown, L., 2024. Proposed definition of leaf area index by the Committee of Earth Observation Satellites; Geomatics Canada, Open File 86, 7 p. <https://doi.org/10.4095/p9fzmg1djq>

Fernandes, R., Tang, H., and Brown, L., 2024. Proposed definition of fraction of absorbed photosynthetically activeradiation by the Committee of Earth Observation Satellites; Geomatics Canada, Open File 85, ver. 1.0, 6 p. <https://doi.org/10.4095/p3gy844zex>

Hu, Q., Yang, J., Xu, B., Huang, J., Memon, M. S., Yin, G., Zeng, Y., Zhao, J., & Liu, K. (2020). Evaluation of Global Decametric-Resolution LAI, FAPAR and FVC Estimates Derived from Sentinel-2 Imagery. *Remote Sensing*, *12*(6), 912. <https://doi.org/10.3390/rs12060912>

[Validation of global moderate resolution leaf area index (LAI) products over croplands in northeastern China - ScienceDirect](https://www.sciencedirect.com/science/article/pii/S0034425719303967)

[ValLAI\_Crop, a validation dataset for coarse-resolution satellite LAI products over Chinese cropland | Scientific Data](https://www.nature.com/articles/s41597-021-01024-4)

Document Reference ESA‐ECO‐EOPS‐WGCL‐RP‐17‐0061. Version 2.2.1

CEOS (2025). [Searchable Table of Earth Observation Satellite Missions | CEOS Database](https://database.eohandbook.com/database/missiontable.aspx), accessed at [https://database.eohandbook.com/database/missiontable.aspx on September 25](https://database.eohandbook.com/database/missiontable.aspx%20on%20September%2025), 2025.

*Fang, H., Baret, F., Plummer, S., & Schaepman-Strub, G. (2019). An overview of global leaf area index (LAI): Methods, products, validation, and applications. Reviews of Geophysics. 57, 739–799.*[***https://doi.org/10.1029/2018RG000608***](https://doi.org/10.1029/2018RG000608)

Fernandes, R., Butson, C., Leblanc, S., & Latifovic, R. (2003). Landsat-5 TM and Landsat-7 ETM+ based accuracy assessment of leaf area index products for Canada derived from SPOT-4 VEGETATION data. Canadian Journal of Remote Sensing, 29(2), 241–258. <https://doi.org/10.5589/m02-09>

Garrigues, S., et al. (2008), Validation and intercomparison of global Leaf Area Index products derived from remote sensing data, *J. Geophys. Res.*, 113, G02028, doi:[10.1029/2007JG000635](https://doi.org/10.1029/2007JG000635).

**JCGM, (2008). Evaluation of measurement data — Guide to the expression of uncertainty in measurement, JCGM 100:2008, https://doi.org/10.59161/JCGM100-2008E.**

Lu, X., Wang, X., & Yang, Z. (2023). Leaf area index estimation from the time-series SAR data using the AIEM-MWCM model. *International Journal of Digital Earth*, *16*(2), 4385–4403. https://doi.org/10.1080/17538947.2023.2271879

Pisek, J., & Chen, J. M. (2007). Comparison and validation of MODIS and VEGETATION global LAI products over four BigFoot sites in North America. *Remote Sensing of Environment, 109*(1), 81–94. <https://doi.org/10.1016/j.rse.2006.12.004>

Tao, X., Liang, S., & Wang, D. (2015). Assessment of five global satellite products of fraction of absorbed photosynthetically active radiation: Intercomparison and direct validation against ground-based data. *Remote Sensing of Environment, 163,* 270–285. <https://doi.org/10.1016/j.rse.2015.03.025>

*Frédéric Baret, Marie Weiss, Denis Allard, Sébastien Garrigues, Marc Leroy, et al.. VALERI: a*

*network of sites and a methodology for the validation of medium spatial resolution land satellite*

*products. 2021.*

*Cohen, Warren B.; Maiersperger, Thomas K.; Turner, David P.; Ritts, William D.; Pflugmacher, Dirk; Kennedy, Robert E.; Kirschbaum, Alan; Running, Steven W.; Costa, Marcos; Gower, Stith T. 2006. MODIS land cover and LAI collection 4 product quality across nine states in the western hemisphere. IEEE Transactions on Geoscience and Remote Sensing. 44(7): 1843-1857*

WMO (2022). The 2022 GCOS Implementation Plan (GCOS-244). World Meteorological Organization. Accessed at <https://library.wmo.int/records/item/58104-the-2022-gcos-implementation-plan-gcos-244>​[WMO e-Library](https://library.wmo.int/records/item/58104-the-2022-gcos-implementation-plan-gcos-244?offset=11&utm_source=chatgpt.com) on August 12, 2025.

WMO (2025). The 2022 GCOS ECV Requirements (GCOS-245). World Meteorological Organization. https://library.wmo.int/idurl/4/58111

Zhou, Q., Neigh, C. S. R., Ju, J., Dabney, P., Cook, B., Zhu, Z., Crawford, C. J., Gascon, F., Strobl, P., & Sridhar, M. (2025). Towards seamless global 30-meter terrestrial monitoring: Evaluating 2022 cloud free coverage of harmonized Landsat and Sentinel-2 (HLS) V2.0. *IEEE Geoscience and Remote Sensing Letters,* 1. <https://doi.org/10.1109/LGRS.2025.3533923>

Thompson, A. and Taylor, B. (2008). Guide for the use of international system of units (SI). NIST Special Publication 811, 2008 Edition, National Institute of Standards and Technology (NIST), https://doi.org/ 10.6028/NIST.SP.811e2008.

**CEOS. (2025). Table of Definitions. CEOS Missions, Instruments and Measurements Database, accessed at** [**https://database.eohandbook.com/survey/PDF/CEOS\_MIM\_DB\_TableDefinitionsAndValidValues.pdf on October 12**](https://database.eohandbook.com/survey/PDF/CEOS_MIM_DB_TableDefinitionsAndValidValues.pdf%20on%20October%2012)**, 2025.**

Dubayah, R., Tang, H., Armston, J., Luthcke, S., Hofton, M., & Blair, J. (2021). *GEDI L2B Canopy Cover and Vertical Profile Metrics Data Global Footprint Level V002* [Data set]. NASA Land Processes Distributed Active Archive Center. https://doi.org/10.5067/GEDI/GEDI02\_B.002 Date Accessed: 2025-11-03

# Supplementary Material 1

List of products.

# Supplementary Material 2

GroundedEO Exploratory Data Analysis

A graph of different colored lines

AI-generated content may be incorrect.

Figure 9. Effect of clumping on LAI (not figure is in terms of of PAI to isolate effect)

A collage of graphs

AI-generated content may be incorrect.

Figure 10. Effect of woody area on LAI.

A collage of graphs

AI-generated content may be incorrect.

Figure 11 Effect of woody area on FAPAR.

A group of graphs showing different types of data

AI-generated content may be incorrect.

Figure 12. Effect of understory on LAI

A group of graphs showing different types of data

AI-generated content may be incorrect.

Figure 13. Effect of undertsory on FAPAR.

# Supplementary Material 3

Correction factors (regressions) for FRM with missing measurement components.