Consistency of satellite climate data records for Earth system monitoring

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Abstract

Climate Data Records (CDRs) of Essential Climate Variables (ECVs) derived from satellite instruments help to characterize the main components of the Earth system, to identify the state and evolution of geophysical processes, and to constrain the budgets of key cycles of water, carbon and energy. The ~~European Space Agency's (ESA)~~ Climate Change Initiative (CCI) of the European Space Agency (ESA) coordinates the derivation of CDRs for 21 ~~GCOS~~ ECVs as defined by the Global Climate Observing System (GCOS) in 23 projects. Here we argue that convenient and coherent use of multiple ECVs for Earth system science needs consistency between different CDRs on three levels: consistency in format and metadata to facilitate their synergetic use (technical level); consistency in assumptions and auxiliary datasets to minimize incompatibilities between datasets (retrieval level); and consistency of each ECV with its estimated true values within its uncertainties (scientific level).

Assessing and achieving consistency across the three levels is a challenging task and requires coordination between different observational communities, which is facilitated within the CCI program~~me~~. This ~~paper~~ study defines consistency for the three levels above in the context of satellite-based CDRs and analyses t~~. T~~he inter-dependencies of CCI CDRs for Earth system science applications ~~are analysed~~ to identify where consistency considerations are most important. The study also summariz~~s~~es measures taken in CCI to ensure consistency on the technical level, and illustrates difficulties in and intrinsic value of achieving consistency on the retrieval and scientific levels. It concludes by assessing

the current status of consistency between CCI CDRs and future efforts needed to improve it.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (IPCC, 2013) states that mankind and the biosphere face great threats due to the rapidly changing climate. To support political decisions on climate change mitigation and adaptation, and to quantify the implications for economic loss and damage, the United Nations Framework Convention on Climate Change (UNFCCC) requires systematic monitoring of the global climate system (e.g., Doherty et al. 2009). In particular, systematic monitoring is important in assessing progress on the aims of the Paris Agreement. The main tools at hand to predict the extent and impacts of climate change on local to global scales and understand its causes are a combination of global and regional climate and Earth system models (GCMs, RCMs and ESMs), reanalysis systems, and systematic observations. Systematic observations for all Earth system sub-domains (atmosphere, land, ocean, biosphere, and cryosphere) are indispensable to increase our understanding of both processes and the global carbon, energy, and water cycles in an integrated way.

To promote systematic climate monitoring, the Global Climate Observing System (GCOS) was established in 1992 by the World Meteorological Organization (WMO), Intergovernmental Oceanographic Commission (IOC), United Nations Environment Program~~me~~ (UNEP), and International Council for Science (ICSU), as an international, inter-agency, interdisciplinary framework. GCOS aims at sustained "provision of reliable physical, chemical and biological observations and data records for the total climate system – across the atmospheric, oceanic and terrestrial domains, including hydrological and carbon cycles and the cryosphere" (GCOS, 2016). This led to GCOS establishing a set of currently 54 “Essential Climate Variables” or ECVs (Bojinski et al. 2014), key physical variables which must be observed in a sustained and *consistent* manner to enable detection of climate trends and provide data suitable for climate model evaluation and climate change attribution.

Complementary to relatively sparse airborne and ground-based measurements and inventory data, satellite observations are of ever-growing importance for evaluating, initializing and parameterizing geophysical processes represented in models. This growing importance is due to the increasing ~~satellite~~ global coverage of satellite data (in space and time) and the increasing diversity of relevant observables provided by advances in satellite sensor technologies. Satellite observations provide a significant contribution to the observation network and~~for~~ 21 out of the 54 GCOS ECVs are currently addressed within the Climate Change Initiative (CCI) of the European Space Agency (ESA).~~,~~ S~~s~~ome of ~~which~~ these ECVs (e.g. the Earth Radiation Budget) are exclusively derived from satellite measurements, reflecting the~~ir~~ unique contribution of satellite data to a sustained and systematic observation system. Some ECVs, including above-ground biomass or column atmospheric concentration of CO_2 and CH_4, can be retrieved from dedicated spaceborne sensors with global coverage but with lower accuracy or resolution (though much better coverage) than in situ measurements. Other ECVs, such as soil carbon or ocean interior temperature, cannot be directly observed from space.

Studies of the Earth system require combined analysis of datasets of many variables. Since these are derived from different ~~processing systems~~ sources (satellite-, ground-, air- and model-based) and processing systems, one underlying precondition of any such analysis is that the datasets are *consistent*. ~~With this we intuitively mean that the fact that they have been derived~~This means that their independent retrieval~~ly~~ does not introduce contradictions between them. Possible reasons for inconsistencies include the use of different auxiliary datasets and masks, the use of simplifications in corrections and retrieval algorithms, and differences in sampling and gridding. These may lead to inconsistencies ~~of~~ among the datasets and of any analysis based on them. ~~One could consider as one~~For example~~ for a single variable~~, a time series of a single variable built from independent ~~subsequent~~ parts (e.g. different satellite sensors) may ~~have a significant~~exhibit ‘jumps’ between the parts, which spoils any trend analysis. A~~s a~~nother example for multiple variables ~~one could think of~~is using different glacier masks, which may result in assigning different surface properties (e.g. glacier, water, rock or vegetation) to the same pixel in land cover masks, leading to ~~interpreting the same pixel one time in terms of its glacier properties and another time in terms of vegetation properties; such double analysis could disrupt~~highly variable budget calculations of related exchange processes. Despite of the importance of consistency, many open questions remain, ranging from a clear definition of consistency for single and multiple variables, to systematically assessing consistency between the many data records used and produced. ~~With this paper we present an approach developed in the ESA Climate Change Initiative (CCI).~~

Over the past ten years, several space agencies (including ESA, EUMETSAT, NASA, and NOAA) have emphasised the generation and delivery of satellite-based CDRs. Hollmann et al. (2013) describe the related efforts of ~~the European Space Agency (~~ESA~~)~~ in this endeavour through its ~~the~~ Climate Change Initiative (CCI). CCI leverages and harvests the long-term satellite archives available from Europe, and enhances these records with observations from other space agencies. In addition, CCI extends its newly established CDRs with the most recent satellite instruments to guarantee continuation into the future. During its first six years (2011-2017), CCI implemented 14 projects, each targeting provision of CDRs for one (or two) ECVs; in 2018, the CCI was expanded to include nine additional ECVs, as shown in Figure 1-1.

Together with the Copernicus Climate Change Service (C3S) and contributions from EUMETSAT through its Satellite Application Facilities (SAFs) such as the Climate Monitoring SAF (Schulz et al., 2009), the NOAA Climate Data Record program~~me~~ (https://www.ncdc.noaa.gov/cdr, Bates et al. 2016), and the NASA Measures p~~P~~rogram~~me~~ (https://earthdata.nasa.gov/measures), about 1000 different satellite-based CDRs for GCOS ECVs and further variables are available or will become available in the near future. An overview of these CDRs is given in the ECV inventory (https://climatemonitoring.info/ecvinventory), recently established by the Working Group Climate from CEOS/CGMS. The ECV inventory clearly documents that, for most ECVs, multiple estimates already exist. ~~This is the basis for a regular gap analysis conducted by the CEOS Coordination Group on Meteorological Satellites (CGMS, WGClimate, 2018) to define future satellite development needs.~~

Since this large set of CDRs ~~are~~ is processed in many independent systems, one needs to ascertain their consistency. In this ~~paper~~ study we present a concept developed in CCI to define and assess consistency between multiple satellite-based ECVs. Based on this, any pair or group of CDRs can be assessed with regard to their consistency. Such an assessment allows to identify and quantify remaining inconsistencies in the light of given CDR uncertainties and the relevant physical principles (our understanding of “the truth”). One key application of having assessed ~~consistency are~~consistency are closure studies where multiple CDRs are used together. This paper only briefly initiates a discussion of examples of closure studies which themselves would need each a full publication~~ and thus go far beyond this paper~~.

In the next Section 2 we provide~~s~~ types of inconsistencies and develop~~s~~ a definition of consistency, followed by a brief analysis of CCI ECVs and consistency needs in Section 3. Section 4 provides several examples to illustrate different aspects of testing or achieving consistency, including the impact of inconsistencies and the status of CCI-related closure studies. Section 5 presents a discussion of the main findings and identifies remaining consistency gaps.

2. Consistency in Earth system monitoring

2.1 Background on the terminology

Consistency is normally understood as “*agreement*”, “*compatibility*” or “*not contradictory*”. This captures the required characteristics and possible tests needed to ensure a set of CDRs is consistent. In a strict physical sense, consistency can be understood as fulfilling a conservation balance equation (of mass or energy) or exhibiting a correlation in time or space between two data records as expected by a physical theory. In the practice of CDR production also simple category errors occur which ~~mean~~ result in severe inconsistencies (e.g. for one pixel land cover assigns bare soil, while biomass gives a non-zero carbon mass to it).

Immler et al. (2010) defined consistency between measurements of the GCOS Reference Upper Air Network (GRUAN) as “when the independent measurements agree to within their individual uncertainties”, which requires knowledge of their uncertainties. This definition applies to different measurements of the same variable, but in the wider context of Earth s~~S~~ystem m~~M~~onitoring, a definition of consistency across multiple ECVs is also needed so that they can meaningfully be used together to study climate change.

Several types of inconsistency between different data records can be recognised:

- Single-ECV inconsistencies (of the same quantity) and multi-ECV inconsistencies (between several variables)

- Inconsistencies due to differences of auxiliary data used in retrievals (e.g., input climatologies or other CDRs), if the dependence to this auxiliary data is significant and the auxiliary data used differ
- Inconsistencies due to differences in applied masks (e.g. land-sea, snow, glacier, clouds, shadows), if the dependence to this auxiliary data is significant and the auxiliary data used differ
- Inhomogeneities in time series (e.g. due to biases or degradation in the data obtained from a sequence of different input data records, e.g. satellite instruments)
- Inconsistencies due to labelling slightly different variables as the same retrieved quantity (e.g. due to wavelength-dependencies of retrieved information)
- Inconsistencies due to sampling differences (measurement time, frequency, geographical coverage during gridding), if ~~amalgated~~ merged into a single product

Many of these inconsistencies are linked to the statistical properties of the raw data used to create a CDR, when for practical reasons simplifications and aggregations cannot be avoided. Inconsistencies between multiple variables can only be assessed in the light of some physical principle connecting them. The principle can be simple (e.g. if the land cover says bare soil and the biomass product provides a biomass value, something is wrong), or a more complex model may be needed to supply the physical principle.

2.2 Levels of consistency

To ~~clarify~~ order the discussion, we consider three complementary levels of consistency:

(1) Consistency on the technical level: Harmonised data format and metadata description to ease acquisition and combined usage of multiple CDRs;

(2) Consistency on the retrieval level: Use of the same assumptions (e.g. land-sea mask) and auxiliary datasets where they may have large impact in retrievals to minimize contradictions between datasets;

(3) Consistency on the scientific level: Agreement of the relevant characteristics of each CDR (e.g., patterns, variability, trends, ...) with a reference (represented by a physical equation, a model or a fiducial reference). For multiple ECVs this requires agreement of relations between them based on physical understanding and within their combined uncertainties.

(1) While consistency on a **technical level** is easy to define and needs limited scientific insight, it is often a resource-consuming barrier hindering data use. This has led the Earth observation community to seriously address this area in recent years (e.g., by adopting common metadata standards following the climate and forecast (CF) convention and the obs4MIPs data format guidelines). We therefore summarize here that in particular, the CCI program~~me~~ has adopted existing solutions (and when needed developed new ones) that facilitate combined satellite-based CDR use. The level of technical harmonization achieved in CCI is a major step towards enabling cross-ECV climate studies. It includes a harmonized data format (netCDF, with a few exceptions where a different standard is needed for a particular community, e.g. shapefiles for glaciers) and a

common metadata convention (CCI data standards (ESA, 2019)) which follow the CF convention (http://cfconventions.org). This includes additional cross-ECV standardized metadata attributes, using common vocabularies for index terms and harmonized variable names, as well as a harmonized / interoperable data access portal with common catalogue and data services to simplify multi-variable data search and download within the CCI portfolio (http://cci.esa.int/data). Furthermore, the underlying documentation of algorithms and datasets in CCI has been harmonized to some extent, as in other initiatives such as the SAF network or NOAA CDR program~~me~~. This information helps users to quickly understand each dataset and its strengths, weaknesses and limitations. In addition, a toolbox (https://climatetoolbox.io) is provided to help with harmonized data pre-processing, analysis and visualisation.

(2) On the **retrieval level**, consistency aims at using the same (or a similar) observation strategy (same or similar satellite sensors, frequencies, etc.), masks, climatologies or ancillary datasets for the same variable in different retrieval algorithms. Frequently used ancillary datasets include land-sea, sea ice, snow cover, and glacier masks, since many retrieval algorithms behave differently over different surface types. Other datasets commonly needed across many variables are meteorological fields (e.g., from reanalysis) and cloud masks, since many retrievals in the visible to thermal spectral range need to avoid contamination by (typically very bright or cold) clouds. A related aspect of consistency for some ECVs is to achieve consistent (within scientific understanding) data fields across borders in space (horizontally and vertically) and in time, in cases where data from different sources are

used. For example, a dust plume should not have a steep gradient at a land-sea border, while true land-sea contrasts, e.g. of surface temperature, should be preserved. An additional level of auxiliary dataset inconsistency occurs when one variable is needed as a correction term in retrieving another variable. Here, understanding differences between the two datasets for the same variable (but auxiliary in one ECV and the main output in the other) is crucial, so that an erroneous assumption in the correction applied to one ECV does not introduce a bias against the other. As one example, the use of Aerosol Optical Depth (AOD) profiles and water vapour content for atmospheric correction can lead to inconsistencies in the retrieval of surface reflectances that are themselves inputs to classification and detection algorithms.

(3) There is no sharp border between retrieval and **scientific consistency**. Ultimately, scientific ~~level~~ consistency deals with the similarity in CDR properties relevant for processes and geophysical cycles. All data records of a single ECV if obtained from different sources need to be consistent within their uncertainties and within sampling differences. Most importantly, systematic biases between datasets need to be avoided as they may lead to errors when evaluating model performance (e.g., Waugh and Eyring, 2009). This applies to different combinations such as one variable / multiple sensors, one sensor / multiple algorithms, or satellite / model / in situ data and can sometimes be assessed visually (by looking at maps, time series or trends to see similar patterns) or mathematically by quantifying bias, noise and correlation. Finally, when several datasets of different variables are included in a physical model or budget equation, multi-variable consistency needs to distinguish

uncertainties of calculated closure budgets due to propagated input uncertainties from those due to real physical process imbalances or net effects.

A particular element within the CCI program~~me~~ is the CCI Climate Model User Group, which independently analyses the quality of CCI CDRs, and particularly cross-ECV consistency, in a climate modelling context. Assessing and achieving consistency is important for meaningful use of multiple ECVs but is challenging because of the many links and dependencies between variables, as discussed in Section 3.

3. Consistency needs for CCI Earth System Climate Data Records

In this section we first assess the needs for consistency between CCI ECVs on the retrieval level. Retrievals of geophysical variables from satellite observations aim to produce high quality CDRs by constraining the (often under-determined) inversion equations as ~~well~~ good as possible. Typically, the measurements exploited have high sensitivity to the target variable, but they may also be subject to perturbations from other variables. In such cases, the inversion needs to either co-retrieve these additional variables or use auxiliary datasets to describe their spatio-temporal distributions. ~~Also~~ Moreover, often different retrieval algorithms are optimal over different ~~domains~~ surface types as their reflectance or spectral characteristics are highly variable (e.g. over dark water or over bright land). The use of different approaches for obtaining the same variable in different retrieval algorithms is one possible source of inconsistency between CDRs.

All CDRs have to pass validation against external reference datasets (e.g. from ground-based stations) to quantify their accuracy. CCI insists that CDRs be accompanied by proper uncertainty characterisation (using error propagation or uncertainty characterization during validation) within their data files (Merchant et al., 2017), so that uncertainties can be assessed when using the datasets. However, since reference data can have temporal or spatial representativeness issues and different validation methods also have their inconsistencies, unexplored uncertainties may remain (for the retrieved values themselves and for the estimated uncertainties).

Validation and error propagation implicitly quantify inconsistencies from using imperfect auxiliary datasets and retrieval simplifications to within uncertainties. However, prove of consistency needs to explicitly test together the CDRs considered. Table 3-1 above the diagonal summarizes links between ECVs generated and analysed by CCI with regard to their retrieval consistency. We identify the need for retrieval consistency, i.e., where either one or both retrievals rely on consistent co-retrieved or auxiliary variables. We indicate links identified only within CCI, while recognising that there are other variables, algorithms or sensors for which these may not apply.

In order to understand ~~which~~ the needs for consistency between CCI ECVs on the scientific level~~CDRs may need to be scientifically consistent with each other~~, we briefly recall the relevance of each ECV for the energy, water and carbon cycles. The term ‘cycle’ describes movement of matter or energy through the Earth system involving different processes and transformations between physical or chemical states. Figure 3-1 is an overview of the main Earth system cycles and lists the available or upcoming ESA CCI CDRs that contribute to their characterisation. For simplicity, we attribute each CDR only to the cycle in which it plays the most important role. Practically all ECVs contribute to the energy cycle, either directly through radiation interaction or through mass-attached energy transport in the water or carbon cycle. Studies of sub-elements of these main cycles may also be relevant (e.g. physical processes such as emission, transport, deposition or radiation interactions, chemical transformations, also regional limitations, such as ice-free conditions) which may only require consistency between a reduced set of ECVs.

Carbon cycle: Human activity, through fossil fuel burning and land cover change, has significantly affected the natural balance of the carbon cycle with wide-ranging consequences including global warming, air pollution, and ocean acidification. Monitoring changes in the carbon cycle is crucial to defining limits for CO_2 emissions to keep global warming to below a given temperature threshold.

CCI CDRs help by quantifying the amount of carbon stored in the atmosphere, oceans and terrestrial biosphere and of the fluxes between these reservoirs. The land biosphere and the ocean currently each take up approximately 25% of the emitted CO_2, i.e., together approximately 50% of the human emissions (Le Quére et al., 2018). The ocean uptake depends on sea-surface temperature (SST) and ocean photosynthetic activity (monitored using ocean colour observations). CCI CDRs also constrain carbon fluxes from the land biosphere (e.g. Reuter, et al., 2017) including land use change and biomass burning, together with direct estimates of above-ground biomass. Other CCI CDRs of importance to the carbon cycle are snow cover (which affects the duration and start of photosynthetic processes in boreal forests; Pulliainen et al., 2017), similar to the impact of sea ice on marine photosynthesis in high latitudes, soil moisture (which affects land-atmosphere CO2 fluxes), ~~and~~ permafrost (which contains frozen carbon stores with about twice the mass of atmospheric carbon), and sea surface salinity that, together with SST, determines CO_2 solubility, with a particularly important impact in rainy regions and which can serve as a proxy for sea water alkalinity (see a review in Vinogradova et al., 2019).

***Water cycle**:* Climate change is predicted to lead to changes in the water cycle, affecting available water resources through changes in precipitation patterns, snow and glacier melt, and increasing demand for water (Arnell et al., 2013). Changes in the water cycle are also associated with extreme events such as floods and droughts. Melting of glaciers and mass loss of ice sheets ~~is the~~are main drivers of sea level change, which has far-reaching consequences on livelihoods in continental coastal areas and on ocean islands (IPCC, 2014). Characterising the natural local to regional variability and long-term trends of high and low frequency changes in the water cycle is therefore crucial to help implementing adaptation and mitigation measures (Hegerl et al., 2013).

CCI helps to quantify the global water cycle over land and ocean by providing CDRs related to the reservoirs within the water cycle (lake levels, sea level, sea ice, ice sheets, glaciers, soil moisture, and snow), atmospheric water vapour content (water vapour), ~~and~~ clouds and aerosols (which impact on cloud properties and lifetime and ultimately can change radiation and precipitation). From these, processes such as precipitation and runoff that transfer water between the various reservoirs may be inferred. CCI delivers additional relevant parameters such as sea surface salinity (related to precipitation, evaporation and runoff), sea surface temperature (SST, determining evaporation), land cover and biomass (both linked to evapotranspiration).

***Energy cycle**:* The Earth's energy cycle is driven by incoming shortwave radiation from the sun and is balanced by outgoing short- and long-wave radiation. Water vapour transports energy from the surface to the upper troposphere (via latent heat) and clouds interact with radiation (Allan, 2012). Both processes connect the energy cycle to the water cycle. Land and ocean surface temperatures play a key role in determining surface energy budgets, and hence the temperature profiles of the lower atmosphere and soil (Crago and Qualls, 2014). The sea state affects the drag and hence momentum transfer over the ocean, thereby having a considerable impact on both synoptic scale weather and climate (Konmen et al., 1998; Smedman et al., 2003) , as well as the depth of the surface mixed-layer in the ocean, which in turn has implications for marine photosynthesis. Together with temperature, salinity determines the density of sea water, and hence the depth of the surface mixed layer; in regions with large freshwater input related to river runoff, ice melting or rain, sea surface salinity helps the formation and maintenance of a thin surface mixed layer, the so-called barrier layer, with strong impact on ocean-atmosphere exchanges (see a review in Vinogradova et al., 2019). Increases in aerosol and greenhouse gases since pre-industrial times have altered the global radiation budget and thereby affected the Earth’s energy cycle.

CCI helps to constrain the global energy cycle by providing CDRs for SST and land surface temperature (LST), land and sea ice, as well as snow cover, sea level (which is affected ~~i. a.~~e.g. by the ocean heat content and land ice melt), sea state, clouds, water vapour, ozone, greenhouse gases and aerosols that help determine the vertical temperature structure of the atmosphere. Finally, the biosphere may also be considered a part of the energy cycle since it converts solar energy into chemically-stored energy (organic matter). In the oceans, a significant portion of the organic matter sinks out of the surface layers, exporting the energy to the deep ocean.

The relevant time scales range from less than a day to geological time scales: crude oil and natural gas that we burn today for our energy requirements had their origin millions of years ago in marine plankton, whereas coal and methane are derived from terrestrial plants.

Table 3-1 summarizes below the diagonal the need for scientific consistency because two variables are linked by Earth system processes or geophysical cycles.

4. Assessing and achieving consistency

This section gives examples of what has been done within or related to CCI to assess and assure single and multiple-ECV consistency of its CDRs. The selected examples illustrate different aspects of consistency, and different ways of checking and using consistency. References to the detailed studies are provided where available.

4.1 Examples of retrieval consistency

Example 1: Consistency between CDRs of one physical variable across a land-sea border

Surface temperature (which consists of four different CDRs for land (LST), sea surface (SST), ice (IST) and lake surface water (LSWT) temperatures) requires consideration of several aspects to ensure consistency both within each CDR and between them: temperature retrieval algorithm consistency, a common approach to uncertainty representation and propagation, use of a common land-sea mask (and sea-ice mask), consistency in cloud detection, and consistency in aerosol correction. Within each CDR the primary challenge is to incorporate data from multiple sensors into single CDRs. This may result in applying retrieval and cloud algorithms which perform well for all sensors rather than algorithms which are optimized for some sensors (e.g. with different channel configurations). Across domains the challenge is even greater, since the best algorithms over land are poorer over the sea or lakes, due to the different contributions of surface emissivity and atmospheric attenuation to the signal. Potential discontinuities are naturally more evident at the domain margins, which can be particularly sensitive to differences in the identification of the land-sea boundary. An example is shown in Figure 4-1, which illustrates that optimal cloud masking in the retrievals for LST and SST (choosing different optimal algorithms) has led to discontinuities in the coverage of valid temperature observations at the land-sea border. Consistency in the land-sea mask, and in cloud and aerosol detection, is a challenge across many other ECVs which may require different treatment depending on the magnitude of sensitivity to those perturbations.

Example 2: Consistency of glacier outlines with other glacier variables and ECVs

For the glaciers ECV, consistency among its main variables (glacier outlines, elevation change and velocity) and with other ECVs is a major issue. The most important is spatial consistency, i.e., the exact agreement of locations between the glacier outlines and the other glacier ECV variables and other ECVs. Temporal consistency is also of high importance for elevation change and velocity within the ECV and to a lesser extent across ECVs. Finally, methodological consistency is a major issue as visual interpretation of satellite images is required in the post-processing stage to manually correct debris-covered glaciers. This is not standardized and cannot rely on consistent terminology in different glacier inventories.

Glacier outlines are derived from high resolution satellite imagery (typically 10 to 30 m) or aerial photography (typically 0.2 to 2 m) using semi-automated mapping techniques or manual on-screen digitization (Paul et al. 2015). In most regions, glacier extents change slowly (0.1% to 1% area loss per year) so that updated values are typically required after a decade. Both the high resolution and the slow update cycle make global maps of glacier cover highly suitable for cross-ECV applications, as other ECVs are only available at a much coarser spatial resolution (hundreds of meters to tens of kilometres) or change much more quickly.

The location of glaciers serves as an important input or auxiliary dataset for several other ECVs: for clouds and LST to choose the correct retrieval algorithms; for land cover as an independent validation source for its “permanent ice” and “snow” classes; for permafrost and lakes as a reciprocal mask (these can only occur in places not covered by glaciers). When glaciers shrink, areas of permafrost or pro-glacial lakes are expected to increase. Similarly, regions identified as glacier-covered cannot simultaneously be covered by sea ice or ice sheets. Regions with snow cover include in most cases also coverage by glaciers, apart from in the late summer where bare ice appears when the snow line is higher than the lowest glacier elevation. The end of summer snowline (or snow cover) on a glacier can also be used as a proxy for its mass balance (e.g., Rabatel et al. 2013). For this application a good temporal match of glacier outlines and snow cover data is highly beneficial. Finally, the area covered by glaciers is used to derive their contribution to sea level when combined with regional estimates of glacier mass balance (e.g., Zemp et al. 2019). For all of the above, spatial consistency only plays a critical role when the datasets have about the same spatial resolution (e.g., snow cover or high-resolution land cover). Otherwise the glacier cover will always be located within the larger pixels of other ECVs and might then also be used for validation (e.g., land cover) rather than as a spatial mask.

Example 3: Consistency of cloud masks between two ECVs (aerosol and cloud properties)

Aerosols and clouds interact strongly in the atmosphere and through light scattering both increase the radiation observed by remote sensing instruments (though usually with different magnitudes). The retrieval of both ECVs needs a cloud mask, in the case of aerosol to avoid cloud contamination, in the case of cloud properties to ensure that a pixel truly represents a cloud. When aerosol and cloud property retrievals for the same sensor are implemented as separate algorithms (as is usually the case), individual pixels need to be allocated either to cloud or aerosol; analysis of the same pixel as aerosol and as cloud under the wrong assumption (cloud-free or aerosol-free) could severely degrade the retrievals and must be minimized. To assess if this requirement is fulfilled, the consistency between independent AATSR cloud masks used in the Aerosol and Cloud products was analyzed for four days in September 2008 (covering difficult scenes with high aerosol loads or complicated mixtures of aerosol and clouds). Figure 4-2 shows, that while 21% of observations are not used for aerosol or cloud retrievals at all, only 0.3% of them were found to be inconsistent (i.e., they were double-analysed as clouds and as aerosols). Over land 1% of observations were inconsistent while inconsistency was practically absent over the ocean.

This result demonstrates (for a limited set of test days) that the different cloud masks for the AATSR sensor used in the CCI Aerosol and Cloud projects are highly consistent (in the sense that only a small fraction of pixels is erroneously interpreted at the same time as cloud and as aerosol) and can be used simultaneously in climate applications. It also shows that about 20% of the pixels remain unanalyzed by both aerosol and cloud retrieval to avoid contamination by the other ECV. Attempts have been made to reduce this fraction of pixels in the twilight zone, but always led also to increased fractions of contaminated / inconsistent pixels.

4.3 Examples of scientific consistency

Example 4: Consistency of multi-sensor merged greenhouse gas CDRs

The GHG ECV satellite-derived data products are column-averaged dry-air mole fractions (“vertical columns”) of carbon dioxide (XCO_2) and methane (XCH_4). Initial versions of these products have been generated in the framework of the GHG project (Buchwitz et al., 2015). These data products are input data for inverse modelling schemes used to improve our knowledge on the various natural and anthropogenic sources and sinks (e.g., Reuter et al., 2017, and references therein). These applications require very high accuracy (e.g., Buchwitz et al., 2015) because even small spatial or temporal biases may result in significant errors in the derived surface fluxes. Thus, consistency is important for each GHG variable with respect to quality assessments (e.g., using a common validation reference for all products), and between individual datasets for their merging into a multi-sensor CDR covering the entire time period as consistently as possible. To achieve this temporal consistency, a merging algorithm (EMMA, Reuter et al., 2013) corrects for potential remaining obvious inconsistencies, e.g., by performing an offset correction to the ensemble members to avoid jumps in the merged time series. Figure 4-3 shows globally averaged monthly mean XCO_2 computed from the merged product covering 2003-2017 (thick red line). As can be seen, XCO_2 increases nearly linearly with time, primarily due to fossil fuel burning, and shows a seasonal cycle primarily attributable to the regular uptake and release of CO_2 by vegetation due to photosynthesis and respiration. From mid-2009 onwards this product is based on an ensemble of SCIAMACHY/Envisat (until April 2012) and several TANSO-FTS/GOSAT individual sensor products (Reuter et al., 2013; Buchwitz et al., 2015, 2018b), which are shown as thin grey lines. No remaining inconsistency is visible in Figure 4-3 (but see also Buchwitz et al., 2018b, for a detailed analysis of this time series with respect to the CO2 growth rate).

Example 5: Consistent trends of homogenized records of the same variable (water vapour)

Within the GEWEX Water Vapour Assessment (G-VAP, see http://gewex-vap.org/ for details) the majority of long-term water vapour data records were and are characterized to describe their strength and weaknesses. Among others, total column water vapour (TCWV) data and associated trend estimates have been inter-compared and their degree of temporal homogeneity has been assessed. Schröder et al. (2016, 2019) concluded that the trend estimates are generally significantly different and that several data records do not exhibit agreement with the physical expectation from the Clausius-Clapeyron equation using data over the global ice-free ocean. After homogenisation of the different TCWV data records, better agreement with theoretical expectations, and thus consistency, was achieved (Schröder et al., 2019). Here, a new analysis was also applied to trend estimates and associated results are shown in

Figure 4-4. The diversity in trend estimates is largely reduced after homogenisation, i.e., all trend estimates are closer to the Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite data (HOAPS) trend estimate (HOAPS was used for computing anomaly differences as basis for break point detection). Consequently, G-VAP recommends that satellite observations should be carefully recalibrated and inter-calibrated to improve retrieval, assimilation and aggregation schemes (Schröder et al., 2016, 2019). Accordingly, the improvement of retrieval and aggregation schemes is an ongoing effort within CCI projects.

Example 6: Consistency of wave height trends and sea ice concentration

It is well established that sea ice extent in the Arctic has been decreasing since 1992 (e.g. Cavalieri and Parkinson, 2012). A larger ocean area is now open to the atmosphere and intuitively one would expect that sea states are becoming enhanced, with increased wave heights (Wang et al., 2015; Stopa et al., 2016). The consistency of the multi-year time series between sea state parameters and sea ice is assessed in Stopa et al. (2016) through use of sea ice concentrations, numerical models and satellite altimetry. Daily sea ice concentrations produced from the Special Sensor Microwave Imager (SSM/I) by IFREMER (Ezraty et al., 2007) were used to define open ocean versus sea ice conditions. The 15% concentration defines the presence of sea ice at 12.5 km resolution within the Arctic Ocean. For the period 1992-2014, the SSM/I ice concentrations are used along with wind vectors from the Climate Forecast System Reanalysis to reproduce the wave field through the numerical wave model, WAVEWATCH3 (WW3, Tolman et al., 2014). WW3 includes wave-ice interaction through an under-ice parameterization of wave dissipation (Stopa et al., 2016).

In Figure 4-5 we show the trends of the significant wave height (H_s) from altimetry (denoted ALT, Queffeulou and Croize-Fillon 2015) and from the co-located model data from WW3 (denoted WW3 CoLoc). Qualitatively the regional patterns match between the two datasets, despite the stronger trends in the altimeters. The altimeter confidence interval encompasses the model results, so statistically they are equivalent. Since WW3 accurately predicts H_s (RMSE < 0.35 m relative to ALT), we can conclude that the 23-year trends from the model using SSM/I ice concentrations and H_s satellite altimetry are consistent with the truth and each other. This convergence of data and model suggests that all three to some degree reflect the truth. Remaining significant differences between the plots indicate the need for further improvement to reduce the inconsistencies. Accordingly this methodology can be used to indirectly assess the consistency of the model with other complementary remotely-sensed parameters (e.g., wind, sea ice and wave parameters).

Example 7: Using a model to test the consistency of different satellite data records

In the lower stratosphere, water vapour is known to broadly follow variations in tropical tropopause temperatures. This is due to the dehydration of air masses at the tropical cold point tropopause during their slow ascent into the stratosphere. The strength and seasonality in this process is dictated by the strength of the stratospheric general circulation (e.g., Fueglistaler et al., 2009). The strong physical dependency of lower stratospheric water vapour on tropical tropopause temperatures can be exploited to test the consistency between climate data records of temperature and stratospheric water vapour as highlighted by Hegglin et al. (2014). This study proposed a new merging method that uses a chemistry-climate model as transfer function between different satellite instrument records to create a CDR. The methodology allows for the bias between instruments to be determined throughout the instrument’s lifetime and not only for the overlap period (when old instruments may show first signs of degradation), hence improving characterization of systematic differences (or biases) between datasets. By using the correlation between the newly merged stratospheric water vapour record and the zonal mean temperature from ERA-interim, it was shown that the new merging method led to physically more consistent results than the traditional one based on bias-correction of instruments during overlap periods. Figure 4-6 shows the time series of a prototype version of the CCI stratospheric water vapour CDR merged using the methodology introduced by Hegglin et al. (2014) in comparison with zonal mean temperatures from ERA5 (left panel). The relatively high correlation (right panel) suggests that the two variables are physically consistent.

Example 8: ENSO consistency across multiple ECVs

The El Niño Southern Oscillation (ENSO) is the most important coupled ocean-atmosphere phenomenon affecting global climate variability on seasonal to inter-annual time scales. It is an irregular periodical variation (time scale of 2-7 years), that can be measured by various indices, e.g.

sea surface temperature anomalies in the tropical Pacific Ocean. The relatively short timescale, large amplitude and multiple ECVs affected by ENSO makes it an ideal natural candidate for investigating consistency of different CCI satellite data records with this phenomenon. We compare the ENSO variability in sea surface temperatures (SST), sea level heights (SL), Sea Surface Salinity (SSS), Ocean Colour chlorophyll-*a* (Chlor_a), high cloud cover (CFChigh), Soil moisture (CCI SM), burned area (fire), 550 nm aerosol optical depth (AOD550) and TCWV (from HOAPS). For SST and SL we calculate monthly means from daily data, for the other ECVs we use pre-calculated monthly mean fields. All variables are interpolated to a common 1° grid, de-seasonalised by removing the corresponding monthly mean value and normalised by dividing by the standard deviations for their respective available time period.

Figure 4-7 shows the variability across the tropical Pacific Ocean for the ECVs in time-longitude anomaly cross sections. The ocean (SST, SL, Sea Surface Salinity, Chlor_a) and atmosphere (CFChigh, TCWV) ECV time series show consistent spatio-temporal co-variability for the Niño3.4 region (5°S-5°N, 190°E-240°E) as expected, with correlation coefficients of 0.87 (SST and SL), 0.82 (SST and CFChigh) and 0.84 (SST and TCWV). The SST and SL have their largest variability in the Niño3.4 region, while the variability for the CFChigh and TCWV peak further west (~180°E), except for the strong El Niño years 1982/83, 1997/98 and 2015/16 when the atmospheric anomalies extended further east similarly to the SST and SL anomalies. Sea Surface Salinity and Ocean Colour are anti-correlated with SST with values -0.63 and -0.68, respectively, as expected from a reduced upwelling. For fire, aerosol and soil moisture, which are affected indirectly by El Niño from dry conditions and wild fires over Indonesia, the correlation coefficient between the SST Niño3.4 time series and their Indonesia time series (10°S-10°N, 100°E-150°E) are lower with values of -0.57 (soil moisture), 0.49 (fire) and 0.52 (AOD550). However, for certain El Niño3.4 years, e.g. 1997, 2007 and 2015 there are clear indicators of co-variability between them and CCI SST (Fig 4-7g). In conclusion, based on their consistency ascertained through (anti-)correlations as expected by our scientific understanding of the ENSO phenomenon these nine independently derived satellite ECVs can be used to further investigate the observed ENSO phenomena, the direct and remote linkages, as well as evaluate and constrain the ENSO representation in climate models.

4.3 Outlook: Status of closure studies

Several examples of closure / budget studies of partial geophysical cycles within the CCI program~~me~~ demonstrate the usefulness of CCI (and additional other) CDRs that are consistent at all three levels. For example, closure of the carbon budget is still an outstanding scientific challenge (Le Quéré et al. 2018). Different CCI products provide direct and indirect constraints on carbon fluxes that help to improve the consistency of carbon budgets: CCI greenhouse gas products are used to inform atmospheric inversions. Top down inversion results can be complemented by other ECVs to attribute diagnosed fluxes to different components such as biomass and soil carbon changes, fire emissions (CCI products on burned area and fire size) and land use change emissions (land cover CCI products).

Another example is the regional closure of the water budget, based on multiple satellite ECVs which demonstrates that the water budget can be closed within less than 10% at a continental annual time scale. However, at monthly time scales, its residuals and uncertainty estimates are larger (about 20%; Rodell et al., 2015). These uncertainties in the water budget closure can be reduced by introducing additional constraints, e.g. by using multiple CDRs with different uncertainties of a single variable or by additionally forcing closure of the atmosphere and ocean terms. Uncertainties in existing CDRs need to be further reduced and new CDRs of other key variables (most importantly, river discharge and irrigation water use) need to be included or developed to reach the 5% closure error targeted by GCOS (GCOS, 2016).

The global mean sea level budget closure has also been assessed within the CCI program~~me~~ by comparing the sum of changes in ocean thermal expansion, land ice melt and liquid water storage on continents with the total observed sea level change. All these components can be estimated globally from satellite altimetry with an accuracy of about 10% on different time scales (e.g., ~~The~~ WCRP sea level budget group, 2018). These observations enable closure of the trend in the sea level budget with an uncertainty of ±0.3 mm/yr over the last 25 years. The sea level budget involves additional variables from the global water budget (through land ice and liquid water components) and from the global energy budget (through thermal expansion directly related to global ocean heat content; Meyssignac et al. 2019) and thus connects the energy and water budgets. At regional scale, uncertainties in the observed components of the sea level budget are considerably larger (few tens of percent) and need to be further reduced to reach the regional GCOS target.

5. Summary, discussion and conclusions

Climate Data Records (CDRs) of Essential Climate Variables (ECVs) derived from satellite instruments provide essential information to monitor the state of the Earth system. A key requirement for these CDRs to be useful for Earth system science is that the CDRs ~~should be~~are internally and mutually consistent. The ESA CCI program~~me~~ provides a set of CDRs for 21 GCOS ECVs in a common framework, and from the outset has invested heavily in establishing their consistency, as presented in this study. Using a three-level definition of consistency, a basis is presented for checking if two or more CDRs are consistent with each other and possibly with reference data. On the technical level, straightforward data access and usage, including availability of comprehensive documentation and product user guides is needed. On the retrieval level, one needs to limit differences of masks, auxiliary datasets, or fields of the same variables in separate processing chains to avoid disagreements. On the scientific level, consistency of multiple ECVs means judging their relevant correlations, patterns, periodicity, trends, etc. (for a given variable, process or cycle) in the light of underlying geophysical processes (e.g. by jointly confronting them with a model). Finding inconsistencies in one or more ECV datasets (i.e. finding patterns whose disagreements exceed underlying uncertainties and/or contradict physical principles or a well-founded model) often indicates errors in a dataset or model whose resolution can lead to new scientific understanding.

This study provides a summary of the technical consistency of CCI CDRs (common format and metadata standards, common portal, harmonized documentation, common uncertainty reporting) and illustrates different aspects of retrieval and scientific consistency using eight examples. On the retrieval level, these examples include the CDRs for surface temperature, aerosol and clouds, and glaciers to illustrate the importance of using consistent sea-land or cloud masks or glacier outlines. On the scientific level, these examples include the CDRs of greenhouse gases and total column water vapour to illustrate the importance of using bias-corrected instrument time series for data merging and trend analyses, and the CDRs of sea-ice and stratospheric water vapour to show the value of using known physical relationships with other variables to test the agreement of datasets with models. In addition, the effects of a geophysical phenomenon (ENSO) on the time evolution of different Earth system variables is used to investigate the consistency of a range of CDRs via their correlations. We also provide a brief high level analysis of the inter-dependencies of CCI ECVs at the retrieval and scientific levels (see T~~t~~able 3-1) to understand where consistency is needed and thus needs to be checked.

An open issue regarding technical consistency and standards is harmonization across program~~me~~s and communities. Here, the CCI program~~me~~ has made an important step by adopting the netCDF format, with the CF and ACDD conventions (the de facto standard in the modelling community) for its gridded satellite data records. The Climate Data Store (CDS) of the Copernicus Climate Change Service (C3S) is also based largely on CCI standards. Moreover, such common standards are a prerequisite for the use of automated~~ic~~ data services for accessing multiple data sources with little manual interaction, hence facilitates use of the data and scientific studies across multiple ECVs.

When discussing consistency, datasets from sources other than satellite data (e.g. Earth system models) are often required to comprehensively study an Earth system cycle, and their uncertainties also need to be considered, together with uncertainties in simplified or estimated budget equations. It is well understood that establishing consistency between two or more variables requires targeted analysis and a lot remains to be done in this area. To this end, Table 5-1 provides an assessment of the current state of affairs regarding consistency between the CCI CDRs. This assessment is based on the combined scientific expertise of the CCI community; it is not meant to be exhaustive but is intended as initial guidance for use of multiple ECV CDRs or for defining priorities in further consistency analysis. For each pair of CDRs the consistency status is indicated as either: “no evident need to consider consistency” (empty), “further studies needed” (X), “consistency explicitly ensured by shared processing or co-retrieving” (*), or “studies already performed”, referenced to T~~t~~able A-2 with the underlying publication or technical report (characterized as “theoretical” (t), “exemplary / partial” (e) or “comprehensive” (c)). This assessment is based on the combined scientific expertise of the CCI community; it is not meant to be exhaustive but is intended as initial guidance for use of multiple ECV CDRs or for defining priorities in further consistency analysis.

6. Acknowledgements

This ~~paper~~ study is based on the ongoing work of altogether 30 projects which jointly build the ESA Climate Change Initiative including 23 old and new ECV projects, the Climate Model User Group, the cross-cutting outreach components (portal, toolbox, visualisation) and CCI working groups on data standards and system engineering. We are grateful to ESA for creating the CCI ~~programme~~program which has strengthened the consistency of the many research communities related to developing, processing, qualifying and using satellite CDRs. We are grateful to the several hundred scientists building the CCI community for making a consistent Earth observation based data repository real. The "operational" part of the CCI program has in the meantime been transferred to the Copernicus Climate Change Service (C3S), where (re-)processing activities to extend the CDRs are conducted with associated quality control and user support. We are also thankful for many other datasets from programs and projects outside CCI and C3S which help cover all relevant ECVs for Earth System studies. GOSAT Level 1 data from JAXA and GOSAT Level 2 data products from NIES and NASA have been used as input for the generation of the GHG data products. HOAPS data have been obtained from the CM-SAF, water vapour records from the G-VAP data archive, CAMS and ERA-5 data from ECMWF / Copernicus Services for Atmosphere and Climate Change, SSM/I daily sea ice concentrations from IFREMER and wind vectors from the Climate Forecast System Reanalysis.

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8. Appendix

Table A-1: Information on the datasets used for figure 4-7: versions, DOIs and references. The correlations between the SST Niño3.4 region (averaged 5°S to 5°N, 190°E to 240°E) time series and the other ECVS's Niño3.4 time series (and for SM, BA and AOD time series with Indonesia (averaged 10°S to 10°N, 100°E to 150°E) are given in the right column.

ECV	Dataset version, time period used, DOI, references:	Correlation of Niño3.4 SST with
SST	ESA SST CCI ATSR and/or AVHRR product version v2.1, 1982-2016 **DOI: n/a** **Merchant et al 2019**	Niño3.4 SST: 1.00
SL	SL_cci data v2.0, 1993-2015 DOI: 10.5270/esa-sea_level_cci-1993_2015-v_2.0-201612 Legeais et al 2018 and Quartly et al 2017	Niño3.4 SL: 0.87
~~SSS~~Sea Surface Salinity (SSS)	SEASURFACESALINITY_CCI_DATA v1.6, 2010-~~2017~~2018 DOI: n/a	Niño3.4 SSS: -0.63
Chlor_a	CCI Chlor_a v3.1 (4km_GEO_PML), 1998-2017 **DOI: n/a** **Sathyendranath et al 2012**	Niño3.4Chlor_a: -0.68
CFChigh	**Cloud_cci AVHRR-PMv3, 1982-2016** **DOI: n/a** **Stengel et al 2019**	Niño3.4 CFChigh: 0.82
TCWV	HOAPS 4, 1988-2015 DOI:10.5676/EUM_SAF_CM/HOAPS/V002 Andersson et al., 2017, data from 2015 as beta version of HOAPS 4	Niño3.4 TCWV: 0.84
Fire	FireCCI51, 2001-2017 DOI: dx.doi.org/10.5285/3628cb2fdba443588155e15dee8e5352 Chuvieco, E. et al (2019)	Indonesia Fire: 0.49
AOD550	CCI ATSR-2/AATSR Swansea v4.1, 1997-2011 https://esgf-node.llnl.gov/search/obs4mips/obs4mips.SU.ATSR2-AATSR.od550aer.mon.v20160922 |eridanus.eoc.dlr.de **Bevan, S., et al., 2012; North, P., et al., 1999; Popp, et al., 2016**	Indonesia AOD550: 0.52
SM	ESA CCI SM merged v04.5, 1991-2018 **DOI: n/a** **Dorigo et al. 2017, Gruber et al. 2019**	Indonesia SM: -0.57

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Table captions

Table 3-1: Links between ECVs on the retrieval (above the diagonal) and scientific (below the diagonal) level which need to be consistent if used together. Weak linkages are indicated in brackets. Cycles are indicated with the following acronyms: C=carbon cycle, W=water cycle, E=energy cycle. Processes are indicated with the following acronyms: r=radiation interaction, d=deposition, e=emission / evaporation, t=transport, c=chemical transformation, mtf=melting / thawing / freezing, i=ecosystem interaction, a=air sea fluxes of carbon and water, m=mask.

Table 5-1: Consistency analysis status between pairs of CCI ECVs: intrinsically assured (*****), study needed (X), study done (c = comprehensive, e = exemplary, t = theoretical) - empty fields indicate that no study is needed, this link cannot be studied (e. g. due to resolution) or the link is considered weak. Numbered references for conducted studies are provided in the appendix (Table A-2).

Tables

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ESA CCI ECVs		Aerosol	Clouds	GHGs	Ozone	pourWater	Fire	Ice-Sheets	coverLand	oistureSoil	Glaciers	verHR land	LST	tPermafros	Snow	Biomass	Lakes	lourOcean	Sea Ice	Sea Level	SST	Sea State	surfaceSea
		Retrieval dependencies																					
Aerosol	Direct process dependencies		x	x	(x)	x	x	x	x				x		x		x	x			x		
Clouds		W r		x	x	x	x	x	x		x	x	x		x		x	x	x		x		
GHGs		e				x									(x)						(x)		
Ozone			t	c		x									(x)		x	x			(x)		
Water vapour		E W	E	C	c		(x)	x					x		(x)		x	x		x	x		
Fire		CE		Ce	ce				x			x		(x)			x						
Ice-Sheets		d			r	W	d		x	x	x									x			
Land cover		de		C e			Ci et			x	x	x	x	x	x		(x)						
Soil moisture		e	E	e		W e d	i		i		x	x	x		x	x	x	(x)	(x)	(x)	(x)	(x)	(x)
Glaciers		d					d	W	r			x		x	x		x		x				
HR land cover				Ce			Ct			i	m		x		x								
LST		Er	Er		r	E W r	EC e	W r	r	W r	m	r		x	x		x		x		x		
Permafros t			Er	Ce		W e	Er	m	Er	Er	m	Er	E W r		x		(x)			(x)			
Snow		d	r		r	W e	d	W	ri	m	Er m	ri	W tm rf	Er mt f		(x)	x			(x)			
Biomass				C			Cc		ic	i			C		i								
Lakes		d e				W	d	W t	ti	W	E m	t	E W r	W Ee	W					x	x		
Ocean colour		d e		C	r		d							Cd	m		t		x		x	x	
Sea Ice					r		d						W r	m				i		x	x	x	(x)
Sea Level						W		W		W	W			W	W		W		W		(x)	x	~~x~~
SST		Er	Er	r	r	Er	E	mt f					E W t					Er	m	E		(x)	~~(x)~~
Sea State																		i		m			x
Sea surface salinity				C		ea								m	m			C W i	W m	W E	W a	a	

Table 5-1: Consistency analysis status between pairs of CCI ECVs: intrinsically assured (*), study needed (X), study done (c = comprehensive, e = exemplary, t = theoretical) - empty fields indicate that no study is needed, this link cannot be studied (e. g. due to resolution) or the link is considered weak. Numbered references for conducted studies are provided in the appendix (Table A-2).

ESA CCI ECVs	Aerosol	Clouds	GHGs	Ozone	pourWater	Fire	Ice-Sheets	coverLand	oistureSoil	Glaciers	verHR land	LST	Permafros	Snow	Biomass	Lakes	olourOcean	Sea Ice	Sea Level	SST	Sea State	surfaceSea
	Done / needed consistency analysis (retrieval or scientific level)																					
Aerosol		e[10]	*		t	X	X	X	e			X		X		e	t[11]			X		
Clouds			*			X	X	X	X	X	X	X	X	X		e[24]	X	X		X		
GHGs					*	e[19]		X	X		X		t[1]		X		X			X		X
Ozone						X	X					X		X		e	X			X		
Water vapour							X		X			t	t[2]	X		e	X		X	X		X
Fire								e	e[23]	X	X	t[16,17]	t[3]	e[13]	e	e[15]	X	e		e[18]		
Ice-Sheets										c[21,22]		X	X	X	X				e[20]	X		
Land cover											X	t	t[4]	X	X	c[25]						
Soil moisture													t[5]	X	X	*	*	*		*	*	*
Glaciers														X		*		*	e[20]			
HR land cover																c[25]						
LST																		X		t		
Permafrost																		X	X			X
Snow																						X
Biomass																						
Lakes																						
Ocean colour																						X
Sea Ice																			X	*	c	X
Sea Level																					X	X
SST																						X
Sea State																						X
~~SS salinity~~SSS																						

Technical level of consistency achieved

Common data format
Common data access portal
Common metadata standards
Common documentation standards
Common visualisation & analysis tools
(partly) also adopted by C3s Climate
Data Store

Figure captions

Figure 1-1: Temporal coverage of CDRs for ECVs analysed by CCI. Filled bars indicate CDRs available in 2019, outlined bars CDRs that are planned within the ongoing phase of the CCI ~~programme~~program.

Figure 3-1: The ECVs covered by ESA CCI CDRs, ordered according to the key Earth system cycle (energy, carbon, water) they help characterise. The cycles are inter-linked, and the energy cycle encompasses most of the water and carbon cycles since energy is stored and transported in water and matter, at least on transient timescales.

Figure 4-1: Discontinuities in coverage of surface temperature fields (LST and SST from SLSTR on Sentinel-3A) across a land-sea boundary due to different cloud clearing approaches over land and sea.

Figure 4-2: Consistency overview between Aerosol_cci (Swansea University) and Cloud_cci (FAME-C) AATSR cloud masks for observations of four selected days in September 2008. No cloud/no cloud and cloud/cloud situations are solely analysed as aerosol or clouds in Aerosol_cci and Cloud_cci, respectively. No cloud/cloud situations are wrongly analysed as aerosols and clouds, while cloud/no cloud situations are not analysed at all.

Figure 4-3: Time series of monthly mean globally averaged XCO_2 (red thick line) based on merging individual ensemble members (grey lines), extended with 2018 preliminary Copernicus Atmosphere Monitoring Service (CAMS) near-real-time product (red diamonds) (Heymann, et al., 2015).

Figure 4-4: Trend estimates computed after (green) and before (black) homogenisation for all long-term TCWV data records available from the G-VAP data archive (Schröder et al., 2018). Trend estimates are sorted in ascending order without homogenisation. The grey horizontal line marks a trend of 0 kg/m^2/decade (updated from Schröder et al., 2019).

Figure 4-5: Trends of monthly averaged significant wave height H_s data sets with the Mann–Kendall test (thatched areas) from satellite altimetry (left: ALT), and co-located model WW3 hindcast (right: CoLoc) both given in cm year^{-1}.

Figure 4-6: The left panel shows the co-variation between a prototype version of the stratospheric water vapour CDR H_2O (produced within the Water_Vapour_cci) and ERA5 monthly zonal mean temperatures T at 100 hPa. The right panel shows the correlation between the two datasets.

Figure 4-7: Zonal month-longitude cross sections (averaged 5°S and 5°N) for 150°E to 280°E normalized indices of a) SST CCI analysis v2.1, b) SL_cci data v2.0, c) SSS cci v1.6, d) Chlor_a cci v3.1, e) Cloud_cci AVHRR-PMv3 CFChigh, f) HOAPS 4 TCWV. All ECVs are plotted for their respective full year availability and normalized by their respective longitudinal varying standard deviations. The black lines in the Hovmöller plots show the Niño3.4 box. g) Time series of Niño3.4 CCI SST and Indonesia CCI SM v04.5, FireCCI51, and AOD550 (ATSR-2/AATSR Swansea v4.1). The time series are normalized by their respective standard deviation. Information on the used datasets is provided in Table A-1 in the Appendix.

Figures

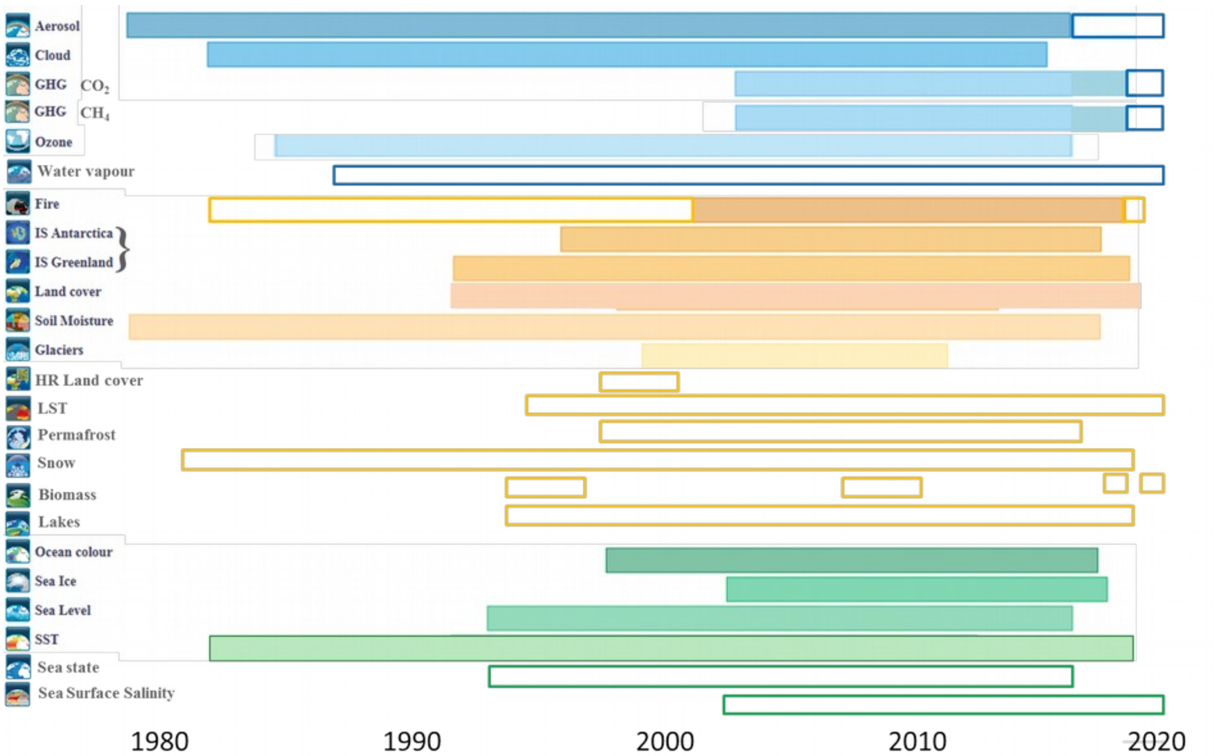


Figure 1-1: Temporal coverage of CDRs for ECVs analysed by CCI. Filled bars indicate CDRs available in 2019, outlined bars CDRs that are planned within the ongoing phase of the CCI ~~programme~~program. For Sea Surface Salinity, the bar should be filled from 2010 to October 2018.

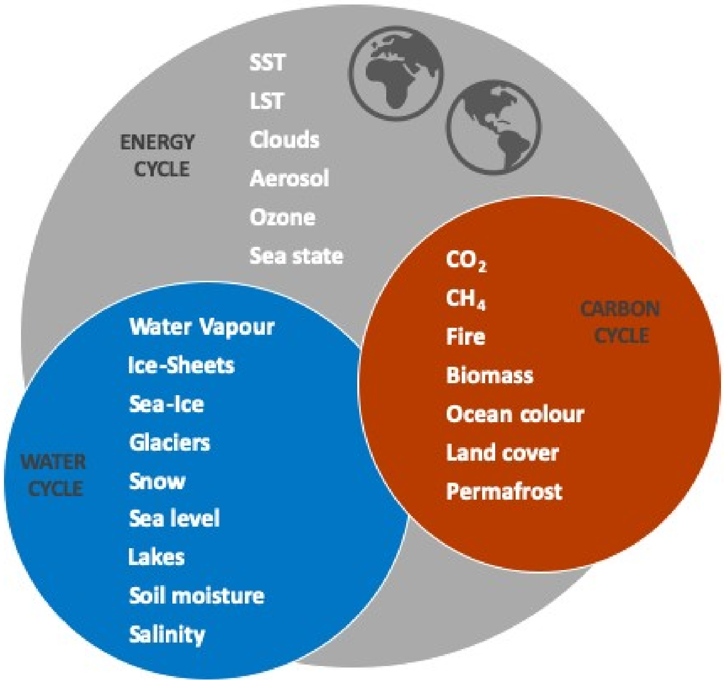


Figure 3-1: The ECVs covered by ESA CCI CDRs, ordered according to the key Earth system cycle (energy, carbon, water) they help characterise. The cycles are inter-linked, and the energy cycle encompasses most of the water and carbon cycles since energy is stored and transported in water and matter, at least on transient timescales. <u>Salinity should be replaced by Sea Surface Salinity</u>

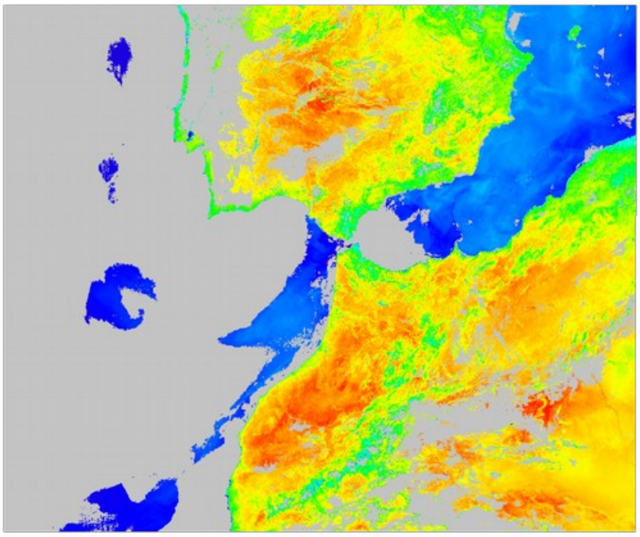


Figure 4-1: Discontinuities in coverage of surface temperature fields (LST and SST from SLSTR on Sentinel-3A) across a land-sea boundary due to different cloud clearing approaches over land and sea.

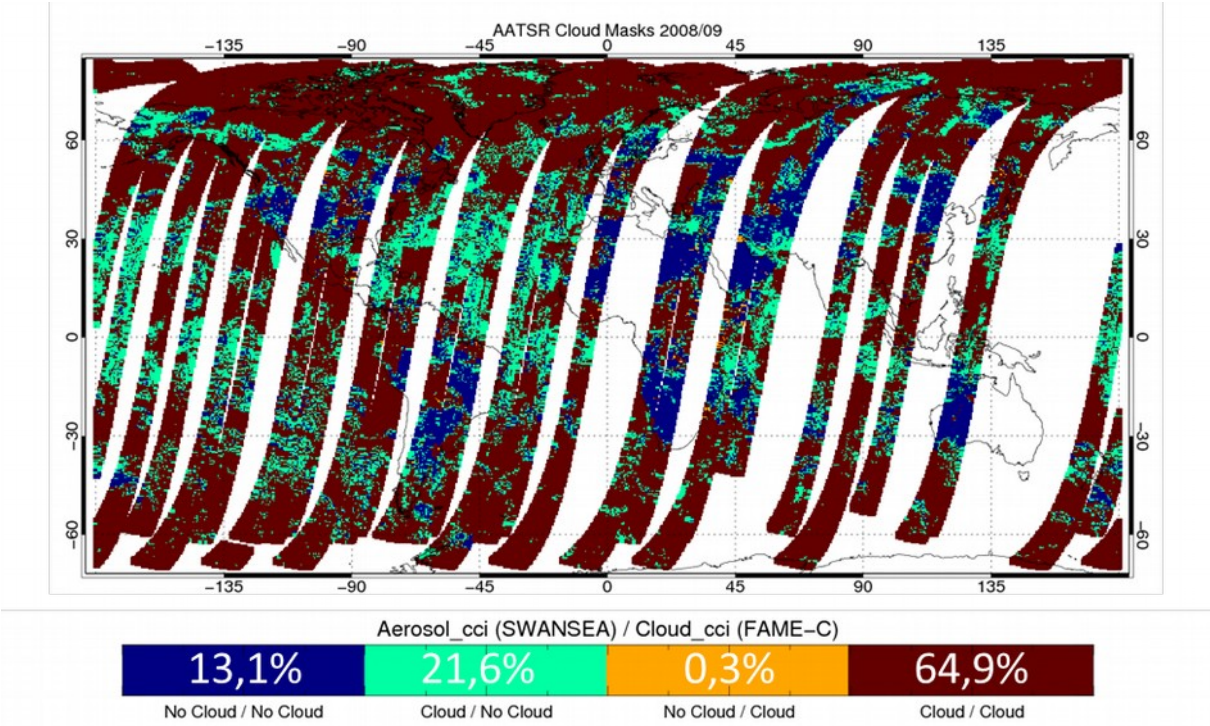


Figure 4-2: Consistency overview between Aerosol_cci (Swansea University) and Cloud_cci (FAME-C) AATSR cloud masks for observations of four selected days in September 2008. No cloud/no cloud and cloud/cloud situations are solely analysed as aerosol or clouds in Aerosol_cci and Cloud_cci, respectively. No cloud/cloud situations are wrongly analysed as aerosols and clouds, while cloud/no cloud situations are not analysed at all.

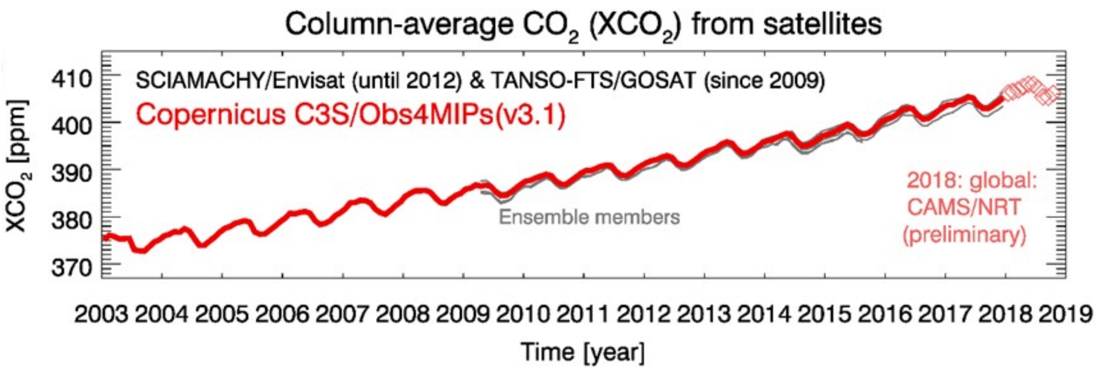
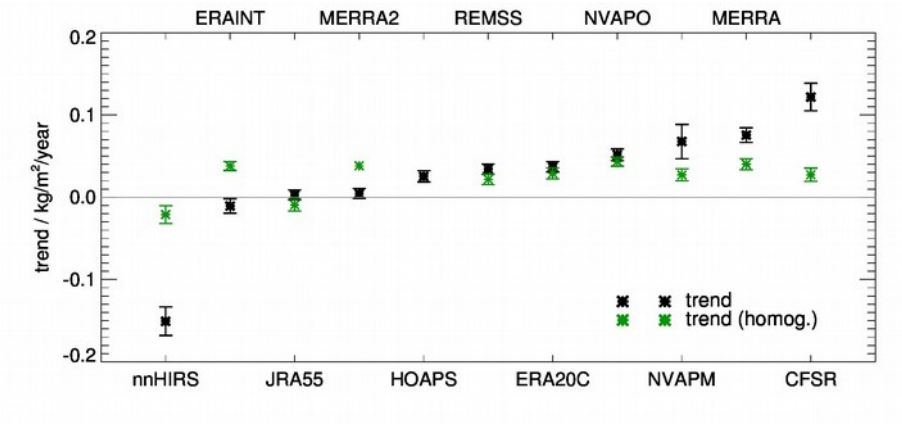


Figure 4-3: Time series of monthly mean globally averaged XCO_2 (red thick line) based on merging individual ensemble members (grey lines), extended with 2018 preliminary Copernicus Atmosphere Monitoring Service (CAMS) near-real-time product (red diamonds) (Heymann, et al., 2015).



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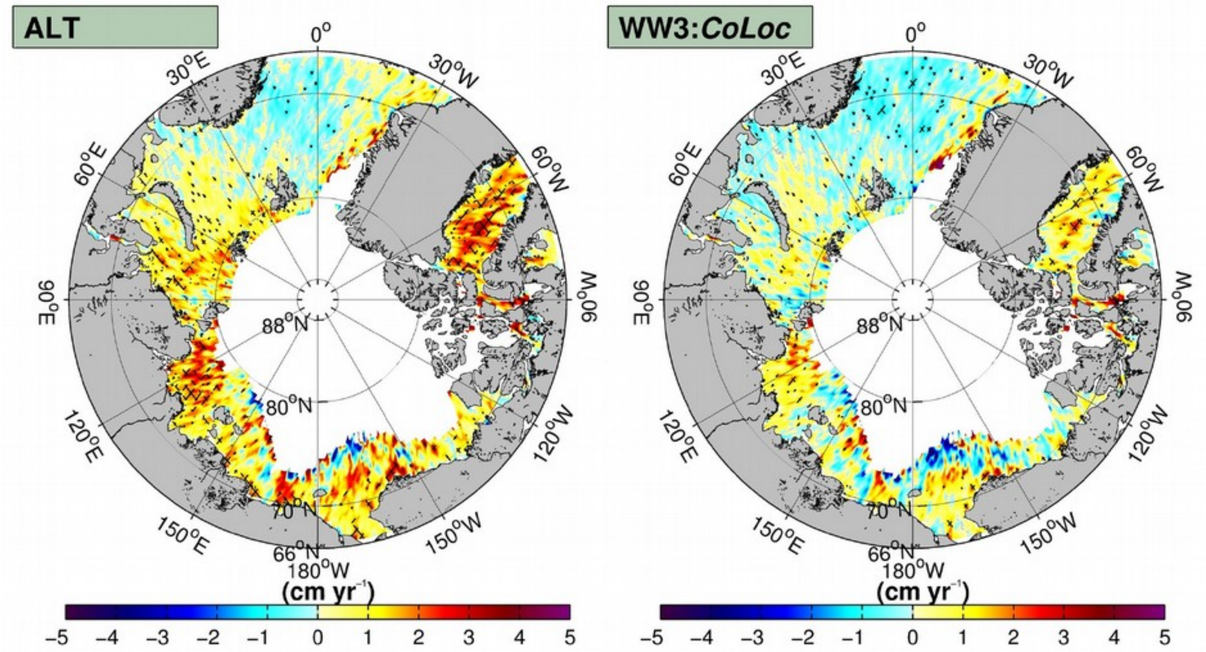

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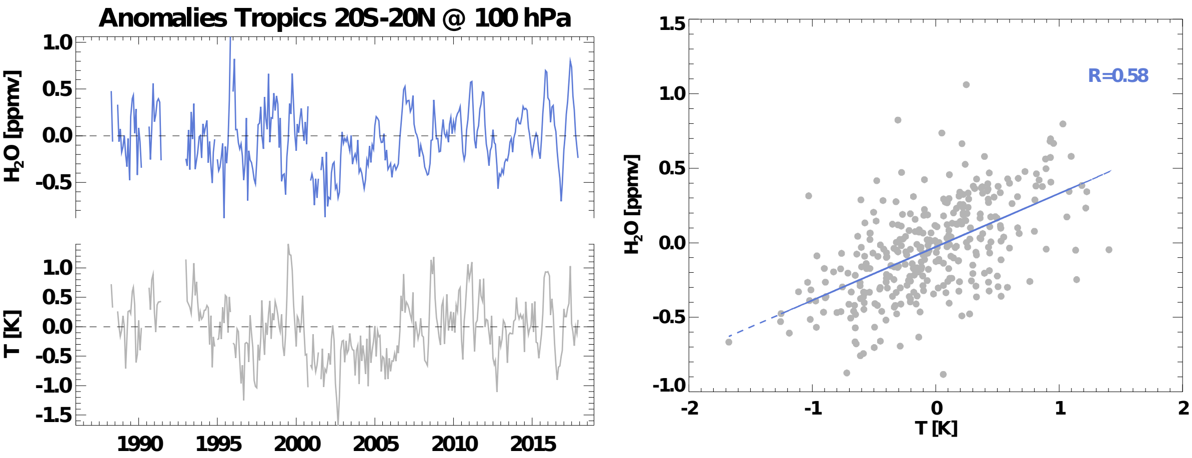

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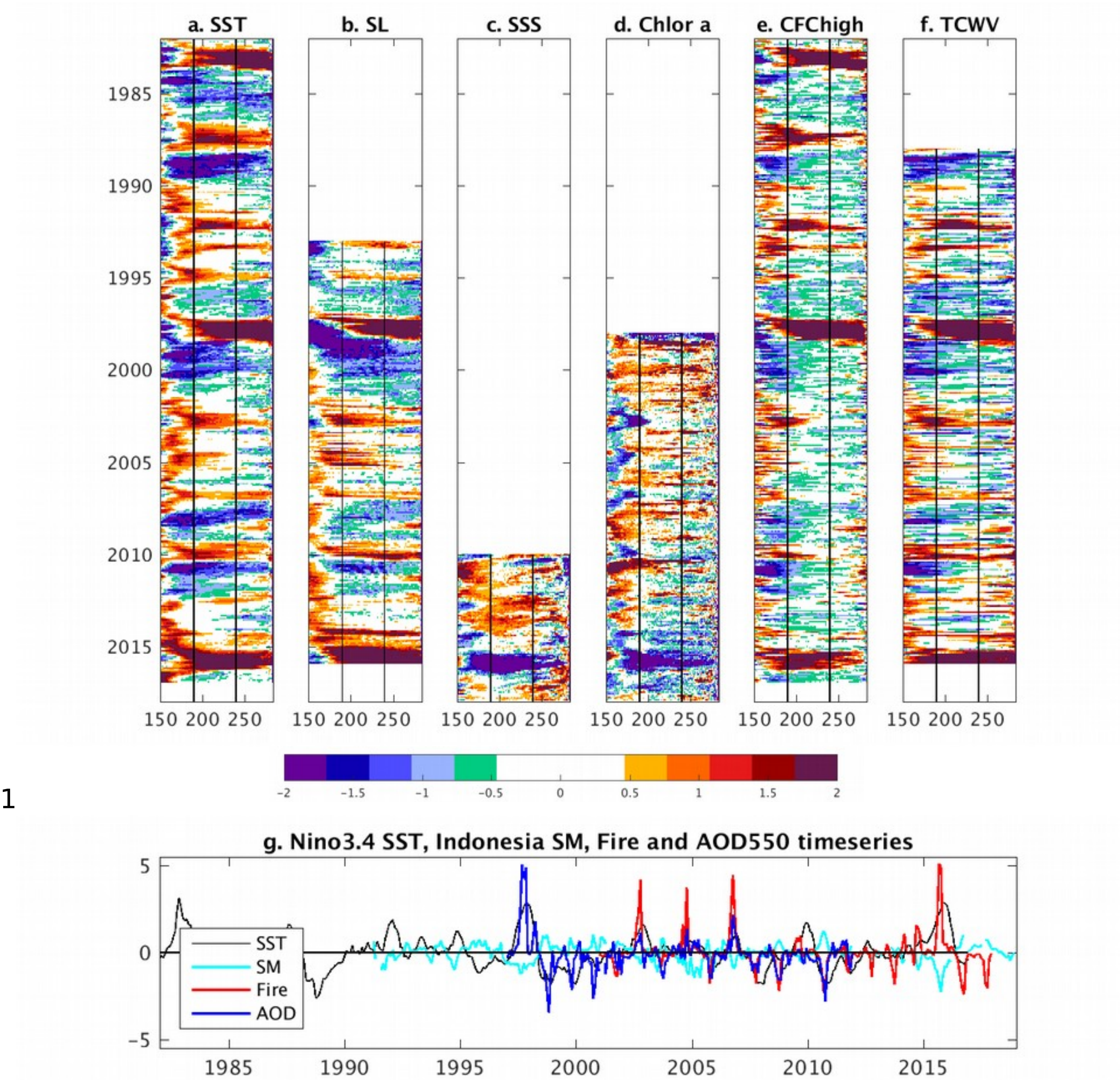

Figure 4-7: Zonal month-longitude cross sections (averaged 5°S and 5°N) for 150°E to 280°E normalized indices of a) SST CCI analysis v2.1, b) SL_cci data v2.0, c) ~~SSS~~ Sea Surface Salinity cci v1.6, d) Chlor_a cci v3.1, e) Cloud_cci AVHRR-PMv3 CFChigh, f) HOAPS 4 TCWV. All ECVs are plotted for their respective full year availability and normalized by their respective longitudinal varying standard deviations. The black lines in the Hovmöller plots show the Niño3.4 box. g) Time series of Niño3.4 CCI SST and Indonesia CCI SM v04.5, FireCCI51, and AOD550 (ATSR-2/AATSR Swansea v4.1). The time series are normalized by their respective standard deviation. Information on the used datasets is provided in Table A-1 in the Appendix.