International Journal of Applied Earth Observations and Geoinformation 95 (2021) 102240

Contents lists available at ScienceDirect

International Journal of Applied Earth Observations and Geoinformation

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

Toward operational validation systems for global satellite-based terrestrial essential climate variables

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ARTICLE INFO

Keywords:
Operational validation systems
Essential climate variables
Terrestrial
Satellite products
In situ measurements
Good practice protocol
Long-term
Global scale

ABSTRACT

Terrestrial Essential Climate Variables, known as terrestrial ECVs, are key sources of information for both application- and scientific- oriented research. A large number of global terrestrial ECV products have been derived from satellite observations, and more are forthcoming. To unlock the full potential of these products, end-users need to know their uncertainties and error magnitudes. Due to the lack of conformity among validation strategies, a wide range of validation approaches have been employed to assess the quality of these products, and have resulted in reduced comparability even for the same terrestrial ECV. Addressing this challenge in validation practices requires the use of unified, standard, publicly available, traceable and objective validation procedures that are operational for all products of a specific terrestrial ECV, and preferably also applicable for all ECVs at the global scale. This can allow end-users to perform comparative assessments. To this end, the current study aims to investigate the readiness status of a selected group of seven global long-term satellite-based terrestrial ECVs for operational validation. Selected variables are Leaf Area Index (LAI), Land Surface Temperature (LST), Evapotranspiration (ET), Soil Moisture (SM), Albedo, the fraction of Absorbed Photosynthetically Active Radiation (fAPAR), and Land Cover (LC). For each of these terrestrial ECVs, we reviewed key prerequisites and primary tools [notably, long term global product availability, globally distributed in situ measurement availability, a validation good practice protocol, and an online validation platform] required for developing an operational validation system. With respect to the "readiness level", the investigation results demonstrate that LAI, SM, and LC are at the highest level of readiness for moving toward a full operational validation at the global scale. However, ET is at the lowest level of readiness, mainly due to the lack of standard validation good practice protocol and lack of a pilot online validation platform. The remainder of the selected terrestrial ECVs are identified to be at mid-level readiness, mainly because either a validation platform (i.e., LST and albedo) or good practice protocol (i.e., fAPAR) still needs to be developed. This review can pave the way for open-access, traceable, transparent, and operational validation procedures of satellite-based global terrestrial ECVs.

1. Introduction

Knowledge of land surface variable information is one of the main requirements for quantifying the state of the environment and successful modeling of Earth system processes (Balsamo et al., 2018; Bayat et al., 2020, 2018; Cayrol et al., 2000). One promising approach to gain such information in an efficient way is through the collection of a set of crucial observable indicators, known as "Essential Climate Variables (ECVs)". ECVs were defined for the first time in 2003 by the Global Climate Observing System (GCOS), and endorsed by the United Nations Framework Convention on Climate Change (UNFCCC) as "a physical, chemical, or biological variable, or a group of linked variables, that

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https://doi.org/10.1016/j.jag.2020.102240
Received 30 May 2020; Received in revised form 19 September 2020; Accepted 21 September 2020
Available online 16 October 2020

critically contribute to the characterization of Earth's climate" (Bojinski et al., 2014; Pettorelli et al., 2016). Subsequently, the concept of ECV has been extended to broader domains of science (Patias et al., 2019). The primary assumption of the ECV concept is that a certain key variables exist which are essential to quantifying the primary states and fluxes and for monitoring the trends of a system without losing vital information. In this respect, several specific ECVs are also grouped by thier purpose of use or by their physical interdependence (Bombelli et al., 2015; Hayes et al., 2015; Miloslavich et al., 2018; Patias et al., 2019; Pereira et al., 2013; Schmeller et al., 2017).

Concerning the production of ECVs with long-term records and appropriate local-to-global coverage, satellite remote sensing can provide cost-effective, reproducible, regular observations (Balsamo et al., 2018; Buchanan et al., 2009; Franklin and Wulder, 2002; GCOS - 154, 2011; Geller et al., 2017; Liang and Wang, 2019; Patias et al., 2019; Pettorelli et al., 2016) by exploiting multispectral, hyperspectral, thermal-infrared, LiDAR, radar, and radiometer sensor data (Liang, 2007). The Working Group on Climate (WGClimate) (http://ceos.org/ourwork/workinggroups/climate; last access: 1 March 2020) of the Coordination Group for Meteorological Satellites (CGMS) (https://www.cgms-info.org/index_.php/cgms/index.html; last access: 1 March 2020) within the Committee on Earth Observation Satellites (CEOS) (http://ceos.org; last access: 1 March 2020) devotes significant effort to define and implement an architecture for a consistent space-based climate monitor. WGClimate activities facilitate the implementation and exploitation of ECV time-series by closely collaborating with other CEOS working groups and member agencies. They review and evaluate the production of Fundamental Climate Data Records (FCDRs) and derived ECVs. Further, the WGClimate identifies implementation teams from different agencies for each ECV product, works on strategies required for climate monitoring from space, and reviews actions taken for each product to ensure the sustainable production of ECVs. Several satellite observations have also been used to generate time series of ECV products by individual members of the community. Overall, satellite-based ECV products have been continuously released, covering different spatio-temporal scales by means of so-called observation operators of varying complexities.

We focus on terrestrial ECVs that are more complex, mainly due to the fact that they are inherently more heterogeneous compared to the ECVs in the oceanic and the atmospheric domains (Bojinski et al., 2014). For potential end-users of satellite products the following questions are relevant:

- "*Is a specific satellite-based terrestrial ECV product fit for purpose?*"
- "*How good or reliable is the specific satellite-based ECV product?*"

To address these two critical questions, Earth Observation (EO) communities have proposed numerous approaches, all dealing with the validation aspects of satellite products and the quantification of their accuracy.

By definition, validation is "the process of assessing by independent means the accuracy of data products derived from the system outputs" (Justice et al., 1998). Following the definition, there have been several validation practices proposed and developed for satellite-based terrestrial ECVs. Not only were various validation workflows executed for data producers (i.e., producer side validation), but also additional variable-specific validation frameworks were developed through international collaboration networks (i.e., community and user side validation).

Climate data created by the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), environmental data sets created by the National Oceanographic and Atmospheric Administration (NOAA) (Yost, 2016), the Climate Change Initiative (CCI) operated by the European Space Agency (ESA) (Dorigo et al., 2017) and EO data records from the National Aeronautics and Space Administration (NASA) (Justice et al., 2013) are only a few examples of data with thorough validation on the producer side. A variable-specific validation practice at the community/user side level has been established by the CEOS Working Group on Calibration and Validation (WGCV), and more specifically, its subgroup on Land Product Validation (LPV) (https://lpvs.gsfc.nasa.gov; last access: 1 March 2020), hereafter called CEOS LPV. The aim of CEOS LPV is to establish a standard validation framework for specific terrestrial ECVs (Fernandes et al., 2014; Guillevic et al., 2018; Morisette et al., 2006; Strahler et al., 2006; Wang et al., 2019).

Despite CEOS LPV validation good practice recommendations, the validation workflows are rather diverse in terms of adopted methods, utilized reference data, traceability and transparency, locations, coverage, representation, scaling, metrics, target accuracies, and uncertainty reports, all of which cause a considerable lack of homogeneity in published validation reports. Such a vast diversity, not only in the validation methods but also in the data product quality flagging, has recently been identified as one of the ten substantial gaps related to ECV quality assessment (Nightingale et al., 2019). Thus, most of the current validation results may not be directly comparable, even for different products of the same ECV. Consequently, further use of such heterogeneously validated satellite-based ECV products in scientific research or terrestrial applications can be questionable and may add more uncertainty due to validation procedure-induced errors in addition to the methodology-induced and sensor-specific noise. This is simply because similar ECV products have been validated in relatively different and incomparable ways.

To better express potential challenges that might be posed by making use of heterogeneously validated satellite products, it is worth looking at an example in which three satellite-based Leaf Area Index (LAI) products have been employed in the study by Zhu et al. (2016). They used the third generation Global Inventory Modeling and Mapping Studies (GIMMS3g), Global LAand Surface Satellite (GLASS), and the GLOBal MApping Project (GLOBMAP), along with an ensemble of ten various ecosystem models, to investigate the trend of Earth greening and its drivers at the global scale (Zhu et al., 2016). Since their primary objective was not to perform a validation of selected LAI products, they mostly relied on original validation reports of these products and considered the mean values of the three products during the growing season for their global greenness analysis. However, Zhu et al. (2016) pointed out that the biases from these LAI products could be a potential reason for the observed mismatch between satellite-based LAI and model-simulated LAI. This may not be surprising since the original validation of these three products demonstrated that: (1) the GIMMS3g LAI product was originally validated using 45 sets of scaled field measurements at 29 sites mostly located in northern latitudes (Zhu et al., 2013). They compared GIMMS3g and LAI field measurements on a group of pixels belonging to specific biomes (i.e., cropland, grassland, savanna, and forest) considering the distribution properties of the corresponding LAI values in the validation. They reported LAI accuracies of RMSE = 0.68 and R^2 = 0.79 for GIMMS3g products (Zhu et al., 2013); (2) the GLASS product was validated using 48 high-resolution LAI maps at 28 sites (Xiao et al., 2016). High-resolution LAI maps obtained mostly from VALERI (http://w3.avignon.inra.fr/valeri; last access: 1 March 2020) and BigFoot (https://daac.ornl.gov/cgi-bin/dataset_lister.pl?p = 1; last access: 1 March 2020) initiatives. They aggregated the high-resolution LAI maps and GLASS products over windows of 3 km by 3 km centered on the ground sites by means of a spatial-average approach. Further, they used a linear interpolation method to obtain the GLASS products corresponding to the acquisition time of ground LAI measurements, as necessary. They used a total number of 64 LAI values for ground measurements and GLASS products. They reported accuracy results of RMSE = 0.78 and R^2 = 0.81 for GLASS LAI products (Xiao et al., 2016); (3) the GLOBMAP product was validated using 45 ground measured LAI and 45 fine resolution LAI maps at 29 sites (Liu et al., 2012). Fine resolution LAI maps were obtained using regression algorithms established between ground measured LAI and satellite (Landsat

Table 1
The selected group of terrestrial ECVs, their definitions, and importance.

Terrestrial ECVs	Abbr.	Unit	Definition	Importance	Reference
Leaf Area Index	LAI	[m^2 m^{-2}]	LAI is defined as one-half of the total green area of the leaf per unit ground surface area. This describes the amount of ecosystem canopy leaf material.	LAI is an essential parameter controlling canopy photosynthesis, evapotranspiration, respiration, and rain interception. It is needed in the majority of hydrological and land surface models as an input to consider vegetation-atmosphere interactions.	(Chen and Black, 1992; Fernandes et al., 2014)
Land Surface Temperature	LST	[K]	LST is defined as the accumulated radiometric temperature of the surface elements located in the sensor's field of view.	LST is a primary variable for understanding all processes at the land surface and land-atmosphere exchanges and interactions. It is used extensively to constrain land surface energy budgets and climate models' parameters.	(Guillevic et al., 2018; Norman and Becker, 1995)
Evapotranspiration	ET	[mm day^{-1}]	ET is defined as the sum of evaporation from the soil, plant (known as transpiration), and ocean surface to the atmosphere.	ET is an essential component of the surface energy balance and the water cycle. It also plays a vital role in understanding land surface energy and water budgets.	(Jia et al., 2012; Kustas, 1990; Kustas and Norman, 1996)
Soil Moisture	SM	[m^3 m^{-3}]	The volumetric SM is defined as the ratio of the volume of the water to the total volume, including dry soil, air, and water of a soil sample. Here we refer to surface SM (down to 5 cm soil depth)	SM is a crucial hydrologic variable that connects the land surface processes to those of the atmosphere. This variable is needed to quantify hydrological, environmental, and land surface processes.	(Babaeian et al., 2019; Gruber et al., 2020)
Albedo	[-]	[-]	Albedo is defined as the ratio of the land surface reflected radiant flux to the total incident flux.	Albedo is a primary variable contributing to the surface radiative energy budget and has a crucial role in the partitioning of total incoming energy between the atmosphere and the surface.	(Wang et al., 2016, 2013, 2019)
Fraction of Absorbed Photosynthetically Active Radiation	fAPAR	[-]	fAPAR is defined as the fraction of photosynthetically active radiation (between 0.4−0.7 μm spectral region) which is actively absorbed by vegetated canopies.	fAPAR is linked to ecosystem status and functioning. It has an essential role in carbon balance estimation and, therefore, is a crucial input for vegetation photosynthesis and productivity models.	(Nestola et al., 2017)
Land Cover	LC	[-]	LC is defined as the observed (bio)-physical coverage of the ground surface. LC includes vegetation and non-vegetated classes (e.g., man-made features, bare soil, rock, inland water bodies).	LC information is essential to parametrize climate, water, and carbon models at various scales from local, to regional and global-scale by assigning physical attributes to different classes of LC. Moreover, it can be used to address land management.	(Di Gregorio, 2005; Strahler et al., 2006)

TM/ETM+, SPOT, and ASTER)-derived vegetation indices (VIs), followed by aggregating to the GLOBMAP product scale. They reported the accuracy results of RMSE = 1.08 and R^2 = 0.59 for GLOBMAP LAI products (Liu et al., 2012). This example reveals that for various products of the same ECV (in this case LAI), either CEOS LPV-defined validation guidelines have not been followed (for GIMMS3g), or different methodologies [i.e., spatial-averaging approach (for GLASS) and regression-based algorithm (for GLOBMAP)] have been adopted. Moreover, there was a lack of consistent numbers of in situ measurements from heterogeneously distributed stations [i.e., for GIMMS3g and GLOBMAP: 45 sets; for GLASS: 64 sets] and there was a diversity of types of high-resolution reference data sets that were employed during validation [i.e., for GIMMS3g: none used; for GLASS: high-resolution VALERI and BigFoot LAI products; for GLOBMAP: Landsat TM/ETM+, SPOT, and ASTER-derived VIs]. Most importantly, data set traceability has not been properly documented; therefore, it is not clear to what extent the utilized in situ measurements and reference data sets are traceable to the International System (SI). Such a variety of different configurations in validation procedures make product accuracy inter-comparisons problematic.

Resolving these inconsistencies requires making use of unified (standard) publicly available procedures operational for all products of a specific terrestrial ECV, and preferably applicable for all ECVs at the global scale, with community agreed-upon good practice protocols, precise ground data, and an accepted framework originating from realistic target accuracy. If such standardized operational procedures are available, a fair comparison of satellite ECVs products can be made possible since the validation-procedure-induced errors are quantified consistently. Such standardization will be significant, may increase the value of satellite ECVs, and can pave the way for synergistic use of various satellite ECVs with higher confidence, unlocking the full capacity of satellite data for a better understanding of environmental state and for monitoring global change. However, currently, it is not clear how far the community is from such a fully operational standard validation system in general, and more specifically, for terrestrial ECVs.

The primary objective of this contribution is to provide an overview of the readiness status of key prerequisites and primary tools [notably, long term global product availability, globally distributed in situ measurement availability, a validation good practice protocol, and an online validation platform] required for developing operational validation systems for a selected group of seven satellite-based terrestrial ECVs at the global scale with a long-term perspective. Selected variables are LAI, Land Surface Temperature (LST), Evapotranspiration (ET), Soil Moisture (SM), Albedo, the fraction of Absorbed Photosynthetically Active Radiation (fAPAR), and Land Cover (LC).

To meet this objective, our discussions are centered on the following topics: Section 2 focuses on definitions and highlights the importance of selected terrestrial ECVs. Section 3 reviews the availability of potential satellite-based terrestrial ECVs products as suitable candidates to be included in an operational validation system. Section 4 explores the existing global in situ and fiducial reference measurements as the core of any validation system and Section 5 focuses on progress made towards online validation workflows. Section 6 gathers all information from previous sections together to discuss the readiness status of selected terrestrial ECVs for moving toward a full operational validation at the global scale based on different criteria. This section further discusses the required maintenance and regular upgrade of system components to ensure the sustainability of an operational validation system for selected terrestrial ECVs. Section 7 provides a summary and outlook of the study. Finally, we provide a list of satellite product characteristics (e.g., original sensor, resolution, data time span, production algorithm, publication reference), and data access for selected terrestrial ECVs in Appendix A.

2. Selection of terrestrial ECVs

An urgent need for systematic global observations was first identified in 1988 for addressing human-induced warming effects on climate (https://www.nytimes.com/1988/06/24/us/global-warming-has-begun-expert-tells-senate.html; last access: 1 March 2020). Four years later (in 1992), the GCOS program was founded by the World Meteorological Organization (WMO) to assure the collection of sufficient observations, mainly for climatologists. In 2003, for the first time, the term ECV was introduced by GCOS with the aim of collecting a limited set of crucial variables to be able to describe the Earth's system structure and quantify the state of the environment. To this end, robust ECVs must be observable at the global scale to fulfill the criteria set out by the United Nations Framework Convention on Climate Change (UNFCCC) (Pettorelli et al., 2016).

In this study, we focus on investigating a selected group of seven terrestrial ECVs that are systematically produced from satellite data, have global long-term coverage, are adequately archived, and publicly accessible. Table 1 briefly presents the selected terrestrial ECVs, their simple definitions, and their importance.

Generally, these selected satellite-based terrestrial ECV products have been widely used by various scientific communities to obtain spatio-temporal information for better understanding, quantification, and prediction of the evolution of environmental ecosystems. Moreover, these products can also guide approaches for mitigation and adaptation, assess risks, and enable the understanding of relationships of extreme events to their underlying causes, as well as inform and justify environmental decision support services (Bojinski et al., 2014). Overall, the selected variables are relevant for understanding land-atmosphere interactions, for modeling of exchanges of energy, mass (i.e., water and carbon), and momentum transfer between the land surface and atmospheric boundary layer at various scales. More specifically, LAI and fAPAR are often routine state inputs in hydrological, climatological, agricultural, biological, biogeochemical and land surface process models (Myneni et al., 2002; Piao et al., 2015; Sellers et al., 1997; Zhu et al., 2016, 2013). LST is an essential input for land surface energy balance modeling and weather prediction algorithms (Dash et al., 2002; Reichle et al., 2010). Further, a reliable estimate of LST is of significant importance for monitoring the Earth's surface radiation budget (Islam et al., 2017). LST has also been used frequently for drought and heat-wave monitoring (Dousset et al., 2011; Rhee et al., 2010), ET estimation (Li et al., 2015), and detection of urban heat islands (Lai et al., 2018; Liu and Zhang, 2011; Weng, 2009). ET is a crucial component for modeling climate change, water balance, and net primary productivity at the global scale (Fisher et al., 2008). ET also plays a vital role in understanding land surface energy and water budgets (Zhang et al., 2019). SM is a crucial hydrologic variable that connects the processes of the land surface to those of the atmosphere (Robinson et al., 2008). It can also provide valuable information for a better understanding of the water and carbon cycles, weather forecasting and predicting extreme climate events (Li et al., 2007; Montzka et al., 2017, 2013; Robock and Li, 2006; Seneviratne et al., 2010; Vereecken et al., 2014). As a result, SM has proven to be a critical input for operational applications related to floods (Komma et al., 2008; Norbiato et al., 2008), droughts (Ahmadalipour et al., 2017; Anderson et al., 2012,), and crop conditions (Boken et al., 2005; Bolten and Crow, 2012; Mladenova et al., 2020). Land surface albedo is an essential variable that links the land surface to the climate system through shortwave energy exchange regulation (Wang et al., 2016, 2013; Zhou et al., 2016). Albedo can play an essential role in parametrizing global and regional climate models and quantifying surface energy balance (Liang, 2003). LC data is an essential input variable for ecosystem, hydrologic, and atmospheric models and can significantly affect the performance of such models (Bounoua et al., 2002; Foley et al., 2005; Jung et al., 2006; Tucker et al., 1985). LC maps are also widely utilized for climate change research (Bounoua et al., 2002; Ge et al., 2007; Hibbard et al., 2010), habitat and biodiversity studies (Buchanan et al., 2009; Hall et al., 2011), carbon cycling (De Moraes et al., 1998; Ganzeveld et al., 2010; Liu et al., 2011; Poulter et al., 2011) and global satellite product algorithms (Mu et al., 2011, 2007; Raoufi and Beighley, 2017; Ryu et al., 2011). It can provide valuable information for a better understanding of complex human activity and global change (Gong et al., 2013; Running, 2008).

All selected variables (i.e., LAI, LST, ET, SM, albedo, fAPAR and LC) are listed in the GCOS table of terrestrial ECVs (https://gcos.wmo.int/en/essential-climate-variables/table; last access: 1 March 2020). Thus, we focus on seven terrestrial ECVs in our contribution. Further studies that consider other terrestrial, atmospheric and oceanic ECVs will need to be performed in the future.

It is crucial to produce accurate time-series maps of these terrestrial ECVs, or at least maps of known accuracy, at the global scale for various terrestrial applications and scientific research.

3. Global satellite products for selected terrestrial ECVs

3.1. Current status

Satellite remote sensing is the only feasible means of obtaining the time-series of global ECV products (Balsamo et al., 2018; Dubayah et al., 1995; GCOS - 154, 2011; Geller et al., 2017). Satellite observations offer valuable spatial measures of ECVs and can contribute to a synoptic overview of the variations in space and time (Balsamo et al., 2018). This is very important since ground observations can currently only provide information over a limited or sparse coverage area. However, satellite-based ECV products exhibit differences originating from their corresponding sensors. As the first step toward operational validation, it is of utmost importance to study and understand these differences to better select potential and suitable candidates to be included in an operational validation system. In Appendix A, we review the products' main characteristics (e.g., original sensor, resolution, data time span, production algorithm, publication reference), and data access. The products listed for each of the selected terrestrial ECVs had to pass certain criteria, including global coverage, long-term (at least 10 years of data record) availability, free access, known to the scientific community either through a published peer-review paper or a public online database. It should be noted that all listed terrestrial ECV products in Appendix A are among publicly available ones (principal selection) that passed our defined criteria and, therefore, do not claim to be complete.

Various methodologies have been proposed to estimate LAI from satellite data in passive and active domains (Liang, 2007; Liang and Wang, 2019). Some of these methods produced global LAI products from, for instance, the Advanced Very High-Resolution Radiometer (AVHRR) sensor (Claverie et al., 2016; Sellers et al., 1996; Xiao et al., 2016; Zhu et al., 2013), the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor (Knyazikhin et al., 1998; Myneni et al., 2002; Xiao et al., 2016), the Satellite Pour l'Observation de la Terre -VEGETATION (SPOT-VGT) sensor (Baret et al., 2013, 2007; Deng et al., 2006), and the Multiangle Imaging Spectro-Radiometer (Diner et al., 2008b). Table A1 recalls the general characteristics of available global satellite-based LAI products and data access. For a detailed discussion of the various LAI estimation methods, their uncertainties, and applications in remote sensing, the reader is referred to Fang et al. (2019). As can be seen from Table A1, existing LAI products are available from 1981 to present (2020), covering a range of spatial resolution from 500 m to 25 km, with the opportunity to access new products from daily to monthly. Most of the available products used MODIS and AVHRR satellite data for LAI production by applying a variety of approaches and methodologies. The AVH15C1 LAI product (Claverie et al., 2016) is the most temporally extensive and complete data set with a daily time series of 39 years, starting from 1981 to present (2020).

LST can be derived using radiometric measurements from either thermal (TIR) emission at the infrared wavelengths or from the microwave domain (Martin et al., 2019). However, most available LST operational products are derived from the TIR domain (8−14 μm) of the spectrum based on land-surface energy balance theory using generalized split-window and dual algorithm (Becker and Li, 1990; Wan and Dozier, 1996) or, more recently, a water vapor scaling model used in the Temperature Emissivity Separation (TES) algorithm (Hulley et al., 2018). Thus, the spatio-temporal changes of LST can also reflect surface energy balance variations (Balsamo et al., 2018). Various satellite data sets have been used to generate global LST products, for instance, MODIS sensor (Hulley, 2015; Wan et al., 2015a,b,c), the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (NASA, 2001), a combination of the Meteosat Second Generation (MSG), Geostationary Operational Environmental Satellite (GOES), Multi-Function Transport Satellite (MTSAT) and Himawari (Freitas et al., 2013), the Along Track Scanning Radiometer (ATSR) and Advanced Along-Track Scanning Radiometer (AATSR) (Ghent et al., 2017). Table A2 recalls the general characteristics of available global satellite-based LST products and data access. For a detailed discussion of LST retrieval methods, backgrounds, their uncertainties, and implications in remote sensing, the reader is referred to (Hulley et al., 2012; Li et al., 2013). Table A2 shows that existing LST products are available from 1995 to present (2020), covering a considerable range of spatial resolution, from 90 m to 6 km, with the opportunity to access new products from hourly, daily, to monthly. Particularly, the Copernicus Global Land Service (CGLS) LST product can provide a diurnal cycle of LST since it is derived from a constellation of geostationary (GEO) satellites (i.e., MSG, GOES East, MTSAT and Himawari). Most of the available products used MODIS satellite data set for LST production. The ASTER and MODIS-derived products are the most temporally extensive and complete data set with a daily time series of 20 years, starting from 2000.

ET estimation from optical and TIR observations started in the 1980s and has evolved into multiple algorithms and models. Surface energy balance models using single and double sources, Penman-Monteith approach, Priestly-Taylor methods, and vegetation indices are among the most-used ET estimation methodologies (Zhang et al., 2016a). Optical and TIR observations have mostly been employed in the majority of global ET production from MODIS (Jiang and Ryu, 2016; Jung et al., 2019; Raoufi and Beighley, 2017; Running et al., 2017a, 2017b, 2017c; Ryu et al., 2011; Zhang et al., 2019), MODIS/AVHRR (He et al., 2018; Zhang et al., 2016b), the Sea-viewing Wide Field-of-view Sensor (SeaWiFS), AVHRR and the MEdium Resolution Imaging Spectrometer (MERIS) (Jung et al., 2010, 2009). Furthermore, other supplementary observations have occasionally been included in some cases, for instance, groundwater storage change information from Gravity Recovery And Climate Experiment (GRACE) (Zeng et al., 2012). Table A3 recalls the general characteristics of available global satellite-based ET products and data access. For a detailed discussion of the primary ET production, remote sensing methods, their histories, and uncertainties, the reader is referred to (Courault et al., 2005; Li et al., 2009; Liou and Kar, 2014; Zhang et al., 2016a). Table A3 shows that existing ET products are available from 1980 to present (2020), covering spatial resolution from 500 m to 100 km, with the opportunity to access new products from hourly, daily, monthly to annually. Most of the available products used MODIS and AVHRR satellite data for ET production. The GLEAM (Miralles et al., 2011b, 2011a) and FLUXCOM (Jung et al., 2019) ET products are the most temporally extensive and complete data set with a daily time series of more than 38 years, starting from 1980.

Numerous approaches have been proposed to retrieve SM information from optical reflectance (Sadeghi et al., 2015; Schnur et al., 2010; Zhang et al., 2014), TIR emission (Lei et al., 2014; Rahimzadeh-Bajgiran et al., 2013; Verstraeten et al., 2006), active microwave (Bartalis et al., 2007; Vinnikov et al., 1999; Wagner et al., 2012), passive microwave frequencies (Chen et al., 2018; Jackson et al., 2010; Kerr et al., 2016; Njoku and Entekhabi, 1996) covering a wide range of scales from the field, to catchment, to regional and global scales. Moreover, links have been established between remotely-sensed surface SM and root-zone SM by means of data assimilation techniques implemented in hydrological models (Das and Mohanty, 2008; Draper et al., 2012; Dumedah et al., 2015; Montzka et al., 2012, 2011). Various sensors and instruments used for long-term global operational SM products, such as the Soil Moisture and Ocean Salinity (SMOS) (Al Bitar et al., 2017; Chung et al., 2017; Fernandez-Moran et al., 2017b, 2017a; Kerr et al., 2013, 2011; Pablos et al., 2019), the Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) (Njoku, 2004; Owe et al., 2008), Advanced SCATterometer (ASCAT) (Albergel et al., 2008; Wagner et al., 1999) and Microwave Imager/Tropical Rainfall Measuring Mission (MI/TRMM) (Owe et al., 2008). To achieve consistency in spatial resolution between sensors, considerable efforts have been made to develop a downscaling approach for improving SM product spatial scale (Merlin et al., 2008; Montzka et al., 2018; Peng et al., 2017; Verhoest et al., 2015). In addition, much progress has been made in the development of data assimilation-based products that strategically blend land surface models and satellite-based SM products. These advances enable SM products at improved fidelity with increased temporal and spatial resolutions (Bolten et al., 2009; Reichle et al., 2017). Table A4 recalls the general characteristics of available global satellite-based SM products and data access. For a detailed discussion of SM retrieval methods, including downscaling, and recent advances of observation techniques and their applications, the reader is referred to Babaeian et al. (2019). As Table A4 demonstrates, existing SM products are available from 1978 to present (2020), covering a range of spatial resolution from 15 km to 45 km, with the opportunity to access new products at daily basis. Most of the available products used SMOS, ASCAT, and AMSR-E data for global SM production by applying a variety of approaches and methodologies. The ESA CCI product (Chung et al., 2018; Gruber et al., 2019) is the most temporally extensive and complete data set with a daily time series of 40 years starting from 1978.

Global land surface albedo products have been widely produced from optical remote sensing. Various approaches have been employed to derive albedo from polar-orbiting satellite observations, e.g., MODIS (Liu et al., 2013a;b; Schaaf, 2019; Strahler and Muller, 1999), AVHRR (Karlsson et al., 2017), MODIS/AVHRR (Liu et al., 2013a;b), SPOT-VGT/PROVA-V (Carrer et al., 2010; Geiger et al., 2008), SPOT-VGT, PROVA-V/AVHRR (Carrer et al., 2019b, 2019a, 2018), MERIS/SPOT-VGT (Muller et al., 2012) and MISR (Diner et al., 2008a). Table A5 recalls the general characteristics of available long-term global satellite-based albedo products and data access. For a detailed discussion of the Earth albedo principle and methods, the reader is referred to Stephens et al. (2015). As Table A5 indicates, existing albedo products are available from 1981 to present (2020), covering a range of spatial resolution from 500 m to 50 km, with the opportunity to access new products from daily, monthly, quarterly, to annual. Most of the available products utilized MODIS, MERIS, MISR, and SPOT-VGT data for global albedo production by applying a variety of approaches and methodologies. The Copernicus Climate Change Service (C3S) product (Carrer et al., 2019b, 2019a, 2018) is the most temporally extensive and complete data set with a 10-day time series of 39 years starting from 1981.

Various empirical and physically-based methods have been proposed to retrieve fAPAR products from remote sensing observations (Myneni et al., 2002; Myneni and Williams, 1994; Wu et al., 2010; Zhang et al., 2005). Some of these methods have been employed to produce global operational fAPAR products, for instance, from MODIS (Huang et al., 2008; Knyazikhin et al., 1998; Myneni and Knyazikhin, 2015; Myneni et al., 2015; Pinty et al., 2011), AVHRR (Zhu et al., 2013), SPOT-VGT/PROBA-V (Baret et al., 2013; Verger et al., 2014), AVHRR, SPOT-VGT (Baret et al., 2013) and MISR (Diner et al., 2008b) data sets. Table A6 recalls the general characteristics of global satellite-based fAPAR products and data access. For more information about fAPAR retrieval methods at the local and global scale, the reader is referred to Weiss and Baret (2011). As Table A6 indicates, existing fAPAR products are available from 1981 to present (2020), covering a range of spatial resolution from 500 m to 50 km, with the opportunity to access new products from daily, monthly, quarterly, to annually. Most of the

Table 2
Available global reference data sets (principal selection) and their general characteristics and repository links (links last accessed: 1 March 2020).

ECVs in situ	Data set name	Number of sites/ stations	The time span from the first data set in the archive	Reference	Access link
LAI, fAPAR	BELMANIP (DIRECT 2.0)	140	2000 - 2017	(Camacho et al., 2013; Weiss et al., 2014)	http://calvalportal.ceos.org/web/olive/site-description
LST, ET	FLUXNET	459	1999 - present	(Baldocchi et al., 2001; Running et al., 1999)	https://fluxnet.fluxdata.org
SM	ISMN	2068	1952- present	(Dorigo et al., 2011)	https://ismn.geo.tuwien.ac.at/en
Albedo	BSRN	76	1992 - present	(Driemel et al., 2018)	https://bsrn.awi.de
	FLUXNET	459	1999 - present	(Baldocchi et al., 2001; Running et al., 1999)	https://fluxnet.fluxdata.org
LC	FROM-GLC	38,664	2009 - 2011	(Zhao et al., 2014)	http://data.ess.tsinghua.edu.cn
	GRUMP	3532	2000 - 2008	(Miyazaki et al., 2011)	http://www.gofcgold.wur.nl/sites/gofcgold_refdataportal-urban.php

ISMN: International Soil Moisture Network; BSRN: the Baseline Surface Radiation Network; FROM-GLC: the Finer Resolution Observation and Monitoring of Global Land Cover, GRUMP: the Global Rural-Urban Mapping Project.

available products utilized MODIS, MISR, AVHRR, and SPOT-VGT data for global fAPAR production by applying different methodologies. The CGLS SPOT-VGT and PROBA-V V1 (Baret et al., 2013) and V2 (Verger et al., 2014) products are the most temporally extensive and complete data sets with a 10-day time series of 21 years starting from 1998.

LC thematic mapping from optical remote sensing observations is usually performed by means of various classification approaches (Foody, 2002). Long-term time series of global LC maps produced from cloud-free composites of medium to coarse-resolution data, e.g., from Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+) (Gong et al., 2013), AVHRR/ SPOT-VGT/MERIS (ESA, 2017) and MODIS (Friedl and Sulla-Menashe, 2015). Table A7 recalls the general characteristics of the global satellite-based LC products and data access. For a detailed discussion about various classification methods and their principles, the reader is referred to Dhingra and Kumar (2019). Moreover, for more information about the use of optical satellite time series data for classification, the reader is referred to (Franklin and Wulder, 2002; Gómez et al., 2016). As Table A7 shows, most of the existing LC products are produced from Landsat, MODIS, and a combination of AVHRR, SPOT-VGT, MERIS observations by means of different classifiers. LC products are available from 1992 to 2018, covering a range of spatial resolutions from 30 m to 5 km, with the opportunity to access new products annually. The ESA CCI product (ESA, 2017) derived from AVHRR, SPOT-VGT, and MERIS is the most temporally extensive and complete data set with a time series of 26 years starting from 1992 to 2018.

3.2. Planned products

Section 3.1 demonstrates that there are plenty of satellite-based long-term terrestrial ECV products available at the global scale. This is indeed a very strong incentive for operational validation and provides end-users with a selection of terrestrial ECV products to fulfill their specific purposes. What is even more promising, these historical records of terrestrial ECVs derived by harmonizing the satellite record from past and current sensors may also be extended by leveraging future missions.

Space agencies often strategically assign new mission sensors in order to maintain satellite data continuity, while making the necessary improvements in data product accuracy and resolution. They recognize the long term value of consistent data records for ECVs, given the time scales necessary for climate monitoring and modeling.

Among relatively new missions that are suitable for producing higher resolution terrestrial ECVs are the Sentinel missions (i.e., Sentinel-1A, Sentinel-1B, Sentinel-2A, Sentinel-2B, Sentinel-3A, Sentinel-3B) (https://sentinel.esa.int/web/sentinel/missions; last access: 1 March 2020) and the Landsat 8 program (https://www.usgs.gov/land-resources/nli/landsat/landsat-8; last access: 1 March 2020), with very promising results that can be utilized for ensuring satellite-based product continuity.

The potential of forthcoming ESA missions can be exploited to complete the current terrestrial ECV product inventory. Besides the Sentinel expansion program, new Earth Explorers (e.g., Earth Clouds Aerosols and Radiation Explorer (EarthCARE) [planned launch: 2021], Fluorescence Explorer (FLEX) [planned launch: 2022], and Biomass [planned launch: 2021] are in development for the future that can be used for terrestrial ECV production. For detailed information about ESA's future missions (Sentinels and Earth Explorers), the reader is referred to ESA planned missions (https://earth.esa.int/web/guest/missions/esa-future-missions; last access: 1 March 2020).

NASA has recently launched the Global Ecosystem Dynamics Investigation (GEDI) (https://gedi.umd.edu; last access: 1 March 2020) sensor on the International Space Station (ISS), that will also enhance the production of key terrestrial ECVs. NASA has more Earth science missions on the horizon, including Landsat 9 [planned launch: 2021], the Climate Absolute Radiance and Refractivity Observatory (CLARREO) [planned launch: 2023], and Geostationary Carbon Cycle Observatory (EVM-2) (GeoCarb) [planned launch: 2022]) that will all provide EO community with new data sets encouraging the production of terrestrial ECVs. Additionally, NASA and India's space agency, ISRO, are mission partners in the NASA-ISRO Synthetic Aperture Radar mission (NISAR) [planned launch: 2022]. For detailed information about NASA's future EO missions, the reader is referred to NASA planned missions (https://eospso.nasa.gov/future-missions; last access: 1 March 2020). Moreover, NASA Harmonized Landsat-8 and Sentinel-2 (HLS) project opens up a new avenue to support seamless production of terrestrial ECVs with innovation to augment existing space assets. The potential of HLS moderate (<30 m) spatial resolution data set can be exploited to create much denser global observations of the land (every 2–3 days) than would be possible for separate Operational Land Imager (OLI) onboard the Landsat-8 and Multi-Spectral Instrument (MSI) onboard the Sentinel-2. For more information about HLS data set, the reader is referred to (Claverie et al., 2018; Skakun et al., 2018).

The development of global long-term terrestrial ECV products from these new missions and their integration into a climate-scale data records, however, is a challenge. For instance, validation strategies need to be adopted to accommodate very high resolution (order of 10 m) LAI or fAPAR derived from Sentinel-2/Landsat-8 observations. Moreover, such combined records need a special temporal evaluation of uncertainties during operational validation procedures. The error levels may change discontinuously from early satellite missions to new sensor and platform concepts.

4. In situ and fiducial reference measurements for selected terrestrial ECVs

4.1. Current status

In situ measurements are the backbone of any remote sensing-based observing system validation program (Balsamo et al., 2018). A suite of continuous, independent, and representative ground measurements of terrestrial ECVs is needed for the validation of terrestrial ECVs derived from satellite data. Besides the application of in situ data for direct validation of satellite products, such ground measurements can also assist in revealing ecosystem responses to environmental and climate changes (Nightingale et al., 2019). Considerable efforts have been made to analyze and post-process the data from available in situ networks to establish a long-term record to support multiple terrestrial ECVs (Mekis and Vincent, 2011; Menne and Williams, 2009; Rohde et al., 2013; Willett et al., 2014, 2013; Yang et al., 2005) from regional to global scales (Hartmann et al., 2013). The objectives of these monitoring systems are often different from those of the satellite product validation research, which aims at reaching global coverage with full and free access to available in situ data. Table 2 presents the most complete data sets at the global scale available for validation of the selected terrestrial ECVs products.

Investigating existing networks demonstrate that, among all available in situ data for LAI and fAPAR, the most extended reference at the global scale are BELMANIP (DIRECT 2.0) used in the OnLine Interactive Validation Exercise (OLIVE) (Weiss et al., 2014). There are 113 DIRECT sites (ground validation sites issued from networks and other data provided by the community) distributed globally for LAI and fAPAR (Camacho et al., 2013; Garrigues et al., 2008). The DIRECT sites included in situ measurements upscaled according to the CEOS LPV good practice protocols using fine-resolution imagery and having data records from 2000. For more detailed information about this LAI and fAPAR in situ data set, the reader is referred to (Camacho et al., 2013; Garrigues et al., 2008). Recently the DIRECT 2.0 database has been expanded including data from the Implementation of Multi-scale Agricultural Indicators Exploiting Sentinels (ImagineS) (http://fp7-imagines.eu; last access: 1 March 2020). Up to 140 sites and 242 samples compliant with CEOS LPV criteria, making this data set optimal for validation of LAI and fAPAR ECVs. More relevant and current LAI and fAPAR in situ data sets at the regional scale are available, for instance, through the United States (US) National Ecological Observatory Network (NEON) (https://www.neonscience.org; last access: 1 March 2020) and the Integrated Carbon Observation System (ICOS) (https://www.icos-cp.eu; last access: 1 March 2020).

For long-term LST and ET in situ data, the most extensive reference at the global scale is the FLUXNET data set (Baldocchi et al., 2001; Running et al., 1999). FLUXNET is a global network for water, carbon, and energy eddy covariance flux measurements, including 914 registered stations through 2017 (https://fluxnet.fluxdata.org/about/history; last access: 1 March 2020) and approximately 459 currently active sites globally. FLUXNET organization is based on a collection of regional networks [e.g., America (AmeriFlux), Asia (AsiaFlux), Europe (EuroFlux), China (ChinaFlux)]. Complementary LST in situ data sets that can be used for validation are NOAA's Surface Radiation (SURFRAD) network (https://www.esrl.noaa.gov/gmd/grad/surfrad; last access: 1 March 2020), Karlsruhe Institute of Technology (KIT) stations through EUMETSAT's Land Surface Analysis Satellite Application Facility (LSA SAF) (http://www.imk-asf.kit.edu/english/MSA-Validiation.php; last access: 1 March 2020) and the NASA's Jet Propulsion Laboratory (JPL) validation sites (https://calval.jpl.nasa.gov; last access: 1 March 2020). Moreover, ICOS, as a European network, provides in situ standardized, traceable, and high-precision LST and ET measurements. ICOS near real-time (level 1) and final (level 2) in situ data sets are available within 24 h and between 6–12 months after measurements, respectively.

For long-term SM in situ data, the most extensive reference at the global scale is the International Soil Moisture Network (ISMN) (Dorigo et al., 2011). The ISMN is an international cooperative funded by ESA, that maintains a database of independent soil moisture in situ data sets from a variety of regional and national networks and mesonets. The partners in this effort include the CEOS, the Global Energy and Water Exchanges project (GEWEX), the Global Climate Observing System - Terrestrial Observation Panel for Climate (GCOS-TOPC), the Global Earth Observation (GEO), and the Global Terrestrial Network on Hydrology (GTN-H). Currently, the ISMN includes data from about 2068 stations distributed all over the world.

For long-term albedo in situ data, the best quality reference network data at the global scale is the Baseline Surface Radiation Network (BSRN) data set (Driemel et al., 2018). BSRN, initiated by the World Climate Research Program (WCRP) radiative fluxes working group, offers high-quality surface radiation measurements. For more detailed information about BSRN, the reader is referred to Driemel et al. (2018). Radiation budgets are typically measured at all FLUXNET sites, which can provide access to additional surface albedo globally. NOAA's Global Monitoring Laboratory maintains the US SURFRAD network, a collection of seven widely distributed stations (Augustine et al., 2000) established in 1993, that are also part of BSRN.

For global LC, the most extensive reference data set at global scale is probably the one produced within the Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC) project (Zhao et al., 2014). The FROM-GLC reference data set is based on the interpretation of Landsat (TM and ETM+) observations over 38,664 sample units with an equal-area stratification sampling scheme. Another reference data set has been created in urban and non-urban areas at global scale through the Global Rural-Urban Mapping Project (GRUMP) (Miyazaki et al., 2011) that includes a total of 3532 samples (2144 in urban and 1388 in rural areas). The data set was created based on visual interpretation of ASTER visible and near-infrared images for the period of 2000–2008.

Along with this relatively long time-series, there are other global LC reference data sets collected during a shorter period of one year. Among them, the Global Land Cover (GLC) reference data set for the year 2000, called GLC-2000 (Bartholome and Belward, 2005), was originally created as a joint effort of 30 different international partners coordinated by the European Commission's (EC) Joint Research Center (JRC). The original data set contains 1265 samples providing information at two levels; detailed information at the continental scale and a simplified version at global scale that unified the continental legends to generate a consistent LC product. A consolidation effort was carried out on this original GLC data through the Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD) project, which resulted in a new version of data set with 1253 samples classified into eleven classes (http://www.gofcgold.wur.nl/sites/gofcgold_refdataportal-glc2k.php; last access: 1 March 2020). The GlobCover 2005 reference data set was created for the year 2005 through a collaboration of different international experts as part of the ESA GlobCover project (Bicheron et al., 2008; Defourny et al., 2016, 2009). Virtual verification methods were employed by experts to collect ground truth data by means of high-resolution images within Google Earth and NDVI temporal profiles. The GOFC-GOLD project consolidated the GlobCover 4258-sample reference data set into a subset of 500, generating a simplified version by re-interpreting the data set using Google Earth and quantifying the level of confidence for the LC classes (http://www.gofcgold.wur.nl/sites/gofcgold_refdataportal-globcover2005.php; last access: 1 March 2020). The reference LC in situ data set created for the year 2013 to validate the Visible Infrared Imaging Radiometer Suite (VIIRS) NOAA Surface Type (ST) product was based on a stratification implemented according to Köppen climate-vegetation classes and population density (Olofsson et al., 2012; Stehman et al., 2012). A total of 21 strata were considered and 500 global reference sample sites were selected. Very high-resolution imagery (e.g., QuickBird satellite data) were used to better allocate the samples within each stratum. All pixels located within sample blocks were manually interpreted to label the classes according to the 17 classes defined in the International Geosphere-Biosphere Programme (IGBP) legend. For more information about the suitability of available LC reference data sets, the reader is referred to Tsendbazar et al. (2015).

In addition to the aforementioned data sets, volunteer crowdsourced data sets have been shown to provide flexible, cost-effective and timely reference data complementing available LC reference data records collected through traditional methods (Fritz et al., 2015; See et al., 2017). For instance, Geo-Wiki (http://www.geo-wiki.org; last access: 1 March 2020) has been employed as a crowdsourced tool to design and implement several campaigns to collect LC and cropland reference data sets (Fritz et al., 2017, 2012; Laso Bayas et al., 2017). The Geo-Wiki tool basically provides an online platform enabling volunteer (and registered) users to be trained for visual image classification. The volunteers are then assigned images to interpret for the production of LC mapping at particular locations around the world. Users can further visualize LC maps and analyze them by overlaying on medium to high-resolution imagery. Two examples of LC data sets derived from the Geo-Wiki crowdsourced platform are; (1) a reference data set collected in areas where data set disagreement has been reported between the GLC, GlobCover and MODIS LC data sets, and (2) a reference data set collected at the same in situ sample locations used for validation of the FROM-GLC map. For more detailed information about these reference data sets and their corresponding campaigns, the reader is referred to (Fritz et al., 2017, 2012). In addition, a set of crowdsourced reference data set has been used to develop hybrid products (Lesiv et al., 2016; Schepaschenko et al., 2015) and an entirely new and open access LC data set (Fritz et al., 2015). The concept of crowdsourced data set collection has been further expanded through the LandSense citizen observatory for monitoring LC and its changes (https://www.landsense.eu; last access: 1 March 2020). The main goal of such open access initiatives is to exploit citizen science potential to better understand, interpret, and validate satellite-based LC products. However, such potential can only be realized if the data sets are of high quality. Therefore, quality assurance and control of crowdsourced data from around the world, is also a crucial aspect that needs further considerations.

4.2. Planned networks

To compensate for the inhomogeneities of in situ measurement protocols, account for historical changes (e.g., various stakeholder pressures and possible progress in measurement technologies) and to increase end-user confidence in long-term measurement records, the concept of Fiducial Reference Measurements (FRM) has recently been proposed (Thorne et al., 2018). FRM are expected to offer temporally-stable, high-quality, and very precise representation of in situ observing variables. The NOAA's US Climate Reference Network (USCRN) (Diamond et al., 2013) is a national-level example of an FRM network, collecting some vital climate variables (e.g., LST, SM, radiation, relative humidity, precipitation). A similar national-level program has also been initiated by Environment Canada (EC) (Milewska and Vincent, 2016). To further expand the collection of FRM, ESA has initiated multiple new FRM programs. FRM for validation of Surface Temperature from Satellites (FRM4STS) (http://www.frm4sts.org; last access: 1 March 2020), was established to conduct needed reference measurements globally to validate satellite-based surface temperature (of the sea, ice, and land) products (Göttsche et al., 2017). The FRM4VEG program has been initiated to collect FRM for vegetation-related parameters (http://www.frm4veg.org; last access: 1 March 2020).

Additional activities are underway to link different research and operational in situ networks to a network of networks. The Long Term Ecosystem Research in Europe (e-LTER), the European Network of Earth Observation Networks (ENEON), and the Critical Zone Observatory (CZO) are three examples of a network of networks facilitating in situ data access regionally. LTER is a world-wide effort to develop a network for better characterizing ecosystem structural properties and functioning and to quantify their feedback to various environmental, societal, and economic drivers (https://www.lter-europe.net/lter-europe; last access: 1 March 2020). The e-LTER consists of 26 countries sharing in situ data from a network of 45 e-LTER sites. ENEON encompasses all European in situ networks active in Global Earth Observation System of Systems (GEOSS) research as a single entity (http://www.eneon.net; last access: 1 March 2020). Incorporating all active EO networks and thematic in situ sites in Europe, harmonizing the collected in situ data and ECVs, and assuring the continuity of the observations are some of the main objectives of the ENEON infrastructure. CZO is a network offering a platform to serve the international scientific community through research, infrastructure, data, and models at nine observation sites, all located in the US (http://criticalzone.org; last access: 1 March 2020).

In situ measurements are of vital importance for all EO systems and data users, but are often limited in availability. To help remedy this issue, the European Copernicus program has established a new service component, Copernicus In Situ (https://insitu.copernicus.eu; last access: 1 March 2020), to coordinate the availability, set the requirements and access to in situ data. It is not always possible to gain access to these valuable data through a proper international platform. This is identified through the Copernicus In Situ component and, therefore, all member states are encouraged to contribute to the component by sharing and providing access to their own in situ data and monitoring infrastructure at the national level.

Moreover, the Copernicus In Situ component has established data collection and sharing at the international level, mostly through research infrastructures. In 2014, the European Environment Agency (EEA) took the lead in coordinating the Copernicus In Situ component (EEA, 2017). The EEA aimed to improve and assure the in situ data availability and accessibility for all the Copernicus services. This was performed mainly through managing partnerships with different national and international organizations (as data providers) and by launching an operational portal to provide access to the COpernicus Reference DAta (CORDA) (https://corda.eea.europa.eu; last access: 1 March 2020) to support Copernicus service providers. For more detailed information about EEA partners and collaborators, the reader is referred to EEA (2016a).

Recently, eleven fact sheets have been published by the Copernicus In Situ component that identify the most important in situ data sources, partnership challenges, and in situ data gaps (https://insitu.copernicus.eu/news/new-copernicus-in-situ-website-and-fact-sheets; last access: 1 March 2020). One of these fact sheets is dedicated to land monitoring and identifies the in situ data needed for global ECV support (https://insitu.copernicus.eu/FactSheets/CLMS_Global; last access: 1 March 2020).

To further provide reliable, consistent, and high-quality long-term in situ data at the global scale for validation purposes, the CGLS initiated Ground-Based Observations for Validation (GBOV) program (https://land.copernicus.eu/global/gbov/overview; last access: 1 March 2020). GBOV will facilitate the use of data sets from international operational networks. In situ measurements are planned to be collected over the selected international in situ networks (e.g., SURFRAD, FLUXNET, NEON, BSRN). Of our selected terrestrial ECVs in this study, GBOV will, as the first step, collect in situ data for LAI, fAPAR, albedo, LST, and SM at 50 core validation sites worldwide. For the second step, GBOV will establish new sites for collecting in situ data and upgrade existing sites needed to close observation gaps at the ground scale.

Overall, various activities have been (and still are being) initiated, as briefly described above, for making in situ data available at regional and global scales. This is indispensable for any direct validation practice. The existing global in situ networks (Table 2) indicate the potential for operational validation. However, a spatially well-distributed in situ network at the global scale is still missing. As pointed out in various GCOS reports and implementation plans (GCOS-107, 2006; GCOS - 154, 2011; GCOS - 200, 2016; GCOS - 92, 2004), despite all progress that has been made toward long-term continuity of in situ measurements, there are still large areas without any in situ observations. Even in areas that have a considerable amount of in situ stations, they may not be spatially well distributed. Therefore, the available in situ networks are probably not adequate, and therefore, may not be a truly representative globally. Inadequacy of in situ data (at the global scale) for proper validation of satellite products is also identified as one of the main scientific gaps

(Nightingale et al., 2019). The shortage of in situ networks in one area and extensive records of stations in another area can result in significant inconsistency and may lead to an unreliable or biased assessment of global terrestrial ECVs (EEA, 2016b). Therefore, we need to expand these networks in such a way that enables a collection of data samples over different biomes and climates targeting representative global coverage. Space agencies through CEOS can play an important role here by funding supplementary field campaigns and establishing new stations to collect additional in situ data. Moreover, considerable in situ measurements are owned by specific research groups, national meteorological services, and hydrological modelers that are well-organized and unique. However, in many cases, this data is operated as a commercial network, funding the networks through subscriptions. There is a need at the national authority funding agency level to fund and encourage those data owners to share such data through an international, standard and traceable repository.

In order to assess changes in the climate system, we rely on an ensemble of related ECVs to help us understand the climate system and its state. One motivation to establish so-called supersites was to ensure consistency within all ECVs. Indeed, CEOS LPV has identified a new set of CEOS validation sites, so-called LPV supersites, that will be super characterized (of canopy structure and bio-geophysical variables), active long-term measurements, supporting the validation of multiple satellite-based ECV products per site, and eventually, a validation using 3D radiative transfer modeling approaches. The supersites were selected primarily from well-known and established networks (e.g., ICOS, NEON, LTER), and all sites were evaluated for their suitability by ranking them based on the availability of data and their spatial representativeness. Based on this, a total of 55 supersites were finally selected (https://lpvs.gsfc.nasa.gov/LPV_Supersites/LPVsites.html; last access: 1 March 2020) and endorsed as CEOS calibration and validation sites (http://calvalportal.ceos.org/calvalsites; last access: 1 March 2020).

5. Toward operational validation workflows

A rigorous accuracy assessment of satellite-based ECV products using reliable in situ data is fundamental for scientists to gain a realistic understanding of the Earth system and for end-users to make effective decisions (Nightingale et al., 2019). Satellite-based ECVs are being extensively validated by space agencies and affiliated organizations and researchers based on different protocols, especially for quality assessment of new satellite products (Dorigo et al., 2017; Justice et al., 2013; Yost, 2016).

Thus, most of the current validation activities and workflows are not directly comparable, even for different products of the same ECV. In fact, the validation practices are rather diverse in terms of methods, reference data, lack of traceability and transparency, locations, coverage, representation, scaling, metrics, target accuracies, and uncertainty reports, which cause a considerable lack of consistency in final products. This suggests a need to move toward operational validation workflows at the global scale. The community urgently needs to develop these unified validation workflows in an operational framework for each of the ECVs.

An operational validation workflow to assess the quality of satellite-based global terrestrial ECV products should consider, at least, four key components; (1) the long-term record of satellite-based terrestrial ECVs discussed in section 3, (2) a set of representative, reliable, and globally distributed in situ measurements discussed in section 4, (3) a suitable standard assessment framework based on a community-agreed-upon validation good practice protocol and, (4) an online validation platform.

Regarding a suitable standard assessment framework, considerable efforts have been made to establish such standardized validation frameworks for assessing satellite product quality. For instance, Zeng et al. (2015) provided a general overview of existing validation practices for climate data records of ECVs in Europe. They reviewed various aspects of validation practices by different European initiatives and finally proposed a generic validation framework with a focus on generating long-term climate data records for ECVs. Loew et al. (2017) provided a thorough review of different methodologies used by various communities for satellite product validation and discussed similarities in terminology and differences among communities followed by detailed formulations of validation problems and metrics. Su et al. (2018) provided details of validation practices employed in the Coordinating Earth Observation Data Validation for Reanalysis for Climate Services project (CORE-CLIMAX) for supporting C3S and other international activities. They specifically reported on European production of ECVs, proposed a generic validation framework, and suggested a feedback mechanism in order to use the reanalysis results for updating climate data records. More recently, Zeng et al. (2019) discussed a global quality assessment framework in order to analyze various ECV products. Their study aimed to identify a structure for the quality assessment and to perform a usability evaluation to deliver quality-assured data for end-users. Nightingale et al. (2019) discussed the ten most important scientific gaps in the quality assessment of climate data records. They first presented the Evaluation and Quality Control (EQC) framework for satellite-based climate products and in situ measurements that will be cataloged through the C3S climate data store (https://cds.climate.copernicus.eu; last access: 1 March 2020). The C3S will implement the EQC framework as a component of their quality assurance initiative. Further, they described a prototype to evaluate and present the quality aspects of desired data products useful for the end-users.

The Quality Assurance framework for Earth Observation (QA4EO) has been endorsed by CEOS (https://qa4eo.org; last access: 1 March 2020) with the aim to facilitate providing traceable quality indicators. The key objective of QA4EO is to provide all end-users with the opportunity to readily assess satellite-based data products for their desired purpose (QA4EO, 2010). In fact, QA4EO provides a set of top-level guidance and reference documents for the users to assist in obtaining and reporting data product quality in a strict way. For instance, it encourages all users to strictly follow the "Guide to the expression of Uncertainty in Measurement (GUM)" (GUM, 2008) for uncertainty estimate in the observations and the propagated errors to the data products.

In 2011, the LandFlux-EVAL (https://iac.ethz.ch/group/land-climate-dynamics/research/landflux-eval.html; last access: 1 March 2020) project, supported by the GEWEX and Integrated Land Ecosystem Atmosphere Processes Study (ILEAPS), aimed at the assessment and intercomparison of various global ET data sets available over a longer time period in order to develop a reference benchmarking data set. The LandFlux-EVAL effort was a key component of the GEWEX LandFlux initiative through its Radiation Panel (GRP) program. Although the main objective of the GEWEX LandFlux activity was mainly to identify a robust and routine procedure for an operational production of global land-based surface turbulent heat flux (i.e., ET and sensible heat flux) at the global scale (Jiménez et al., 2011; Mueller et al., 2011), their activities could additionally provide a framework for evaluating land-based heat flux products through intercomparison and quantifying the range of uncertainty. For more detailed information about the LandFlux-EVAL, the reader is referred to Mueller et al. (2013). Moreover, OpenET (https://openETdata.org; last access: 1 March 2020) is a new initiative, scheduled to launch in 2021, with the aim of developing a web-based platform for effective water management. The project is being led by NASA, the Desert Research Institute (DRI), and Environmental Defense Fund (EDF), with in-kind support from Google Earth Engine. OpenET will serve the community as a single platform to bring publicly available satellite data and weather stations to calculate ET at field scale using various well-established algorithms in the western US. Therefore, OpenET platform is designed mainly to generate ET products from satellite data by means of various algorithms initially in the western US but with the potential to expand to other regions across the globe. Additionally, this platform can provide the users with the opportunity to evaluate the accuracy and help refine the strength of various ET algorithms through the intercomparison of generated ET products.

Further, in 2014, the Quality Assurance for Essential Climate Variables (QA4ECV) (http://www.qa4ecv.eu; last access: 1 March 2020) initiative was launched to provide necessary guidelines, based on the primary achievements of QA4EO, for a traceable quality assessment (Scanlon et al., 2017). The proposed QA4ECV assurance framework utilized to assess the quality and accuracy of three terrestrial ECVs (i.e., LAI, albedo, fAPAR) and three atmospheric domain ECVs (i.e., nitrogen dioxide, formaldehyde, and carbon monoxide). The QA4EO and QA4ECV guidelines have been embraced by the C3S (https://climate.copernicus.eu; last access: 1 March 2020) to set up quality assured, reliable and fully traceable climate data records (Nightingale et al., 2018).

In 2014, the OLIVE (http://calvalportal.ceos.org; last access: 1 March 2020) was initiated by CEOS LPV, funded by ESA and hosted at the CEOS CAL/VAL portal, to provide an online web service for benchmarking and assessment of global land products. The key objective of OLIVE was to be an effective tool to ensure that all validation exercises of various biophysical variables would follow CEOS LPV guidelines and be compliant with QA4EO recommendations targeting stage 4 in the CEOS LPV validation hierarchy. However, it was eventually utilized only for LAI and fAPAR validation. To this end, the OLIVE was designed, envisioned, and used as a model going forward.

In 2015, LACO-Wiki (http://laco-wiki.net; last access: 1 March 2020) was developed by merging the ESA-funded Land COver Validation (LACOVAL) prototype (See et al., 2015) with the web architecture and database design of Geo-Wiki (Fritz et al., 2012) to provide a framework for LC validation. Two primary goals of LACO-Wiki are: (1) to develop a workflow to facilitate and simplify LC validation procedures, to make it user friendly for users from different communities, and (2) to offer a platform where users can store and share LC maps and validation reference data sets (See et al., 2017). To this end, LACO-Wiki provides end-users with an online platform to upload LC maps, choose sound sampling designs, offer guidance through validation procedures, and generate accuracy reports.

In 2018, the Quality Assurance for Soil Moisture (QA4SM) initiative (https://qa4sm.eodc.eu; last access: 1 March 2020) was launched to serve the SM remote sensing community with a traceable validation service of SM products . In QA4SM, the satellite SM products can be validated against in situ measurements and model generated reference data. The QA4SM, aims to provide the SM product users with traceable validation results based on community validation protocols and methodologies. In addition to QA4SM, “pytesmo” (https://doi.org/10.5281/zenodo.1215760; last access: 1 March 2020) is an open-access software program developed in python for validation of SM.

Overall, all these contributions are very crucial steps toward reaching an operational standard validation framework for each ECV. One of the most basic needs in the process, however, is the preparation of a unified and community-agreed-upon validation protocol for satellite-based ECVs. To address this need, at the international level, the CEOS LPV subgroup has been coordinating and investigating variable-specific validation practices and preparing unique validation good practice protocols for several terrestrial satellite ECV products. The LPV subgroup’s key mission is to provide a forum for coordination of validation activities, led by a group of subject matter experts, who engage their respective communities, resulting in the development and publication of validation good practice documents for satellite-based land products. The LPV subgroup currently focuses on eleven different areas [biophysical (LAI, fAPAR), SM, LC, LST and emissivity, fire disturbance, surface radiation (albedo, bidirectional reflectance distribution function), phenology, vegetation indices, snow cover, and biomass]. Publication of such validation good practice documents is a big step toward operational validation procedures. The CEOS LPV defined four progressive stages through a validation hierarchy for satellite products (Nightingale et al., 2011). These stages were adopted first through the community consensus in 2006 (Morisette et al., 2006) with further adjustment in 2009 (Baret et al., 2009). The validation hierarchy and its stages demonstrate the validation maturity level of specific data products under investigation. Table 3 presents the current validation status for the selected terrestrial ECVs in the CEOS LPV validation hierarchy.

Table 3
The current validation status for the selected terrestrial ECVs in the CEOS LPV validation hierarchy (https://lpvs.gsfc.nasa.gov; last access: 1 March 2020).

Validation stage - definition and current state		Terrestrial ECVs
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.	LAI fAPAR LC
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.	LST SM Albedo
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 over a global network of sites and time periods (if available).	–

Based on Table 3, among selected terrestrial ECVs, three products (i.e., LAI, fAPAR, and LC) reached level 2, and three other products (i.e., LST, SM, and albedo) reached level 3 in the CEOS LPV validation hierarchy. However, ET is currently not among the CEOS LPV focus areas, while, listed in the GCOS table of terrestrial ECVs (https://gcos.wmo.int/en/essential-climate-variables/table; last access: 1 March 2020). With this respect, there is still room for improvement in CEOS LPV activities by expanding their focus areas to include more terrestrial ECVs. Further, based on CEOS LPV recommendations, to reach validation stage four in the case of each product, an integrated automated platform should be developed in which quantitative validation tests can be performed regularly, and standardized reports generated accordingly. CEOS LPV efforts to investigate individual validation frameworks and publish a unified and standard validation good practice protocols for each ECV provides a very significant step forward toward operational validation procedures.

Additionally, moving from individual validation practice toward fully operational validation workflows require important general considerations beyond the technical aspects: (1) all validation workflows should be open access with full transparency and traceability. The implementations can be either through public web service providers or open-source software programs, (2) free public access to the utilized in situ data in the system and their metadata catalogs are strongly encouraged, (3) providing flexibility in the system in such a way that meets the needs of the users from different communities. For instance, researchers from different communities might be interested in using different validation metrics and specific figures and graphs proposed by the best experts in the field. In this case, the system should allow selection from a list of metrics, figures, and graphs implemented within the system to be selected by the user to customize the final report based on demand, (4) the platform should be regularly updated with newly available ECV products, enabling end-users to select their desired products, and (5) employing high-performance and cloud computing technology in the operational validation system is highly encouraged. This can improve the system functionality to ingest a longer time series of satellite-based ECVs and promote the operational assessment of these products.

6. Current status of operational validation for selected terrestrial ECVs

Ideally, an operational validation system should be: (1) fully transparent and traceable in which the user would have free and open access to the available long-term global satellite-based ECV products and related global in situ data set, and (2) the user should be able to execute a community-agreed-upon good practice protocol to validate ECV products in an objective fashion to generate standardized validation reports. To the best of our knowledge, such an operational system is still not available at the global scale for the terrestrial ECVs. However, significant progress has been made toward designing variable-specific online validation platforms.

With respect to SM, the QA4SM service is an online platform providing open-access tools for validation (Dorigo et al., 2011). QA4SM makes use of a standard validation good practice (Gruber et al., 2020) through an online platform to assess satellite SM quality based on in situ and model-generated reference data at the global scale. Additional functionalities have also been considered for QA4SM, for instance, various filtering and scaling options are implemented in the validation. Satellite SM products that are included in QA4SM are C3S, ESA CCI, SMAP level-3, ASCAT, and SMOS. For the in situ data sets, QA4SM includes ISMN reference data set. Additionally, GLDAS model-generated SM data, ECMWF Reanalysis 5th Generation (ERA5), and ERA5-land reanalysis data are available in the platform that could be used for intercomparison purposes. The QA4SM is perhaps the most advanced online validation platform compared to the other ECVs investigated in this study. However, there is certainly room for improvement in QA4SM. Particularly, there is a need to include more satellite SM products, especially those with global coverage and longer time-series, e.g., those mentioned in Table A4. It should also have the ability to implement user-generated SM products in the near future. This can provide end-users with an opportunity to compare a local or regional product of their own. For example, end-users can assess data generated from airborne campaigns, and compare them with standard global products. Of course, it should be noted that all new additions to the platform, either from the satellite or in situ, should pass the CEOS LPV SM protocol requirements.

OLIVE was an implemented online platform for the validation of LAI and fAPAR (Weiss et al., 2014). OLIVE could provide objective assessment, transparency and traceability based on CEOS LPV recommendations for LAI and fAPAR products. Satellite LAI and fAPAR products initially included in OLIVE were GEOLAND (V1), CYCLOPES (V3.1), GLOBCARBON, MODIS/TERRA, and MERIS Global Vegetation Index (MGVI) (V1). For the in situ data set, OLIVE included DIRECT validation sites (Camacho et al., 2013; Garrigues et al., 2008) explained in Section 4. Currently, OLIVE is not operational. There are multiple challenges that would need to be overcome to make the platform ready for public use again. The first and the most important would be the financial support for OLIVE administration, functionality improvements, and regular system update and maintenance. To this end, space agencies and data providers could contribute by providing required support in line with their own missions to make OLIVE an active platform. Given funding support, one possible direction for improvement is related to OLIVE configuration control since the original source code is in MATLAB, making it problematic to set up an instance of the tool online. Translation of the source code to an open-source programming language (e.g., either Python or R and provisioned fully through a GitHub type of interface) following the state-of-the-art code structure is strongly recommended. In this way, the OLIVE platform could continue to be developed by various groups within the community, and technical issues can regularly be reported and effectively solved. Further recommendation for the next generation of OLIVE is to adapt the platform in such a way that higher resolution terrestrial ECVs (e.g., LAI and fAPAR derived from Landsat and Sentinel missions) can also be included in both OLIVE inter-comparison and direct validation modules, as it was designed for medium resolution (order of km) products. Finally, the data repository in the next generation of OLIVE platform could potentially be complemented by available long-term products, e.g., those mentioned in Tables 2 and 7, after careful consideration of their suitability based on CEOS LPV requirements.

Regarding the LST variable, to date, there is currently a gap for an online validation platform. CEOS LPV has published a validation good practice protocol for LST (Guillevic et al., 2018) that is an important and promising step. However, significant effort is required from individual members of scientific and developer communities to design a pilot online validation platform for LST. One major challenge for moving toward an operational LST system is the lack of sufficient in situ data with appropriate global coverage. Surface in situ measurement of LST at the global scale is currently too sparse for use in an operational system for performing a systematic validation. This is mainly due to the difficulties and limitations in collecting crucial ancillary data (e.g., land surface emissivity and atmospheric properties) since such ancillary data sets are not routine measurements globally (Guillevic et al., 2018). Therefore, there is a need to further expand available LST in situ measurements and establish new networks. The GBOV and FRM4STS are very promising programs and may address the challenge of in situ data to a certain extent. LST data sets from these new initiatives along with FLUXNET provided global measurements are among possible candidates to be used in a potential validation platform. At FLUXNET stations, the ground-based LST can be obtained from the outgoing longwave radiation (surface-leaving radiance) and downwelling sky radiance using Planck's law (Guillevic et al., 2018). The surface-leaving radiance and downwelling sky radiance are both routine measurements at the FLUXNET stations.

With respect to the albedo variable, to date, there also is a gap for an online validation platform. For global albedo, the validation good practice protocol has been published by the CEOS LPV (Wang et al., 2019). Similar to LST, the key challenge for moving toward full operational validation in albedo might be the lack of sufficiently distributed in situ data (Wang et al., 2019). Although surface albedo is a routine measurement at a variety of research sites, the measurement networks for albedo are not adequate at the global scale. Access to the available albedo in situ data is also not straightforward as they are managed by different in situ networks (Wang et al., 2019). Therefore, there is a need to further expand available albedo in situ measurements and establish new networks as necessary. Among the available networks, BSRN and FLUXNET networks have made significant contributions, and further development of these sites in order to expand the coverage might address the inadequacy in reference albedo in situ data, to a certain extent. Scientists in collaboration with CEOS LPV have started adapting the Surface Albedo Validation (SALVAL) tool (Sanchez-Zapero et al., 2017), used for validation of C3S products, to an online validation platform for other albedo products based on the CEOS LPV good practice protocol. The SALVAL tool can also be used for available long-term satellite-based global albedo products, e.g., those described in Table 5A, as input for a potential operational validation system.

For LC, LACO-Wiki is an implemented online platform providing an open-access tool for validation of LC at local to global scales (See et al., 2017, 2015). The key objective of LACO-Wiki is to offer an easy-to-use online tool to validate LC products based on the LACOVAL prototype (See et al., 2015). LACO-Wiki enables end-users to adopt methodologically sound sampling designs from their desired LC products and then provides step-by-step guidance to visually interpret and analyze the samples. The final step in the LACO-Wiki workflow is to generate standardized validation reports. Since LACO-Wiki is originally developed based on the LACOVAL prototype, there is room for improvement by

Table 4
Readiness level of selected terrestrial ECVs for moving toward operational validation based on four criteria with equal weighting coefficients (of 25 %) assigned for each criterion (long term satellite products, global in situ data set, CEOS LPV validation good practice protocol, and an online validation platform). Tick mark (✓) displayed when the criterion passed, and cross mark ( ) displayed when the criterion failed. (Links last accessed: 1 March 2020).

Terrestrial ECV	Long-term global data record		CEOS LPV protocol		online validation platform	Overall readiness for operational validation (%)
	Satellite products	In situ data	Published good practice document	Reference to CEOS LPV good practice		
LAI	✓	✓	✓	(Fernandes et al., 2014)	✓	100
fAPAR	✓	✓	*x*	*x*	✓	75
LST	✓	✓	✓	(Guillevic et al., 2018)	*x*	75
ET	✓	✓	*x*	*x*	*x*	50
SM*	✓	✓	✓	https://www.esa-soilmoisture-cci.org/index.php?q = validation https://suzaku.eorc.jaxa.jp/GCOM_W/data/data_w_calval.html (Gruber et al., 2020)	✓	100
Albedo**	✓	✓	✓	(Wang et al., 2019)	*x*	75
LC	✓	✓	✓	(Strahler et al., 2006)	✓	100

* The CEOS LPV validation good practice document for SM is currently under discussion by SM group of top experts within the community and is expected to be published by CEOS LPV soon.
** The SALVAL online platform developed in collaboration with CEOS LPV is expected to be published soon.

considering CEOS LPV proposed recommendations and standards for LC validation (Strahler et al., 2006). Currently, LACO-Wiki does not include any global satellite-based LC products. This means the users should upload their own LC maps to the platform before performing any validation practice. One of the key features of LACO-Wiki is that all user-uploaded LC maps can also be shared with other users. However, we recommend importing all available satellite LC products, especially those with global coverage and longer time-series, e.g., those mentioned in Table A7, in the LACO-Wiki repository. This can give end-users more flexibility in the process of their LC product selections. It should be further noted that the reference data set in LACO-Wiki does not include ground-based observations of LC, i.e., true in situ measurements. Instead, it utilizes satellite and aerial imagery mainly from Google, Bing, and OpenStreetMap as reference data sets in the validation procedure (See et al., 2017). Therefore, it is recommended to consider using supplementary in situ data sets (e.g., Table 2) to enrich the reference data repository in the future generations of LACO-Wiki. For importing a new reference data sets into the system, it is recommended to follow CEOS LPV proposed methods (Strahler et al., 2006). For most existing LC reference data, additional efforts are needed to make them ready to use in validation practices. For instance, the reference data should be reclassified to match those of the target classification scheme; this is due to the fact that in the majority of cases, the reference data were collected for other purposes and are not specifically for global LC validation. Therefore, besides the evaluation of existing in situ data to ensure their compatibility with the desired validation practice, one must investigate the in situ data sampling design (Strahler et al., 2006). To address the in situ reference data challenges, GOFC-GOLD reference data portal was created to evaluate the existing reference data and provide public access to suitable reference data for all users. Therefore, it is necessary to further investigate the current in situ data and also explore the suitability of reference data from additional sources. Local expertise and information at the national and regional levels can enrich the available LC data set. New LC reference data sets generated from forthcoming crowdsourced campaigns (e.g., Geo-Wiki and LandSense) can significantly assist in closing a large gap in available LC in situ data and further supports the production of new reference data sets at the global scale. LACO-Wiki, if extended as described above, can be served as a proper online validation platform to move toward full operational validation procedures of satellite-based LC products.

Regarding the ET variable, to date, there is neither an online validation platform nor a validation good practice protocol. Therefore, considerable effort is needed here to pave the way toward operational validation for ET compared to the other terrestrial ECVs under discussion in this study. Available global FLUXNET stations could be accessed to provide global ET in situ data. Two actions may be considered for the case of ET; the first is to establish a new focus area in CEOS LPV dedicated to ET to initiate preparation of validation good practice protocol for this crucial terrestrial ECV, and second is to encourage individual members from scientific and developer communities to outline a pilot online validation platform for ET. The availability of long-term satellite-based global ET products, e.g., those described in Table 4, provide input for a potential operational validation system.

As described above, a few of the selected terrestrial ECVs are in a position to move toward operational validation procedures, while others are at different levels of readiness and, therefore, more effort is still required. To provide an overview of the readiness level of selected terrestrial ECVs for moving toward operational validation, we assigned equal weighting coefficients (of 25 %) to each criterion highlighting the importance of four defined criteria (i.e., long term satellite-based global product availability, globally distributed in situ measurement availability, a validation good practice protocol, and an online validation platform). Table 4 shows, the readiness level of selected terrestrial ECVs for operational validation procedures. The defined criteria are adopted based on the CEOS LPV definition for reaching stage four of the validation hierarchy and are in good agreement with their proposed standard validation framework. As Table 4 shows, LAI, SM and LC are in the highest level of readiness (i.e., 100 % ready, note: of course there may always be some issues, before or after launching the systems) for operational validation procedure at the global scale since these three terrestrial ECVs passed all four criteria successfully. However, ET is in the lowest level of readiness (i.e., 50 % ready) due to the fact that it does not meet two of the criteria, no CEOS LPV protocol nor an online validation platform. The remainder of the terrestrial ECVs (i.e., LST, albedo and fAPAR) is located in the middle level of readiness (i.e., 75 % ready). The LST and albedo have passed long-term global satellite product availability, in situ measurement accessibility, not globally extensive though, and CEOS validation good practice protocols. However, there is no online platform for validation purposes of the LST and albedo yet. It should be noted that the albedo is in transition from 75 % to 100 % readiness since the SALVAL tool is currently being adapted to an online tool that will allow it to reach the highest level of readiness soon. For fAPAR (i.e., 75 % readiness), the CEOS LPV validation protocol has not yet developed, even if fAPAR products can benefit from the LAI protocol and the same validation tool, but the specificities of fAPAR still need to be addressed separately.

To summarize, as can be seen from Fig. 1, LAI (Fig. 1a), SM (Fig. 1e), and LC (Fig. 1g), communities have made considerable progress in

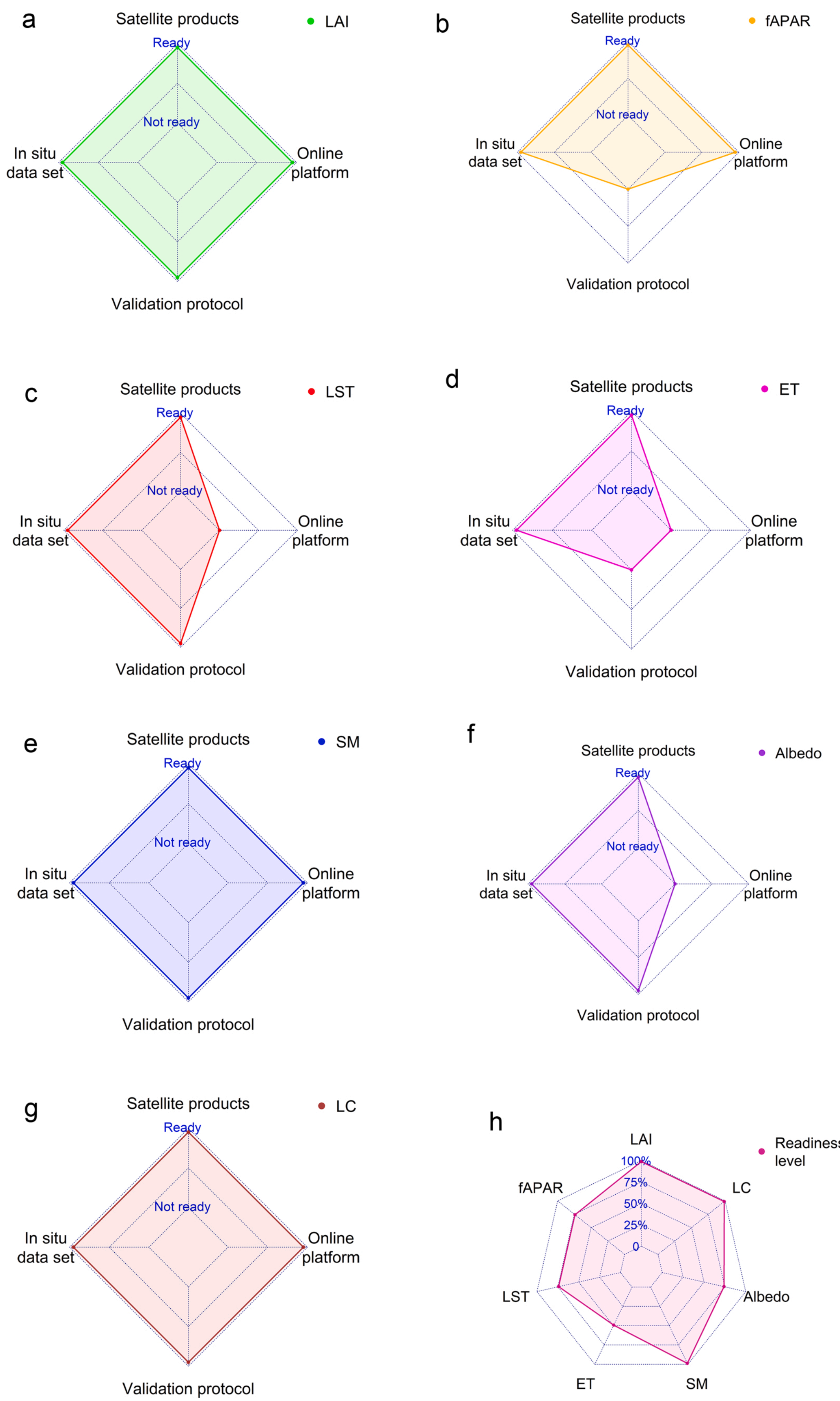

Fig. 1. Radar charts with readiness status of operational validation systems for each of terrestrial ECVs (a: LAI, b: fAPAR, c: LST, d: ET, e: SM, f: albedo, g: LC) with respect to four main needed components (long term satellite products, global in situ data set, CEOS LPV validation good practice protocol, and an online validation platform) and a summary of the readiness level of selected terrestrial ECVs for moving toward operational validation systems (h).

establishing minimum required validation system components (i.e., long term satellite products, global in situ data set, CEOS LPV validation good practice protocol, and an online validation platform). Regarding fAPAR (Fig. 1b), LST (Fig. 1c), and albedo (Fig. 1f), three components are relatively ready; however, a validation good practice protocol and pilot online validation platforms need further development. For ET (Fig. 1d), much effort from the community is required since compared to other ECVs investigated in this study, ET is at the lowest level of readiness, mainly due to the lack of standard validation good practice protocol and a pilot online validation platform. Fig. 1h summaraizes the readiness level of selected terrestrial ECVs for moving toward operational validation systems.

One of the key considerations in the design of an operational system is ensuring its sustainability through regular maintenance and upgrading all system components according to user feedback and demands. In an operational validation system, one needs to maintain and update satellite-based ECV data products, in situ measurements, validation protocol, and online platform.

Upcoming satellite missions initiated and approved by space agencies, e.g., described in Section 3.2, can ensure the long-term sustainability of terrestrial ECVs production. Regarding in situ components, these are usually maintained and updated by the principal investigators of each site or by organized networks at the national or international level. New in situ initiatives, e.g., described in Section 4.2, can help to maintain in situ data continuity beyond current measurements, which is vital to sustain product validation into the future. Furthermore, there is a unique opportunity here for the interaction of operational validation systems for selected terrestrial ECVs and international open repositories. Such interactions enable crucial information exchange and updates that can be beneficial not only for the operational validation system but also for the international repository. For instance, the Observing Systems Capability Analysis and Review tool (OSCAR) (https://www.wmo-sat.info/oscar; last access: 1 March 2020) of the WMO Integrated Global Observing System (WIGOS) Information Resource (WIR) is a good example of an open repository at the international level providing information for WIGOS metadata. There are two key components within OSCAR; the surface- and space-based components. These components record observing platform/station metadata following the WIGOS standards. OSCAR can provide valuable detailed information on ground stations (i.e., surface-based capabilities) and satellite sensors (i.e., space-based capabilities) at global scale to enrich in situ and satellite products metadata of an operational validation system. In return, global operational validation systems might also contribute to OSCAR by sharing the information on new satellite products and in situ networks planned for the system but have not been ported into OSCAR yet.

However, substantial effort is required to maintain and update ECVs validation good practice protocols and online platforms. The CEOS LPV coordinates protocol development through the volunteer efforts of its focus area leads and their respective communities, and supports the publication of these validation good practice protocols. The subgroup should continue to encourage those focus areas with published protocols to review and update the protocols to keep them current. For instance, the global LC validation good practice protocol was published in 2006 and since that time, new LC products have been made available, new quality assessment methods tested, and new reference data sets have been collected, thus an update is clearly past due.

The maintenance and upgrade of online validation platforms are also of utmost importance. The platforms should regularly incorporate new products into the validation system. Among the validation online platforms investigated in this study: (1) the LACO-Wiki needs to consider the time-series of available satellite-based LC products and more reference data sets following CEOS LPV recommendations in the next system updates, (2) the OLIVE platform needs considerable maintenance and upgrade since it is not currently operational, and (3) the QA4SM platform may also include more satellite SM products, especially those with global coverage and longer time-series in system updates.

7. Summary and outlook

The GCOS has stressed the need for systematic validation of satellite-based ECV data products. One possibility for meeting this validation need effectively is through unified validation procedures leveraging operational validation systems at the global scale. This study investigates the current readiness and shortcomings of achieving such operational systems in the validation of satellite-based terrestrial ECVs. We explored the strengths and weaknesses with respect to required components of a potential operational validation system: (1) long-term availability of satellite-based global ECV products, (2) reliable in situ global data sets, (3) community-agreed validation good practice protocols and, (4) online validation platforms. This study focus was on a selected group of seven terrestrial ECV products [notably: LAI, LST, ET, SM, albedo, fAPAR, and LC] at the global scale with long-term (+10 years) perspective.

A survey of selected satellite-based terrestrial ECVs indicates their considerable readiness. Long-term availability of global products generated from various satellites, particularly those from MODIS, SPOT-VGT, and PROBA-V can contribute to the goal of operational validation systems. NASA's VIIRS will be entering its 10th year on orbit in 2021, thus providing several more long-term ECVs for operational validation. For each of the terrestrial ECVs under investigation, several products were identified as ready and available. There are also several newly launched and forthcoming ESA and NASA and other space agency satellite missions that can ensure future continuity of terrestrial ECVs to complement the time-series of existing products and cross-walk to and beyond them.

Investigation of existing in situ measurements for the target terrestrial ECVs demonstrates that there is at least one common global database providing open access to in situ data needed for validation of each of selected terrestrial ECVs. These in situ data repositories are vital to developing an operational validation system. However, there continues to be insufficient reference networks and resources to reach global representativeness and even, in some cases, this is the fundamental limitation. This highlights an urgent need to establish more partnerships globally for completing and, most importantly, maintaining and expanding in situ networks into the future. In addition, these networks need to be developed so that they can be considered as spatially representative validation reference data sets for each terrestrial ECV. To address this, new initiatives (e.g., ESA FRM, a network of networks [e-LTER, ENEON, CZO], and Copernicus' GBOV program) have been planned which are very promising and targeted to close the gaps of in situ data globally. Existing in situ data sets, with all complementary ongoing and forthcoming initiatives, at the global scale might be considered a positive point toward developing operational validation systems.

With respect to the available validation framework for the target terrestrial ECVs, at the international level, the CEOS LPV community-developed validation good practice protocols are very useful and can significantly contribute to operational validation at the global scale by providing a unified framework for each terrestrial ECV. CEOS LPV is currently addressing eleven variables but there might be a need to expand such voluntary activities and include other variables (e.g., ET) which are listed in the GCOS table of terrestrial ECVs. To address this need, further scientific supports of internationally recognized individual members from the community is necessary.

Among all selected terrestrial ECVs products, SM, LAI, fAPAR, and LC have online validation platforms. QA4SM is an online platform for SM validation, OLIVE was an online platform for LAI and fAPAR validation, and LACO-Wiki is an online platform for LC validation. Further, the SALVAL tool is currently being adapted to an online platform to be operational for albedo validation soon. Lessons learned from these validation platforms are invaluable and should be employed for developing similar online validation platforms for other terrestrial ECV products. Online validation platforms could potentially assist for the lack of traceability and transparency in existing validation procedures.

Considering all these components needed for operational validation systems, we quantified the "readiness level" for the seven selected terrestrial ECVs. Based on our investigations LAI, SM and LC are in the highest level of readiness for moving toward full operational validation at the global scale. However, ET is in the lowest level of readiness, mainly due to the lack of community-agreed validation good practice protocol and a pilot online platform. The remainder of selected terrestrial ECVs were determined at the middle level of readiness, mainly because of either validation platform (i.e., LST and albedo) or standard protocol (i.e., fAPAR) require further development.

This study outlines the readiness status of operational validation systems for a selected group of seven terrestrial ECVs. Currently, it is up to the scientific and developer communities to decide to take this further step forward. One potential long-term perspective is to integrate variable-specific operational validation systems into a system of systems that includes all terrestrial ECVs, or at least those that can be validated with a similar type of in situ data. Such an integrated validation system must follow community-agreed-upon good practice protocols and generate standardized validation reports (e.g., metrics, uncertainties, figures, tables) for various ECVs. It could also be employed as an open-access tool for benchmarking forthcoming satellite products and a proper host for the inclusion of new in situ data sets. Finally, to ensure the sustainability of "operational" validation systems for long-term usage, effective maintenance and regular system updates are crucial.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the European Commission HORIZON 2020 Program ERA-PLANET/GEOEssential project [grant number: 689443]. The authors would like to thank three anonymous reviewers for their constructive comments and suggestions to improve the quality of our paper. USDA is an equal opportunity employer and provider.

Appendix A

Tables A1–A7 review selected satellite products' main characteristics

Table A1
Available long-term global LAI products (principal selection) and their general characteristics and repository links (considering products with +10 years of availability) (links last accessed: 1 March 2020).

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
AVH15C1	AVHRR	0.05°	daily	1981 - present	NN (LTDR AVHRR)	(Claverie et al., 2016)	https://www.ncei.noaa.gov/data/avhrr-land-leaf-area-index-and-fapar/access
GLASS	AVHRR	1 km	8-day	1981–2018	NN (Red, NIR)	(Xiao et al., 2016, 2014)	http://glass.umd.edu/LAI/AVHRR
GLASS	MODIS	1 km, 0.05°	8-day	2000–2015			http://glass.umd.edu/LAI/MODIS
GIMMS3 g V1	AVHRR	1/12°	15-day	1981–2011	NN (GIMMS NDVI3 g, MODIS LAI)	(Zhu et al., 2013)	http://cliveg.bu.edu/modismisr/lai3 g-fpar3 g.html
GIMMS3 g V2	AVHRR	0.25°	Monthly	1981–2015		(Mao and Yan, 2019)	https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id = 1653
GLOBMAP V1	AVHRR/MODIS	500 m	8-day	1981–2015	VI-LAI empirical relationship	(Liu et al., 2012)	http://www.resdc.cn/data.aspx?DATAID = 336
GLOBMAP V2	AVHRR/MODIS	0.08°	Half-monthly	1981–2015			
MOD15A2H	MODIS/TERRA	500 m	8-day	2000 - present	LUT inversion (Red, NIR) and a backup algorithm using empirical relationships between NDVI and LAI	(Myneni et al., 2015)	https://lpdaac.usgs.gov/products/mod15a2hv006
MOD15A2H	MODIS/AQUA	500 m	8-day	2000 - present		(Myneni, R., Y. Knyazikhin, 2015)	https://lpdaac.usgs.gov/products/myd15a2hv006
MOD15A2H	MODIS/TERRA-AQUA	500 m	8-day	2002 - present	LUT inversion (Red, NIR)	(Huang et al., 2008; Knyazikhin et al., 1998)	https://lpdaac.usgs.gov/products/mcd15a2hv006
MOD15A3H	MODIS/TERRA-AQUA	500 m	4-day	2002 - present			https://lpdaac.usgs.gov/products/mcd15a3hv006
MISR V2	MISR	1.1 km	Daily	2000 - present	LUT inversion (Red, NIR)	(Diner et al., 2008b)	https://eosweb.larc.nasa.gov/project/misr/MISR_table
CGLS V1	SPOT-VGT/PROBA-V	1/112°	10-day	1998 - present	NN (CYCLOPES and MODIS LAI)	(Baret et al., 2013)	https://land.copernicus.vgt.vito.be/PDF/portal/Application.html#Browse;Root = 512,260;Collection = 1,000,169;Time = NORMAL,NORMAL,-1,-1,
CGLS V2	SPOT-VGT/PROBA-V	1/112°	10-day	1998 - present	NN (CYCLOPES and MODIS LAI), smoothing and gap filling	(Verger et al., 2014)	https://land.copernicus.vgt.vito.be/PDF/portal/Application.html#Browse;Root = 512,260;Collection = 1,000,083;Time = NORMAL,NORMAL,-1,-1,
TIP	MODIS/TERRA-AQUA	0.01°	16-day	2000–2012	One dimensional two-stream scheme of the radiative transfer, called TIP, applied	(Pinty et al., 2011)	http://www.fastopt.de/products/tip/tip.shtml
C3S V1	AVHRR/SPOT-VGT	4 km [AVHRR],1 km [SPOT-VGT]	10-day	1981–2014	NN (CYCLOPES and MODIS LAI)	(Baret et al., 2013)	https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-lai-fapar?tab = form

NN: Neural Network; LTDR: Long-Term Data Record; GLASS: Global LAnd Surface Satellite; NIR: Near-InfraRed; GIMMS3 g: third-generation Global Inventory Modeling and Mapping Studies; GLOBMAP: GLOBal MApping Project; VI: Vegetation Index; GIMMS3 g: Global Inventory Modeling and Mapping Studies third-generation; GIMMS NDVI3 g: Global Inventory Modeling and Mapping Studies third-generation Normalized Difference Vegetation Index; LUT: Look-Up Table; NDVI: Normalized Difference Vegetation Index; PROBA-V: PROBA-Vegetation; CGLS: Copernicus Global Land Service; TIP: Two-stream Inversion Package; C3S: Copernicus Climate Change Service.

Table A2
Available long-term global LST products (principal selection) and their general characteristics and repository links (considering products with +10 years of availability) (links last accessed: 1 March 2020).

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
LST	ASTER	90 m	16-day	2000-present	Temperature/ emissivity separation algorithm	(NASA, 2001)	https://lpdaac.usgs.gov/products/ast_08v003
CGLS LST	MSG/ GOES East/ MTSAT/ Himawari	5 km	Hourly	2010-present	Generalized split-window and dual-algorithm	(Freitas et al., 2013)	https://land.copernicus.vgt.vito.be/PDF/portal/Application.html#Browse;Root = 520,752;Collection = 1,000,300;Time = NORMAL,NORMAL,-1,,,-1,,
LST MOD11 Level-2	MODIS/ TERRA MODIS/AQUA	1 km	Daily	2000-present 2002-present	Generalized split-window algorithm	(Wan et al., 2015a) (Wan et al., 2015b)	https://lpdaac.usgs.gov/products/mod11_l2v006
LST MOD11 Level-3	MODIS/ TERRA MODIS/AQUA	1 km, 6 km	Daily, 8-day (only 1 km)	2000-present 2002-present	Derived from MOD11Level-2	(Wan et al., 2015c)	https://lpdaac.usgs.gov/products/mod11a1v006
LST MOD11 Level-3	MODIS/ TERRA MODIS/AQUA	0.05°	Daily, 8-day, monthly	2000-present 2002-present	Derived from MOD11Level-2	(Wan et al., 2015d)	https://lpdaac.usgs.gov/products/mod11c1v006
LST MOD21 Level-2	MODIS/AQUA	1 km	Daily	2002-present	Temperature/ emissivity separation technique	(Hulley, 2015)	https://lpdaac.usgs.gov/products/myd21v006
LST MOD21 Level-3	MODIS/AQUA	1 km	Daily, 8-day	2002-present	Derived from MOD21Level-2	(Hulley, 2015)	https://lpdaac.usgs.gov/products/myd21a1dv006
LST	AATSR	1 km, 0.05°	Daily	2002–2012	Nadir two-channel, split-window	(Ghent et al., 2017)	http://data.globtemperature.info
LST	AATSR	1 km	Daily	2002–2012	Preset retrieval coefficients applied	https://earth.esa.int/web/guest/-/aatsr-level-2-lst-products-from-uol	https://earth.esa.int/web/guest/-/aatsr-level-2-lst-products-from-uol
LST	MODIS/ TERRA	1 km	Daily	2000–2016	Generalized split-window algorithm	http://data.globtemperature.info/	http://data.globtemperature.info
LST	MODIS/AQUA	1 km	Daily	2002–2016	Generalized split-window algorithm	http://data.globtemperature.info/	http://data.globtemperature.info
LST	ATSR/ AATSR	0.05°	Daily, monthly	1995–2012	Generalized split-window algorithm	http://data.globtemperature.info/	http://data.globtemperature.info

Table A3
Available long-term global ET products (principal selection) and their general characteristics and repository links (considering products with +10 years of availability) (links last accessed: 1 March 2020).

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
PML ET	AVHRR/ MODIS	0.5°	Monthly	1981–2012	PML model (LAI, emissivity, albedo and land cover)	(Y. Zhang et al., 2016a)	Contact the corresponding author in the reference (Y. Zhang et al., 2016a)
PML ET V2	MODIS	500 m	8-day	2002–2017	PML model (LAI, emissivity, albedo)	(Zhang et al., 2019)	https://code.earthengine.google.com/?asset = projects/pml_evapotranspiration/PML/OUTPUT/PML_V2_8day_v014
BEPS ET	AVHRR/ MODIS	0.5°× 0.6°	Hourly	1982–2016	The BEPS model (MERRA-2, r GLOBMAP and GIMMS3 g LAI)	(He et al., 2018)	Contact the corresponding author in the reference (He et al., 2018)
BESS ET	MODIS	1 km, 5 km, 0.5°	8-day, monthly	2000–2015	Process-based BESS model (MODIS aerosol product, water vapor product, cloud product, atmospheric profile product, LST product, LC, LAI, albedo)	(Jiang and Ryu, 2016; Ryu et al., 2011)	http://environment.snu.ac.kr/bess_flux
MTE ET	SeaWiFS/ AVHRR/MERIS	0.5°	Monthly	1982–2008	MTE and machine learning (FLUXNET ET data, landuse and fAPAR)	(Jung et al., 2010, 2009)	https://www.bgc-jena.mpg.de/geodb/projects/Home.php
FLUXCOM latent heat flux	MODIS	0.08° 0.5°	8-day, monthly Daily, monthly	2001–2015 1980-present	An ensemble of nine machine learning methods (fAPAR, EVI, LST) An ensemble of three machine learning methods with four global climate forcing data sets (fAPAR, EVI, LST, NDVI, NDWI)	(Jung et al., 2019)	https://www.bgc-jena.mpg.de/geodb/projects/Home.php
MOD16A2	MODIS/TERRA	500 m	8-day	2001-present	Penman-Monteith- remote sensing (MODIS derived		https://modis.gsfc.nasa.gov/data/dataprod/mod16.php

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Table A3 (*continued*)

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
	MODIS/AQUA			2002-present	vegetation property dynamics, albedo, and land cover)	(Running et al., 2017a, 2017b)	
MOD16A3	MODIS/TERRA	500 m	Annual	2001-present	Penman-Monteith- remote sensing (MODIS derived vegetation property dynamics, albedo, and land cover)	(Running et al., 2017c)	https://modis.gsfc.nasa.gov/data/dataprod/mod16.php
ET LST	MODIS/TERRA-AQUA	0.05°, 0.25°	Daily	2000–2013	Penman-Monteith- Remote sensing (LST, LAI, albedo, LC)	(Raoufi and Beighley, 2017)	Contact the corresponding author in the reference (Raoufi and Beighley, 2017)
GLEAM	Various sensors [see Table 1 in (Miralles et al., 2011a)]	0.25°	Daily	1980–2018	Priestly-Taylor model (microwave VOD and root-zone SM	(Miralles et al., 2011b, 2011a)	https://www.gleam.eu/#downloads
ET WB	GRACE/AVHRR	0.5°	Annual	1982–2009	WB equation, empirical approach and remote sensing observation (GRACE and NDVI)	(Zeng et al., 2012)	https://www.zhenzhongzeng.com/resources/
Merged ET synthesis product	–	1°	Monthly, annual	1989–2005	Merging various existing ET data products [see Table 2 in (Mueller et al., 2013)]	(Mueller et al., 2013)	https://iac.ethz.ch/group/land-climate-dynamics/research/landflux-eval.html

PML: Penman-Monteith-Leuning; BEPS: the Boreal Ecosystem Productivity Simulator; MERRA-2: The Modern-Era Retrospective analysis for Research and Applications, Version 2; BESS: the Breathing Earth System Simulator; MTE: Model Tree Ensemble; EVI: Enhanced Vegetation Index; NDWI: Normalized Difference Water Index; GLEAM: Global Land-surface Evaporation: the Amsterdam Methodology; VOD: Vegetation Optical Depth; WB: Water Balance.

Table A4
Available long-term global SM products (principal selection) and their general characteristics and repository links (considering products with +10 years of availability) (links last accessed: 1 March 2020).

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
SM Level-2	SMOS	15 km (ISEA 4H9 grid)	1–2-day	2010 - present	Processing of L-band two-dimensional SAR with multi-angular and full polarimetric capabilities	(Chung et al., 2017; Kerr et al., 2011)	https://smos-diss.eo.esa.int/oads/access
SM Level-2 NRT	SMOS	15 km (ISEA 4H9 grid)	Daily	2010 - present	NN (SMOS Level-2 soil moisture data retrieved from ESA Level-1C NRT product)		
SM Level-3 CATDS	SMOS	25 km (EASE grid version 2)	Daily, 3-day, 10-day, monthly	2010 - present	A multi-orbit approach applied to ESA Level-1B product	(Al Bitar et al., 2017; Kerr et al., 2013)	www.catds.fr/Products/Available-products-from-CPDC
SM Level-3 BEC	SMOS	15 km (ISEA 4H9 grid) and 25 km (EASE grid)	Daily, 3-day, 9-day, monthly, annual	2010 - present	Retrieved from the ESA Level-2 soil moisture product	(Pablos et al., 2019)	http://bec.icm.csic.es/land-datasets
Root zone (0–1 m soil depth) SM Level-4 CATDS	SMOS	25 km (ISEA grid)	Daily	2010 - present	Retrieved from the Level-3 CATDS soil moisture data and surface temperature information from ECMWF model reanalysis	(Al Bitar et al., 2017; Kerr et al., 2013)	www.catds.fr/Products/Available-products-from-CEC-SM/L4-Land-research-product
Synergy SM	AMSR-E/SMOS	25 km (ISEA grid)	Daily	2003–2017	NN (SMOS Level-3 products)		
SMOS-IC SM	SMOS	25 km (EASE grid version 2)	1–2-day	2010-present	Inversion of the L-MEB model and considering homogeneity of the pixel.	(Fernandez-Moran et al., 2017b, 2017a)	https://www.catds.fr/Products/Available-products-from-CEC-SM/SMOS-IC
Assimilated SM (Soil Wetness Index)	ASCAT	25 km	Daily	2007-present	Scatterometer data assimilation in a land data assimilation system	(HSAF, 2018)	ftp://ftp.meteoam.it
CGLS Soil Water Index	ASCAT	0.1°	Daily	2007-present	Computed from Surface SM by means of a two-layer WB model	(Albergel et al., 2008; Wagner et al., 1999)	https://land.copernicus.vgt.vito.be/PDF/portal/Application.html#Browse; Root = 514,690;Collection = 735,734; Time = NORMAL,NORMAL,-1,,,-1,
Surface SM	ASCAT	12.5 km	1–2-day			(HSAF, 2016)	

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Table A4 (*continued*)

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
				2007-present	A change detection method based on TU Wien soil moisture retrieval algorithm		http://hsaf.meteoam.it/description-h25-h108-h111.php
ESA CCI SM V4.5	Merged active and passive microwave sensors [Table 1 in (Gruber et al., 2019)]	0.25°	Daily	1978–2018	Harmonizing and merging soil moisture retrievals from multiple satellites	(Chung et al., 2018; Gruber et al., 2019)	https://www.esa-soilmoisture-cci.org/index.php?q = node/145
Surface SM	MI/TRMM	45 km	1–3-day	1997–2015	Soil moisture retrieval by radiative-transfer-based LPRM	(Owe et al., 2008)	https://disc.gsfc.nasa.gov/datasets/LPRM_TMI_SOILM2_V001/summary?keywords = TRMM
Surface SM Level-3	AMSR-E	25 km	Daily	2002–2011	Soil moisture retrieval by a radiative-transfer-based model	(Njoku, 2004)	https://nsidc.org/data/ae_land3/versions/2
Surface SM (LPRM) Level-3	AMSR-E	25 km	Daily	2002–2011	Soil moisture retrieval by radiative-transfer-based LPRM	(Owe et al., 2008)	https://disc.gsfc.nasa.gov/datasets/LPRM_AMSRE_A_SOILM3_V002/summary?keywords = LPRM

ISEA: Icosahedron Snyder Equal Area; SAR: synthetic aperture radiometer; NRT: near real-time; CATDS: Centre Aval de Traitement des Données SMOS; EASE: Equal-Area Scalable Earth; BEC: Barcelona Expert Centre; ECMWF: European Centre for Medium-Range Weather Forecasts; SMOS-IC: SMOS INRA-CESBIO; L-MEB: L-band Microwave Emission of the Biosphere; TU Wien: Vienna University of Technology; LPRM: Land Parameter Retrieval Model.

Table A5
Available long-term global albedo products (principal selection) and their general characteristics and repository links (considering products with +10 years of availability) (links last accessed: 1 March 2020).

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
Surface albedo V006 MCD43	MODIS/TERRA-AQUA	500 m,30 arc sec,0.05°	Daily	2000-present	Retrieved using a kernel-driven semi-empirical BRDF model	(Strahler and Muller, 1999)	https://modis-land.gsfc.nasa.gov/brdf.html
Surface albedo V006 MCD43GF	MODIS/TERRA-AQUA	30 arc second	Daily	2000-present	Retrieved from the 30 arc second climate modeling grid MCD43D V6	(Schaaf, 2019)	https://lpdaac.usgs.gov/products/mcd43 gfv006
Surface albedo	MISR	1.1 km, 0.5°	Daily, monthly, quarterly, annual	2000-present	Level-2 observations from multiple orbits are combined to obtain albedo Level-3	(Diner et al., 2008a)	https://eosweb.larc.nasa.gov/project/misr/cgal_table
Surface albedo GLASS	MODIS	1 km, 0.05°	8-day	2000–2017	Generated by means of a radiative transfer process and statistics-based temporal filtering	(N. F. Liu et al., 2013a; Q. Liu et al., 2013a)	http://glass.umd.edu/Albedo
Surface albedo GLASS	AVHRR	0.05°	8-day	1981–2017			
C3S albedo V1	SPOT-VGT/PROBA-V/AVHRR	1 km [SPOT-VGT and PROBA-V], 4 km [AVHRR]	10-day	1981-present	Inversion of a semi-empiric, kernel-driven reflectance model, computing spectral albedo and converting to broadband albedo	(Carrer et al., 2019b, 2019a, 2018)	https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-albedo?tab = form
CGLS Surface albedo	SPOT-VGT/PROBA-V	1 km	10-day	1998-present	Inversion of a semi-empiric, kernel-driven reflectance model, computing spectral albedo and converting to broadband albedo	(Carrer et al., 2010; Geiger et al., 2008)	https://land.copernicus.vgt.vito.be/PDF/portal/Application.html#Browse;Root = 511,344;Collection = 1,000,174;Time = NORMAL,NORMAL,-1,,,-1,,
Surface albedo GlobAlbedo	MERIS/SPOT-VGT	1 km, 0.5°, 0.05°	8-day, monthly	1998–2011	Radiative transfer models applied	(Muller et al., 2012)	http://www.globalbedo.org/get.php
Surface albedo QA4ECV	AVHRR/GEO/MODIS	0.05°, 0.5°	Daily, monthly	1982–2016	Big data analytics and radiative transfer models applied and white-sky and black-sky albedo are then integrated from the BRDF for a particular solar angle range every day	(Kharbouche et al., 2017)	http://www.qa4ecv-land.eu/global.php
Surface albedo CLARA-A2	AVHRR	0.25°	5-day, monthly	1982–2015	After performing atmospheric, topographic and anisotropy corrections, a narrowband-to-broadband conversion is made to obtain surface albedo	(Karlsson et al., 2017)	https://wui.cmsaf.eu/safira/action/viewPeriodEntry?eid = 21,707&fid = 18

GF: Gap-Filled; QA4ECV: Quality Assurance for Essential Climate variables; CLARA-A: The CM SAF cLoud, Albedo and Radiation data set from AVHRR data.

Table A6
Available long-term global fAPAR products (principal selection) and their general characteristics and repository links (considering products with +10 years of availability) (links last accessed: 1 March 2020).

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
AVH15C1	AVHRR	0.05°	Daily	1981-present	NN (LTDR AVHRR)	(Claverie et al., 2016)	https://www.ncei.noaa.gov/data/avhrr-land-leaf-area-index-and-fapar/access
GLASS fAPAR	AVHRR	1 km	8-day	1981–2018	NN (Red, NIR)	(Xiao et al., 2016, 2014)	http://glass.umd.edu/FAPAR/AVHRR
GLASS fAPAR	MODIS	1 km, 0.05°	8-day	2000–2015			http://glass.umd.edu/FAPAR/MODIS
GIMMS3 g fAPAR	AVHRR	1/12°	15-day	1981–2011	NN (GIMMS NDVI3 g, MODIS LAI)	(Zhu et al., 2013)	http://cliveg.bu.edu/modismisr/lai3 g-fpar3 g.html
MOD15A2H	MODIS/ TERRA	500 m	8-day	2000 - present	LUT inversion (Red, NIR) and a backup algorithm using empirical relationships between NDVI canopy FPAR.	(Myneni et al., 2015)	https://lpdaac.usgs.gov/products/mod15a2hv006
MOD15A2H	MODIS/ AQUA	500 m	8-day	2000 - present		(Myneni, R., Y. Knyazikhin, 2015)	https://lpdaac.usgs.gov/products/myd15a2hv006
MOD15A2H	MODIS/ TERRA-AQUA	500 m	8-day	2002 - present	LUT inversion (Red, NIR)	(Huang et al., 2008; Knyazikhin et al., 1998)	https://lpdaac.usgs.gov/products/mcd15a2hv006
MOD15A3H	MODIS/ TERRA-AQUA	500 m	4-day	2002 - present			https://lpdaac.usgs.gov/products/mcd15a3hv006
MISR V2 fAPAR	MISR	1.1 km	Daily	2000 - present	LUT inversion (Red, NIR)	(Diner et al., 2008b)	https://eosweb.larc.nasa.gov/project/misr/MISR_table
CGLS fAPAR V1	SPOT-VGT/ PROBA-V	1/112°	10-day	1998 - present	NN (CYCLOPES and MODIS LAI)	(Baret et al., 2013)	https://land.copernicus.vgt.vito.be/PDF/portal/Application.html#Browse; Root = 512,260;Collection = 1,000,169; Time = NORMAL,NORMAL,-1,,,-1,,
CGLS fAPAR V2	SPOT-VGT/ PROBA-V	1/112°	10-day	1998 - present	NN (CYCLOPES and MODIS LAI) and smoothing and gap filling	(Verger et al., 2014)	https://land.copernicus.vgt.vito.be/PDF/portal/Application.html#Browse; Root = 512,260;Collection = 1,000,083; Time = NORMAL,NORMAL,-1,,,-1,,,,
TIP	MODIS/ TERRA-AQUA	0.01°	16-day	2000–2012	One dimensional two-stream scheme of the radiative transfer, called TIP, applied	(Pinty et al., 2011)	http://www.fastopt.de/products/tip/tip.shtml
C3S V1	AVHRR/ SPOT-VGT	4 km [AVHRR],1 km [SPOT-VGT]	10-day	1981–2014	NN (CYCLOPES and MODIS LAI)	(Baret et al., 2013)	https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-lai-fapar?tab = form

FPAR: fraction of photosynthetically active radiation.

Table A7
Available long-term global LC products (principal selection) and their general characteristics and repository links (considering products with +10 years of availability) (links last accessed: 1 March 2020).

Products	Sensor	Spatial resolution	Temporal resolution	Time span	Adopted algorithm (observation method)	Reference	Access link
Global LC type	MODIS/ TERRA-AQUA	0.05° 500 m 1 km	Annual	2001–2018 2001–2017	A supervised decision-tree classification method applied	(Friedl and Sulla-Menashe, 2015)	https://modis-land.gsfc.nasa.gov/landcover.html
Global LC type	Landsat TM/ ETM+	30 m	Circa decadal	2000–2010	Four classifiers (MLC, RF, SVM and JDT) applied	(Gong et al., 2013)	http://data.ess.tsinghua.edu.cn
ESA CCI Global LC type	AVHRR/ SPOT-VGT/ MERIS	300 m	Annual	1992–2018	Baseline global map generated by machine learning and unsupervised spectral classifications approach and converted to global LC map	https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-land-cover?tab = doc (ESA, 2017)	http://maps.elie.ucl.ac.be/CCI/viewer/index.php https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-land-cover?tab = overview

MLC: the conventional maximum likelihood classifier; RF: Random Forest; SVM: Support Vector Machine; JDT: J4.8 Decision Tree.

(e.g., original sensor, resolution, data time span, production algorithm, publication reference), and data access. The products listed for each of the selected terrestrial ECVs had to pass certain criteria, including the global coverage, long-term (at least 10 years of data record) availability, free access, known to the scientific community either through a published peer-review paper or a public online database. It should be noted that all listed terrestrial ECV products in Appendix A are among publicly available ones (principal selection) that passed our defined criteria and, therefore, do not claim to be complete.

References

Ahmadalipour, A., Moradkhani, H., Yan, H., Zarekarizi, M., 2017. Remote sensing of drought: vegetation, soil moisture, and data assimilation. Remote Sensing of Hydrological Extremes. Springer, pp. 121–149.

Al Bitar, A., Mialon, A., Kerr, Y., Cabot, F., Richaume, P., Jacquette, E., Quesney, A., Mahmoodi, A., Tarot, S., Parrens, M., Al-yaari, A., Pellarin, T., Rodriguez-Fernandez, N., Wigneron, J.-P., 2017. The Global SMOS Level 3 daily soil moisture and brightness temperature maps. Earth Syst. Sci. Data Discuss 1–41. https://doi.org/10.5194/essd-2017-1.

Albergel, C., Rüdiger, C., Pellarin, T., Calvet, J.C., Fritz, N., Froissard, F., Suquia, D., Petitpa, A., Piguet, B., Martin, E., 2008. From near-surface to root-zone soil moisture using an exponential filter: an assessment of the method based on in-situ

observations and model simulations. Hydrol. Earth Syst. Sci. Discuss. 12, 1323–1337. https://doi.org/10.5194/hess-12-1323-2008.
Anderson, W.B., Zaitchik, B.F., Hain, C.R., Anderson, M.C., Yilmaz, M.T., Mecikalski, J., Schultz, L., 2012. Towards an Integrated Soil Moisture Drought Monitor for East Africa.
Augustine, J.A., DeLuisi, J.J., Long, C.N., 2000. SURFRAD–A national surface radiation budget network for atmospheric research. Bull. Am. Meteorol. Soc. 81, 2341–2358.
Babaeian, E., Sadeghi, M., Jones, S.B., Montzka, C., Vereecken, H., Tuller, M., 2019. Ground, proximal, and satellite remote sensing of soil moisture. Rev. Geophys. 57, 530–616. https://doi.org/10.1029/2018RG000618.
Baldocchi, D., Falge, E., Gu, L.H., Olson, R., Hollinger, D., Running, S., Anthoni, P., Bernhofer, C., Davis, K., Evans, R., Fuentes, J., Goldstein, A., Katul, G., Law, B., Lee, X.H., Malhi, Y., Meyers, T., Munger, W., Oechel, W., Pilegaard, U.K.T.P., Schmid, K., Valentini, H.P., Verma, R., Vesala, S., Wilson, T., Wofsy, K., 2001. FLUXNET: a new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities. Bull. Am. Meteorol. Soc. 82, 2415–2434. https://doi.org/10.1175/1520-0477(2001)082. S.https://doi.org/.
Balsamo, G., Agusti-Panareda, A., Albergel, C., Arduini, G., Beljaars, A., Bidlot, J., Bousserez, N., Boussetta, S., Brown, A., Buizza, R., Buontempo, C., Chevallier, F., Choulga, M., Cloke, H., Cronin, M.F., Dahoui, M., Rosnay, P.De, Dirmeyer, P.A., Drusch, M., Dutra, E., Ek, M.B., Gentine, P., Hewitt, H., Keeley, S.P.E., Kerr, Y., Kumar, S., Lupu, C., Mahfouf, J.F., McNorton, J., Mecklenburg, S., Mogensen, K., Muñoz-Sabater, J., Orth, R., Rabier, F., Reichle, R., Ruston, B., Pappenberger, F., Sandu, I., Seneviratne, S.I., Tietsche, S., Trigo, I.F., Uijlenhoet, R., Wedi, N., Woolway, R.I., Zeng, X., 2018. Satellite and in situ observations for advancing global earth surface modelling: a review. Remote Sens. 10, 1–72. https://doi.org/10.3390/rs10122038.
Baret, F., Hagolle, O., Geiger, B., Bicheron, P., Miras, B., Huc, M., Berthelot, B., Niño, F., Weiss, M., Samain, O., Roujean, J.L., Leroy, M., 2007. LAI, fAPAR and fCover CYCLOPES global products derived from VEGETATION. Part 1: Principles of the algorithm. Remote Sens. Environ. 110, 275–286. https://doi.org/10.1016/j.rse.2007.02.018.
Baret, F., Nightingale, J., Garrigues, S., Nickeson, J., 2009. Report on the CEOS land product validation sub-group meeting Missoula, Montana, 15 June 2009. Earth Obs. 21, 26–30.
Baret, F., Weiss, M., Lacaze, R., Camacho, F., Makhmara, H., Pacholcyzk, P., Smets, B., 2013. GEOV1: LAI and FAPAR essential climate variables and FCOVER global time series capitalizing over existing products. Part1: principles of development and production. Remote Sens. Environ. 137, 299–309. https://doi.org/10.1016/j.rse.2012.12.027.
Bartalis, Z., Wagner, W., Naeimi, V., Hasenauer, S., Scipal, K., Bonekamp, H., Figa, J., Anderson, C., 2007. Initial soil moisture retrievals from the METOP-A Advanced Scatterometer (ASCAT). Geophys. Res. Lett. 34.
Bartholome, E., Belward, A.S., 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. Int. J. Remote Sens. 26, 1959–1977.
Bayat, B., Van der Tol, C., Verhoef, W., 2018. Integrating satellite optical and thermal infrared observations for improving daily ecosystem functioning estimations during a drought episode. Remote Sens. Environ. 209, 375–394. https://doi.org/10.1016/j.rse.2018.02.027.
Bayat, B., Van der Tol, C., Verhoef, W., 2020. Retrieval of land surface properties from an annual time series of Landsat TOA radiances during a drought episode using coupled radiative transfer models. Remote Sens. Environ. 238 https://doi.org/10.1016/j.rse.2018.09.030.
Becker, F., Li, Z.-L., 1990. Towards a local split window method over land surfaces. Remote Sens. 11, 369–393.
Bicheron, P., Defourny, P., Brockmann, C., Schouten, L., Vancutsem, C., Huc, M., Bontemps, S., Leroy, M., Achard, F., Herold, M., 2008. GLOBCOVER: Products Description and Validation Report. others.
Bojinski, S., Verstraete, M., Peterson, T.C., Richter, C., Simmons, A., Zemp, M., 2014. The concept of essential climate variables in support of climate research, applications, and policy. Bull. Am. Meteorol. Soc. 95, 1431–1443.
Boken, V.K., Cracknell, A.P., Heathcote, R.L., 2005. Monitoring and Predicting Agricultural Drought: a Global Study. Oxford University Press.
Bolten, J., Crow, W., 2012. Improved prediction of quasi-global vegetation conditions using remotely-sensed surface soil moisture. Geophys. Res. Lett. 39 (19), L19406 [10.1029/2012GL053470].
Bolten, J.D., Crow, W.T., Zhan, X., Jackson, T.J., Reynolds, C.A., 2009. Evaluating the utility of remotely sensed soil moisture retrievals for operational agricultural drought monitoring. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 3, 57–66.
Bombelli, A., Serral, I., Blonda, P., Masó, J., Plag, H.-P., Jules-Plag, S., McCallum, I., 2015. D2.2. EVs Current Status in Different Communities and Way to Move Forward. ConnectinGEO Consortium.
Bounoua, L., DeFries, R., Collatz, G.J., Sellers, P., Khan, H., 2002. Effects of land cover conversion on surface climate. Clim. Change 52, 29–64.
Buchanan, G.M., Nelson, A., Mayaux, P., Hartley, A., Donald, P.F., 2009. Delivering a global, terrestrial, biodiversity observation system through remote sensing. Conserv. Biol. 23, 499–502.
Camacho, F., Cernicharo, J., Lacaze, R., Baret, F., Weiss, M., 2013. GEOV1: LAI, FAPAR essential climate variables and FCOVER global time series capitalizing over existing products. Part 2: validation and intercomparison with reference products. Remote Sens. Environ. 137, 310–329.
Carrer, D., Roujean, J.L., Meurey, C., 2010. Comparing operational MSG/SEVIRI Land Surface albedo products from Land SAF with ground measurements and MODIS. IEEE Trans. Geosci. Remote Sens. 48, 1714–1728. https://doi.org/10.1109/TGRS.2009.2034530.
Carrer, D., Pinault, F., Ramon, D., Benhadj, I., Swinnen, E., 2018. Algorithm theoretical basis document (ATBD): CDR VGT-based surface albedo v1.0. Tech. Rep. Prep. Copernicus Clim. Chang. Serv. 52.
Carrer, D., Ceamanos, X., Pinault, F., Benhadj, I., Toté, C., 2019a. Algorithm theoretical basis document: PROBA-V CDR and ICDR surface albedo v1.0. Tech. Rep. Prep. Copernicus Clim. Chang. Serv. 36–73.
Carrer, D., Pinault, F., Ramon, D., Benhadj, I., Swinnen, E., 2019b. Algorithm theoretical basis document (ATBD): CDR AVHRR-based surface albedo v1.0. Tech. Rep. Prep. Copernicus Clim. Chang. Serv. 36–73.
Cayrol, P., Kergoat, L., Moulin, S., Dedieu, G., Chehbouni, A., 2000. Calibrating a coupled SVAT–vegetation growth model with remotely sensed reflectance and surface temperature—a case study for the HAPEX-sahel grassland sites. J. Appl. Meteorol. Climatol. 39, 2452–2472.
Chen, J.M., Black, T.A., 1992. Defining leaf area index for non-flat leaves. Plant Cell Environ. 15, 421–429.
Chen, F., Crow, W.T., Bindlish, R., Colliander, A., Burgin, M.S., Asanuma, J., Aida, K., 2018. Global-scale evaluation of SMAP, SMOS and ASCAT soil moisture products using triple collocation. Remote Sens. Environ. 214, 1–13.
Chung, D., Dorigo, W., Reimer, C., Hahn, S., Melzer, T., Paulik, C., Vreugdenhil, M., Wagner, W., Kidd, R., 2017. ESA Climate Change Initiative Phase II - Soil Moisture: Algorithm Theoretical Baseline Document (ATBD), pp. 1–25.
Chung, D., Dorigo, W., Hahn, S., Melzer, T., Paulik, C., Reimer, C., Vreugdenhil, M., Wagner, W., Kidd, R., 2018. ESA Climate Change Initiative Phase II - Soil Moisture, Algorithm Theoretical Baseline Document, D2.1 Version 04.4. Technical report prepared by Earth Observation Data Centre for Water Resources Monitoring (EODC) GmbH.
Claverie, M., Matthews, J.L., Vermote, E.F., Justice, C.O., 2016. A 30+ year AVHRR LAI and FAPAR climate data record: algorithm description and validation. Remote Sens. 8, 1–12. https://doi.org/10.3390/rs8030263.
Claverie, M., Ju, J., Masek, J.G., Dungan, J.L., Vermote, E.F., Roger, J.C., Skakun, S.V., Justice, C., 2018. The Harmonized Landsat and Sentinel-2 surface reflectance data set. Remote Sens. Environ. 219, 145–161. https://doi.org/10.1016/j.rse.2018.09.002.
Courault, D., Seguin, B., Olioso, A., 2005. Review on estimation of evapotranspiration from remote sensing data: from empirical to numerical modeling approaches. Irrig. Drain. Syst. Eng. 19, 223–249.
Das, N.N., Mohanty, B.P., 2008. Temporal dynamics of PSR-based soil moisture across spatial scales in an agricultural landscape during SMEX02: a wavelet approach. Remote Sens. Environ. 112, 522–534.
Dash, P., Göttsche, F.-M., Olesen, F.-S., Fischer, H., 2002. Land surface temperature and emissivity estimation from passive sensor data: theory and practice-current trends. Int. J. Remote Sens. 23, 2563–2594.
De Moraes, J.F.L., Seyler, F., Cerri, C.C., Volkoff, B., 1998. Land cover mapping and carbon pools estimates in Rondonia. Brazil. Int. J. Remote Sens. 19, 921–934.
Defourny, P., Schouten, L., Bartalev, S., Bontemps, S., Cacetta, P., De Wit, A.J.W., Di Bella, C., Gérard, B., Giri, C., Gond, V., 2009. Accuracy Assessment of a 300 M Global Land Cover Map: the GlobCover Experience. others.
Defourny, P., Mayaux, P., Herold, M., Bontemps, S., 2016. Global land-cover map validation experiences: toward the characterization of quantitative uncertainty. Remote Sensing of Land Use and Land Cover: Principles and Applications. CRC Press, pp. 207–223.
Deng, F., Chen, J.M., Plummer, S., Chen, M., Pisek, J., 2006. Algorithm for global leaf area index retrieval using satellite imagery. IEEE Trans. Geosci. Remote Sens. 44, 2219–2229.
Dhingra, S., Kumar, D., 2019. A review of remotely sensed satellite image classification. Int. J. Electr. Comput. Eng. 9, 1720–1731. https://doi.org/10.11591/ijece.v9i3.pp.1720-1731.
Di Gregorio, A., 2005. Land cover classification system: classification concepts and user manual: LCCS. Food & Agriculture Org.
Diamond, H.J., Karl, T.R., Palecki, M.A., Baker, C.B., Bell, J.E., Leeper, R.D., Easterling, D.R., Lawrimore, J.H., Meyers, T.P., Helfert, M.R., 2013. US Climate Reference Network after one decade of operations: status and assessment. others Bull. Am. Meteorol. Soc. 94, 485–498.
Diner, D.J., Abdou, W.A., Ackerman, T.P., Crean, K., Gordon, H.R., Kahn, R.A., Martonchik, J.V., McMuldroch, S., Paradise, S.R., Pinty, B., 2008a. Multi-angle imaging SpectroRadiometer level 2 aerosol retrieval algorithm theoretical basis, revision g, JPL D-11400. others Jet Propuls. Lab. Calif. Inst. Technol. Pasadena.
Diner, D.J., Martonchik, J.V., Borel, C., Gerstl, S., Gordon, H.R., Knyazikhin, Y., Myneni, R., Pinty, B., Verstraete, M.M., 2008b. Multi-angle imaging spectroradiometer (MISR) level 2 surface retrieval algorithm theoretical basis (version E). Jet Propuls. Lab. Pasadena.
Dorigo, W.A., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Xaver, A., Gruber, A., Drusch, M., Mecklenburg, S., Van Oevelen, P., Robock, A., Jackson, T., 2011. The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements. Hydrol. Earth Syst. Sci. 15, 1675–1698. https://doi.org/10.5194/hess-15-1675-2011.
Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., Chung, D., Ertl, M., Forkel, M., Gruber, A., Haas, E., Hamer, P.D., Hirschi, M., Ikonen, J., de Jeu, R., Kidd, R., Lahoz, W., Liu, Y.Y., Miralles, D., Mistelbauer, T., Nicolai-Shaw, N., Parinussa, R., Pratola, C., Reimer, C., van der Schalie, R., Seneviratne, S.I., Smolander, T., Lecomte, P., 2017. ESA CCI Soil Moisture for improved Earth system understanding: state-of-the art and future directions. Remote Sens. Environ. 203, 185–215. https://doi.org/10.1016/j.rse.2017.07.001.
Dousset, B., Gourmelon, F., Laaidi, K., Zeghnoun, A., Giraudet, E., Bretin, P., Mauri, E., Vandentorren, S., 2011. Satellite monitoring of summer heat waves in the Paris metropolitan area. Int. J. Climatol. 31, 313–323. https://doi.org/10.1002/joc.2222.

Draper, C.S., Reichle, R.H., De Lannoy, G.J.M., Liu, Q., 2012. Assimilation of passive and active microwave soil moisture retrievals. Geophys. Res. Lett. 39.

Driemel, A., Augustine, J., Behrens, K., Colle, S., Cox, C., Cuevas-Agulló, E., Denn, F.M., Duprat, T., Fukuda, M., Grobe, H., Haeffelin, M., Hyett, N., Ijima, O., Kallis, A., Knap, W., Kustov, V., Long, C.N., Longenecker, D., Lupi, A., Maturilli, M., Mimouni, M., Ntsangwane, L., Ogihara, H., Olano, X., Olefs, M., Omori, M., Passamani, L., Pereira, E.B., Schmithüsen, H., Schumacher, S., Sieger, R., Tamlyn, J., Vogt, R., Vuilleumier, L., Xia, X., Ohmura, A., König-Langlo, G., 2018. Baseline Surface Radiation Network (BSRN): structure and data description (1992– 2017). Earth Syst. Sci. Data Discuss. 1–17. https://doi.org/10.5194/essd-2018-8.

Dubayah, R., Wood, E.F., Lettenmaier, D., 1995. Combining hydrological modeling and remote sensing for large scale water and energy balance studies. Int. Geosci. Remote Sens. Symp. 1, 751–753. https://doi.org/10.1109/igarss.1995.520576.

Dumedah, G., Walker, J.P., Merlin, O., 2015. Root-zone soil moisture estimation from assimilation of downscaled Soil Moisture and Ocean Salinity data. Adv. Water Resour. 84, 14–22.

EEA, 2016a. Assistance to EEA in Setting up and Coordinating the Copernicus in Situ Component – EU and Global Level Networks.

EEA, 2016b. Copernicus in Situ Data Gaps State of Play.

EEA, 2017. Lot 1 in Situ - Observations State of Play Report.

ESA, 2017. Land Cover CCI Product User Guide Version 2. https://doi.org/maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf.

Fang, H., Baret, F., Plummer, S., Schaepman-Strub, G., 2019. An overview of global leaf area index (LAI): methods, products, validation, and applications. Rev. Geophys. 1–61. https://doi.org/10.1029/2018rg000608.

Fernandes, R.A., Plummer, S.E., Nightingale, J., Baret, F., Camacho, F., Fang, H., Garrigues, S., Gobron, N., Lang, M., Lacaze, R., Leblanc, S.G., Meroni, M., Martinez, B., Nilson, T., Pinty, B., Pisek, J., Sonnentag, O., Verger, A., Welles, J.M., Weiss, M., Widlowski, J.-L., Schaepman-Strub, G., Román, M.O., Nicheson, J., 2014. Global Leaf Area Index Product Validation Good Practices. CEOS Working Group on Calibration and Validation - Land Product Validation Sub-Group. https://doi.org/10.5067/doc/ceoswgcv/lpv/lai.002. Version 2.0.

Fernandez-Moran, R., Al-Yaari, A., Mialon, A., Mahmoodi, A., Al Bitar, A., De Lannoy, G., Rodriguez-Fernandez, N., Lopez-Baeza, E., Kerr, Y., Wigneron, J.P., 2017a. SMOS-IC: an alternative SMOS soil moisture and vegetation optical depth product. Remote Sens. 9, 1–21. https://doi.org/10.3390/rs9050457.

Fernandez-Moran, R., Wigneron, J.-P., De Lannoy, G., Lopez-Baeza, E., Parrens, M., Mialon, A., Mahmoodi, A., Al-Yaari, A., Bircher, S., Al Bitar, A., 2017b. A new calibration of the effective scattering albedo and soil roughness parameters in the SMOS SM retrieval algorithm. others Int. J. Appl. Earth Obs. Geoinf. 62, 27–38.

Fisher, J.B., Tu, K.P., Baldocchi, D.D., 2008. Global Estimates of the Land – Atmosphere Water Flux Based on Monthly AVHRR and ISLSCP-II Data, Validated at 16 FluxNET Sites, 112, pp. 901–919. https://doi.org/10.1016/j.rse.2007.06.025.

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., 2005. Global consequences of land use. others Science (80-.) 309, 570–574.

Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ. 80, 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4.

Franklin, S.E., Wulder, M.A., 2002. Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. Prog. Phys. Geogr. 26, 173–205. https://doi.org/10.1191/0309133302pp332ra.

Freitas, S.C., Trigo, I.F., Macedo, J., Barroso, C., Silva, R., Perdigão, R., 2013. Land surface temperature from multiple geostationary satellites. Int. J. Remote Sens. 34, 3051–3068.

Friedl, M., Sulla-Menashe, D., 2015. MCD12C1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 0.05Deg CMG V006. NASA EOSDIS L. Process. DAAC, p. 10.

Fritz, S., McCallum, I., Schill, C., Perger, C., See, L., Schepaschenko, D., der Velde, M., Kraxner, F., Obersteiner, M., 2012. Geo-Wiki: an online platform for improving global land cover. Environ. Model. Softw. 31, 110–123.

Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., 2015. Mapping global cropland and field size. others Glob. Chang. Biol. 21, 1980–1992.

Fritz, S., See, L., Perger, C., McCallum, I., Schill, C., Schepaschenko, D., Duerauer, M., Karner, M., Dresel, C., Laso-Bayas, J.C., Lesiv, M., Moorthy, I., Salk, C.F., Danylo, O., Sturn, T., Albrecht, F., You, L., Kraxner, F., Obersteiner, M., 2017. A global dataset of crowdsourced land cover and land use reference data. Sci. Data 4, 1–8. https://doi.org/10.1038/sdata.2017.75.

Ganzeveld, L., Bouwman, L., Stehfest, E., van Vuuren, D.P., Eickhout, B., Lelieveld, J., 2010. Impact of future land use and land cover changes on atmospheric chemistry-climate interactions. J. Geophys. Res. Atmos. 115.

Garrigues, S., Lacaze, R., Baret, F., Morisette, J.T., Weiss, M., Nickeson, J.E., Fernandes, R., Plummer, S., Shabanov, N.V., Myneni, R.B., Knyazikhin, Y., Yang, W., 2008. Validation and intercomparison of global Leaf Area Index products derived from remote sensing data. J. Geophys. Res. Biogeosciences 113. https://doi.org/10.1029/2007JG000635.

GCOS - 154, 2011. Systematic Observation Requirements for Satellite-based Data Products for Climate 2011 Update: Supplemental Details to the Satellite-based Component of the "Implementation Plan for the Global Observing System for Climate in Support of the UNFCCC (2010 Upd.

GCOS - 200, 2016. The global observing system for climate implementation needs. World Meteorol. Organ. 200, 316 https://doi.org/GCOS-200.

GCOS - 92, 2004. Implementation plan for the global observing system for climate in support of the UNFCCC. 85th AMS Annual Meeting, American Meteorological Society - Combined Preprints.

GCOS-107, 2006. Systematic Observation Requirements for Satellite-based Products for Climate - GCOS-107 (WMO/TD No. 1338).

Ge, J., Qi, J., Lofgren, B.M., Moore, N., Torbick, N., Olson, J.M., 2007. Impacts of land use/cover classification accuracy on regional climate simulations. J. Geophys. Res. Atmos. 112.

Geiger, B., Carrer, D., Franchistéguy, L., Roujean, J.L., Meurey, C., 2008. Land surface albedo derived on a daily basis from meteosat second generation observations. IEEE Trans. Geosci. Remote Sens. 46, 3841–3856. https://doi.org/10.1109/TGRS.2008.2001798.

Geller, G.N., Halpin, P.N., Helmuth, B., Hestir, E.L., Skidmore, A., Abrams, M.J., Aguirre, N., Blair, M., Botha, E., Colloff, M., Dawson, T., Franklin, J., Horning, N., James, C., Magnusson, W., Santos, M.J., Schill, S.R., Williams, K., 2017. Remote sensing for biodiversity. In: Walters, M., Scholes, R. (Eds.), In The GEO Handbook on Biodiversity Observation Networks. Cham: Springer, pp. 187–210. https://doi.org/10.1007/978-3-319-27288-7.

Ghent, D.J., Corlett, G.K., Göttsche, F.M., Remedios, J.J., 2017. Global land surface temperature from the along-track scanning radiometers. J. Geophys. Res. Atmos. 122 (12) https://doi.org/10.1002/2017JD027161, 167-12,193.

Gómez, C., White, J.C., Wulder, M.A., 2016. Optical remotely sensed time series data for land cover classification: a review. ISPRS J. Photogramm. Remote Sens. 116, 55–72. https://doi.org/10.1016/j.isprsjprs.2016.03.008.

Gong, P., Wang, J., Yu, L., Zhao, Yongchao, Zhao, Yuanyuan, Liang, L., Niu, Z., Huang, X., Fu, H., Liu, S., Li, C., Li, X., Fu, W., Liu, C., Xu, Y., Wang, X., Cheng, Q., Hu, L., Yao, W., Zhang, Han, Zhu, P., Zhao, Z., Zhang, Haiying, Zheng, Y., Ji, L., Zhang, Y., Chen, H., Yan, A., Guo, J., Yu, Liang, Wang, L., Liu, X., Shi, T., Zhu, M., Chen, Y., Yang, G., Tang, P., Xu, B., Giri, C., Clinton, N., Zhu, Z., Chen, Jin, Chen, Jun, 2013. Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data. Int. J. Remote Sens. 34, 2607–2654. https://doi.org/10.1080/01431161.2012.748992.

Göttsche, F., Olesen, F.S., Hoyer, J.L., Wimmer, W., Nightingale, T., 2017. Fiducial Reference Measurements for Validation of Surface Temperature From Satellites (FRM4STS) Technical Report TR-3: a Framework to Verify the Field Performance of TIR FRM.

Gruber, A., Scanlon, T., Van Der Schalie, R., Wagner, W., Dorigo, W., 2019. Evolution of the ESA CCI Soil Moisture climate data records and their underlying merging methodology. Earth Syst. Sci. Data 11, 717–739. https://doi.org/10.5194/essd-11-717-2019.

Gruber, A., De Lannoy, G., Albergel, C., Al-Yaari, A., Brocca, L., Calvet, J.C., Colliander, A., Cosh, M., Crow, W., Dorigo, W., Draper, C., Hirschi, M., Kerr, Y., Konings, A., Lahoz, W., McColl, K., Montzka, C., Muñoz-Sabater, J., Peng, J., Reichle, R., Richaume, P., Rüdiger, C., Scanlon, T., van der Schalie, R., Wigneron, J. P., Wagner, W., 2020. Validation practices for satellite soil moisture retrievals: what are (the) errors? Remote Sens. Environ. 244, 111806 https://doi.org/10.1016/j.rse.2020.111806.

Guillevic, P., Göttsche, F., Nickeson, J., Hulley, G., Ghent, D., Yu, Y., Trigo, I., Hook, S., Sobrino, J.A., Remedios, J., Román, M., Camacho, F., 2018. Land surface temperature product validation Best practice protocol. In: Guillevic, P., Göttsche, F., Nickeson, J., Román, M. (Eds.), Best Practice for Satellite- Derived Land Product Validation. Land Product Validation Subgroup (WGCV/CEOS, p. 58. https://doi.org/10.5067/doc/ceoswgcv/lpv/lst.001. Version 1.1.

GUM, 2008. Evaluation of measurement data — guide to the expression of uncertainty in measurement. Int. Organ. Stand. Geneva ISBN 50, 134. https://doi.org/10.1373/clinchem.2003.030528.

Hall, F.G., Bergen, K., Blair, J.B., Dubayah, R., Houghton, R., Hurtt, G., Kellndorfer, J., Lefsky, M., Ranson, J., Saatchi, S., 2011. Characterizing 3D vegetation structure from space: Mission requirements. others Remote Sens. Environ. 115, 2753–2775.

Hartmann, D.L., Tank, A.M.G.K., Rusticucci, M., Alexander, L.V., Brönnimann, S., Charabi, Y.A.R., Dentener, F.J., Dlugokencky, E.J., Easterling, D.R., Kaplan, A., 2013. Observations: Atmosphere and Surface, in: Climate Change 2013 the Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. others. Cambridge University Press, pp. 159–254.

Hayes, K.R., Dambacher, J.M., Hosack, G.R., Bax, N.J., Dunstan, P.K., Fulton, E.A., Thompson, P.A., Hartog, J.R., Hobday, A.J., Bradford, R., 2015. Identifying indicators and essential variables for marine ecosystems. others Ecol. Indic. 57, 409–419.

He, L., Chen, J.M., Gonsamo, A., 2018. Changes in the Shadow : The Shifting Role of Shaded Leaves in Global Carbon and Water Cycles Under Climate Change 5052–5061. https://doi.org/10.1029/2018GL077560.

Hibbard, K., Janetos, A., van Vuuren, D.P., Pongratz, J., Rose, S.K., Betts, R., Herold, M., Feddema, J.J., 2010. Research priorities in land use and land-cover change for the Earth system and integrated assessment modelling. Int. J. Climatol. 30, 2118–2128.

HSAF, 2016. Algorithm theoretical baseline document (ATBD) surface soil moisture ASCAT NRT orbit, SAF/HSAF/CDOP2/ATBD/. Tech. Rep.

HSAF, 2018. Algorithm Theoretical Baseline Document (ATBD) for Products H27 and H140, Soil Wetness Index in the Roots Region, Version 0.6. Thechnical report for the EUMETSAT Network of Satellite Application Facilities.

Huang, D., Knyazikhin, Y., Wang, W., Deering, D.W., Stenberg, P., Shabanov, N., Tan, B., Myneni, R.B., 2008. Stochastic transport theory for investigating the three-dimensional canopy structure from space measurements. Remote Sens. Environ. 112, 35–50. https://doi.org/10.1016/j.rse.2006.05.026.

Hulley, G., 2015. MYD21 MODIS/Aqua land surface Temperature/3-Band emissivity 5-Min L2 1km V006. NASA EOSDIS L. Process. DAAC 10.

Hulley, G.C., Hughes, C.G., Hook, S.J., 2012. Quantifying uncertainties in land surface temperature and emissivity retrievals from ASTER and MODIS thermal infrared data. J. Geophys. Res. Atmos. 117, 1–18. https://doi.org/10.1029/2012JD018506.

Hulley, G.C., Malakar, N.K., Islam, T., Freepartner, R.J., 2018. NASA's MODIS and VIIRS land surface temperature and emissivity products: a long-term and consistent earth system data record. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 11, 522–535. https://doi.org/10.1109/JSTARS.2017.2779330.

Islam, T., Hulley, G.C., Malakar, N.K., Radocinski, R.G., Guillevic, P.C., Hook, S.J., 2017. A physics-based algorithm for the simultaneous retrieval of land surface temperature and emissivity from VIIRS thermal infrared data. IEEE Trans. Geosci. Remote Sens. 55, 563–576. https://doi.org/10.1109/TGRS.2016.2611566.

Jackson, T.J., Cosh, M.H., Bindlish, R., Starks, P.J., Bosch, D.D., Seyfried, M., Goodrich, D.C., Moran, M.S., Du, J., 2010. Validation of advanced microwave scanning radiometer soil moisture products. IEEE Trans. Geosci. Remote Sens. 48, 4256–4272.

Jia, Z., Liu, S., Xu, Z., Chen, Y., Zhu, M., 2012. Validation of remotely sensed evapotranspiration over the Hai River Basin. China. J. Geophys. Res. Atmos. 117, 1–21. https://doi.org/10.1029/2011JD017037.

Jiang, C., Ryu, Y., 2016. Multi-scale evaluation of global gross primary productivity and evapotranspiration products derived from Breathing Earth System Simulator (BESS). Remote Sens. Environ. 186, 528–547.

Jiménez, C., Prigent, C., Mueller, B., Seneviratne, S.I., McCabe, M.F., Wood, E.F., Rossow, W.B., Balsamo, G., Betts, A.K., Dirmeyer, P.A., Fisher, J.B., Jung, M., Kanamitsu, M., Reichle, R.H., Reichstein, M., Rodell, M., Sheffield, J., Tu, K., Wang, K., 2011. Global intercomparison of 12 land surface heat flux estimates. J. Geophys. Res. Atmos. 116, 1–27. https://doi.org/10.1029/2010JD014545.

Jung, M., Henkel, K., Herold, M., Churkina, G., 2006. Exploiting synergies of global land cover products for carbon cycle modeling. Remote Sens. Environ. 101, 534–553.

Jung, M., Reichstein, M., Bondeau, A., 2009. Towards Global Empirical Upscaling of FLUXNET Eddy Covariance Observations: Validation of a Model Tree Ensemble Approach Using a Biosphere Model.

Jung, M., Reichstein, M., Ciais, P., Seneviratne, S.I., Sheffield, J., Goulden, M.L., Bonan, G., Cescatti, A., Chen, J., De Jeu, R., 2010. Recent decline in the global land evapotranspiration trend due to limited moisture supply. others Nature 467, 951–954.

Jung, M., Koirala, S., Weber, U., Ichii, K., Gans, F., Camps-Valls, G., Papale, D., Schwalm, C., Tramontana, G., Reichstein, M., 2019. The FLUXCOM ensemble of global land-atmosphere energy fluxes. Sci. Data 6, 1–14. https://doi.org/10.1038/s41597-019-0076-8.

Justice, C., Starr, D., Wickland, D., Privette, J., Suttles, T., 1998. EOS land validation coordination: an update. Earth Obs. 10, 55–60.

Justice, C.O., Román, M.O., Csiszar, I., Vermote, E.F., Wolfe, R.E., Hook, S.J., Friedl, M., Wang, Z., Schaaf, C.B., Miura, T., Tschudi, M., Riggs, G., Hall, D.K., Lyapustin, A.I., Devadiga, S., Davidson, C., Masuoka, E.J., 2013. Land and cryosphere products from Suomi NPP VIIRS: overview and status. J. Geophys. Res. Atmos. 118, 9753–9765. https://doi.org/10.1002/jgrd.50771.

Karlsson, K.G., Anttila, K., Trentmann, J., Stengel, M., Fokke Meirink, J., Devasthale, A., Hanschmann, T., Kothe, S., Jaäskelaïnen, E., Sedlar, J., Benas, N., Van Zadelhoff, G. J., Schlundt, C., Stein, Di., Finkensieper, S., Häkansson, N., Hollmann, R., 2017. CLARA-A2: The second edition of the CM SAF cloud and radiation data record from 34 years of global AVHRR data. Atmos. Chem. Phys. 17, 5809–5828. https://doi.org/10.5194/acp-17-5809-2017.

Kerr, Y.H., Waldteufel, P., Richaume, P., Davenport, I., Ferrazzoli, P., Wigneron, J.P., 2011. Algorithm theoretical basis document (ATBD) for the SMOS level 2 soil moisture processor development continuation project. SMOS Lev. 2, 3–6.

Kerr, Y.H., Jacquette, E., Al Bitar, A., Cabot, F., Mialon, A., Richaume, P., Quesney, A., Berthon, L., 2013. CATDS SMOS L3 soil moisture retrieval processor, algorithm theoretical baseline document (ATBD). Tech. Note SO-TN-CBSA-GS-0029 (2.0), 73. I Issue nst. CBSA, 73.

Kerr, Y.H., Al-Yaari, A., Rodriguez-Fernandez, N., Parrens, M., Molero, B., Leroux, D., Bircher, S., Mahmoodi, A., Mialon, A., Richaume, P., 2016. Overview of SMOS performance in terms of global soil moisture monitoring after six years in operation. others Remote Sens. Environ. 180, 40–63.

Kharbouche, S., Muller, J., Danne, O., Gobron, N., 2017. QA4ECV : 35 YEARS OF DAILY ALBEDO BASED ON AVHRR AND GEO. Conference on Big Data from Space (BIDS' 2017) 6–9.

Knyazikhin, Y., Martonchik, J.V., Myneni, R.B., Diner, D.J., Running, S.W., 1998. Synergistic algorithm for estimating vegetation canopy leaf area index and fraction of absorbed photosynthetically active radiation from MODIS and MISR data. J. Geophys. Res. Atmos. 103, 32257–32275. https://doi.org/10.1029/98JD02462.

Komma, J., Blöschl, G., Reszler, C., 2008. Soil moisture updating by Ensemble Kalman Filtering in real-time flood forecasting. J. Hydrol. 357, 228–242.

Kustas, W.P., 1990. Estimates of evapotranspiration with a one- and two-layer model of heat transfer over partial canopy cover. J. Appl. Meteorol. 29, 704–715. https://doi.org/10.1175/1520-0450.

Kustas, W.P., Norman, J.M., 1996. Use of remote sensing for evapotranspiration monitoring over land surfaces. Hydrol. Sci. Journal-Journal Des Sci. Hydrol. 41, 495–516. https://doi.org/10.1080/02626669609491522.

Lai, J., Zhan, W., Huang, F., Voogt, J., Bechtel, B., Allen, M., Peng, S., Hong, F., Liu, Y., Du, P., 2018. Identification of typical diurnal patterns for clear-sky climatology of surface urban heat islands. Remote Sens. Environ. 217, 203–220. https://doi.org/10.1016/j.rse.2018.08.021.

Laso Bayas, J.C., Lesiv, M., Waldner, F., Schucknecht, A., Duerauer, M., See, L., Fritz, S., Fraisl, D., Moorthy, I., McCallum, I., Perger, C., Danylo, O., Defourny, P., Gallego, J., Gilliams, S., Akhtar, I.U.H., Baishya, S.J., Baruah, M., Bungnamei, K., Campos, A., Changkakati, T., Cipriani, A., Das, Krishna, Das, Keemee, Das, I., Davis, K.F., Hazarika, P., Johnson, B.A., Malek, Z., Molinari, M.E., Panging, K., Pawe, C.K., Pérez-Hoyos, A., Sahariah, P.K., Sahariah, D., Saikia, A., Saikia, M., Schlesinger, P., Seidacaru, E., Singha, K., Wilson, J.W., 2017. A global reference database of crowdsourced cropland data collected using the Geo-Wiki platform. Sci. Data 4, 1–10. https://doi.org/10.1038/sdata.2017.136.

Lei, S., Bian, Z., Daniels, J.L., Liu, D., 2014. Improved spatial resolution in soil moisture retrieval at arid mining area using apparent thermal inertia. Trans. Nonferrous Met. Soc. China 24, 1866–1873.

Lesiv, M., Moltchanova, E., Schepaschenko, D., See, L., Shvidenko, A., Comber, A., Fritz, S., 2016. Comparison of data fusion methods using crowdsourced data in creating a hybrid forest cover map. Remote Sens. 8 https://doi.org/10.3390/rs8030261.

Li, H., Robock, A., Wild, M., 2007. Evaluation of Intergovernmental Panel on Climate Change Fourth Assessment soil moisture simulations for the second half of the twentieth century. J. Geophys. Res. Atmos. 112.

Li, Z.L., Tang, R., Wan, Z., Bi, Y., Zhou, C., Tang, B., Yan, G., Zhang, X., 2009. A review of current methodologies for regional Evapotranspiration estimation from remotely sensed data. Sensors 9, 3801–3853. https://doi.org/10.3390/s90503801.

Li, Z.L., Tang, B.H., Wu, H., Ren, H., Yan, G., Wan, Z., Trigo, I.F., Sobrino, J.A., 2013. Satellite-derived land surface temperature: current status and perspectives. Remote Sens. Environ. 131, 14–37. https://doi.org/10.1016/j.rse.2012.12.008.

Li, Z., Jia, L., Lu, J., 2015. On uncertainties of the Priestley-Taylor/LST-Fc feature space method to estimate evapotranspiration: case study in an arid/semiarid region in northwest China. Remote Sens. 7, 447–466. https://doi.org/10.3390/rs70100447.

Liang, S., 2003. A direct algorithm for estimating land surface broadband albedos from MODIS imagery. IEEE Trans. Geosci. Remote Sens. 41, 136–145. https://doi.org/10.1109/TGRS.2002.807751.

Liang, S., 2007. Recent developments in estimating land surface biogeophysical variables from optical remote sensing. Prog. Phys. Geogr. 31, 501–516. https://doi.org/10.1177/0309133307084626.

Liang, S., Wang, J., 2019. Advanced Remote Sensing: Terrestrial Information Extraction and Applications. Academic Press.

Liou, Y.A., Kar, S.K., 2014. Evapotranspiration estimation with remote sensing and various surface energy balance algorithms-a review. Energies 7, 2821–2849. https://doi.org/10.3390/en7052821.

Liu, J., Vogelmann, J.E., Zhu, Z., Key, C.H., Sleeter, B.M., Price, D.T., Chen, J.M., Cochrane, M.A., Eidenshink, J.C., Howard, S.M., 2011. Estimating California ecosystem carbon change using process model and land cover disturbance data: 1951–2000. others Ecol. Modell. 222, 2333–2341.

Liu, Y., Liu, R., Chen, J.M., 2012. Retrospective retrieval of long-term consistent global leaf area index (1981-2011) from combined AVHRR and MODIS data. J. Geophys. Res. G Biogeosciences 117, 1–14. https://doi.org/10.1029/2012JG002084.

Liu, N.F., Liu, Q., Wang, L.Z., Liang, S.L., Wen, J.G., Qu, Y., Liu, S.H., 2013a. A statistics-based temporal filter algorithm to map spatiotemporally continuous shortwave albedo from MODIS data. Hydrol. Earth Syst. Sci. Discuss. 17, 2121.

Liu, Q., Wang, L., Qu, Y., Liu, N., Liu, S., Tang, H., Liang, S., 2013b. Preliminary evaluation of the long-term GLASS albedo product. Int. J. Digit. Earth 6, 69–95.

Liu, L., Zhang, Y., 2011. Urban heat island analysis using the landsat TM data and ASTER Data: a case study in Hong Kong. Remote Sens. 3, 1535–1552. https://doi.org/10.3390/rs3071535.

Loew, A., Bell, W., Brocca, L., Claire, E.B., Burdanowitz, J., Calbet, X., Reik, V.D., Ghent, D., Gruber, A., Kaminski, T., Kinzel, J., Klepp, C., Lambert, J., Schaepman-Strub, G., Schröder, M., Verhoelst, T., 2017. Validation practices for satellite-based Earth observation data across communities. Rev. Geophys. 55, 779–817. https://doi.org/10.1002/2017RG000562.

Mao, J., Yan, B., 2019. Global Monthly Mean Leaf Area Index Climatology, pp. 1981–2015. https://doi.org/10.3334/ORNLDAAC/1653.

Martin, M.A., Ghent, D., Pires, A.C., Göttsche, F.M., Cermak, J., Remedios, J.J., 2019. Comprehensive in situ validation of five satellite land surface temperature data sets over multiple stations and years. Remote Sens. 11 https://doi.org/10.3390/rs11050479.

Mekis, É., Vincent, L.A., 2011. An overview of the second generation adjusted daily precipitation dataset for trend analysis in Canada. Atmos. - Ocean 49, 163–177. https://doi.org/10.1080/07055900.2011.583910.

Menne, M.J., Williams, C.N., 2009. Homogenization of temperature series via pairwise comparisons. J. Clim. 22, 1700–1717.

Merlin, O., Walker, J.P., Chehbouni, A., Kerr, Y., 2008. Towards deterministic downscaling of SMOS soil moisture using MODIS derived soil evaporative efficiency. Remote Sens. Environ. 112, 3935–3946.

Milewska, E.J., Vincent, L.A., 2016. Preserving continuity of long-term daily maximum and minimum temperature observations with automation of reference climate stations using overlapping data and meteorological conditions. AtmosphereOcean 54, 32–47.

Miloslavich, P., Bax, N.J., Simmons, S.E., Klein, E., Appeltans, W., Aburto-Oropeza, O., Andersen Garcia, M., Batten, S.D., Benedetti-Cecchi, L., Checkley Jr., D.M., 2018. Essential ocean variables for global sustained observations of biodiversity and ecosystem changes. others Glob. Chang. Biol. 24, 2416–2433.

Miralles, D.G., Holmes, T.R.H., Jeu, R.A.M.De, Gash, J.H., Meesters, A.G.C.A., Dolman, A.J., 2011a. Global Land-surface Evaporation Estimated From Satellite-based Observations, pp. 453–469. https://doi.org/10.5194/hess-15-453-2011.

Miralles, D.G., Jeu, R.A.M..De, Gash, J.H., Holmes, T.R.H., Dolman, A.J., 2011b. Magnitude and Variability of Land Evaporation and Its Components at the Global Scale, pp. 967–981. https://doi.org/10.5194/hess-15-967-2011.

Miyazaki, H., Iwao, K., Shibasaki, R., 2011. Development of a new ground truth database for global urban area mapping from a gazetteer. Remote Sens. 3, 1177–1187. https://doi.org/10.3390/rs3061177.

Mladenova, I.E., Bolten, J., Crow, W., Sazib, N., Reynolds, C., 2020. Agricultural drought monitoring via the assimilation of SMAP soil moisture retrievals into a global soil water balance model. Front. Big Data 3, 10.

Montzka, C., Moradkhani, H., Weihermüller, L., Franssen, H.-J.H., Canty, M., Vereecken, H., 2011. Hydraulic parameter estimation by remotely-sensed top soil moisture observations with the particle filter. J. Hydrol. 399, 410–421.
Montzka, C., Pauwels, V., Franssen, H.-J.H., Han, X., Vereecken, H., 2012. Multivariate and multiscale data assimilation in terrestrial systems: a review. Sensors 12, 16291–16333.
Montzka, C., Grant, J.P., Moradkhani, H., Franssen, H.-J.H., Weihermüller, L., Drusch, M., Vereecken, H., 2013. Estimation of radiative transfer parameters from L-Band passive microwave brightness temperatures using advanced data assimilation. Vadose Zone J. 12 https://doi.org/10.2136/vzj2012.0040 vzj2012.0040.
Montzka, C., Bogena, H.R., Zreda, M., Monerris, A., Morrison, R., Muddu, S., Vereecken, H., 2017. Validation of spaceborne and modelled surface soil moisture products with Cosmic-Ray Neutron probes. Remote Sens. 9, 1–30. https://doi.org/10.3390/rs9020103.
Montzka, C., Rötzer, K., Bogena, H.R., Sanchez, N., Vereecken, H., 2018. A new soil moisture downscaling approach for SMAP, SMOS, and ASCAT by predicting sub-grid variability. Remote Sens. 10, 427.
Morisette, J.T., Baret, F., Privette, J.L., Myneni, R.B., Nickeson, J.E., Garrigues, S., Shabanov, N.V., Weiss, M., Fernandes, R.A., Leblanc, S.G., 2006. Validation of global moderate-resolution LAI products: a framework proposed within the CEOS land product validation subgroup. others IEEE Trans. Geosci. Remote Sens. 44, 1804–1817.
Mu, Q., Heinsch, F.A., Zhao, M., Running, S.W., 2007. Development of a global evapotranspiration algorithm based on MODIS and global meteorology data. Remote Sens. Environ. 111, 519–536.
Mu, Q., Zhao, M., Running, S.W., 2011. Improvements to a MODIS global terrestrial evapotranspiration algorithm. Remote Sens. Environ. 115, 1781–1800. https://doi.org/10.1016/j.rse.2011.02.019.
Mueller, B., Seneviratne, S.I., Jimenez, C., Corti, T., Hirschi, M., Balsamo, G., Ciais, P., Dirmeyer, P., Fisher, J.B., Guo, Z., Jung, M., Maignan, F., McCabe, M.F., Reichle, R., Reichstein, M., Rodell, M., Sheffield, J., Teuling, A.J., Wang, K., Wood, E.F., Zhang, Y., 2011. Evaluation of global observations-based evapotranspiration datasets and IPCC AR4 simulations. Geophys. Res. Lett. 38, 1–7. https://doi.org/10.1029/2010GL046230.
Mueller, B., Hirschi, M., Jimenez, C., Ciais, P., Dirmeyer, P.A., Dolman, A.J., Fisher, J.B., Jung, M., Ludwig, F., Maignan, F., Miralles, D.G., McCabe, M.F., Reichstein, M., Sheffield, J., Wang, K., Wood, E.F., Zhang, Y., Seneviratne, S.I., 2013. Benchmark products for land evapotranspiration: LandFlux-EVAL multi-data set synthesis. Hydrol. Earth Syst. Sci. 17, 3707–3720. https://doi.org/10.5194/hess-17-3707-2013.
Muller, J.-P., López, G., Watson, G., Shane, N., Kennedy, T., Yuen, P., Lewis, P., Fischer, J., Guanter, L., Domench, C., 2012. The ESA GlobAlbedo Project for Mapping the Earth's Land Surface Albedo for 15 Years From European Sensors. others. Geophysical Research Abstracts, p. 10969.
Myneni, R.Y., Knyazikhin, T.P., 2015. MYD15A2H MODIS/Aqua leaf area Index/FPAR 8-Day L4 global 500m SIN grid V006. NASA EOSDIS L. Process. DAAC.
Myneni, R.B., Williams, D.L., 1994. On the relationship between FAPAR and NDVI. Remote Sens. Environ. 49, 200–211. https://doi.org/10.1016/0034-4257(94)90016-7.
Myneni, R.B., Hoffman, S., Knyazikhin, Y., Privette, J.L., Glassy, J., Tian, Y., Wang, Y., Song, X., Zhang, Y., Smith, G.R., Lotsch, A., Friedl, M., Morisette, J.T., Votava, P., Nemani, R.R., Running, S.W., 2002. Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. Remote Sens. Environ. 83, 214–231. https://doi.org/10.1016/S0034-4257(02)00074-3.
Myneni, R., Knyazikhin, Y., Park, T., 2015. MOD15A2H MODIS/terra leaf area index/FPAR 8-day L4 global 500 m SIN grid V006. NASA EOSDIS L. Process. DAAC.
NASA, 2001. ASTER level 2 surface temperature product. NASA EOSDIS L. Process. DAAC. https://doi.org/10.5067/ASTER/AST_08.003.
Nestola, E., Calfapietra, C., Mazzenga, F., Sánchez-Zapero, J., Latorre, C., Camacho, F., Matteucci, G., 2017. Validation of PROBA-V GEOV1 and MODIS C5 & C6 fAPAR products in a deciduous beech forest site in Italy. Remote Sens. 9 https://doi.org/10.3390/rs9020126.
Nightingale, J., Schaepman-Strub, G., Nickeson, J., Baret, F., Herold, M., 2011. Assessing satellite-derived land product quality for earth system science applications: results from the ceos lpv sub-group. In Proceedings of the 34th International Symposium on Remote Sensing of Environment.
Nightingale, J., Boersma, K.F., Muller, J.P., Compernolle, S., Lambert, J.C., Blessing, S., Giering, R., Gobron, N., Smedt, I..De, Coheur, P., George, M., Schulz, J., Wood, A., 2018. Quality assurance framework development based on six new ECV data products to enhance user confidence for climate applications. Remote Sens. 10 https://doi.org/10.3390/rs10081254.
Nightingale, J., Mittaz, J.P.D., Douglas, S., Dee, D., Ryder, J., Taylor, M., Old, C., Dieval, C., Fouron, C., Duveau, G., Merchant, C., 2019. Ten priority science gaps in assessing climate data record quality. Remote Sens. 11, 1–21. https://doi.org/10.3390/rs11080897.
Njoku, E.G., 2004. AMSR-E/Aqua Daily L3 Surface Soil Moisture, Interpretive Parameters, & QC EASE-Grids. Version 2. NASA National Snow and Ice Data Center Distributed Active Archive Center, Boulder, Colorado USA. https://doi.org/10.5067/AMSR-E/AE_LAND3.002.
Njoku, E.G., Entekhabi, D., 1996. Passive microwave remote sensing of soil moisture. J. Hydrol. 184, 101–129.
Norbiato, D., Borga, M., Degli Esposti, S., Gaume, E., Anquetin, S., 2008. Flash flood warning based on rainfall thresholds and soil moisture conditions: an assessment for gauged and ungauged basins. J. Hydrol. 362, 274–290.
Norman, J.M., Becker, F., 1995. Terminology in thermal infrared remote sensing of natural surfaces. Agric. For. Meteorol. 77, 153–166.
Olofsson, P., Stehman, S.V., Woodcock, C.E., Sulla-Menashe, D., Sibley, A.M., Newell, J. D., Friedl, M.A., Herold, M., 2012. A global land-cover validation data set, part I: fundamental design principles. Int. J. Remote Sens. 33, 5768–5788.
Owe, M., de Jeu, R., Holmes, T., 2008. Multisensor historical climatology of satellite-derived global land surface moisture. J. Geophys. Res. Earth Surf. 113, 1–17. https://doi.org/10.1029/2007JF000769.
Pablos, M., González-Haro, C., BEC Team, 2019. BEC SMOS Land Products Description, p. 37.
Patias, P., Verde, N., Tassopoulou, M., Georgiadis, C., Kaimaris, D., 2019. Essential variables: describing the context, progress, and opportunities for the remote sensing community. Seventh International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2019) 111740C.
Peng, J., Loew, A., Merlin, O., Verhoest, N.E.C., 2017. A review of spatial downscaling of satellite remotely sensed soil moisture. Rev. Geophys. 55, 341–366.
Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R.J., Bruford, M.W., Brummitt, N., Butchart, S.H.M., Cardoso, A.C., 2013. Essential biodiversity variables. others Science (80-.) 339, 277–278.
Pettorelli, N., Wegmann, M., Skidmore, A., Mücher, S., Dawson, T.P., Fernandez, M., Lucas, R., Schaepman, M.E., Wang, T., O'Connor, B., Jongman, R.H.G., Kempeneers, P., Sonnenschein, R., Leidner, A.K., Böhm, M., He, K.S., Nagendra, H., Dubois, G., Fatoyinbo, T., Hansen, M.C., Paganini, M., de Klerk, H.M., Asner, G.P., Kerr, J.T., Estes, A.B., Schmeller, D.S., Heiden, U., Rocchini, D., Pereira, H.M., Turak, E., Fernandez, N., Lausch, A., Cho, M.A., Alcaraz-Segura, D., McGeoch, M.A., Turner, W., Mueller, A., St-Louis, V., Penner, J., Vihervaara, P., Belward, A., Reyers, B., Geller, G.N., 2016. Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. Remote Sens. Ecol. Conserv. 2, 122–131. https://doi.org/10.1002/rse2.15.
Piao, S., Yin, G., Tan, J., Cheng, L., Huang, M., Li, Y., Liu, R., Mao, J., Myneni, R.B., Peng, S., Poulter, B., Shi, X., Xiao, Z., Zeng, N., Zeng, Z., Wang, Y., 2015. Detection and attribution of vegetation greening trend in China over the last 30 years. Glob. Chang. Biol. 21, 1601–1609. https://doi.org/10.1111/gcb.12795.
Pinty, B., Andredakis, I., Clerici, M., Kaminski, T., Taberner, M., Verstraete, M.M., Gobron, N., Plummer, S., Widlowski, J.L., 2011. Exploiting the MODIS albedos with the Two-Stream Inversion Package (JRC-TIP): 1. Effective leaf area index, vegetation, and soil properties. J. Geophys. Res. Atmos. 116, 1–20. https://doi.org/10.1029/2010JD015372.
Poulter, B., Frank, D.C., Hodson, E.L., Zimmermann, N.E., 2011. Impacts of land cover and climate data selection on understanding terrestrial carbon dynamics and the CO2 airborne fraction. Biogeosciences 8, 2026–2027.
Rahimzadeh-Bajgiran, P., Berg, A.A., Champagne, C., Omasa, K., 2013. Estimation of soil moisture using optical/thermal infrared remote sensing in the Canadian Prairies. ISPRS J. Photogramm. Remote Sens. 83, 94–103.
Raoufi, R., Beighley, E., 2017. Estimating daily global evapotranspiration using penman–monteith equation and remotely sensed land surface temperature. Remote Sens. 9, 1138.
Reichle, R.H., Kumar, S.V., Mahanama, S.P.P., Koster, R.D., Liu, Q., 2010. Assimilation of satellite-derived skin temperature observations into land surface models. J. Hydrometeorol. 11, 1103–1122. https://doi.org/10.1175/2010JHM1262.1.
Reichle, R.H., De Lannoy, G.J.M., Liu, Q., Koster, R.D., Kimball, J.S., Crow, W.T., Ardizzone, J.V., Chakraborty, P., Collins, D.W., Conaty, A.L., 2017. Global assessment of the SMAP Level-4 surface and root-zone soil moisture product using assimilation diagnostics. others J. Hydrometeorol. 18, 3217–3237.
Rhee, J., Im, J., Carbone, G.J., 2010. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. Remote Sens. Environ. 114, 2875–2887. https://doi.org/10.1016/j.rse.2010.07.005.
Robinson, D.A., Binley, A., Crook, N., Day-Lewis, F.D., Ferré, T.P.A., Grauch, V.J.S., Knight, R., Knoll, M., Lakshmi, V., Miller, R., 2008. Advancing process-based watershed hydrological research using near-surface geophysics: a vision for, and review of, electrical and magnetic geophysical methods. others Hydrol. Process. An Int. J. 22, 3604–3635.
Robock, A., Li, H., 2006. Solar dimming and CO2 effects on soil moisture trends. Geophys. Res. Lett. 33.
Rohde, R., Muller, R.A., Jacobsen, R., Muller, E., Perlmutter, S., Rosenfeld, A., Wurtele, J., Groom, D., Wickham, C., 2013. A new estimate of the average earth surface land temperature spanning 1753 to 2011. Geoinfor Geostat: An Overview 1, 2, 1. of 7.
Running, S.W., 2008. Ecosystem disturbance, carbon, and climate. Science (80-.) 321, 652–653.
Running, S.W., Baldocchi, D.D., Turner, D.P., Gower, S.T., Bakwin, P.S., Hibbard, K.A., 1999. A global terrestrial monitoring network integrating tower fluxes, flask sampling, ecosystem modeling and EOS satellite data. Remote Sens. Environ. 70, 108–127. https://doi.org/10.1016/S0034-4257(99)00061-9.
Running, S., Mu, Q., Zhao, M., 2017a. MYD16A2 MODIS/Aqua Net Evapotranspiration 8-Day L4 Global 500m SIN Grid V006. NASA EOSDIS L. Process. DAAC 6. https://doi.org/10.5067/MODIS/MYD16A2.006.
Running, S., Mu, Q., Zhao, M., 2017b. MOD16A2 MODIS/Terra net evapotranspiration 8-Day L4 global 500m SIN grid V006. NASA EOSDIS L. Process. DAAC 6. https://doi.org/10.5067/MODIS/MOD16A2.006.
Running, S., Mu, Q., Zhao, M., 2017c. MOD16A3 MODIS/Terra net evapotranspiration yearly L4 global 500m SIN grid V006. NASA EOSDIS L. Process. DAAC 6. https://doi.org/10.5067/MODIS/MOD16A3.006.
Ryu, Y., Baldocchi, D.D., Kobayashi, H., Ingen, C..Van, Li, J., Black, T.A., Beringer, J., Gorsel, E.Van, Knohl, A., Law, B.E., Roupsard, O., 2011. Integration of MODIS Land and Atmosphere Products With a Coupled-Process Model to Estimate Gross Primary Productivity and Evapotranspiration from 1 Km to Global Scales, 25, pp. 1–24. https://doi.org/10.1029/2011GB004053.

Sadeghi, M., Jones, S.B., Philpot, W.D., 2015. A linear physically-based model for remote sensing of soil moisture using short wave infrared bands. Remote Sens. Environ. 164, 66–76.
Sanchez-Zapero, J., Madrid, L.dela, Camacho, F., 2017. SALVAL: a semi-automatic surface albedo validation tool. In: Proceeding of the V International Symposium on Recent Advances in Quantitative Remote Sensing (RAQRS). Valencia (Spain),, p. 2017, 18-22 September,.
Scanlon, T., Nightingale, J., Boersma, F., Muller, J.-P., Farquhar, C., Compernolle, S., Lambert, J.-C., 2017. Outline of QA4ECV Quality Assurance Service (version 2.0).
Schaaf, C., 2019. MODIS/Terra+Aqua BRDF/Albedo gap-filled snow-free daily L3 global 30ArcSec CMG V006. NASA EOSDIS Land Processes DAAC.
Schepaschenko, D., See, L., Lesiv, M., McCallum, I., Fritz, S., Salk, C., Moltchanova, E., Perger, C., Shchepashchenko, M., Shvidenko, A., Kovalevskyi, S., Gilitukha, D., Albrecht, F., Kraxner, F., Bun, A., Maksyutov, S., Sokolov, A., Dürauer, M., Obersteiner, M., Karminov, V., Ontikov, P., 2015. Development of a global hybrid forest mask through the synergy of remote sensing, crowdsourcing and FAO statistics. Remote Sens. Environ. 162, 208–220. https://doi.org/10.1016/j.rse.2015.02.011.
Schmeller, D.S., Mihoub, J.-B., Bowser, A., Arvanitidis, C., Costello, M.J., Fernandez, M., Geller, G.N., Hobern, D., Kissling, W.D., Regan, E., 2017. An operational definition of essential biodiversity variables. others Biodivers. Conserv. 26, 2967–2972.
Schnur, M.T., Xie, H., Wang, X., 2010. Estimating root zone soil moisture at distant sites using MODIS NDVI and EVI in a semi-arid region of southwestern USA. Ecol. Inform. 5, 400–409.
See, L., Perger, C., Hofer, M., Weichselbaum, J., Dresel, C., Fritz, S., 2015. Laco-wiki: an open access online portal for land cover validation. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2, 167–171. https://doi.org/10.5194/isprsannals-II-3-W5-167-2015.
See, L., Laso Bayas, J., Schepaschenko, D., Perger, C., Dresel, C., Maus, V., Salk, C., Weichselbaum, J., Lesiv, M., McCallum, I., Moorthy, I., Fritz, S., 2017. LACO-wiki: a new online land cover validation tool demonstrated using GlobeLand30 for Kenya. Remote Sens. 9, 754. https://doi.org/10.3390/rs9070754.
Sellers, P.J., Randall, D.A., Collatz, G.J., Berry, J.A., Field, C.B., Dazlich, D.A., Zhang, C., Collelo, G.D., Bounoua, L., 1996. A revised land surface parameterization (SiB2) for atmospheric GCMs. Part I: model formulation. J. Clim. https://doi.org/10.1175/1520-0442(1996)009<0676:ARLSPF>2.0.CO;2.
Sellers, P.J., Dickinson, R.E., Randall, D.A., Betts, A.K., Hall, F.G., Berry, J.A., Collatz, G.J., Denning, A.S., Mooney, H.A., Nobre, C.A., 1997. Modeling the exchanges of energy, water, and carbon between continents and the atmosphere. others Science (80-.) 275, 502–509.
Seneviratne, S.I., Corti, T., Davin, E.L., Hirschi, M., Jaeger, E.B., Lehner, I., Orlowsky, B., Teuling, A.J., 2010. Investigating soil moisture–climate interactions in a changing climate: a review. Earth-Science Rev. 99, 125–161.
Skakun, P.S., Ju, J., Claverie, M., Roger, J., Vermote, E., Franch, B., Dungan, J.L., Masek, J., 2018. Harmonized landsat Sentinel-2 (HLS) product user's guide. Natl. Aeronaut. Sp. Adm. Washington, DC, USA 2, 1–30.
Stehman, S.V., Olofsson, P., Woodcock, C.E., Herold, M., Friedl, M.A., 2012. A global land-cover validation data set, II: augmenting a stratified sampling design to estimate accuracy by region and land-cover class. Int. J. Remote Sens. 33, 6975–6993.
Stephens, G.L., O'Brien, D., Webster, P.J., Pilewski, P., Kato, S., Li, J., 2015. The albedo of earth. Rev. Geophys. 53, 141–163.
Strahler, A.H., Muller, J.P., 1999. MODIS BRDF albedo product : algorithm theoretical basis document. MODIS Prod. ID MOD43 Version 5, 1–53.
Strahler, A.H., Boschetti, L., Foody, G.M., Friedl, M.A., Hansen, M.C., Herold, M., Mayaux, P., Morisette, J.T., Stehman, S.V., Woodcock, C.E., 2006. Global land cover validation: Recommendations for evaluation and accuracy assessment of global land cover maps. Eur. Communities, Luxemb. 51.
Su, Z., Timmermans, W., Zeng, Y., Schulz, J., John, V.O., Roebeling, R.A., Poli, P., Tan, D., Kaspar, F., Kaiser-Weiss, A.K., Swinnen, E., Toté, C., Gregow, H., Manninen, T., Riihelä, A., Calvet, J.C., Ma, Y., Wen, J., 2018. An overview of european efforts in generating climate data records. Bull. Am. Meteorol. Soc. 99, 349–359. https://doi.org/10.1175/BAMS-D-16-0074.1.
Thorne, P.W., Diamond, H.J., Goodison, B., Harrigan, S., Hausfather, Z., Ingleby, N.B., Jones, P.D., Lawrimore, J.H., Lister, D.H., Merlone, A., Oakley, T., Palecki, M., Peterson, T.C., de Podesta, M., Tassone, C., Venema, V., Willett, K.M., 2018. Towards a global land surface climate fiducial reference measurements network. Int. J. Climatol. 38, 2760–2774. https://doi.org/10.1002/joc.5458.
Tsendbazar, N.E., de Bruin, S., Herold, M., 2015. Assessing global land cover reference datasets for different user communities. ISPRS J. Photogramm. Remote Sens. 103, 93–114. https://doi.org/10.1016/j.isprsjprs.2014.02.008.
Tucker, C.J., Townshend, J.R.G., Goff, T.E., 1985. African land-cover classification using satellite data. Science (80-.) 227, 369–375.
Vereecken, H., Huisman, J.A., Pachepsky, Y., Montzka, C., Van Der Kruk, J., Bogena, H., Weihermüller, L., Herbst, M., Martinez, G., Vanderborght, J., 2014. On the spatio-temporal dynamics of soil moisture at the field scale. J. Hydrol. 516, 76–96.
Verger, A., Baret, F., Weiss, M., 2014. Near real-time vegetation monitoring at global scale. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 7, 3473–3481. https://doi.org/10.1109/JSTARS.2014.2328632.
Verhoest, N.E.C., Van Den Berg, M.J., Martens, B., Lievens, H., Wood, E.F., Pan, M., Kerr, Y.H., Al Bitar, A., Tomer, S.K., Drusch, M., 2015. Copula-based downscaling of coarse-scale soil moisture observations with implicit bias correction. others IEEE Trans. Geosci. Remote Sens. 53, 3507–3521.
Verstraeten, W.W., Veroustraete, F., van der Sande, C.J., Grootaers, I., Feyen, J., 2006. Soil moisture retrieval using thermal inertia, determined with visible and thermal spaceborne data, validated for European forests. Remote Sens. Environ. 101, 299–314.
Vinnikov, K.Y., Robock, A., Qiu, S., Entin, J.K., Owe, M., Choudhury, B.J., Hollinger, S.E., Njoku, E.G., 1999. Satellite remote sensing of soil moisture in Illinois, United States. J. Geophys. Res. Atmos. 104, 4145–4168.
Wagner, W., Lemoine, G., Rott, H., 1999. A method for estimating soil moisture from ERS scatterometer and soil data. Remote Sens. Environ. 70, 191–207.
Wagner, W., Dorigo, W., de Jeu, R., Fernandez, D., Benveniste, J., Haas, E., Ertl, M., 2012. Fusion of active and passive microwave observations to create an essential climate variable data record on soil moisture. others ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. (ISPRS Ann. 7, 315–321.
Wan, Z., Dozier, J., 1996. A Generalized Split- Window Algorithm for Retrieving Land-Surface Temperature from Space, 34, pp. 892–905.
Wan, Z., Hook, S., Hulley, G., 2015a. MOD11A2 MODIS/Terra land surface Temperature/Emissivity 5-Min L2 swath 1km V006. NASA EOSDIS L. Process. DAAC 10.
Wan, Z., Hook, S., Hulley, G., 2015b. MYD11_L2 MODIS/Aqua land surface Temperature/Emissivity 5-Min L2 swath 1km V006. NASA EOSDIS L. Process. DAAC 10.
Wan, Z., Hook, S., Hulley, G., 2015c. MOD11A1 MODIS/Terra land surface Temperature/Emissivity daily L3 global 1km SIN grid V006. NASA EOSDIS L. Process. DAAC 10.
Wan, Z., Hook, S., Hulley, G., 2015d. MOD11C1 MODIS/Terra land surface Temperature/Emissivity daily L3 global 0.05Deg CMG V006. NASA EOSDIS L. Process. DAAC 10.
Wang, D., Liang, S., He, T., Yu, Y., 2013. Direct estimation of land surface albedo from VIIRS data: algorithm improvement and preliminary validation. J. Geophys. Res. Atmos. 118, 12577–12586. https://doi.org/10.1002/2013JD020417.
Wang, D., Liang, S., Zhou, Y., He, T., Yu, Y., 2016. A new method for retrieving daily land surface albedo from VIIRS data. IEEE Trans. Geosci. Remote Sens. 55, 1765–1775. https://doi.org/10.1109/TGRS.2016.2632624.
Wang, Z., Schaaf, C., Lattanzio, A., Carrer, D., Grant, I., Román, M., Camacho, F., Yu, Y., Sánchez-Zapero, J., Nickeson, J., 2019. Global surface albedo product validation Best practices protocol. In: Wang, Z., Nickeson, J., Román, M. (Eds.), Best Practice for Satellite Derived Land Product Validation. Land Product Validation Subgroup (WGCV/CEOS), p. 45. https://doi.org/10.5067/DOC/CEOSWGCV/LPV/ALBEDO.001 others Version 1.0.
Weiss, M., Baret, F., 2011. fAPAR (fraction of absorbed photosynthetically active radiation) estimates at various scale. 34th International Symposium on Remote Sensing of Environment.
Weiss, M., Baret, F., Block, T., Koetz, B., Burini, A., Scholze, B., Lecharpentier, P., Brockmann, C., Fernandes, R., Plummer, S., Myneni, R., Gobron, N., Nightingale, J., Schaepman-Strub, G., Camacho, F., Sanchez-Azofeifa, A., 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. https://doi.org/10.3390/rs6054190.
Weng, Q., 2009. Thermal infrared remote sensing for urban climate and environmental studies: methods, applications, and trends. ISPRS J. Photogramm. Remote Sens. 64, 335–344. https://doi.org/10.1016/j.isprsjprs.2009.03.007.
Willett, K.M., Williams, C.N., Dunn, R.J.H., Thorne, P.W., Bell, S., De Podesta, M., Jones, P.D., Parker, D.E., 2013. HadISDH: an updateable land surface specific humidity product for climate monitoring. Clim. Past 9, 657–677. https://doi.org/10.5194/cp-9-657-2013.
Willett, K.M., Dunn, R.J.H., Thorne, P.W., Bell, S., De Podesta, M., Parker, D.E., Jones, P.D., Williams, C.N., 2014. HadISDH land surface multi-variable humidity and temperature record for climate monitoring. Clim. Past 10, 1983–2006. https://doi.org/10.5194/cp-10-1983-2014.
Wu, C.Y., Munger, J.W., Niu, Z., Kuang, D., 2010. Comparison of multiple models for estimating gross primary production using MODIS and eddy covariance data in Harvard Forest. Remote Sens. Environ. 114, 2925–2939. https://doi.org/10.1016/j.rse.2010.07.012.
Xiao, Z., Liang, S., Wang, J., Chen, P., Yin, X., Zhang, L., Song, J., 2014. Use of general regression neural networks for generating the GLASS leaf area index product from time-series MODIS surface reflectance. IEEE Trans. Geosci. Remote Sens. 52, 209–223. https://doi.org/10.1109/TGRS.2013.2237780.
Xiao, Z., Liang, S., Wang, J., Xiang, Y., Zhao, X., Song, J., 2016. Long-time-Series global land surface satellite leaf area index product derived from MODIS and AVHRR surface reflectance. IEEE Trans. Geosci. Remote Sens. 54, 5301–5318. https://doi.org/10.1109/TGRS.2016.2560522.
Yang, D., Kane, D., Zhang, Z., Legates, D., Goodison, B., 2005. Bias corrections of long-term (1973–2004) daily precipitation data over the northern regions. Geophys. Res. Lett. 32.
Yost, F.R., 2016. Sharing the data: the information policies of NOAA and EUMETSAT. IFLA J. 42, 5–15. https://doi.org/10.1177/0340035215611135.
Zeng, Z., Piao, S., Lin, X., Yin, G., Peng, S., Ciais, P., Myneni, R.B., 2012. Global evapotranspiration over the past three decades: estimation based on the water balance equation combined with empirical models. Environ. Res. Lett. 7 https://doi.org/10.1088/1748-9326/7/1/014026.
Zeng, Y., Su, Z., Calvet, J.C., Manninen, T., Swinnen, E., Schulz, J., Roebeling, R., Poli, P., Tan, D., Riihelä, A., Tanis, C.M., Arslan, A.N., Obregon, A., Kaiser-Weiss, A., John, V.O., Timmermans, W., Timmermans, J., Kaspar, F., Gregow, H., Barbu, A.L., Fairbairn, D., Gelati, E., Meurey, C., 2015. Analysis of current validation practices in Europe for space-based climate data records of essential climate variables. Int. J. Appl. Earth Obs. Geoinf. 42, 150–161. https://doi.org/10.1016/j.jag.2015.06.006.
Zeng, Y., Su, Z., Barmpadimos, I., Perrels, A., Poli, P., Boersma, K.F., Frey, A., Ma, X., de Bruin, K., Goosen, H., John, V.O., Roebeling, R., Schulz, J., Timmermans, W., 2019.

Towards a traceable climate service: assessment of quality and usability of essential climate variables. Remote Sens. 11 https://doi.org/10.3390/rs11101186.

Zhang, Q., Xiao, X., Braswell, B., Linder, E., Baret, F., Moore, B., 2005. Estimating light absorption by chlorophyll, leaf and canopy in a deciduous broadleaf forest using MODIS data and a radiative transfer model. Remote Sens. Environ. 99, 357–371. https://doi.org/10.1016/j.rse.2005.09.009.

Zhang, F., Zhang, L.-W., Jing-Jing, S.H.I., Huang, J.-F., 2014. Soil moisture monitoring based on land surface temperature-vegetation index space derived from MODIS data. Pedosphere 24, 450–460.

Zhang, K., Kimball, J.S., Running, S.W., 2016a. A review of remote sensing based actual evapotranspiration estimation. Wiley Interdiscip. Rev. Water 3. https://doi.org/10.1002/wat2.1168.

Zhang, Y., Peña-arancibia, J.L., Mcvicar, T.R., Chiew, F.H.S., Vaze, J., Liu, C., Lu, X., Zheng, H., Wang, Y., Liu, Y.Y., Miralles, D.G., Pan, M., 2016b. Multi-decadal trends in global terrestrial evapotranspiration and its components. Nat. Publ. Gr. 1–12. https://doi.org/10.1038/srep19124.

Zhang, Y., Kong, D., Gan, R., Chiew, F.H.S., Mcvicar, T.R., 2019. Coupled estimation of 500 m and 8-day resolution global evapotranspiration and gross primary production in 2002–2017. Remote Sens. Environ. 222, 165–182. https://doi.org/10.1016/j.rse.2018.12.031.

Zhao, Yuanyuan, Gong, P., Yu, L., Hu, L., Li, X., Li, C., Zhang, H., Zheng, Y., Wang, J., Zhao, Yongchao, Cheng, Q., Liu, C., Liu, S., Wang, X., 2014. Towards a common validation sample set for global land-cover mapping. Int. J. Remote Sens. 35, 4795–4814. https://doi.org/10.1080/01431161.2014.930202.

Zhou, Y., Wang, D., Liang, S., Yu, Y., He, T., 2016. Assessment of the suomi NPP VIIRS land surface albedo data using station measurements and high-resolution albedo maps. Remote Sens. 8 https://doi.org/10.3390/rs8020137.

Zhu, Z., Bi, J., Pan, Y., Ganguly, S., Anav, A., Xu, L., Samanta, A., Piao, S., Nemani, R.R., Myneni, R.B., 2013. Global data sets of vegetation leaf area index (LAI)3g and fraction of photosynthetically active radiation (FPAR)3g derived from global inventory modeling and mapping studies (GIMMS) normalized difference vegetation index (NDVI3G) for the period 1981 to 2. Remote Sens. 5, 927–948. https://doi.org/10.3390/rs5020927.

Zhu, Z., Piao, S., Myneni, R.B., Huang, M., Zeng, Z., Canadell, J.G., Ciais, P., Sitch, S., Friedlingstein, P., Arneth, A., Cao, C., Cheng, L., Kato, E., Koven, C., Li, Y., Lian, X., Liu, Y., Liu, R., Mao, J., Pan, Y., Peng, S., Peuelas, J., Poulter, B., Pugh, T.A.M., Stocker, B.D., Viovy, N., Wang, X., Wang, Y., Xiao, Z., Yang, H., Zaehle, S., Zeng, N., 2016. Greening of the Earth and its drivers. Nat. Clim. Chang. 6, 791–795. https://doi.org/10.1038/nclimate3004.