CCI Vegetation

Product Validation Plan

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1 Executive summary

CCI Vegetation Parameters is part of the ESA Climate Change Initiative. It aims at the identification and the development and improvement of algorithms for the consistent retrieval of vegetation ECVs such as LAI and fAPAR from multi- platform and multi-mission satellite data and interact with the user community to match their requirements. The work plan includes three cycles, in which different data sources are combined and the algorithms' scientific and operational maturity is increased, and user feedback is incorporated.

This document describes the Product Validation Plan (PVP) used in cycle 1 of the project. Scientific Quality Assurance constitutes the means of guaranteeing the compliance of products with user requirements and new products must pass an exhaustive scientific evaluation before to be delivered to the users. The validation methodology follows, as much as possible, the guidelines, protocols and metrics defined by the CEOS WGCV LPV (Committee on Earth Observations Satellites Working Ground on Calibration and Validation Land Product Validation) group for the validation of LAI satellite-derived land products, and QA4EO (Quality Assurance for Earth Observation) recommendations.

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LIST OF ACRONYMS

4SAILH	Scattering of Arbitrarily Inclined Leaves, with 4-stream extension and hot-spot
AMMA	African Monsoon Multidisciplinary Analysis
ANN	Artificial Neural Network
APU	Accuracy, Precision and Uncertainty
B	Mean Bias
BHR	Bi-Hemispheric Reflectances
BRDF	Bidirectional reflectance distribution function
C3S	Copernicus Climate Change Service
CAL/VAL	CALibration/VALidation
CATCH	Cycle Atmosphérique et Cycle Hydrologique
CCI	Climate Change Initiative
CDR	Climate Data Record
CEOS	Committee on Earth Observation Satellites
CGLS	Copernicus Global Land Service
CUL	Cultivated
CYCLOPES (or CYC)	Carbon cYcle and Change in Land Observational Products from an Ensemble of Satellites
DBF	Deciduous Broadleaf Forest
EBF	Evergreen Broadleaf Forest
ECV	Essential Climate Variable
ESA	European Space Agency
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation
FRM4Veg	Fiducial Reference Measurements for Vegetation
GBOV	Ground-Based Observations for Validation
GPR	Gaussian Process
HER	Herbaceous
LAI	Leaf Area Index
LANDVAL	LAND VALidation
LTA	Long Term Average
LP	Land Products
LPV	Land Product Validation
LSA SAF	Land Surface Analysis - Satellite Application Facilities
MAD	Median Absolute Deviation
MAR	Major Axis Regression
MD	Median Deviation
MOD	MODIS products based on TERRA data
MODIS	Moderate Resolution Imaging Spectroradiometer
N	Number of samples
NASA	National Aeronautics and Space Administration
NLF	Needle-Leaf Forest
NIR	Near-InfraRed
OF	Other Forests
OLCI	Ocean and Land Colour Instrument
OLIVE	On Line Validation Exercise

OLS	Ordinary Least Squares
PDF	Probability Density Function
PROSPECT-D	simulation of leaf spectra, version D including senescence
PROBA-V	Project for On Board Autonomy – Vegetation
PROSAIL	Combined Model of Leaf Optical Properties Spectra (PROSPECT)+ Scattering by Arbitrary Inclined Leaves (SAIL) Model
PVP	Product Validation Plan
QFLAG	Quality FLAGs
R	Correlation coefficient
RM	Reference Measurements
RMSD	Root Mean Square Deviation
RTM	Radiative Transfer Model
SBA	Sparse and Bare areas
SHR	Shrublands
SPOT/VGT	Satellite Pour l'Observation de la Terre/VEGetation
STD	STandard Deviation
TARTES	Two-streAm Radiative TransfEr in Snow
TIP	Two-stream-Inversion-Package
TOC	Top-of-Canopy
VIS	VISible domain
WGCV	Working Group on Calibration and Validation

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2 Introduction

2.1 Scope of this document

This Validation Plan document provides a description of the whole product validation methodology for ESA CCI vegetation (LAI and FAPAR) products.

2.2 Related documents

Internal documents

Reference ID	Document
VP-CCI_D2.1_ATBD_V1.0	Algorithm Theoretical Basis Document: fAPAR and LAI, ESA CCI+ Vegetation Parameters

External documents

Reference ID	Document
GCOS-200, 2016	GCOS-200 (2016). The Global Observing System for Climate: Implementation Needs. WMO, Geneva, Switzerland https://library.wmo.int/opac/doc_num.php?explnum_id=3417
GCOS-154, 2011 Update	Systematic observation requirements for satellite-based data products for climate. Supplemental details to the satellite-based component of the “Implementation Plan for the GCOS in Support of the UNFCCC”. [GCOS-154, 2011 Update]. https://library.wmo.int/doc_num.php?explnum_id=3710
JCGM, 2014	JCGM, 2014. International Vocabulary of Metrology–Basic and General Concepts and Associated Terms, Chemistry International -- Newsmagazine for IUPAC. Walter de Gruyter GmbH. https://doi.org/10.1515/ci.2008.30.6.21
Fernandes, 2014	Global Leaf Area Index Product Validation Good Practices. Version 2.0. In G. Schaepman-Strub, M. Román, & J. Nickeson (Eds.), Best Practice for Satellite-Derived Land Product Validation (p. 76): Land Product Validation Subgroup (WGCV/CEOS) https://doi.org/10.5067/doc/ceoswgcv/lpv/lai.002
C3S_QAR_ LAI_fAPAR_v4	Product Quality Assessment Report: LAI and fAPAR v4.0 based on Sentinel-3 https://datastore.copernicus-climate.eu/documents/satellite-lai-fapar/D2.3.10-v4.1_PQAR_CDR-ICDR_LAI_FAPAR_SENTINEL3_v4.0_PRODUCTS_v1.1.pdf
C3S_QAR_ LAI_fAPAR_v3	Product Quality Assessment Report: Multi-sensor LAI and fAPAR v3.0 https://datastore.copernicus-climate.eu/documents/satellite-lai-fapar/D2.3.9-v3.0_PQAR_CDR_LAI_FAPAR_MULTI_SENSOR_v3.0_PRODUCTS_v1.1.pdf
C3S_QAR_ LAI_fAPAR_v2	Product Quality Assessment Report: LAI and fAPAR v2.0 based on PROBA-V https://datastore.copernicus-climate.eu/documents/satellite-lai-fapar/D2.3.8-v2.0_PQAR_CDR-ICDR_LAI_FAPAR_PROBAV_v2.0_PRODUCTS_v1.1.pdf
C3S_ATBD_	Algorithm Theoretical Basis Document: Sentinel-3 CDR and ICDR LAI and

LAI_fAPAR_v4	fAPAR v4.0 https://datastore.copernicus-climate.eu/documents/satellite-lai-fapar/D1.4.5-v4.0_ATBD_CDR-ICDR_LAI_FAPAR_SENTINEL3_v4.0_PRODUCTS_v1.0.pdf
C3S_ATBD_ LAI_fAPAR_v3	Algorithm Theoretical Basis Document: Multi-sensor CDR LAI and fAPAR v3.0 https://datastore.copernicus-climate.eu/documents/satellite-lai-fapar/D1.4.4-v3.0_ATBD_CDR_LAI_FAPAR_MULTI_SENSOR_v3.0_PRODUCTS_v1.0.1.pdf
C3S_ATBD_ LAI_fAPAR_v2	Algorithm Theoretical Basis Document: PROBA-V CDR and ICDR LAI and fAPAR v2.0 https://datastore.copernicus-climate.eu/documents/satellite-lai-fapar/D1.4.3-v2.0_ATBD_CDR-ICDR_LAI_FAPAR_PROBAV_v2.0_PRODUCTS_v1.0.pdf
CAN_EYE_UG	CAN_EYE V6.4.91 USER MANUAL. Updated October 10th 2017. https://www6.paca.inrae.fr/can-eye/content/download/3052/30819/version/4/file/CAN_EYE_User_Manual.pdf
CGLOPS_ATBD_PBV300_V1	ATBD for LAI, FAPAR and FCOVER from PROBA-V Collection 300m V1. https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/ImagineS_RP2.1_ATBD-LAI300m_I1.73.pdf
CGLOPS_ATBD_OLCI_V1.1	ATBD for LAI, FAPAR and FCOVER from Sentinel-3 OLCI Collection 300m V1.1. https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_ATBD_LAI300m-V1.1_I1.10.pdf

2.3 General definitions

- **CDR** (Climate Data Record): time series of measurements of sufficient length (typically multi-decadal), consistency, and continuity to determine climate variability and change.
- **Essential Climate Variable** (ECV) is a variable or group of related variables that critically contribute to the characterization of Earth's climate state and forcing.
- **Fraction of Absorbed Photosynthetically Active Radiation (fAPAR)** is defined as the fraction of Photosynthetically Active Radiation (PAR; solar radiation reaching the surface in the 400-700 nm spectral region) that is absorbed by a vegetation canopy [GCOS-200, 2016].
- **Leaf Area Index (LAI)** is defined as the total one-sided area of all leaves in the canopy within a defined region, and is a non-dimensional quantity, although units of [m2/m2] are often quoted, as a reminder of its meaning [GCOS-200, 2016].
- **Accuracy** is the degree of the “closeness of the agreement between the result of a measurement and a true value of the measurand” [JCGM, 2014]. Commonly, accuracy represents systematic errors and often is computed as the statistical mean bias, i.e., the difference between the short-term average measured value of a variable and the true value. The short-term average is the average of a sufficient number of successive measurements of the variable under identical conditions, such that the random error is negligible relative to the systematic error. The latter can be introduced by instrument biases or through the choice of remote sensing retrieval schemes [GCOS-200, 2016].
- **Precision** or repeatability is the “closeness of the agreement between the results of successive measurements of the same measurand carried out under the same conditions of measurement” [JCGM, 2014].
- **Uncertainty** is a “parameter, associated with the result of a measurement that characterizes the dispersion of the values that could reasonably be attributed to the measurand” [JCGM, 2014]. Uncertainty includes systematic and random errors.

3 Candidate validated datasets

Two retrieval algorithms [VP-CCI_D2.1_ATBD_V1.0] are evaluated in this cycle. These are the OptiAlbedo albedo retrieval algorithm, which feeds into TIP (Two-stream-Inversion-Package) for the retrieval of fAPAR and effective LAI, and the innovative OptiSAIL which retrieves LAI and fAPAR together with other parameters directly from TOC reflectances.

3.1 TIP

TIP-LAI and TIP-fAPAR are effective Leaf Area Index and Fraction of Absorbed Photosynthetically Active Radiation, respectively. They are retrieved by applying the TIP to visible (VIS) and near-infrared (NIR) broadband albedos. TIP is based on the Two-stream Model (Pinty et al., 2006), which implements the two-stream approximation of radiative transfer for a homogeneous canopy ("1D-canopy"). For efficient processing, the retrievals are taken from tables of pre-computed inversions, generated with the TIP. It allows for the retrieval of effective LAI and fAPAR and their covariance from Top-Of-Canopy (TOC) VIS and NIR Bi-Hemispheric Reflectances (BHRs) and their joint variance-covariance matrix. By using the full variance-covariance matrix of the BHRs, it is an enhancement beyond previous implementations of the TIP (Disney et al., 2016). The retrievals of LAI and fAPAR using TIP are tied to the assumptions used in the Two-stream Model. This is in particular the assumption of horizontal homogeneity over the whole pixel and vertical homogeneity over the canopy (1D approach), which yields effective values of the model's state variables, including the LAI. By means of a clumping factor, as suggested by (Pinty et al., 2006), and a domain average, this can be related to the properties of realistic canopies, which are clumped at multiple scales. Direct measurements or retrievals of LAI-based 3D RT simulations will typically yield higher values (Jonckheere et al., 2004; Weiss et al., 2004). However, the assumptions used in the Two-stream Model are motivated by the need for consistency with those made in many surface flux retrievals, as well as those used in large-scale Land Surface Models (Widlowski et al., 2011). Verification studies of the retrieval algorithm have been done (Pinty et al., 2011a, 2011b, 2011c; Widlowski et al., 2011), and in the framework of the Copernicus C3S (see quality reports, [C3S_QAR_ LAI_fAPAR_v4], [C3S_QAR_ LAI_fAPAR_v3], [C3S_QAR_ LAI_fAPAR_v2])

The implementation of TIP used here is in essence identical to the one used in the C3S documented [C3S_ATBD_ LAI_fAPAR_v4]. An important difference is the availability of correlation information for the input BHRs coming from OptiAlbedo. Whenever this correlation exceeds +/-0.5, different inversion tables are used, which are pre-computed for a correlation of +/-0.5.

3.2 OptiSAIL

OptiSAIL is a retrieval and error propagation framework and uses automatic differentiation for gradient, Jacobian and Hessian computations. It is built around the established components 4SAILH (Scattering of Arbitrarily Inclined Leaves, with 4-stream extension and hot-spot), PROSPECT-D (simulation of leaf spectra, version D including senescence) (Féret et al., 2017), TARTES (Two-streAm Radiative TransfEr in Snow (Libois et al., 2013), with the addition of an empirical soil reflectance model, a semi-empirical soil moisture model, the Ross-Thick-Li-Sparse BRDF model, and a cloud contamination simulation. The model is described with further references and demonstrated in (Blessing and Giering, 2021).

4 Reference datasets

4.1 In-situ reference datasets

4.1.1 CEOS WGCV LPV DIRECT V2.1

Ground references of high quality are needed to validate satellite-based products. The DIRECT V2.1 database hosted at the CEOS cal/val portal (https://calvalportal.ceos.org/lpv-direct-v2.1) compiles LAI and fAPAR averaged values over a 3 km x 3 km area. The ground data was upscaled using high spatial resolution imagery following CEOS WGCV LPV LAI good practices to properly account for the spatial heterogeneity of the site. Ground measurements including in the first version (DIRECT) were resulting from several international activities including VALERI, BigFoot, SAFARI-2000, CCRS, Boston University and ESA campaigns compiled by S. Garrigues (Garrigues et al., 2008), and later ingested in the CEOS WGCV LPV OLIVE tool (Weiss et al., 2014) for accuracy assessment. F. Camacho reviewed DIRECT to remove those sites without understory measurements (Camacho et al., 2013) and after that expanded the database with ImagineS sites (Camacho et al., 2021). DIRECT V2.1 is the last update including 44 new sites from China (Fang et al., 2019; Song et al., 2021) and 2 sites from ESA FRM4Veg (Brown et al., 2021a).

The CEOS WGCV LPV DIRECT V2.1 database constitutes a major effort of the international community to provide ground reference for the validation of LAI and FAPAR ECVs, with a total of 176 sites around the world (7 main biome types) and 280 LAI values, 128 FAPAR and 122 FCOVER values covering the period from 2000 to 2021.

4.1.2 The Ground-Based Observations for Validation (GBOV)

As part of the Copernicus Global Land Service, the Ground-Based Observations for Validation (GBOV) service (https://land.copernicus.eu/global/gbov) aims at facilitating the use of observations from operational ground-based monitoring networks and their comparison to Earth Observation products. In case of LAI and FAPAR, the GBOV service performs the implementation and maintenance of a database for the distribution of reference measurements (RMs) and the corresponding Land Products (LPs) (i.e., upscaled maps). Currently, GBOV provides multi-temporal Land Products over 27 sites.

The current version (V3) of GBOV LP algorithm takes as input the Reference Measurements (RMs) collected over a given site, in addition to a series of high spatial resolution images. Calibration functions are then derived between RM and Radiative Transfer Model (RTM)-based retrievals, enabling high spatial resolution maps of each RM to be produced.

The use of calibrated RTM-based retrievals (GBOV V3) as opposed to vegetation index-based multi temporal transfer functions in previous version (GBOV V2) enables the impact of non-canopy factors that perturb the vegetation index-biophysical variable relationship to be reduced. For example, as viewing and illumination angles are an explicit input, seasonal variations in sun-sensor geometry can be better accounted for, whilst the variety of soil spectra used in the RTM simulations helps reduce the impact of the soil background (Brown et al., 2021b). To maintain computational efficiency, a hybrid method using artificial neural networks (ANNs) trained with RTM simulations was selected as opposed to a pure inversion approach.

As a summary, the main changes of V3 algorithm respect to V2 are:

- A new upscaling method has been implemented, using an RTM-based retrieval approach as opposed to vegetation index-based multitemporal transfer functions. In the new method, RMs are used to establish calibration functions, which enable biases in the raw RTM-based retrievals to be corrected for (Brown et al., 2020);

- A footprint matching procedure has been implemented in which RMs are related to the mean of a variable window of Landsat Operational Land Imager (OLI)/Sentinel-2 Multi-Spectral Instrument (MSI) pixels, whose size depends on the Elementary Sampling Unit (ESU) measurement footprint at the site in question (Brown et al., 2020);
- To improve temporal consistency, the constraint for relating RMs to high spatial resolution imagery has been reduced from ± 7 days to ± 1 day (Brown et al., 2021b);
- In the case of LAI LPs (i.e., LP3), RMs (i.e., RM7) derived according to Wilson approach (Wilson, 1963) is now adopted, as it has been shown to provide more stable estimates under canopies with different leaf angle distributions when compared to Miller's (Miller, 1967) integral (Leblanc and Fournier, 2014)

4.1.3 AMMA – Cycle Atmosphérique et Cycle Hydrologique (CATCH) system

AMMA – Cycle Atmosphérique et Cycle Hydrologique (CATCH) observing system has collected a data set composed of LAI, fAPAR and clumping index in the Sahelian rangelands of *Gourma* region in Mali over the 2005-2017 period. Currently, the dataset is available only for the 2005-2016 period.
The measures were carried out at the sites previously installed in 1984 and monitored till 1994 by the International Livestock Centre for Africa (ILCA) and by the Institut d'Economie Rurale (IER, Bamako) (Hiernaux et al., 2009a, 2009b), and reactivated by the AMMA–CATCH observing system during the AMMA project (Redelsperger et al., 2006). These 1 km x 1 km sites were chosen within large and relatively homogeneous areas to sample the main vegetation types and canopies encountered within the super-site.
The variables were derived from the acquisition and the processing of hemispherical photographs taken along 1 km linear sampling transects for four herbaceous canopies and one millet field. Also, an inundated forest site was measured but it was limited to 0.5 km due to the difficulties associated with the field work in such an environment. At each sampling date, 100 or 50 hemispherical photographs were acquired at the 1 km herbaceous or 0.5 km forest sites, respectively, that is a picture taken every 10 m. At the forest site, photographs were acquired both in the upward and downward directions to sample the forest canopy and the herbaceous understory. When the forest floor was inundated, only the herbaceous vegetation component above the water surface was considered.
The collected hemispherical pictures were analysed using the image processing software CAN-EYE V [CAN_EYE_UG] and the estimated mean vegetation variables at the 1 km scale were computed by averaging all the 100 or 50 measurements acquired along the sampling transect for the herbaceous and forest canopy, respectively.
Generally, hemispherical photographs were taken approximately every 10 days during the growing seasons for the herbaceous canopies, whereas at the *Kelma* forest site, the monitoring took place approximately every 10 days during the leafy period, i.e., from July to January, and every month during the dry season.
Since this dataset was not upscaled over an extended area (i.e., 3 km x 3 km area), it will be used for the qualitative assessment of temporal variations but not for the accuracy assessment.

4.2 Satellite reference datasets

Different satellite products from different services (CGLS, NASA, LSA SAF, C3S) can be used for product intercomparison with candidate TIP and OptiSAIL fAPAR and LAI products. It should be noted that most of the products (CGLS, NASA, LSA SAF) provides actual LAI products whereas TIP, OptiSAIL and C3S provide effective LAI retrievals. Table 1 summarizes the main characteristics of existing LAI and fAPAR products. As some services provides different product versions (e.g., CGLS, C3S), at least one product from each service (CGLS, NASA, LSA SAF, C3S) will be used for product intercomparison

Table 1: Characteristics of the existing LAI/FAPAR global remote sensing reference products. ANN and RTM stands for "Artificial Neural Network", and "Radiative Transfer Model", respectively. GSD stands for "Ground Sampling Distance"

Product	Satellite /Sensor	GSD	Frequency /compositing	Temporal availability	Algorithm	Clumping	Reference
CGLS Collection 1km V1	SPOT/VGT	1 km	10 days /30 days weighted average	1999-2014	ANN trained with CYC and MOD	Weighted of CYC and MOD	(Baret et al., 2013)
	PROBA-V			2014-2020			
CGLS Collection 1km V2	SPOT/VGT	1 km	10 days /variable	1999-2014	ANN trained with CYC and MOD + gap filling & smoothing	Weighted of CYC and MOD	(Verger et al., 2014)
	PROBA-V			2014-2020			
CGLS Collection 300m V1	PROBA-V	300 m	10 days /variable	2014-2020	ANN trained with CYC and MOD + smoothing	Weighted of CYC and MOD	[CGLOPS_ATBD_PBV300_V1]
	Sentinel-3/OLCI			2020-present	ANN trained with PBV 300 m + smoothing		[CGLOPS_ATBD_OLCI_V1.1]
NASA MOD15A2H C6	TERRA /MODIS	500 m	8 days /8 days	2000-present	Inversion RTM 3D	Plant, canopy & landscape	(Knyazikhin et al., 1998)
LSA SAF EPS VEGA	EPS /AVHRR	1 km	10 days /20 days (recursive using prior data)	2015-present	PROSAIL RTM+GPR	lack of clumping at canopy level	(García-Haro et al., 2018)
C3S V2	PROBA-V	1 km	10 days /20 days (recursive using prior data)	2014-2020	TIP	lack of clumping	[C3S_ATBD_ LAI_fAPAR_v2]
C3S multi-sensor V3	SPOT/VGT	1 km	10 days /20 days (recursive using prior VGT data)	1999-2014	TIP	lack of clumping	[C3S_ATBD_ LAI_fAPAR_v3]
	PROBA-V			2014-2020			

It should be noted that, additionally to existing LAI/fAPAR reference products, the consistency of CCI LAI and fAPAR will be evaluated with other CCI satellite datasets (e.g., Fire and Land Cover).

5 Description of the product validation methodology

5.1 General validation strategy

Thanks to the precursor studies on the validation of LAI (Camacho et al., 2013; Fang et al., 2012; Garrigues et al., 2008; Weiss et al., 2007) and the On Line Validation Exercise (OLIVE) tool (Weiss et al., 2014) hosted by CEOS CAL/VAL portal (http://calvalportal.ceos.org/web/olive), the CEOS LPV LAI validation protocol was developed (Fernandes et al., 2014). It is also suitable for fAPAR products. Besides, recommendations of the Global Land Service reviewers have been included to complement the CEOS LPV LAI validation protocol. The proposed methodology relies on direct validation and product intercomparison approaches.

1. The direct validation is computed against ground data set (DIRECT V2.0) up-scaled according with the CEOS LPV recommendations (Fernandes et al., 2014; Morisette et al., 2006). The confidence in the reference ground-based map derived from empirical transfer functions depends on performances of the transfer functions that should be quantified with appropriate uncertainty metrics. Other existing datasets, such as GBOV and AMMA will be used, providing multi-temporal valuable information.
2. Intercomparisons with similar remote sensing products (i.e., indirect validation) can determine whether the products behave similarly in space and time on a global scale and allow us to identify differences between products to be investigated in more detail in order to diagnose product anomalies and devise algorithm refinements. The LAND VALidation (LANDVAL) network of sites (Fuster et al., 2020; Sánchez-Zapero et al., 2020) is used for sampling global conditions in the intercomparison with similar satellite products. The LANDVAL network is composed of 720 sites, of which 521 sites are from Surface Albedo Validation Sites (SAVS 1.0) (Loew et al., 2016), and complemented with additional sites in order to cover under-sampled regions and biome types. To allow comparison between the products, the same temporal (10 days) and spatial (1 km^2) supports are used. These analyses are achieved per aggregated land cover class based on the 8 generic classes: Evergreen Broadleaf Forest (EBF, 9.6% of LANDVAL sites), Deciduous Broadleaf Forest (DBF, 7.5%), Needle-Leaf Forest (NLF, 11.3%), Other Forests (OF, 8.8%), Cultivated (CUL, 19.5%), Herbaceous (HER, 21.3%), Shrublands (SHR, 8.2%), Sparse and Bare areas (SBA, 13.8%), Others (8.4%).

During the cycle 1, two main validation and intercomparison activities will be performed:

- Validation and algorithm selection, where both TIP and OptiSAIL algorithms will be the validated and intercompared over a test dataset generated over a selection of sites (see Figure 1) for 2019. The input data to generate the test dataset come from PROBA-V and Sentinel-3/OLCI.
- The product validation performed over a climate data record (2000-2020 period) at 1000 m of spatial resolution based on SPOT4-5/VGT1-2, PROBA-V and Sentinel-3/OLCI, with focus in the overlap periods. The dataset will be generated over the selected sites and a latitudinal transect (see Figure 1).

Figure 1 illustrates the sampling strategy for the validation. It consists in two approaches:

- A selection of sites for product intercomparison (LANDVAL, calibration sites) and direct validation (DIRECT V2.1, GBOV, AMMA, see section 4.1).
- A latitudinal transect for the evaluation of the spatial consistency and qualitative visual inspection of the reliability of the products.

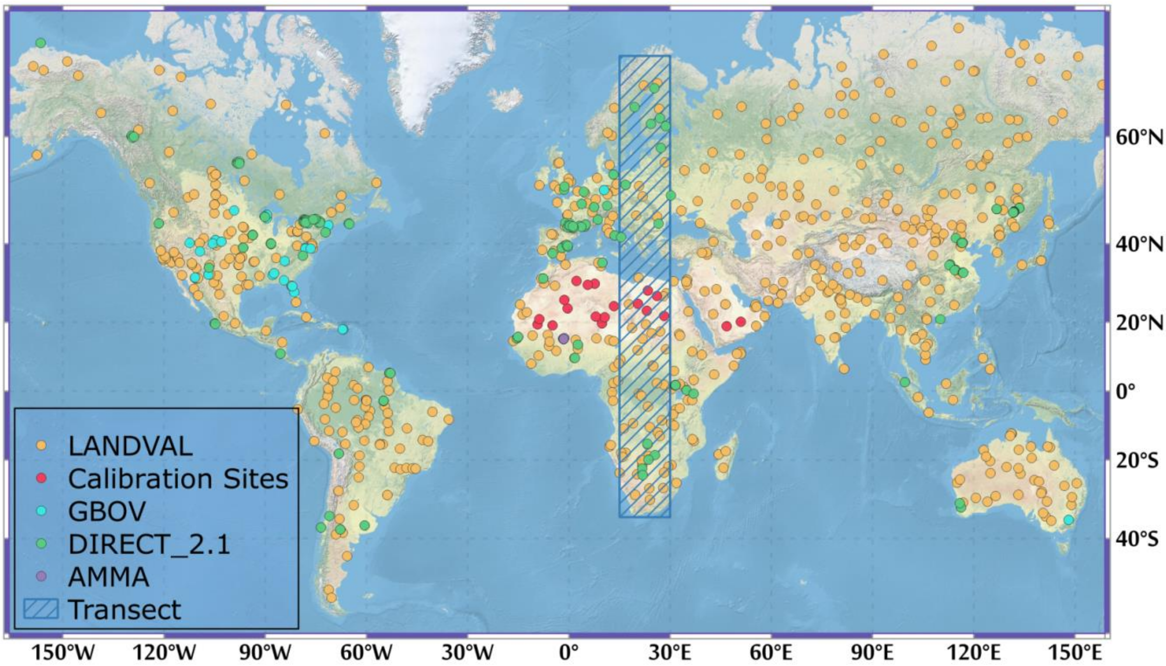

Figure 1: Sampling strategy: A) selected sites from LANDVAL, Calibration Sites, GBOV, DIRECT_2.1 and AMMA. B) Latitudinal Transect (see blue rectangle)

- As said above, the first cycle will result in a 1000 m resolution product from SPOT4-5/VGT1-2, PROBA-V and Sentinel-3 OLCI. In second cycle, the added value of the spectral, spatial, temporal and angular diversity will be evaluated by the exploitation of other sensors and 300 m data. In the third and last cycle, an optimum combination of sensors will be selected, and the computational efficiency optimized, also by considering the use of emulators of the models.

For the next cycles, the validation strategy will be revised in the updates of this validation plan.

5.2 Validation criteria

5.2.1 Product Completeness

Completeness corresponds to the absence of spatial and temporal gaps in the data. Missing data are mainly due to cloud or snow contamination, poor atmospheric conditions, or technical problems during the acquisition of the images and is generally considered by users as a severe limitation of a given product. It is therefore mandatory to document the completeness of the product (i.e., the distribution in space and time of missing data).

- Global maps of missing values for the period under study will be displayed.
- Distribution of gaps as a function of the season will be also analysed, as well as the length of gaps.

5.2.2 Spatial consistency

Spatial consistency refers to the realism and repeatability of the spatial distribution of retrievals over the globe.

A first qualitative check of the realism and repeatability of spatial distribution of retrievals and the absence of strange patterns or artefacts (e.g., missing values, stripes, unrealistic low values, etc.) can

be achieved through systematic visual analysis of all global maps based on the expert knowledge of the scientist.
The spatial consistency can be quantitatively assessed by comparing the spatial distribution of a reference validated product with the product biophysical maps under study. Two products are considered spatially consistent when the residuals are within uncertainty requirements of the variable. The residual (ε) is estimated assuming a linear trend between two products (Y = a X+ b + ε), then the residual can be written as ε = Y- a X - b, which represent the remaining discrepancies regarding the general trend between both products. In this way, systematic trends are not considered, depicting more clearly patterns associated to the spatial distribution of retrievals.

- The methodology for visual analysis includes the visualization of zoom over sub-continental areas and areas of interest at full resolution, and the visualization of animations of global maps at a reduced (1/16 pixels) resolution.
- Global maps and histograms of residuals, at a reduced (1/16 pixels) resolution, between the product under study and reference products will be analysed in order to identify regions showing spatial inconsistencies for further analysis (e.g., temporal profiles). Furthermore, global distribution of pixels within the pre-defined user requirements, histograms of residuals and percentage of residuals within the user requirement levels will be computed.

5.2.3 Temporal consistency

The realism of the temporal variations and the precision of the products will be assessed over the 720-site LANDVAL network plus additional sites with availability of ground measurements (i.e., GBOV, AMMA).

- The temporal variations of the product under study will be qualitatively analysed as compared to reference products and available ground measurements.
- To analyse quantitatively the temporal consistency of the products, cross-correlation and distance measures similarity metrics (Lhermitte et al., 2011) are evaluated. The histograms and empirical cumulative distribution functions of Pearson correlation (R), Euclidean distance (d_E) and Manhattan distance (d_M) are displayed per main biome type.

5.2.4 Error evaluation

Accuracy, Precision and Uncertainty (APU) will be evaluated by several metrics (Table 2) reporting the goodness of fit between the products and the corresponding reference dataset.
Commonly, accuracy represents systematic errors and often is computed as the statistical mean bias (B). Precision represents the dispersion of product retrievals around their expected value and can be estimated by the standard deviation (STD) of the difference between retrieved satellite product and the corresponding reference estimates. Uncertainty includes systematic and random errors and can be estimated by the Root Mean Square Deviation (RMSD). In addition to these metrics, other statistics are useful to evaluate the goodness of fit between two datasets including linear model fits. For this purpose, Major Axis Regression (MAR) is computed instead Ordinary Least Squares (OLS) because it is specifically formulated to handle error in both of the x and y variables (Harper, 2014). In case of LAI, CEOS LPV recommends RMSD as the overall performance statistic to evaluate the accuracy, due to limitation in the temporal availability of ground datasets (Fernandes et al., 2014). It should be noted that strong and/or multiple outliers affect the classical metrics described above (i.e., B and STD): in such cases using the median deviation (MD) instead of the mean bias to estimate systematic error and the median absolute deviation (MAD) as a measure of precision is more suitable.
Note that two aspects of the precision should be also evaluated: inter-annual and intra-annual precision (Fernandes et al., 2014).

- Scatterplots and validation metrics (Table 2) versus references willl be produced. The analysis is complemented with boxplots of Bias per bin.
- Histograms of product values per main biome type are evaluated over LANDVAL sites.
- Intra-annual precision (smoothness) corresponds to temporal noise assumed to have no serial correlation within a season. In this case, the anomaly of a variable from the linear estimate based on its neighbours can be used as an indication of intra-annual precision. It can be characterized (Weiss et al., 2007) as follows: for each triplet of consecutive observations, the absolute value of the difference between the center P(dn+1) and the corresponding linear interpolation between the two extremes P(dn) and P(dn+2) is computed:

$$\delta = \left| \mathrm{P}(\mathrm{d}_{\mathrm{n+1}}) - \mathrm{P}(\mathrm{d}_{\mathrm{n}}) - \frac{\mathrm{P}(\mathrm{d}_{\mathrm{n}}) - \mathrm{P}(\mathrm{d}_{\mathrm{n+2}})}{\mathrm{d}_{\mathrm{n}} - \mathrm{d}_{\mathrm{n+2}}} (\mathrm{d}_{\mathrm{n}} - \mathrm{d}_{\mathrm{n+1}}) \right| \qquad \text{Eq. 1}$$

- The distribution of the intra-annual precision will be analysed, and the median δ value is used as a quantitative indicator of the inter-annual precision (Fernandes et al., 2014; Wang et al., 2019). Hence, the lower median of δ values, the higher the inter-annual precision.
- Anomalies of an upper and lower percentile of variable are indicators of inter-annual precision, i.e. dispersion of variable values from year to year (Fernandes et al., 2014). It can be assessed providing a boxplot of the median absolute deviation of anomalies for a given product between consecutive years per bins. Note that cultivated sites are not considered in this analysis due to the non-natural variability in this land cover type due to agricultural practices (e.g., crop rotation). In addition, Evergreen Broadleaf Forest sites are neither considered in the analysis since they are typically affected by cloud coverage for most of the products, and values are filled in case of products using gap-filling techniques.

Table 2: Validation metrics for product validation

Statistics	Comment
N	Number of samples. Indicative of the power of the validation
B	Mean Bias. Difference between average values of x and y. Indicative of accuracy and offset.
MD	Median deviation between x and y. Best practice reporting the accuracy.
STD	Standard deviation of the pair differences. Indicates precision.
MAD	Median absolute deviation between x and y. Best practice reporting the precision.
RMSD	Root Mean Square Deviation. RMSD is the square root of the average of squared errors between x and y.
MAR	Slope and offset of the Major Axis Regression linear fit. Indicates some possible bias
R	Correlation coefficient. Indicates descriptive power of the linear accuracy test. Pearson coefficient is used.
d_E	Euclidean distance. Normalized by number of samples.
d_M	Manhattan distance. Normalized by number of samples.

5.2.5 Stability

The stability of the CDR will be assessed using the inter-annual precision. In such case, the reference is the Long-Term Average (LTA). Fluctuations on inter-annual precision can provide insights on relative changes of the retrievals that could be associated to sensor degradation and/or degradation of algorithm performance. The precision is calculated for each year of the CDR and a regression function is fitted through these values (Precision = f(time)). The slope of the evolution of inter-annual precision of CDR (obtained by a linear regression) can be considered as an estimate of stability, that will be expressed as % change per decade (10 years).

5.2.6 Conformity test

The final objective of the quality assessment analysis is to verify how much the products are compliant with the user requirements. To achieve this, the compliance matrix of candidate products with user requirements will be provided.

5.2.7 Summary of validation metrics for the quality assessment

Table 3 summarizes the validation criteria used for the quality assessment of the products under study.

Table 3: Criteria with associated metrics for product validation

Criteria	**Validation Metrics**
Completeness	Gap size distribution (annual maps, temporal variations). Length of gaps.
Spatial Consistency	Visual inspection of global maps and sub-continental zooms. Check of ancillary layers (uncertainties and QFLAGs). Global maps and histograms of residuals (and differences).
Temporal Consistency	Qualitative inspection of temporal variations Similarity metrics (cross-correlation and distance measures) per biome type.
Intra-annual Precision	Histograms of the smoothness. Median δ values.
Inter-annual Precision	Boxplot per bin and median absolute anomaly (two consecutive years) of 95th percentile and 5th percentile.
Stability	The slope of the evolution of inter-annual precision
Error evaluation (product inter-comparison)	Scatterplots and validation metrics. Conformity test. Boxplots of bias per product value. PDFs of retrievals, Scatterplots and validation metrics per biome type.
Error evaluation	Scatterplots and validation metrics. Conformity test.

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