ESA Climate Change Initiative Plus - Soil Moisture

Climate Assessment Report

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EODC Earth Observation Data Centre for Water Resources Monitoring GmbH

in cooperation with

TU Wien, VanderSat, ETH Zürich, CESBIO and INRAE

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Authors:	M. Hirschi, P. Stradiotti, N. Nicolai-Shaw*, E. Haas*, S. Mourits-Andersen*, W. Dorigo, R. Kidd *as contributors of ESA CCI Phase 2 CAR		
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1.0		Approved By ESA 26/07/24. Finalised.	R. Kidd

For any clarifications, please contact Martin Hirschi (martin.hirschi@env.ethz.ch).

Project Partners	
Prime Contractor, Project Management	**EODC**, Earth Observation Data Centre for Water Resources Monitoring (Austria)
Earth Observation Partners	**TU Wien**, Vienna University of Technology (Austria) **VDS**, Vandersat (The Netherlands) **CESBIO**, CESBIO (France) **INRAE**, Institut National de la Recherche Agronomique (France)
Climate Research Partner	**ETH Zürich**, Institute for Atmospheric and Climate Science, (Switzerland)

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Acronyms and abbreviations

AAO	Antarctic Oscillation
AMSR-E	Advanced Microwave Scanning Radiometer
ASAR	Advanced Synthetic Aperture Radar
ASCAT	Advanced Scatterometer
ATBD	Algorithm Theoretical Baseline document
CAR	Climate Assessment Report
CCI	Climate Change Initiative
CEDA	Centre for Environmental Data Analysis
CMIP	Coupled Model Intercomparison Project
ECV	Essential Climate Variable
ENSO	El Niño Southern Oscillation
ERA5	5th generation ECMWF Re-Analysis
ERS	European Remote Sensing
ESA	European Space Agency
ESSMI	Empirical Standardized Soil Moisture Index
GCOS	Global Climate Observing System
GIMMS	Global Inventory Modeling and Mapping Studies
GLDAS	Global Land Assimilation System
GPCC	Global Precipitation Climatology Centre
JAG	Journal of Applied Earth Observation and Geoinformation
LAI	Leaf Area Index
LPRM	Land Parameter Retrieval Model
NAO	North Atlantic Oscillation
NASA	National Aeronautics and Space Administration

NDVI	Normalized Difference Vegetation Index
NN	Neural Network
NOAA	National Oceanic and Atmospheric Administration
PSD	Product Specification Document
PVIR	Product Validation and Intercomparison Report
QSR	Quarterly Status Report
SBA	Societal Benefit Area
SIGMA	Simulating Innovation for Global Monitoring of Agriculture
SM	Soil Moisture
SMAP	Soil Moisture Active Passive
SMMR	Scanning Multichannel Microwave Radiometer
SMOS	Soil Moisture Ocean Salinity
SOI	Southern Oscillation Index
SPI	Standardized Precipitation Index
SSI	Standardized Soil Moisture Index
SSM/I	Special Sensor Microwave Imager
TMO	TRMM Microwave Imager
TRMM	Tropical Rainfall Measuring Mission

ESA CCI SM:

over 45 years of satellite observed soil moisture!

The ESA CCI soil moisture dataset (ESA CCI SM) has become a well-established dataset within the scientific climate community. Its long temporal coverage, currently spanning over 45 years (1978-2023, v09.1), and global spatial coverage have been identified by our users as the main features for choosing ESA CCI SM. The long temporal coverage is an essential prerequisite for robust trend assessments and the investigation of soil moisture drivers of hydrological and biogeochemical processes, while the spatial coverage has allowed for studies in previously data-poor regions, or regions where access to ground-based data is difficult, e.g., China, Iran, Africa and South America.

Over 12’400 registrations as of April 2023

Interest in the ESA CCI SM dataset from outside of the scientific community is also steadily growing, e.g., by the non-profit and private sectors. Topics such as disaster, energy, weather, and health are increasingly mentioned in user applications. With the acceptance of ESA CCI SM to the Copernicus Climate Data Store, including a product improvement with a shortened latency, allows for ESA CCI SM to be embedded in monitoring and operational services, e.g., for drought monitoring and flood forecasting.

The overwhelming interest in the ESA CCI SM dataset shows that ESA CCI SM has come a long way and has made it a well-established dataset. Hopefully continuation of this dataset into the future will remain possible. Not only by financial support for the scientific development of ESA CCI SM and operational reprocessing, but also by the availability of continuous sensor data.

1 Introduction

1.1 Purpose of the document

The purpose of the CAR is the assessment of the ESA CCI SM time series for climate science. We highlight here the ESA CCI SM overview paper published in the CCI special issue in Remote Sensing of Environment: "Earth Observation of Essential Climate Variables". Dorigo et al. (2017) gives a comprehensive overview on the ESA CCI SM products. Not only their specifications and error characteristics, but also the wide range of Earth system applications currently using the data. Furthermore, we update new versions of the CAR against the most recent scientific literature that makes use of the ESA CCI SM dataset for the different applications. For this version of the CAR, more than 200 new studies (as of March 2024) citing the ESA CCI SM key publications since April 2023 have been reviewed. The outcome underlines soil moisture to be an essential climate variable and highlights the value of the established global long-term soil moisture time series based on satellite observations. Furthermore, the document provides a critical view on the potentials and limitations of the developed datasets for climate studies.

1.2 Targeted audience

This document targets the scientific science community as it demonstrates the value and application of the global remote sensing observation-based ESA CCI SM time series for climate science. Furthermore, it provides valuable insights in the potential and limitation of the ESA CCI SM time series for climate studies.

2 Executive Summary

2.1 Introduction

The European Space Agency's (ESA) Climate Change Initiative (CCI) soil moisture (SM) program aimed and fulfilled the development of a publicly available surface soil moisture time series that covers more than 45 years (1978-2023, v09.1) and is solely based on remote sensing observations as primary input. In order to produce a soil moisture climate data record sufficiently long for climate research, various single sensor active and passive microwave soil moisture products are combined. Three separate products are available, a merged ACTIVE, a merged PASSIVE and a COMBINED active + passive product. The products, as well as the documents for the algorithm development (ATBD), the product specification (PSD), and the report on the final product validation (PVIR), are all publicly available to the user through the dedicated CCI soil moisture website: https://climate.esa.int/en/projects/soil-moisture/.

The assessment of the ESA CCI SM time series for climate research is a central part within the ESA CCI SM project, as it allows for a critical evaluation of its suitability for climate applications. A search on Google scholar shows that the interest in satellite soil moisture products has increased over time. Updated from de Jeu and Dorigo (2016), Figure 1 (left) shows the number of Google scholar hits per year using SMAP, SMOS[1], AMSR-E, ASCAT, ASAR, Sentinel-1, and ESA CCI in combination with "soil moisture" as a search term (as of March 2024, numbers for full years up to 2023). There is a long-term increase, with signs of levelling off for most products in the last two years.

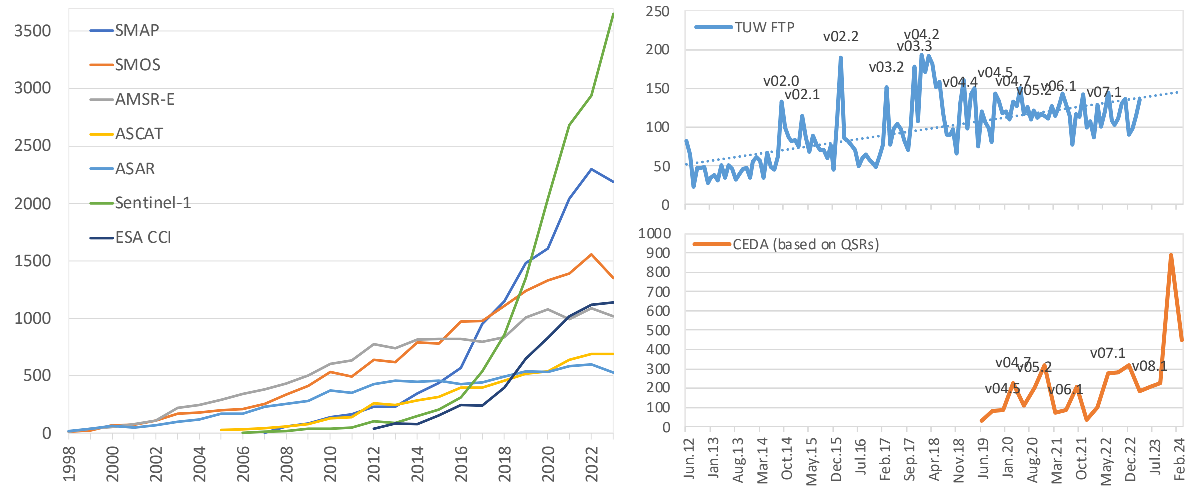

Figure 1 *(left) Number of google scholar hits per year using the sensor name in combination with the term "soil moisture", updated from: de Jeu and Dorigo (2016). (right) Number of registered ESA CCI SM users per month based on the TUW FTP server registrations (top panel, June 2012 to March 2023) and per quarter based on the CEDA users (bottom panel, June 2019 to March 2024).*

[1] Note that the trend in the "SMOS + soil moisture" hits is likely overestimated since soil moisture is part of the acronym, but the results may include applications like VOD, AGB and ocean salinity, which cannot be easily separated in the search.

Figure 1 (right) shows the number of ESA CCI SM users per month from June 2012 to March 2023 based on the TUW FTP server registrations (which was taken offline afterwards), and per quarter from June 2019 to March 2024 based on users obtaining the product from the ESA CCI open data portal through CEDA (numbers as noted in the QSRs). There is a steady increase over the years, with a flattening of the curve after around 2020, which may be due to more users obtaining the product through CEDA. With the start of the TUW FTP server registration downtime, CEDA shows a distinct increase in users. Also, peaks in registration with each new public data release are particularly visible for the pre-v05 releases.

2.2 Investigating the ESA CCI SM user base

Until April 2023, The ESA CCI SM ACTIVE, PASSIVE, and COMBINED products was available for download from the TUW FTP server after completion of a simple registration form[1]. As of April 2023, we counted over 12’400 registrations. Particularly for the pre-v05 releases, distinct peaks in user registration can be seen with each new data release, see Figure 1 (right). We also see a steady upward trend in monthly user registrations, with a flattening in recent years.

Information gained from anonymised registration information gives insight into users’ backgrounds, as well as changes in user composition over time. Figure 2 (top) shows a subdivision of registered users by continent. Originally most users originated from Europe (v0.1), but as the dataset has become more known there is a strong increase in users from Asia and North America. In Asia, most users come from China and India, followed by Iran, Japan, and South Korea. In Europe most users are from

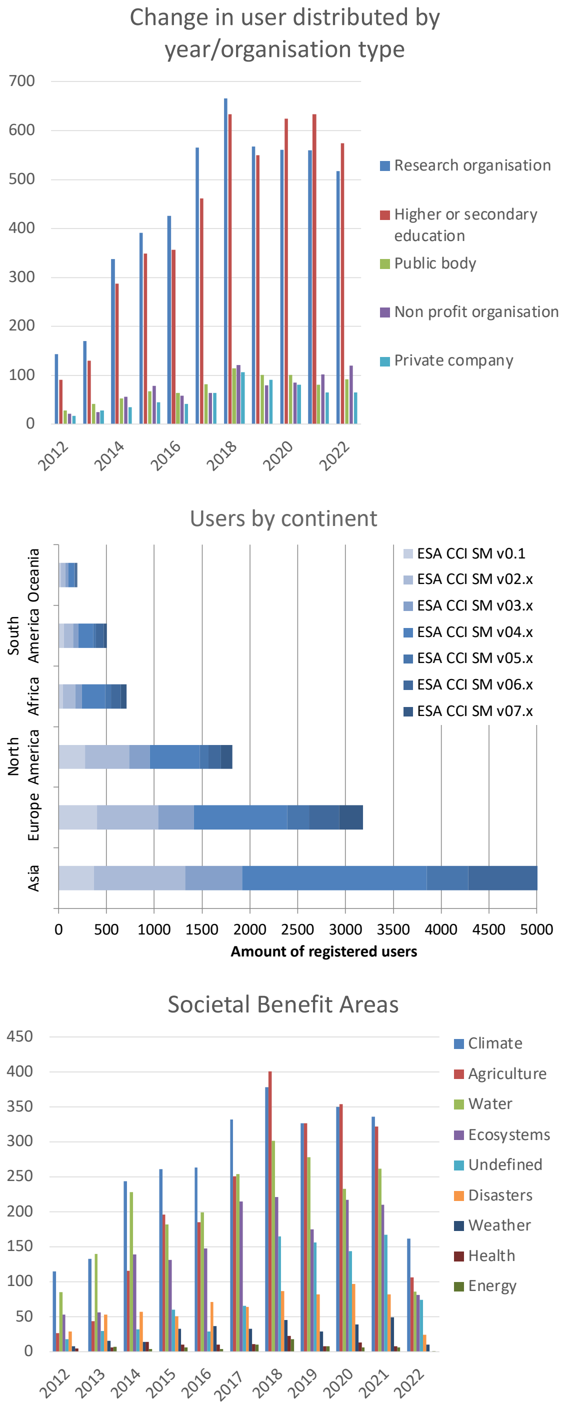

Figure 2 *Registered users subdivided by continent and product version (top), by societal benefit area (middle), and by organisation type (bottom).*

[1] The registration form was taken offline in spring 2023 and users are redirected to the ESA CCI open data portal, from where the data is available through CEDA without user registration.

Germany, followed by France, Italy, the Netherlands, and the UK.

The main application area users indicate since the beginning of ESA CCI SM is climate, see Figure 2 (middle). There is a steady increase in users dealing with water, ecosystems applications and in particular agriculture. Since 2018, agriculture is as often mentioned as climate (except for 2022). Weather, energy and health sectors are lagging behind, but are also slowly growing. While the number of monthly registrations shows a flattening in recent years, there is an apparent decrease in the user declarations of application areas particularly for 2022.

This broadening of application areas is also found when analysing users based on organisation type. Though, research organisations and higher or secondary education are clearly the main users of the ESA CCI SM dataset, more and more, public bodies, private companies as well as non-profit organisations are using the data. This increase of organisations outside of scientific institutions indicates the broad acceptance and maturity of the dataset and assures a growing user base.

2.2.1 *Focus of research within the societal benefit areas*

The three main societal benefit areas (SBA) are Climate, Water and Agriculture (Figure 3). As seen above, there is an apparent decrease in the user declarations of societal benefit areas in 2022, which is also visible here. The qualitative assessment of the user database shows that the usage and focus of research within these SBAs are wide and have different purpose, from status quo of occurrences to the development of models. The span of the usages covers many aspects, such as the exploration of the usability of Earth observation data in new fields. Some of ways the data is used include:

- Development of long-time trends, forecasting & monitoring
- Land evaluation, management, planning and assessments
- Modelling and simulations, big data analytics

The specific themes under each SBA also vary from infrastructure, temperature influences of fungi attacking wood elements to spatial epidemiology, climate -and crop simulation modelling and data analytics in agriculture. The mentioned themes show a glimpse of the span, which the ESA CCI SM data covers and the prospectively wide usage of the data.

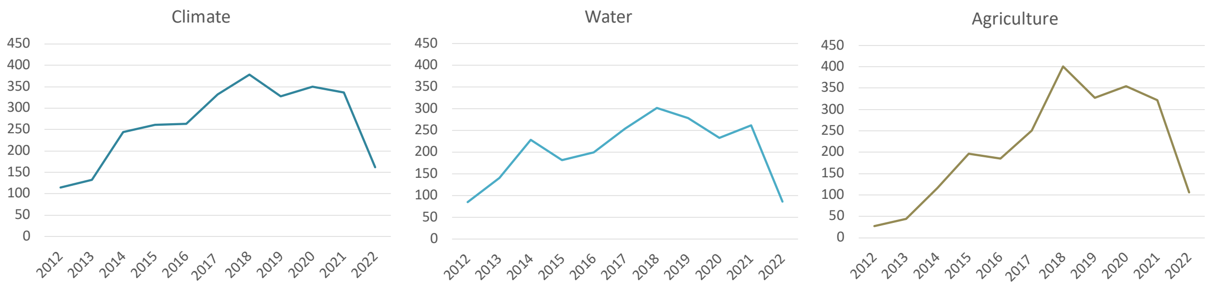

Figure 3 *Temporal development of registered users of the three main SBAs.*

2.2.2 *Maturity increase of ESA CCI SM*

Over the years, the validation of ESA CCI SM as documented in the PVIR (Hirschi et al., 2023b, 2024) has revealed a steady increase in the agreement of the product with in-situ measurements from ISMN (Dorigo et al., 2021). Figure 4 shows the (significantly positive, $p < 0.05$) correlations of the different major ESA CCI SM releases (as represented by the evolution of the merging algorithm; see Gruber et al., 2019), as well as of ERA5-Land layer 1 compared to in-situ stations in the US (where station coverage is most dense) for different temporal subsets (i.e., 1999-2002, 2003-2006, 2007-2010, 2011-2014, 2015-2018 and 2019-2022, as well as 1999 up to the end of the individual time series). The ESA CCI SM versions show a general increase in performance with data releases, pointing to the increasing maturity of the product. This is particularly the case for the periods after 2006. Also, towards later periods, the overall correlations with in-situ measurements tend to increase due to the coverage with more satellites. Note that the reduction in the correlations of the 2019-2022 period is likely related to the reduction in coverage with in-situ stations for this most recent period.

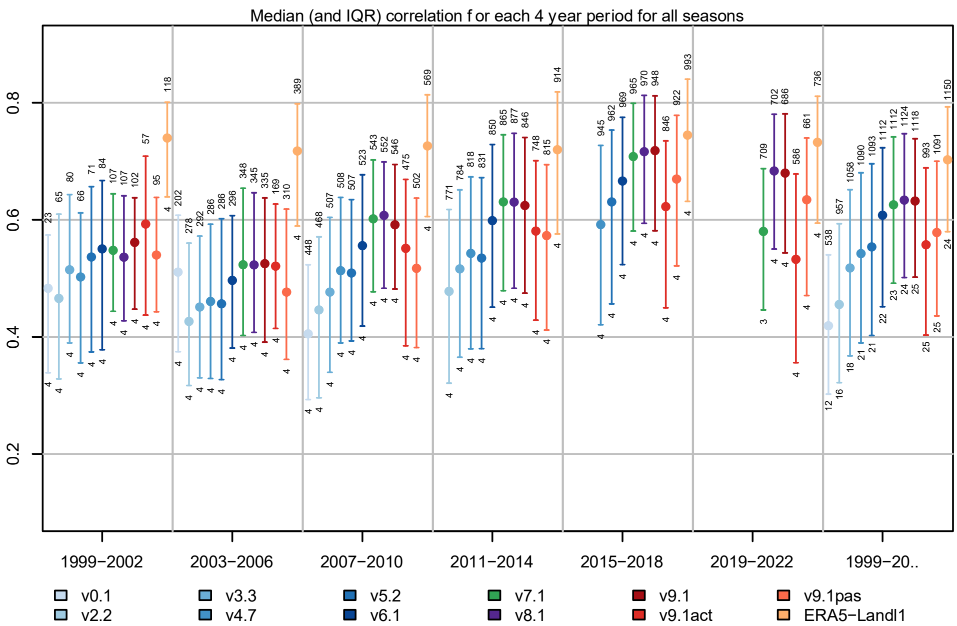

Figure 4 *Correlation of the gridded soil moisture products as compared to in-situ station observations in 5 and 10 cm depth for the full year for the US. Subdivided in consecutive 4-year periods (1999-2002, 2003-2006, 2007-2010, 2011-2014, 2015-2018 and 2019-2022) as well as for the longest period data is available (1999-20.., end date would e.g. be 2010 for CCI v0.1, but is 2023 for e.g. CCI v09.1). Note that data is not masked for common data availability. Whiskers show the median and the IQR. Above indicated the number of stations correlations were calculated for that comply to the following criteria: at least 10% of the time-series is not NA, p-value < 0.05, and the calculated correlation is positive. And below indicated the number of years considered. In addition to the major releases of ESA CCI SM COMBINED, the ACTIVE and PASSIVE products are also shown in case of v09.1 (denoted v9.1act and v9.1pas).*

The ERA5-Land reanalysis shows more stable correlations over time, and overall better agreement with the in-situ data as compared to the ESA CCI SM releases, which is in line with other product inter-comparison studies (e.g., Beck et al., 2021). Within ESA CCI SM, the PASSIVE and ACTIVE products often show lower skill compared to the COMBINED product, showing the benefit of the merging approach.

ESA CCI SM at a glance

Motivation for using ESA CCI SM

- Long temporal coverage
- Large spatial coverage
- Can function as an independent reference dataset
- Constraining errors in models
- Reduce uncertainties

Limitations identified

- Data gaps in time and space, especially prior to 1992
- Changing data quality and coverage over time
- No representation of root-zone soil moisture
- Evaluation of absolute values not possible
- Dependency on GLDAS-Noah as scaling reference
- Too coarse spatial resolution

Future directions and ongoing developments

- Higher spatial resolution, either by including observations with higher native resolution (e.g., SAR, thermal infrared) or by downscaling
- Filling of data gaps is currently being addressed with an additional gap-filled research version of the COMBINED product as of ESA CCI SM v08.1
- Improved temporal sampling is achieved through the integration of daytime observations
- Improved product accuracy
- Improved blending methods
- Improved temporal consistency has been partly addressed through a break-adjustment (Preimesberger et al., 2021), which has been implemented in the v08.1 COMBINED product
- Shorter latency times between data acquisition and data availability have been achieved with the inclusion of the product in the Copernicus Climate Data Store
- Independency of LSMs is being investigated and has been integrated in a research product as of v09.1 by using L-band observations from SMOS and SMAP as new scaling reference
- Creation of a root-zone soil moisture product is currently being addressed and will be included as a research product in v09.1

2.3 Motivation for use, limitations identified and future directions

Table 5 of Dorigo et al. (2017), included in the Appendix as Table 1 - Table 6, gives an extensive overview of the use of ESA CCI SM for scientific studies. These tables also include the motivation for using the ESA CCI SM dataset, as well as the main limitations identified by the users. Here we provide a short overview.

Long temporal and global spatial coverage of the dataset

The main motivation identified by users for using ESA CCI SM is the long temporal and global spatial coverage of the dataset. Long temporal coverage is essential for robust trend and driver assessment, but also for use applications such as researching vegetation activity, investigating fire activity or the creation of a precipitation dataset, while global coverage allows investigations into areas where previously no observations were available. The long temporal and global spatial coverage also make ESA CCI SM a prime candidate to function as a global independent reference for land surface model and reanalysis evaluations. In addition, ESA CCI SM through assimilation has been shown to aid in constraining model errors, reduce uncertainties, and improve model predictions (Miralles et al., 2014b; Tramblay et al., 2014; e.g., Massari et al., 2015). These results show that further studies are clearly needed to assess the full potential of the ESA CCI SM dataset. Also, as documented in the PVIR, larger uncertainties remain regarding the representation of temporal trends, which display distinct and partly diverging global patterns among the ESA CCI SM COMBINED releases and the underlying ACTIVE and PASSIVE products, as well as compared to reanalysis and land-surface model products (Hirschi et al., 2023b; 2024; cf. also Section 3.1.1).

Increase of available satellites and improved retrieval protocols will reduce data gaps

The main limitation identified by users is the presence of data gaps, both in time and space, and the changing data quality over time. This complicates or sometimes even impedes the use of the dataset, and care needs to be taken to properly inform users of this caveat. The increase of available satellites (including FengYun 3E and 3F, and AMSR3 in the upcoming ESA CCI+ SM Phase), as well as the improvement of retrieval protocols and merging methodologies, will mostly solve for this in the future. Though it should be noted that the absence of suitable sensors in the early years, as well the physical limitations of the microwave signal in general, e.g., no retrieval under snow coverage or dense vegetation, will likely prove insurmountable (Dorigo et al., 2017). As an alternative, gap-filling can be achieved by statistical methods for data imputation (e.g., Bessenbacher et al., 2022). An additional gap-filled version of the product which adapts a 3D-smoothing algorithm (Garcia, 2010) and does not rely on ancillary data is being produced as a research product of ESA CCI SM as of v08.1 (Preimesberger et al., 2024).

SMOS and SMAP SM can eliminate the dependency on ancillary model data for scaling

Currently, the merging procedure for the COMBINED product includes scaling against GLDAS-Noah, however various users have expressed a need for a Land Surface Model (LSM) independent dataset. The passive microwave soil moisture data fusion project (Contract No: IPL-PSO/FF/vb/13.886 EXPRO+) has investigated the inclusion of SMOS soil moisture data in the ESA CCI SM dataset. The inclusion of SMOS into ESA CCI SM (v03.2) has shown to improve the quality of the dataset. In addition, SMOS soil moisture has the potential to serve as the reference soil moisture dataset for scaling purposes, thus solving the current dependence on a LSM reference. This has been investigated in the framework of the visiting scientist activity of Maria Piles (U. Valencia) taking place from 01/01/2017 to 13/11/2018 (Piles et al, 2018) Besides, the passive microwave soil moisture data fusion project recommended to further investigate the possibility to build a long-term record from Neural Networks, and to set up merging strategies that use multiple satellites and retrieval methods (van der Schalie et al., 2016). Within the current ESA CCI+ activities, the impacts of replacing GLDAS-Noah as reference for the rescaling is investigated using L-band data from SMOS and SMAP as an alternative. Results show that the best trade-off could be using a merged L-band dataset as scaling reference to benefit from both SMAP (better spatial coverage) and SMOS (longer time series) advantages (Madelon et al., 2021). These developments have been integrated in ESA CCI SM by generating an L-band reference from the BTs-level merging of SMAP and SMOS and the corresponding research product will be distributed with ESA CCI SM v09.1. Such product covers the 2010-2023 period; the time backward-propagation of the L-band reference using L-band-like AMSRE data is under investigation from the previous research base of Rodríguez-Fernández et al. (2016).

ESA CCI SM included in the Copernicus Climate Data Store with improved latency

The latency time between data acquisition and data availability has been identified as a limitation for embedding satellite derived soil moisture in operational services, for example drought monitoring and early warning systems. With the inclusion of ESA CCI SM in the Copernicus Climate Data Store, part of the Copernicus Climate Change Services (C3S; https://climate.copernicus.eu/), an operational product with an update frequency of 10 days is made available. The latest version of this near-real time operational product (v202212.0.0) is based on v07.1 of ESA CCI SM. The use of near-real-time Level 1 and Level 2 data streams in C3S is expected to have only a minor impact on the product quality with respect to ESA CCI SM, since for most datasets merged into C3S the NRT and off-line data streams are similar.

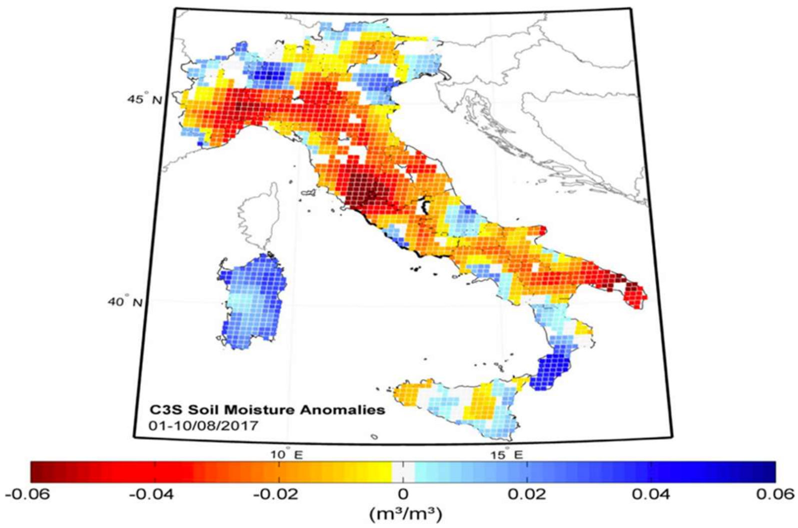

Figure 5 *Soil moisture anomalies (with respect to the 1997–2017 time period) in Italy during early August 2017.*

From: http://www.esa.int/Our_Activities/Observing_the_Earth/Italy_s_drought_seen_from_space

Such a reduced latency will enable new applications for ESA CCI SM. The near real-time soil moisture data (compiled by the ESA CCI SM project) has already been used to monitor drought in Italy during the exceptionally dry August 2017 (see Figure 5), with conditions similar to the 2012 drought. Also, the near real-time availability allows for the integration in the European State of the Climate reports[1] compiled by the C3S.

A satellite observation-based root-zone soil moisture product

As root zone soil moisture is important for e.g., long-term evapotranspiration and water supply, not surprisingly, a user request that frequently surfaces is a satellite observation-based root-zone soil moisture product. But, as the penetration depth of the microwave signal is only a few centimetres at most, at first glance this does not seem feasible. However, a simplified approach using an exponential filter to derive a root-zone soil moisture product, such as the Soil Water Index method (Albergel et al., 2008; Wagner et al., 1999), has already proven useful (Brocca et al., 2012). Alternatively, the assimilation of satellite soil moisture into a land surface model has been shown to improve the root zone correlation with in-situ stations (e.g., Blyverket et al., 2019b). Such an assimilated root-zone product can be a good compromise between a solely observation based and model-based product. An ESA CCI+ soil moisture CCN1 Scientific Evolution study has been concluded with the goal to extend the ESA CCI surface soil moisture product with a global, long-term root-zone soil moisture dataset with daily and 0.25° resolution. The creation of an ESA CCI root-zone soil moisture product based on exponential filtering and using calibrated T-parameters for 4 different soil depth layers determined from in-situ time series (Pasik et al., 2023) is currently ongoing and will be included as a research product in v09.1.

2.4 ESA CCI SM in scientific studies

JAG special issue: Advances in the Validation and Application of Remotely Sensed SM

In 2015, the International Journal of Applied Earth Observation and Geoinformation published the special issue "Advances in the Validation and Application of Remotely Sensed Soil Moisture", with guest editors Wouter Dorigo and Richard de Jeu. Though this special issue was on remotely sensed soil moisture in general, the ESA CCI SM dataset was featured in many of the articles. The special issue highlights the importance of satellite soil moisture for studies in previously data-poor regions, or regions where access to ground-based data is difficult, e.g., China, Iran, Africa and South America. Two clear user requests can be distilled from the JAG special issue. Firstly, continued efforts to enhance spatial resolution and reduce errors of the soil moisture retrievals. And secondly, in the context of a changing climate and with a rise of operational applications, a long-term and consistent soil moisture record. It was therefore concluded that it is essential to not only invest in advancing new technologies, put also to ensure continued satellite missions.

[1] https://climate.copernicus.eu/esotc/

Scientific application of ESA CCI SM in different Earth system areas

Table 5 of Dorigo et al. (2017), here included in a modified and extended form as Table 1 - Table 6 in the Appendix, provides an overview on the use of ESA CCI SM in scientific applications based on peer-reviewed literature. Six Earth system application areas were identified as described in Section 3.1: Climate variability and change, Land atmosphere interactions, Global biogeochemical cycles and ecology, Hydrology and land surface modelling, Drought applications, (Hydro)meteorological applications. The tables list the main purpose of the studies, the main motivation for using the ESA CCI SM dataset, and the identified limitations.

Originally, the tables were made up of scientific papers that correctly cite any of the early key publications on the dataset (i.e., Liu et al., 2011; Dorigo et al., 2012; Wagner et al., 2012a; Dorigo et al., 2015b; Liu et al., 2012) and were listed either in Scopus (http://scopus.com/) or Google Scholar (https://scholar.google.com). For the recent updates of the scientific applications, papers citing Dorigo et al. (2017), Gruber et al. (2019) and Preimesberger et al. (2021) are considered (see Publications under https://climate.esa.int/en/projects/soil-moisture/). For the current version of the CAR, over 200 new publications that appeared since April 2023 were reviewed.

The share of publications within each of these application areas are shown in Figure 6 (as of March 2024), together with the temporal evolution from 2018 to 2023. Overall, hydrology and land surface modelling, biogeochemical cycles and drought applications are the main areas in which ESA CCI SM is used, followed by land-atmosphere interactions and climate. Over time, particularly the hydrological and biogeochemical applications have grown most. Not shown here are the numerous studies that deal with algorithmic improvements such as downscaling, gap filling and validating the ESA CCI SM product.

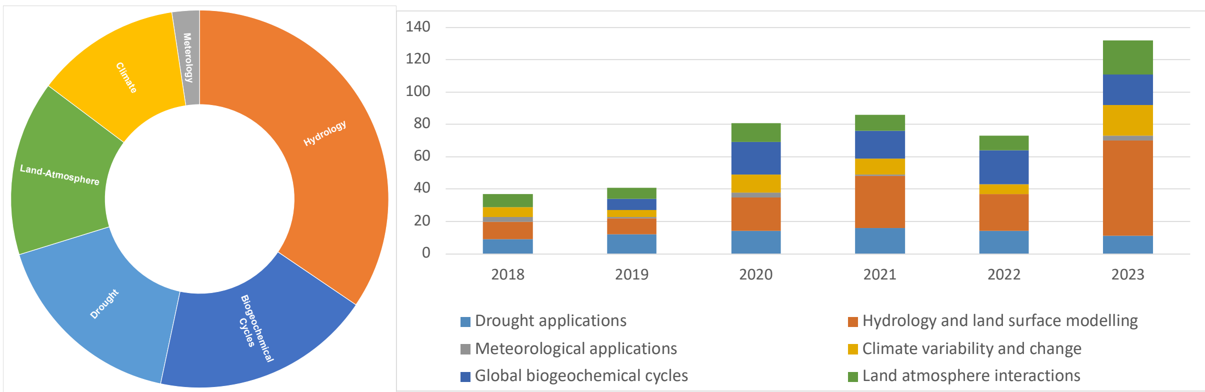

***Figure 6** Share of the six main earth system applications of ESA CCI SM in scientific publications since 2018, and their temporal evolution in numbers of published papers.*

In the following pages we will feature for each topic one or more peer reviewed scientific studies for easy reference. For the complete, non-exhaustive overview on scientific studies using ESA CCI SM, please refer to Section 3 and the applications tables in the Appendix.

Climate variability and change

"ESA CCI SM featured in the BAMS State of the Climate reports for more than 10 consecutive years"

The broad range of application areas and the growing number of publications (see also Appendix) highlights the acceptance of the dataset within the scientific community, as well as the maturity of the dataset. This acceptance is underscored by the contributions to the section on global soil moisture in the Bulletin of the American Meteorological Society (BAMS) State of the Climate reports. The BAMS State of the Climate reports are the yearly returning authoritative summaries of the global climate and are led by the US National Oceanic and Atmospheric Administration. The report features a global overview of recent and historical variations of climatological variables, and since 2010 includes soil moisture from the ESA CCI SM dataset for the chapter on global soil moisture (De Jeu et al., 2011; De Jeu et al., 2012; Dorigo et al., 2014; Dorigo et al., 2015a; Dorigo et al., 2016; Dorigo et al., 2017; Parinussa et al., 2013; Dorigo et al., 2018; Scanlon et al., 2019; Preimesberger et al., 2020; van der Schalie et al., 2021; van der Schalie et al., 2022; Stradiotti et al., 2023b). ESA CCI SM shows a strong similarity with related terrestrial water cycle components such as terrestrial water storage, precipitation, the self-calibrating PDSI, and terrestrial evaporation. Here we show the global soil moisture anomalies for 2021 (left) and 2022 (right), see Figure 7.

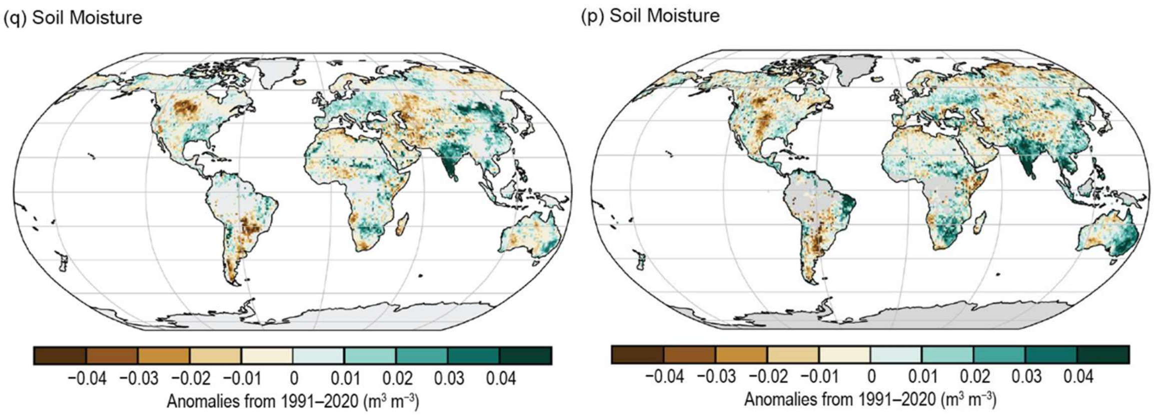

Figure 7 *Global soil moisture anomalies from the 1991-2020 baseline for 2021 (left), and 2022 (right). From: van der Schalie et al. (2022); Stradiotti et al. (2023b).*

Land-atmosphere interactions

Soil moisture plays an essential role in the partitioning of the fluxes of water and energy at the land surface, and as such, influences evapotranspiration and temperature. However, many studies on soil moisture-evapotranspiration and soil moisture-temperature coupling are based on modelling results or use precipitation-based drought indices as a proxy for soil moisture as global long-term soil moisture measurements were not available. The ESA CCI SM dataset now, allows observation-based analysis, and has been used in various studies to evaluate the coupling diagnostics found in models (Miralles et al., 2014a; Hirschi et al., 2014; Casagrande et al., 2015). Moreover, the product (through data assimilation) helped to reconcile the debate on the spatial and temporal soil moisture effects on afternoon rainfall (Guillod et al., 2015; Taylor et al., 2012).

"Inclusion of L-band products in ESA CCI SM will be beneficial for quantifying land-atmosphere coupling strengths"

Dong and Crow (2019) re-addressed soil moisture-air temperature coupling strength based on C- and X-band remote-sensing soil moisture products from ESA CCI SM and from newer L-band products (SMOS, SMAP). In agreement with Hirschi et al. (2014), the older products demonstrated a significantly (at p=0.05 confidence) weaker correlation with number of hot days than the precipitation-based proxy. The newer products however showed comparable (SMOS) or stronger (SMAP) correlations over global hotspot regions. These results suggest that the higher signal-to-noise ratio (SNR, i.e., the relative size of soil moisture signal and random observation error variances) of L-band remote sensing surface soil moisture results in an improved ability to quantify land-atmosphere coupling strengths (Figure 8).

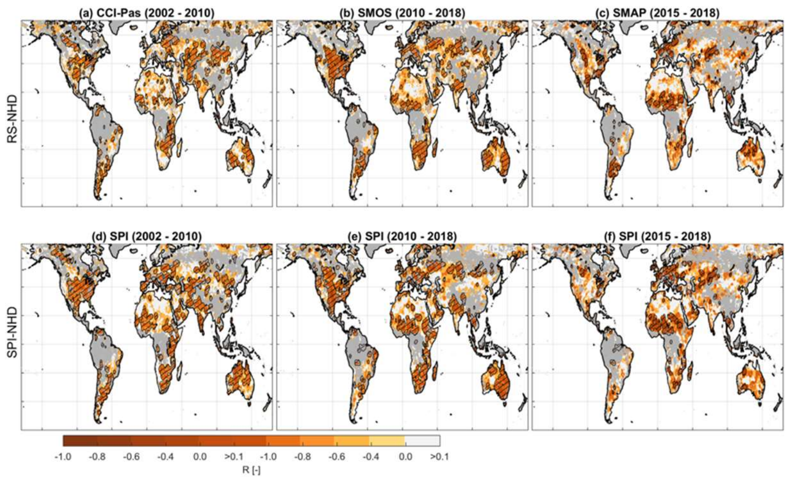

Figure 8 *Correlation coefficients of 1-month lagged soil moisture and number of hot days (NHD) correlations. Top: satellite soil moisture anomalies; bottom: correlations based on 3-month standardized precipitation index (SPI). From: Dong and Crow (2019).*

Global biogeochemical cycles and ecology

“Studies show a clear co-variability between ESA CCI SM and ecosystem variables”

As mentioned previously, the discrepancy in scales between local in-situ observations and satellite derived soil moisture complicates validation. Another approach to validating ESA CCI SM would be to show consistent behaviour between soil moisture and other climate and eco-system variables. For example, Nicolai-Shaw et al. (2017) showed how temperature, precipitation, evapotranspiration and vegetation co-vary with soil moisture drought during the peak of the growing season. In another study, Muñoz et al. (2014) showed that temporal variations in tree growth are largely driven by soil moisture variability. More recently, Martinez-Fernandez et al. (2019) analysed tree growth in Spain through satellite soil moisture monitoring. They found that ESA CCI SM is sensitive enough to track the phenology of Aleppo pine, with increasing influence of soil moisture with reduced water availability during the summer months (Figure 9).

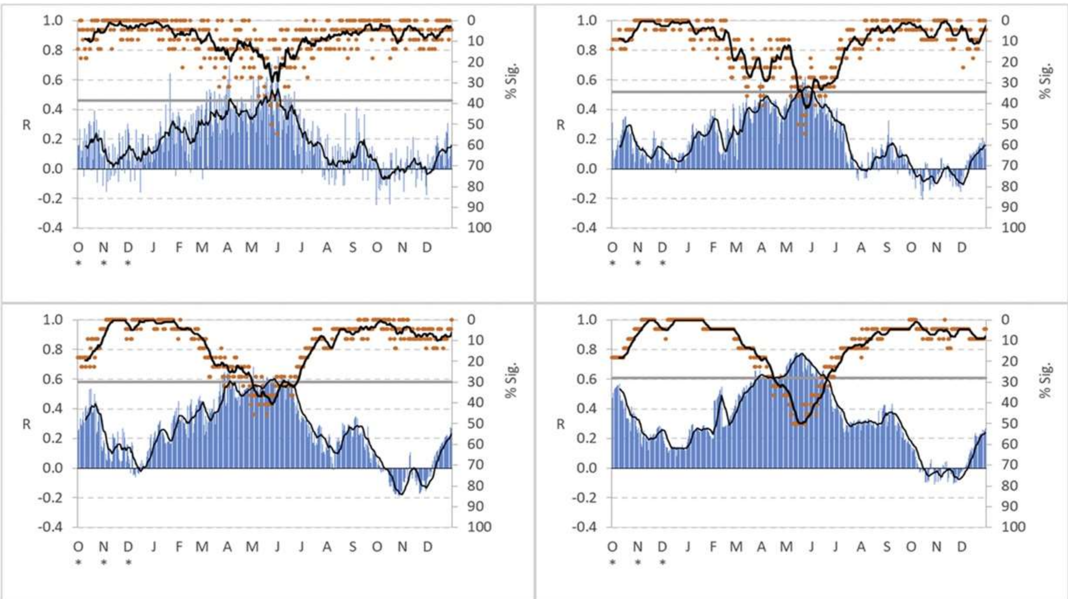

Figure 9 *Temporal evolution of the median R (blue bars and moving average) between the ESA CCI SM and tree growth and the percentage of significant ($p < 0.05$) cases (orange dots and moving average, black line) for daily data (top left) and daily moving window averages of 7 (top right), 15 (bottom left) and 30 (bottom right) days. Asterisks: data from the previous year. Gray line: significance threshold ($p < 0.05$). From: Martinez-Fernandez et al. (2019)*

Hydrological and land surface modelling

"SM2RAIN: a bottom-up approach to creating a novel precipitation dataset"

A novel use of satellite-based soil moisture was made by Brocca et al. (2014). In general, global estimates of rainfall are hampered by the lack of ground observations, and the difficulty of deriving the amount of rainfall that reaches the ground when using satellite observations. So, instead of using the common top-down approach, they applied a bottom-up approach, using variations in soil moisture to infer preceding rainfall amounts. This SM-derived rainfall product shows good correlations with the GPCC dataset (used as main benchmark in the study), especially over areas where soil moisture retrievals are expected to be accurate (Figure 10). The developed algorithm is termed SM2RAIN, and has now successfully been applied to the ESA CCI SM data set, to produce the first soil moisture derived rainfall dataset spanning 37 years (Ciabatta et al., 2018). The SM2RAIN product has already been used to quantify the space-time variability of rainfall, evaporation, runoff and water storage for the Upper Blue Nile river basin in Africa (Abera et al., 2017).

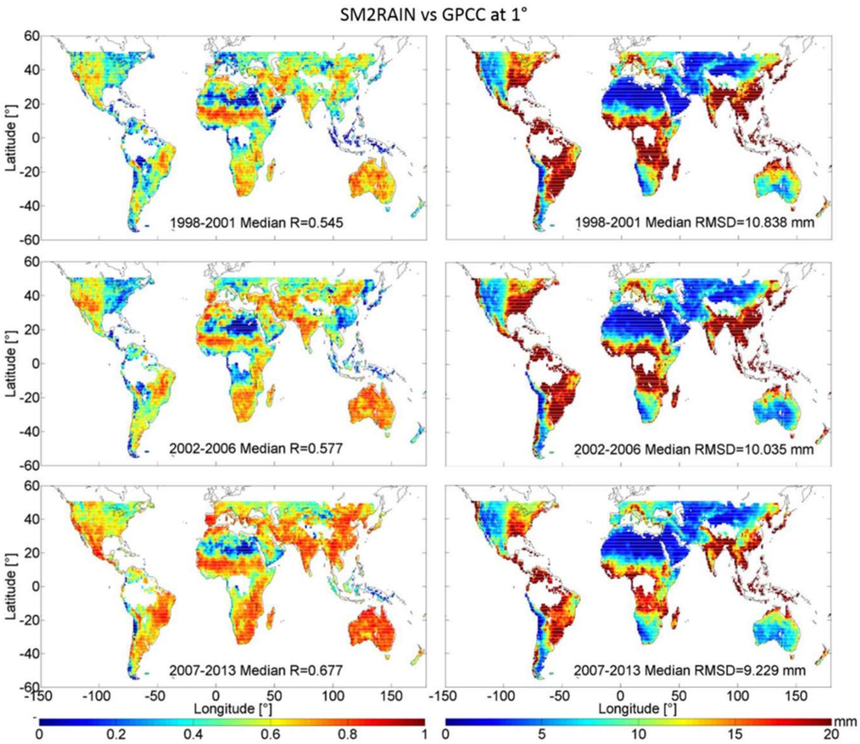

Figure 10 *Global Pearson correlation (left) and Root Mean Square Difference (right) maps obtained between GPCC-FDD 524 and the SM2RAIN-CCI rainfall data set for 5-day accumulated rainfall during the periods 1998-2001 (upper panel), 2002-2006 (middle panel) and 2007-2013 (lower panel). From: (Ciabatta et al., 2018)*

Drought applications

"Soil moisture-based drought indices using ESA CCI SM"

Historically, precipitation and temperature have been used to develop drought monitoring indices, e.g., the standardized precipitation index (SPI) and the Palmer drought severity index (PDSI). These indices, however, are more indicative of meteorological drought rather than agricultural drought. ESA CCI SM now allows to directly monitor agricultural drought, and to develop soil moisture-based drought indices. An example is the Empirical Standardized Soil Moisture Index (ESSMI) developed by Carrão et al. (2016). With this index, they were able to accurately describe the severe and extreme drought intensities in north-eastern Brazil in 1993, 2012, and 2013 (see Figure 11). In addition, they found high correlations between ESSMI and maize, soybean, and wheat crop yields in Latin America.

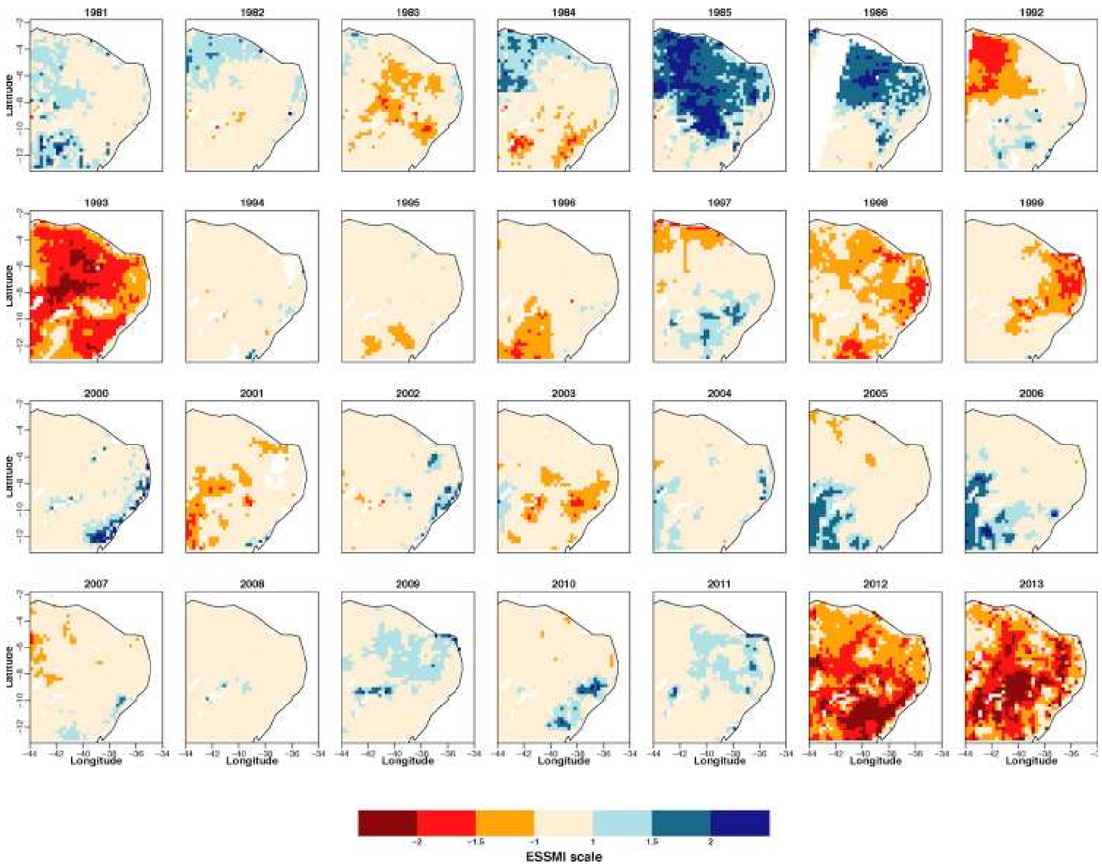

Figure 11 *Time-series of yearly Empirical Standardized Soil Moisture Index (ESSMI) values computed for a region located in Bahia (northeast Brazil). No data values are masked out in white. From: Carrão et al. (2016)*

(Hydro)meteorological applications.

To date not many studies have directly assimilated remotely sensed soil moisture into numerical weather prediction (NWP) and climate models to update their soil moisture fields. One example though is a study by Zhan et al. (2016). Figure 12 shows the root-mean-square-errors (RMSEs) of temperature and humidity forecasts obtained after assimilation of ESA CCI SM into NASAs United Weather Research and Forecast (NUWRF) model coupled with NASA Land Information System. Data assimilation of soil moisture is shown to reduce the bias of longer-term precipitation and short-term temperature forecasts.

<u>"ESA CCI SM data assimilation into NWP and climate models"</u>

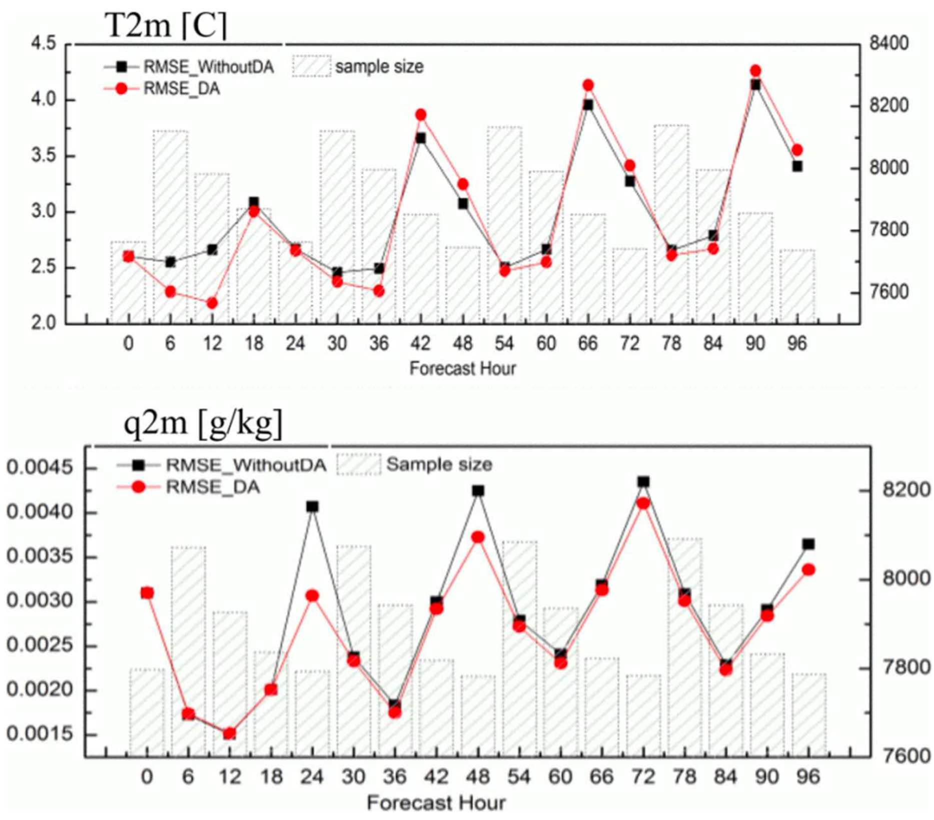

Figure 12 *Root-mean-square-errors (RMSEs) of the forecasts of 2-m temperature (T2m) (top) and humidity (q2m) (bottom) from NUWRF assimilating or without assimilating CCI SM data over CONUS domain from April 1 - October 31, 2012. From: Zhan et al. (2016)*

3 ESA CCI Soil Moisture for improved Earth system understanding: state-of-the art and future directions

Wouter Dorigo[1], Wolfgang Wagner[1], Clement Albergel[2], Franziska Albrecht[3], Gianpaolo Balsamo[4], Luca Brocca[5], Daniel Chung[1], Martin Ertl[6], Matthias Forkel[1], Alexander Gruber[1], Eva Haas[3], Paul Hamer[7], Martin Hirschi[8], Jaakko Ikonen[9], Richard de Jeu[10], Richard Kidd[11], William Lahoz[7], Yi Y. Liu[12], Diego Miralles[13,14], Thomas Mistelbauer[11], Nadine Nicolai-Shaw[8], Robert Parinussa[10], Chiara Pratola[15,16], Christoph Reimer[1,11], Robin van der Schalie[10], Sonia I. Seneviratne[8], Tuomo Smolander[9], Pascal Lecomte[17]

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We include here modified Sections 4 - 6 of Dorigo et al. (2017). Section 3.1 (i.e., Section 4 of Dorigo et al., 2017) gives an overview of a wide variety of studies using the ESA CCI SM dataset. The section is subdivided into the following application areas (corresponding to those used in Table 1 - Table 6 of the Appendix): assessing climate variability and change (Section 3.1.1), land-atmosphere interactions (Section 3.1.2), global biogeochemical cycles and ecosystems (Section 3.1.3), hydrological and land surface modelling (Section 3.1.4), drought applications (Section 3.1.5), and meteorological applications (Section 3.1.6).

Section 3.2 (i.e., Section 5 of Dorigo et al., 2017) gives a thorough overview of the research priorities for improving the ESA CCI SM dataset (and soil moisture climate data requirement in general). The main points considered are, higher spatial resolutions, the filling of data gaps, improvement of temporal sampling, product accuracy, blending methods, and temporal

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[1] Department of Geodesy and Geo-Information, Vienna University of Technology, Vienna, Austria

[2] CNRM, UMR 3589 (Météo-France, CNRS) Toulouse, France

[3] GeoVille Information Systems GmbH, Innsbruck, Austria

[4] European Centre for Medium-range Weather Forecasts, Reading, United Kingdom

[5] Research Institute for Geo-Hydrological Protection, National Research Council, Perugia, Italy

[6] Angewandte Wissenschaft Software und Technologie GmbH, Vienna, Austria

[7] NILU, Kjeller, Norway

[8] Institute for Atmospheric and Climate Science, ETH Zurich, Switzerland

[9] Finnish Meteorological Institute, Arctic Research, Helsinki, Finland

[10] VanderSat B.V. / Transmissivity B.V., Noordwijk, the Netherlands

[11] Earth Observation Data Centre for Water Resource Monitoring GmbH, Wien, Austria

[12] ARC Centre of Excellence for Climate Systems Science & Climate Change Research Centre, UNSW, Sydney, Australia

[13] Department of Earth Sciences, VU University Amsterdam, Amsterdam, The Netherlands

[14] Laboratory of Hydrology and Water Management, Department of Forest and Water Management, Ghent University, Belgium

[15] MaREI Centre- Environmental Research Institute (ERI), University College Cork, Ireland

[16] Starlab, Barcelona, Spain

[17] ESA Climate Office, ECSAT, Harwell Oxford, Didcot, United Kingdom

consistence, shorter latency between data acquisition and data availability, the independence of LSMs, and the creation of a root-zone soil moisture product.

Section 3.3 (i.e., Section 6 of Dorigo et al., 2017) gives the conclusion and outlook. The review shows the uniqueness of the ESA CCI SM product, in particular the global coverage and long period of temporal coverage. There is at this time really no other product available with these characteristics. However, users should also be aware of the limitations of the dataset, e.g., the varying dataset quality through space and time, and the occurrence of data gaps, which can make it difficult for users to integrate the data in their applications. Though it might be possible to overcome many of these limitations through improved science and data availability (e.g., with new sensors like SMOS and SMAP), some limitations might prove to be insuperable. It is therefore essential to always communicate clearly the dataset characteristics to all users.

3.1 ESA CCI SM in Earth system applications

A wide variety of studies have explored the potential of ESA CCI SM product for improving our understanding of Earth system processes. Even though the application fields are seemingly different, in all of them ESA CCI SM plays a central role in benchmarking, calibrating, or providing an alternative to the land surface hydrology in dedicated models. The following sections will provide an extensive synthesis of how ESA CCI SM has been used in the different application areas, the motivation of each study for using this product in particular, and the main drawbacks encountered when using the ESA CCI SM data. A synthesis of the limitations and the unexploited potential of the dataset is given in Section 5. For the original assessment, we reviewed all scientific papers that correctly cite any of the early key publications on the dataset (Dorigo et al., 2012; Liu et al., 2011; Dorigo et al., 2015b; Wagner et al., 2012b; Liu et al., 2012) and were listed either in Scopus (http://scopus.com/) or Google Scholar (https://scholar.google.com) as of June 22, 2017. For the recent update of the scientific applications, papers citing Dorigo et al. (2017) and Gruber et al. (2019) are considered (defined as to be cited compulsorily when using the ESA CCI SM product).

3.1.1 Assessing climate variability and change

As soil moisture is an integrative component of the Earth system, any large-scale variability or change in our climate should manifest itself in globally observed soil moisture patterns. In this role, ESA CCI SM has made a significant contribution to the body of evidence of natural and human-induced climate variability and change. Indicative for this, is the contribution of ESA CCI SM to the State of the Climate Reports that are issued every year by National Oceanic and Atmospheric Administration (e.g., Arndt et al., 2016). Several studies have shown a clear relationship between major oceanic-atmospheric modes of variability in the climate system, e.g., El Niño Southern Oscillation (ENSO), and variations in ESA CCI SM (Bauer-Marschallinger et al., 2013; Miralles et al., 2014b; Nicolai-Shaw et al., 2016; Dorigo et al., 2016).. By applying enhanced statistical methods to the multi-decadal ESA CCI SM v0.1 dataset over Australia, (Bauer-Marschallinger et al., 2013) were able to disentangle the portion of soil moisture variability that is driven by the major climate oscillations affecting this continent, i.e., ENSO, the Indian Ocean Dipole and the Antarctic Oscillation, from other modes of short-term and long-term variability. Miralles et al. (2014b) showed that inter-annual soil moisture variability as observed by ESA CCI SM COMBINED v02.2 largely drives the observed large-scale variability in continental evaporation.

ESA CCI SM has been widely used to assess global trends in soil moisture, mostly in combination with LSMs. Based on ESA CCI SM v0.1, Dorigo et al. (2012) revealed that for the period 1988–2010 27% of the area covered by the dataset showed significant trends, of which almost three quarters were drying trends. A similar conclusion was drawn by Feng and Zhang (2015) based on ESA CCI SM COMBINED v02.1. The strong tendency towards drying was largely confirmed by trends computed for the same period from ERA-Interim and GLDAS-Noah (Dorigo et al., 2012), and ERA-Interim/Land and MERRA-Land (Albergel et al., 2013b), although the spatial trend patterns were not everywhere congruent between datasets. The agreement in trends between a newer version of ESA CCI SM (v02.2) and MERRA-Land were confirmed by Su et al. (2016). Note however that results from the PVIR (Hirschi et al., 2023b, 2024) show that global 1988–2010 trend patterns based on different versions of ESA CCI SM have undergone significant changes in magnitude and sign from these earlier to later product versions of the COMBINED product. Particularly, a large-scale tendency for more widespread positive trends in the northern mid-latitudes is visible with later product versions (most pronounced from v04.7 to v06.1). Also, the partly negative trends in Siberia (most pronounced in v04.7 and v05.2) partly turn into positive trends in the latest product versions (i.e., v07.1 to v09.1). Also, the original significant wetting trend in southern Africa disappears with the latest product releases, while Patagonia starts to experience wetting trends. Over Australia, the widespread drying trend present in v0.1 also mostly disappears and partly turns into a wetting trend in the later versions (v07.1 to v09.1). In addition to these changes of the soil moisture trends with product versions, trend patterns also diverge between the COMBINED (larger fractions of drying trends) and the underlying PASSIVE (mix of wetting and drying trends) and ACTIVE (large fraction of stronger wetting trends) products (Hirschi et al., 2023a).

Trend analyses performed on a more regional scale, but for different time periods (e.g.,Rahmani et al., 2016; e.g., Wang et al., 2016; Li et al., 2015; Zheng et al., 2016; An et al., 2016a) generally confirmed the results obtained at the global scale, while providing a more detailed view on the impact of local land management practices, e.g., irrigation, on observed trends (Qiu et al., 2016), and the impact of soil moisture trends on regional climate (Klingmüller et al., 2016). Feng (2016) assessed the drivers of trends in ESA CCI SM COMBINED v02.2 and concluded that at the global scale climate change is by far the most important driver of long-term changes in soil moisture, although at the regional level land cover and land use change may play a significant role. Similar conclusions were drawn by regional studies over China (Chen et al., 2017; Liu et al., 2015; Meng et al., 2018). Other studies analysed the variability and trends in ESA CCI SM in relation to other atmospheric variables and circulation patterns over Asia (Zhan et al., 2017; Shrivastava et al., 2016; Shrivastava et al., 2017). Nevertheless, given the limited data record length, the impact of low-frequency climate oscillations on trends should first be carefully addressed before any robust conclusion about the sign and magnitude of perpetual changes can be drawn (Miralles et al., 2014b). Likewise, the potential impact of dataset artefacts should be carefully quantified and corrected for (Su et al., 2016).

ESA CCI SM has been widely used as a reference for evaluating model states and trends in global and regional climate simulations. Different versions of ESA CCI SM COMBINED were used to systematically evaluate soil moisture states, trends, and dynamics of models participating in the latest Coupled Model Intercomparison Project (CMIP5(Du et al., 2016; Lauer et al., 2017; Yuan and Quiring, 2017; Huang et al., 2016). At the regional scale, various studies used ESA CCI SM COMBINED to assess the sensitivity to soil moisture of various processes in global and regional climate models (Pieczka et al., 2016; Unnikrishnan et al., 2017; Agrawal and Chakraborty, 2016)or to improve climate simulations by assimilating ESA CCI SM directly (Paxian et al., 2016). Even though most studies report positive experiences, the use of ESA CCI SM for climate model evaluations is primarily limited by discrepancies in surface layer thickness between models and satellite observations, the existence of spatial data gaps, and the fact that it does not provide an independent reference for evaluating absolute values. Despite these limitations, ESA CCI SM has been proposed (together with other land-based products) as an official reference for validating the land surface components of the CMIP6 models (van den Hurk et al., 2016).

3.1.2 Land-atmosphere interactions

As soil moisture is essential in partitioning the fluxes of water and energy at the land surface, it can affect the dynamics of humidity and temperature in the planetary boundary layer. This control of soil moisture on evapotranspiration is important for the intensity and persistence of heatwaves, as the depletion of soil moisture and the resulting reduction in evaporative cooling may trigger an amplified increase in air temperature (Seneviratne et al., 2006a; Hirschi et al., 2011; Fischer et al., 2007; Miralles et al., 2014a).While many studies on soil moisture–evapotranspiration and soil moisture–temperature coupling are based on modelling results or use precipitation-based drought indices as a proxy for soil moisture, ESA CCI SM enables analyses based on long-term observed soil moisture estimates (Miralles et al., 2014a; Hirschi et al., 2014; Casagrande et al., 2015). Therefore, ESA CCI SM in combination with other large-scale observations has been widely used to evaluate the coupling diagnostics found in models (Zhou et al., 2016; Knist et al., 2017; Li et al., 2016; Catalano et al., 2016; Li et al., 2017).

Limitations with respect to the depth of the soil moisture retrievals (i.e., reporting the content of moisture in the first few centimetres as opposed to the entire root depth affecting transpiration) have triggered some debate about the appropriateness of ESA CCI SM to investigate evapotranspiration dynamics and atmospheric feedbacks (Hirschi et al., 2014). Hirschi et al. (2014) showed that the strength of the relationship between soil moisture and temperature extremes appears underestimated with ESA CCI SM compared to estimates based on the Standardized Precipitation Index (SPI; McKee et al., 1993; Stagge et al., 2015), which seems to be related to an underestimation of the temporal dynamics and of large dry/wet anomalies within ESA CCI SM. This effect is enhanced under extreme dry conditions and may lead to a decoupling of the surface layer from deeper layers and from atmospheric fluxes (and resulting temperatures). Thus, the added value of root-zone soil moisture is likely more important for applications dealing with extreme conditions, while for mean climatological applications the information content in the surface layer appears adequate. The assimilation of remote sensing surface soil moisture into a land surface model (e.g., De Lannoy and Reichle, 2016; Albergel et al., 2017) provides a possible alternative here. In fact, root zone soil moisture estimates by the satellite-based Global Land Evaporation Amsterdam Model (GLEAM; Miralles et al., 2011) have been improved by the assimilation of ESA CCI SM, while the overall quality of evaporation estimates remains similar after assimilation (Martens et al., 2017). Also, the assimilation of ESA CCI SM COMBINED v02.1 helped interpreting global land evaporation patterns and multi-annual variability in response to the El Niño Southern Oscillation (Miralles et al., 2014b).The obvious link between soil moisture and evaporation has motivated several studies to use ESA CCI SM COMBINED (v0.1 and v02.1) to attribute trends observed for evaporation (Rigden and Salvucci, 2017; Zeng et al., 2014).

Soil moisture also affects precipitation through evapotranspiration. Yet, the effect of soil moisture on precipitation is much more debated than for air temperature. Studies report both positive or negative feedbacks, and even no feedback. Using a precursor of ESA CCI SM, Taylor et al. (2012) identified a spatially negative feedback of soil moisture on convective precipitation regarding the location, i.e., that afternoon rain is more likely over relatively dry soils due to mesoscale circulation effects. Guillod et al. (2015) revisited the soil moisture effect on precipitation using GLEAM root-zone soil moisture with ESA CCI SM COMBINED v02.1 assimilated, and showed that spatial and temporal correlations with opposite signs may coexist within the same region: precipitation events take place preferentially during wet periods (moisture recycling), but within the area have a preference to fall over comparatively drier patches (local, spatially negative feedbacks).

A more indirect but potentially strong soil moisture – atmosphere feedback was found by Klingmüller et al. (2016), who were able to link an observed positive trend in Aerosol Optical Depth (AOD) in the Middle East to a negative trend in ESA CCI SM COMBINED v02.1. As lower soil moisture translates into enhanced dust emissions, their results suggested that increasing temperature and decreasing relative humidity in the last decade have promoted soil drying, leading to increased dust emissions and AOD. Also Xi and Sokolik (2015) found significant correlations between the variability in AOD and soil moisture. These changes in atmospheric composition again may have considerable impact on radiative forcing and precipitation initiation (Ramanathan et al., 2001) and as such impact the energy and water cycles in the area.

3.1.3 Global biogeochemical cycles and ecosystems

Soil moisture is a regulator for various processes in terrestrial ecosystems such as plant phenology, photosynthesis, biomass allocation, turnover, and mortality, and the accumulation and decomposition of carbon in soils (Carvalhais et al., 2014; Reichstein et al., 2013; Richardson et al., 2013; Nemani et al., 2003). Low soil moisture during drought reduces photosynthesis, enhances ecosystem disturbances such as insect infestations or fires, and thus causes plant mortality and accumulation of dead biomass in litter and soils (Allen et al., 2010; McDowell et al., 2011; Thurner et al., 2016). The release of carbon from soils to the atmosphere through respiration is also controlled by soil moisture (Reichstein and Beer, 2008). Consequently, soil moisture is a strong control on variations in the global carbon cycle (van der Molen et al., 2011; Ahlström et al., 2013; Poulter et al., 2014).

Despite the importance of soil moisture for the global carbon cycle, satellite-derived soil moisture data are currently under-explored in carbon cycle and ecosystem research. Because long-term soil moisture observations were lacking until recently, most studies on the effects of soil moisture on vegetation relied on precipitation estimates (Poulter et al., 2013; Du et al., 2013), indirect drought indices (Ji and Peters, 2003; Hogg et al., 2013), or soil moisture estimates from land surface models (Forkel et al., 2015; Rahmani et al., 2016). More recently, studies used ESA CCI SM to assess impacts of water availability and droughts on plant phenology and productivity based on satellite-derived vegetation indices and variables such as the NDVI or the Leaf Area Index (LAI), or directly of vegetation productivity (Murray-Tortarolo et al., 2016). For example, Szczypta et al. (2014) used ESA CCI SM v0.1, modelled soil moisture, and LAI over the Euro-Mediterranean zone to evaluate two land surface models and to predict LAI anomalies over cropland. LAI was predictable from ESA CCI SM in large homogeneous cropland regions, e.g., in Southern Russia (Szczypta et al., 2014). Strong positive relationships between ESA CCI SM COMBINED and NDVI and/or LAI were also found for Australia (Chen et al., 2014; v0.1; Liu et al., 2017c; v02.1) for croplands in North China (Wang et al., 2016; v0.1; Wang et al., 2017; v02.1) and the Ukraine (Ghazaryan et al., 2016; v02.1), for East Africa (McNally et al., 2016; Wu et al., 2016; v02.0), and Senegal (Cissé et al., 2016; v0.1). Generally, many regions with positive (greening) or negative (browning) trends in NDVI show also positive and negative trends in ESA CCI SM v0.1, respectively (Dorigo et al., 2012). This co-occurrence of soil moisture and NDVI trends reflects the strong water control on vegetation phenology and productivity. Interestingly, soil moisture from ESA CCI SM v0.1 was also correlated with NDVI in some boreal forests, which are primarily temperature-controlled (Barichivich et al., 2014). In these regions, soil moisture and vegetation productivity were controlled by variations in the accumulation and thawing of winter snow packs (Barichivich et al., 2014). However, some water-limited regions showed negative ESA CCI SM v0.1 soil moisture trends with no corresponding trend in NDVI (Dorigo et al., 2012). In these cases, the positive relation between surface soil moisture and vegetation is likely modified by vegetation type and vegetation density (Feng, 2016; McNally et al., 2016). For example, densely vegetated areas in East Africa show stronger correlations between ESA CCI SM COMBINED v02.1 soil moisture and NDVI than sparsely vegetated areas (McNally et al., 2016). Regional differences in the response of ecosystems to soil moisture variability have also been attributed to differences in water use efficiency (Li et al., 2017). Novel data-driven approaches enable quantification of the share of ESA CCI SM in controlling NDVI variability as opposed to other water and climate drivers (Papagiannopoulou et al., 2017a; Papagiannopoulou et al., 2017b). Figure 13 shows the correlation between the latest ESA CCI SM COMBINED (v03.2) product and NDVI GIMMS 3G (Tucker et al., 2005) with a lag time of soil moisture preceding NDVI of 16 days. In most regions and especially in water-limited areas such as the Sahel, there is a strong and direct response of NDVI to soil moisture. On the other hand, correlations are negative in many temperate regions. This is likely because NDVI is highest in summer months when soil moisture decreases. This demonstrates that vegetation productivity in temperate regions is primarily temperature-controlled and strongly affected by human activities through agriculture or forest management (Papagiannopoulou et al., 2017a; Forkel et al., 2015).

Apart from the analysis of relations with vegetation indices, the ESA CCI SM datasets have been used in other ecosystem studies. For example, Muñoz et al. (2014) investigated tree ring chronologies of conifers in the Andeans in conjunction with soil moisture variability from ESA

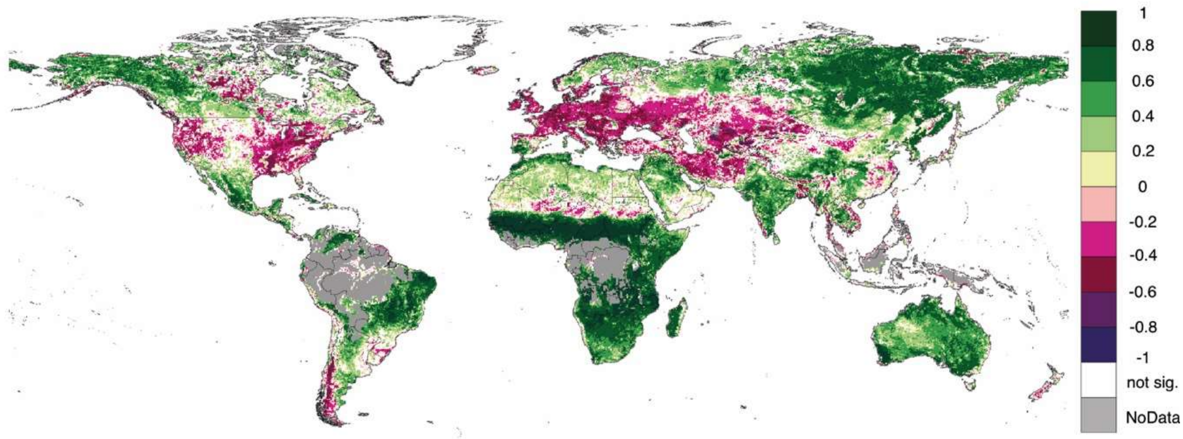

***Figure 13** Mean Pearson correlation coefficient R between ESA CCI soil moisture v03.2 and GIMMS NDVI3g for the period 1991 to 2013 for a lag time of soil moisture preceding NDVI by 16 days. White areas indicate pixels for which correlations are not significant (p>0.05).*

CCI SM v0.1. The study revealed a previously unobserved relation between tree growth and summer soil moisture Muñoz et al. (2014). While most studies have looked at the impact of soil moisture on vegetation, only very few studies have assessed the opposite, i.e., the impact of vegetation on soil moisture. One such example is the study of Jiao et al. (2016) who looked at the impact of large-scale reforestation on soil moisture in China. Indirect links between soil moisture and ecosystem dynamics have been the studies of Madani et al. (2016), who used ESA CCI SM COMBINED v0.1 as one of the predictors of Emu migrations in Australia and of Tang et al. (2017) who assessed the impact of wind farms on ESA CCI SM COMBINED v02.2 and vegetation productivity.

Furthermore, ESA CCI SM v0.1 and vegetation data were used to evaluate ecosystem models (Szczypta et al., 2014; Traore et al., 2014; Willeit and Ganopolski, 2016; Sato et al., 2016). Thereby, the results of Traore et al. (2014) demonstrate that a model that best performs for soil moisture does not necessarily best perform for plant productivity. This demonstrates the need to jointly use soil moisture and vegetation or carbon cycle observations to improve global ecosystem/carbon cycle models (Kaminski et al., 2013; Scholze et al., 2016). The use of the ESA CCI SM in such an analysis could potentially constrain model uncertainties regarding the long-term hydrological control on vegetation productivity and ecosystem respiration (Detmers et al., 2015; Scholze et al., 2017). However, a major source of uncertainty about the future terrestrial carbon cycle is related to how global ecosystem models represent carbon turnover, vegetation dynamics, and disturbances such as fires (Friend et al., 2014). It was previously shown that variations in satellite-derived soil moisture are related to extreme fire events in boreal forests (Bartsch et al., 2009; Forkel et al., 2012). Consequently, the ESA CCI SM COMBINED dataset has been used together with climate, vegetation, and socio-economic data to assess controls on fire activity globally and to identify appropriate model physics structures for global fire models (Ichoku et al., 2016; Forkel et al., 2017). Because of the role of soil moisture on microbial activity, ESA CCI SM v0.1 has been used as one of the forcings to simulate global atmospheric methane uptake by soils (Murguia-Flores et al., 2018).

3.1.4 *Hydrological and land surface modelling*

As soil moisture drives processes like runoff, flooding, evaporation, infiltration, and ground water recharge, it is important that hydrological models accurately map soil moisture states. The potential of using ESA CCI SM to validate surface soil moisture fields in state-of-the-art LSMs, reanalysis products, and large-scale hydrological models has been largely recognized (Szczypta et al., 2014; Loew et al., 2013; Fang et al., 2016; Spennemann et al., 2015; Mao et al., 2017; Lai et al., 2016; Okada et al., 2015; Ghosh et al., 2016; Rakovec et al., 2016; Parr et al., 2015; Mueller and Zhang, 2016; Mishra et al., 2014). Schellekens et al. (2016) exploited the long-term availability of ESA CCI SM COMBINED v02.2 to validate according to the standardised International Land Model Benchmarking (ILAMB) protocol the soil moisture fields of ten global hydrological and land surface models, all forced with the same meteorological forcing dataset for the period 1979–2012. New insights in the model representation of hydrological processes like infiltration have been offered by comparing the memory length (Chen et al., 2016; Lauer et al., 2017) and the frequency domains (Polcher et al., 2016) between LSMs and remote sensing products, including ESA CCI SM COMBINED v02.3. Crow et al. (2015)utilized ESA CCI SM v0.1 to estimate the error covariance matrix for an ensemble of LSM simulations of surface soil moisture in order to optimally merge them. The authors claim that the long period covered by the ESA CCI SM product is essential for removing sampling error in these estimates. Similarly, as for climate model evaluations, the use of ESA CCI SM for hydrological model evaluations is hampered by discrepancies in surface layer thickness between models and satellite observations, the existence of spatial data gaps, heterogeneity of data properties over time, and the dependency of the absolute values in an LSM (Table 4).

Satellite soil moisture data can bring important benefits in runoff modelling and forecasting both through an improved initialization of rainfall-runoff models and through data assimilation techniques that allow for updating the soil moisture states. Several studies have shown the positive impact on flood and runoff prediction through assimilation of single sensor Level 2 products used in ESA CCI SM, e.g., obtained from ASCAT (Brocca et al., 2010), AMSR-E (Sahoo et al., 2013), and SMOS (Lievens et al., 2015). Wanders et al. (2014) and Alvarez-Garreton et al. (2015) showed the improved skill of runoff predictions when jointly assimilating multiple soil moisture products (SMOS, ASCAT and AMSR-E), resulting mainly from improved temporal sampling. Long-term homogeneous soil moisture products like ESA CCI SM become important in flood modelling studies that require a multi-year period for the calibration and validation of model parameters. Assimilating the ESA CCI SM COMBINED v02.2 product over the Upper Niger River basin improved runoff predictions even though the simulation of the rainfall-runoff model was already good (Massari et al., 2015). Tramblay et al. (2014) used ESA CCI SM v0.1 to better constrain model parameters, and hence reduce uncertainties, of a parsimonious hydrological model in the Mono River basin (Africa), with the goal to evaluate the impact of climate change on extreme events. Further studies are clearly needed to assess the full potential of ESA CCI SM product for runoff modelling and forecasting. For example, even a simple model based only on persistence allows for the prediction of soil moisture (Nicolai-Shaw et al., 2016), and exploiting this characteristic could contribute to improved early warning systems. At the local scale, Dahigamuwa et al. (2016) used ESA CCI

SM v0.1 in combination with vegetation cover to improve the prediction of landslide occurrence.

ESA CCI SM products have been used for improving the quantification of the different components of the hydrological cycle, i.e., evaporation (Allam et al., 2016; Martens et al., 2017; Miralles et al., 2014b), groundwater storage (Asoka et al., 2017), and rainfall (Ciabatta et al., 2016; Bhuiyan et al., 2017a; Bhuiyan et al., 2017b). Soil moisture contains information on antecedent precipitation. This principle is being exploited by the SM2RAIN method (Brocca et al., 2014; Brocca et al., 2013), which uses an inversion of the soil-water balance equation to obtain a simple analytical relationship for estimating precipitation accumulations from the knowledge of a soil moisture time-series. The method has been tested on a wide range of Level 2 satellite soil moisture products and ESA CCI SM COMBINED v02.2 (Brocca et al., 2014; Ciabatta et al., 2016). SM2RAIN realistically reproduces daily precipitation amounts when compared to gauge observations and in certain regions may even outperform direct satellite-based estimates of precipitation, even though its performance hinges on the quality of the soil moisture product used as input (Brocca et al., 2014; Ciabatta et al., 2016). Its application to ESA CCI SM COMBINED provides an independent global climatology of precipitation from 1979 onwards. Abera et al. (2017) used the SM2RAIN precipitation product from ESA CCI SM (Ciabatta et al., 2016; Ciabatta et al., 2018) to quantify the space-time variability of rainfall, evaporation, runoff and water storage for the Upper Blue Nile river basin in Africa.

Heimhuber et al. (2017) used ESA CCI SM (version unknown) in a statistical framework to predict the dynamics in surface water in south-eastern Australia. ESA CCI SM has also been used to map large-scale irrigation, which is largely unquantified on a global scale and, consequently, not included in most large scale hydrological and/or land surface models (Qiu et al., 2016). By comparing modelled and satellite soil moisture data, irrigated areas can be detected when satellite data and modelled data (the latter do not include irrigation) show different temporal dynamics. Kumar et al. (2015) used satellite soil moisture observations from ESA CCI SM COMBINED v02.1, ASCAT, AMSR-E, SMOS, and WindSat for detecting irrigation over the United States. Similarly, Qiu et al. (2016) detected irrigated areas in China by evaluating the differences in trends between ESA CCI SM COMBINED v02.1 and precipitation. Liu et al. (2015) used ESA CCI SM v0.1 to support the attribution of negative trends in soil moisture in Northern China to agricultural intensification.

3.1.5 Drought applications

Soil moisture droughts, also referred to as agricultural droughts, may be driven by a lack of precipitation and/or increased evapotranspiration (Seneviratne et al., 2012). In addition to natural variability, human land modification and water management can contribute to agricultural drought (Liu et al., 2015; Van Loon et al., 2016). Prior to the availability of global satellite-based soil moisture datasets, precipitation and temperature gridded datasets were favoured for developing drought monitoring indices. Well-known examples, although primarily indicative of meteorological drought rather than agricultural drought, are the SPI and the Palmer Drought Severity Index (PDSI; Palmer, 1965). ESA CCI SM has been repeatedly used to evaluate the performance of such indices (van der Schrier et al., 2013; Liu et al., 2017b).

ESA CCI SM can be used to directly monitor agricultural drought, or help to set up alternative drought indicators. For example, Carrão et al. (2016) and (Rahmani et al., 2016) used ESA CCI SM COMBINED (v02.0 and v02.1, respectively) to develop a drought index comparable to SPI but based on actual soil moisture observations instead of precipitation, naming them the Empirical Standardized Soil Moisture Index (ESSMI) and Standardized Soil Moisture Index (SSI), respectively. Carrão et al. (2016) found high correlations between ESSMI and maize, soybean, and wheat crop yields in Latin America and with this index could accurately describe the severe and extreme drought intensities in north-eastern Brazil in 1993, 2012, and 2013. Based on SSI, (Rahmani et al., 2016) were able to identify a severe drought event that started in December 2012 in the northern part of Iran. The Enhanced Combined Drought Index (ECDI) proposed by Enenkel et al. (2016b) combines ESA CCI SM COMBINED v02.2 with satellite-derived observations of rainfall, land surface temperature and NDVI for the detection of drought events, and has been successfully used to detect large-scale drought events in Ethiopia between the years 1992–2014.

McNally et al. (2016) specifically evaluated the use of ESA CCI SM COMBINED v02.2 for agricultural drought and food security monitoring in East Africa, and found that ESA CCI SM is a valuable addition to a 'convergence of evidence' framework for drought monitoring. Like Dorigo et al. (2015b) they emphasize that users should be aware of the spatial and temporal differences in data quality caused for example by significant data gaps prior to 1992, the lack of overlap between sensors, or difficulties with soil moisture retrievals over certain terrains such as heavily vegetated areas. Post 1992, McNally et al. (2016) generally found good agreement between ESA CCI SM and other soil moisture products as well as with NDVI in East Africa. Yuan et al. (2015a) assessed the skill of ESA CCI SM v02.1 in capturing short-term soil moisture droughts over China. They found that the PASSIVE and COMBINED products have better drought detection skills over the sparsely vegetated regions in north-western China while ACTIVE worked best in the more densely vegetated areas of eastern China.

At the global scale, (Miralles et al., 2014b) identified the effect of El Niño-driven droughts in soil moisture, NDVI and evaporation, using GLEAM and ESA CCI SM COMBINED v02.1. This in combination with the high persistence of soil moisture (Seneviratne et al., 2006b; Nicolai-Shaw et al., 2016) makes the ESA CCI SM dataset valuable for the monitoring and prediction of drought events. Hence, various versions of ESA CCI SM COMBINED have been used as a piece of evidence for probabilistic drought monitoring and forecasting in India (Padhee et al., 2017; Asoka and Mishra, 2015), Spain (Linés et al., 2017), and the United States (Yan et al., 2017). Recently, ESA CCI SM COMBINED v02.2 was used to validate the predictions of process-based drought forecasting models applied in Sub-Saharan Africa (McNally et al., 2017) and India (Shah and Mishra, 2016).

3.1.6 (Hydro)meteorological applications

Numerical Weather Prediction (NWP) involves the use of computer models of the Earth system to simulate how the state of the Earth system is likely to evolve over a period of a few hours up to 1–2 weeks ahead. It also considers longer timescales (seasonal and climate) through the notion of seamless prediction (Palmer et al., 2008). A number of studies provide strong support for the notion that high skill in short- and medium-range forecasts of air temperature and humidity over land requires proper initialization of soil moisture (Beljaars et al., 1996; Drusch and Viterbo, 2007; van den Hurk et al., 2010; Douville et al., 2000). There is evidence also of a similar impact from soil moisture on seasonal forecasts (Koster et al., 2004; Koster et al., 2011; Weisheimer et al., 2011; Dirmeyer and Halder, 2017).

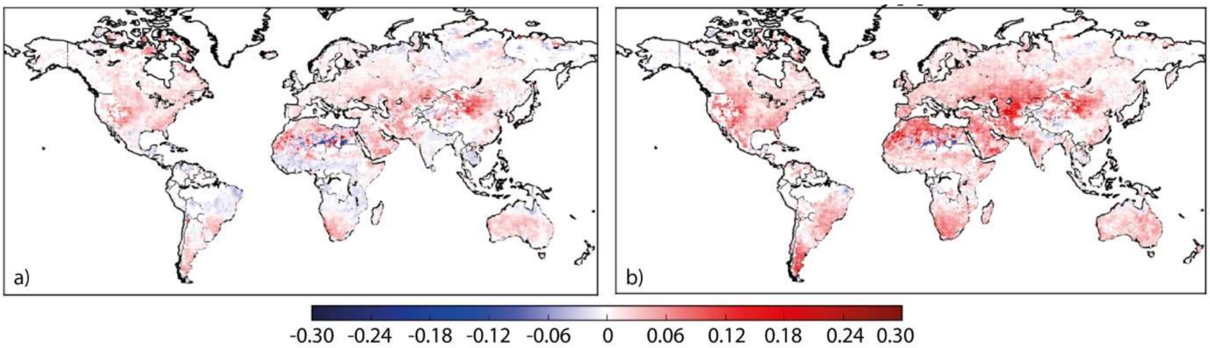

Figure 14 *Differences in correlations of absolute soil moisture values (left) and anomalies (right) differences between ESA CCI SM COMBINED v02.2 and soil moisture from the first layer of soil of two offline experiments over 1979-2014. Experiment GE8F has a first layer of soil of 1 cm depth (0-1cm), GA89 of 7 cm depth (0-7cm). Differences are only shown for pixels that provide significant correlations (p<0.05) for both experiments. Pixels where these conditions are not met have been left blank.*

Remotely sensed soil moisture datasets like ESA CCI SM can serve NWP by offering a long-term, consistent, and independent reference against which NWP output fields can be evaluated. This may eventually improve meteorological forecasts through a better representation of the land surface and of the fluxes between the land surface and the atmosphere in the NWP (see Section 3.1.2). For example, Arnault et al. (2016) used ESA CCI SM (version unknown) to evaluate soil moisture predicted with a Weather Research and Forecast (WRF)-Hydro Coupled Modeling System for West Africa. Recently, ECMWF made an offline development in its Land Surface Model HTESSEL (Balsamo et al., 2009; Balsamo et al., 2015), making it possible to add extra layers of soil as well as changing their thickness (Mueller et al., 2016). An experiment was run which increases the number of soil layers from four to nine and reduces the thickness of the upper soil layer from seven (0–7 cm) to one (0–1) centimetre. One of the rationales for having this thin topsoil layer is having a surface layer that is closer to the depth sampled by existing satellite observations and thus allowing for a better assimilation of these observations. Soil moisture from the first layer of two offline experiments, forced by ERA-Interim reanalysis, and considering either a 1 cm depth (GE8F) or a 7 cm depth (GA89) layer was compared to the ESA CCI SM COMBINED v02.2 over the period 1979–2014. Correlations were computed for absolute soil moisture and anomaly time series from a 35-day moving average (Dorigo et al., 2015b). We illustrate differences in correlation between the two experiments in Figure 14. The red colours illustrate that in most areas using a 1 cm instead of a 7 cm surface layer depth leads to a better match with the ESA CCI SM COMBINED dataset. Positive differences frequently reach values higher than 0.2, particularly for correlations on anomaly time series, which shows that a thinner model layer better mimics satellite-observed surface soil moisture variations, as was expected.

Few studies have assimilated remotely sensed soil moisture directly into NWPs and climate models to update their soil moisture fields. Even though this mostly leads to a significant improvement of the model's soil moisture fields, its impact on the meteorological forecast itself, e.g., on 2 m air (T2 m) temperature (Bisselink et al., 2011), screen temperature or relative humidity predictions (Dharssi et al., 2011; Scipal et al., 2008; de Rosnay et al., 2013), is typically limited in areas with dense coverage of the ground-based meteorological observing network and difficult to evaluate in poorly observed areas. We are only aware of one study that assimilated ESA CCI SM (version unknown) directly into an NWP to update its soil moisture field (Zhan et al., 2016). This study showed that assimilating ESA CCI SM into the NASA Unified WRF model coupled with NASA Land Information System could decrease the RMSEs of near-surface air temperature and humidity for certain forecasts and decrease the biases of NUWRF model longer term rainfall forecasts more significantly than those of the shorter-term forecasts.

3.2 Closing the gap between Earth system research requirements and observations

Our overview of product characteristics in Section 3 (of Dorigo et al., 2017) shows that the ESA CCI SM products are able to overcome several of the drawbacks that single-sensor products have with respect to their applicability in a climate context, particularly concerning the dataset length and revisit times. Even though ESA CCI SM is approaching the requirements outlined in the 2015 GCOS Status Report our analysis also shows that these characteristics vary significantly through space and time. Thus, it is often not meaningful to capture certain dataset characteristics in a single statistical number. Besides, the GCOS requirements present only a high-level consensus view on what is required to meet the increasing and more varied needs for climate data and information (GCOS-200, 2016). Therefore, our review of validation and application studies is crucial for identifying more specific requirements and the degree to which these are currently met by ESA CCI SM. It reveals that not all applications have the same requirements: for example, while for flood forecasting a high observation density appears to be of ultimate importance, this may be less crucial when studying long-term global trends in mean soil moisture. Based on our review we see the following research priorities for improving ESA CCI SM and soil moisture CDRs in general.

3.2.1 Higher spatial resolutions

Higher spatial resolutions are required to serve more regional applications, e.g., to map the impact of irrigation on local water budgets or to assess the impacts of local soil moisture variability on atmospheric instability (Taylor et al., 2013).Higher spatial resolutions of ESA CCI SM can be either achieved by including observations with higher native resolution (e.g., SAR, thermal infrared) or by applying appropriate downscaling techniques to the coarse scale observations (Peng et al., 2016; An et al., 2016b). As part of ESA CCI+ soil moisture, CCN4 currently addresses the creation of an interpolated medium resolution (0.1°) soil moisture product, as well as a regional high-resolution (1 km scale) product from Sentinel data to serve these needs for higher spatial resolutions.

3.2.2 Filling data gaps and improved temporal sampling

Many users and applications have difficulties in dealing with intermittent data. A way to address this would be the creation of gap-filled time series, which would improve the nominal observation density. At the same time, increasing the actual (real) observation density prior to 2002 to a daily resolution would be required to have a significant impact on data assimilation, e.g., in hydrological models or land surface reanalyses (Alvarez-Garreton et al., 2015). This may be partly overcome by improved blending approaches, although data density will remain insufficient in the earliest periods due to a lack of appropriate satellites. Sub-daily resolutions would be necessary to capture the high-frequency components of the soil moisture signal which in the temporal domain are driven mainly by precipitation and the diurnal cycle of solar radiation (Dorigo et al., 2013). A denser temporal sampling is also crucial to better quantify land-atmosphere interactions, e.g., soil moisture controls on convective precipitation (Taylor et al., 2012; Guillod et al., 2014). Fortunately, the current constellation of coarse-scale microwave satellites is capable of providing measurements several times per day (SMOS and SMAP at around 6:00 am and pm, ASCAT at 9:30 am and pm, and AMSR2 at 1:30 am and pm), which are however currently merged at daily resolution to make up for the varying accuracy of the different retrieval times. At the same time, due to physical limitations of microwave remote sensing in providing useful information below snow/ice cover, under frozen conditions, or underneath dense vegetation, spatial data gaps will remain an issue also in the future. As an alternative, gap-filling can be achieved by statistical methods for data imputation (e.g., Bessenbacher et al., 2022; Bessenbacher et al., 2023). An additional gap-filled version of the COMBINED product is being produced as of v08.1 as a research product of ESA CCI SM (Preimesberger et al., 2024). Such product covers the period 1991-2022, which is considered a good trade-off between a sufficient input data density to obtain a robust filling, and a fitting temporal coverage to support climate applications. The algorithm used is an adaptation of the framework given in Garcia (2010), which does not rely on any ancillary information and as such allows to maintain the properties of the observational data set. The filling interpolates information in the time and space domains, to generate a product with the same spatial and temporal resolution of the original COMBINED, and where original observations are preserved.

3.2.3 Improved product accuracy

Section 3 (of Dorigo et al., 2017) showed that there is still considerable room for reducing errors. Especially for Level 2 products from scatterometers a lot could still be gained by an improved modelling of vegetation effects and sub-surface scattering effects in dry soils (Morrison, 2013; Liu et al., 2016; Wagner et al., 2013). Passive microwave Level 2 products would benefit from an improved modelling of the effect of diurnal temperature variations on soil moisture retrievals (Parinussa et al., 2016) and a better quantification of the actual soil depths sampled by the different microwave frequencies (Wilheit, 1978). Both the active and passive Level 2 products would profit from an improved characterisation of the sub-daily behaviour of soil and canopy moisture and the application of de-noising methods (Su et al., 2015). These improved Level 2 products would in turn contribute to reduced errors in the ESA CCI SM products. Not only product errors themselves need to be improved, but also their characterisation in space and time and their communication to the users. As suggested earlier, providing a single error estimate for the entire dataset is impractical and insufficient. Applications based on data assimilation only profit maximally if the product errors are accurately and dynamically characterised at the level of individual observations (Lahoz and Schneider, 2014).

3.2.4 Improved blending methods

Some studies observed a reduced skill of COMBINED with respect to the ACTIVE or PASSIVE products (Yuan et al., 2015a; Szczypta et al., 2014; Chakravorty et al., 2016). Even though this issue has been largely resolved for the reported study areas in the later versions (Figure 15), there remain some areas where ACTIVE and PASSIVE outperform COMBINED. This is especially evident in the region north of the Black Sea and in some scattered areas in central and south-east Asia (dark red areas in Figure 15). In some cases, the scaling of the remote sensing products against a LSM-based climatology could remove some of the observed signal, for instance in the presence of irrigation, which is not accurately (or even explicitly) accounted for in LSMs. More in general, active and passive sensors might retain complementary information which could be devaluated by their merging. However, the merging scheme applied as of ESA CCI SM v08.1 is geared towards maximizing the signal-to-noise ratio in the final product by making use of an error characterization of the input products, leading to statistical merging optimality (Gruber et al., 2019). By property of the method, the merged time series will retain a better performance regardless of the quality of the inputs (Gruber et al., 2017), provided that their uncertainty is sufficiently well characterized. At ESA CCI SM v08.1, the uncertainty characterization scheme was reviewed to account for time-variant sources of errors, which leads to an improved uncertainty representation in the merged products and to an overall improved merging (Stradiotti et al., 2023a).

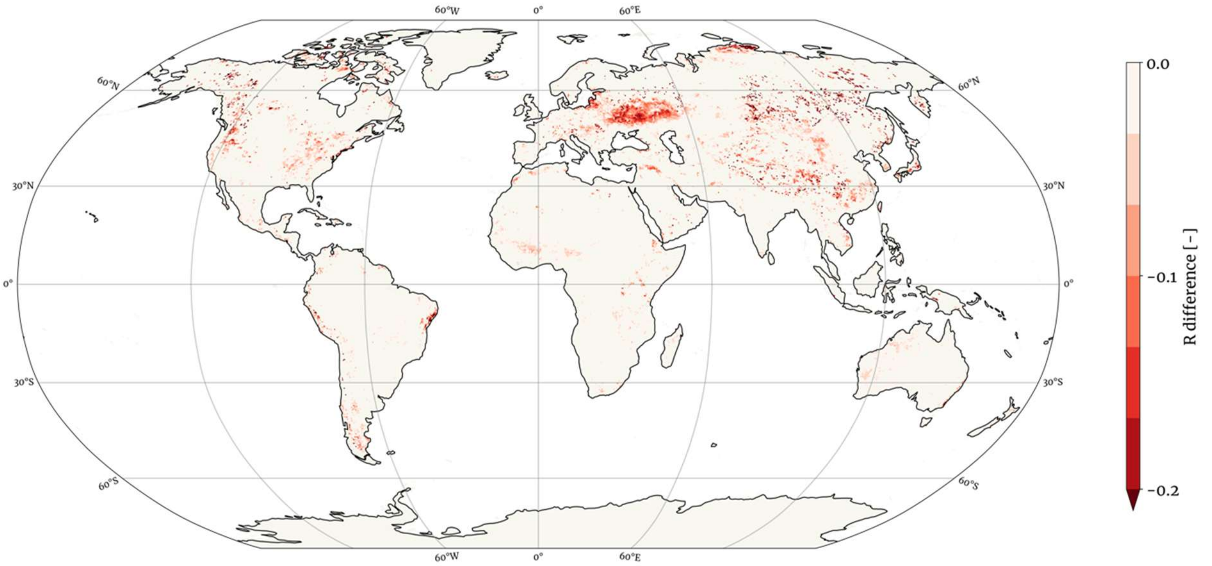

Figure 15 *Differences in correlation between ERA5 and ESA CCI SM v08.1 COMBINED on the one hand, and ERA5 and the best performing ESA CCI SM v08.1 product (either COMBINED, ACTIVE, or PASSIVE) on the other. Differences close or equal to zero indicate that COMBINED*

merges the input products without a substantial loss in skill, while negative values indicate that either ACTIVE or PASSIVE outperforms COMBINED.

3.2.5 Improved temporal consistency

For climate change applications it is of utmost importance that the trend signal contained in the ESA CCI SM products have a geophysical meaning and are not introduced, e.g., by changes in sensor constellation. Assessing, and possibly correcting for such potential artefacts should therefore receive high priority in future product releases (Su et al., 2016). However, despite the potential detection and correction of more obvious inhomogeneities like changes in the mean or variance, more intricate inhomogeneities, e.g., changes in data quality and spatiotemporal coverage, may be easily overlooked. Yet, these may have considerable impact on several applications, e.g., the attribution of the frequency of extreme events (Loew et al., 2013; Yuan et al., 2015a; Padhee et al., 2017) or the assessment of mean global trends (Dorigo et al., 2012). Long-term missions with consistent specifications, e.g., as provided by the ERS and MetOp satellites, are crucial for supporting homogenisation and intercalibration efforts As of v08.1 of ESA CCI SM, a break-adjustment using the methodology set out in Preimesberger et al. (2021) has been implemented for the COMBINED product to correct for structural breaks in the time series. The method yields longer homogeneous time series (Figure 16) which generate regional improvements in the correlation of the product with reanalysis data (Hirschi et al., 2022), and are better suited for long-term trend analysis.

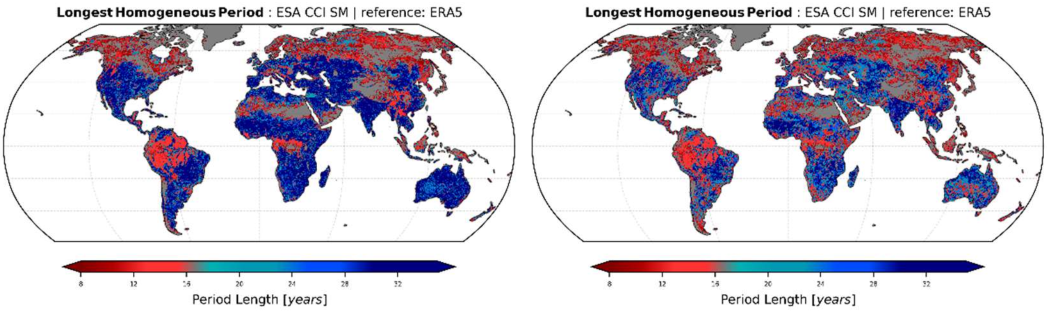

Figure 16 *Longest homogenous period in ESA CCI SM v07.1 (COMBINED) before adjustment (right) and after adjustment (left).*

3.2.6 Shorter latency times between data acquisition and data availability

Short latency times are required for embedding the ESA CCI SM product in operational services. While monitoring services, e.g., drought monitors, would already profit from a latency of several days, operational flood forecasting and the initialization of boundary conditions in NWP models require a near-real-time availability of the product. Enenkel et al. (2016a) demonstrated the feasibility of producing an ESA CCI SM near-real-time dataset, although they also showed that such a service is constrained by the latency and quality of available Level 2 products. Operational production and updating of the dataset with an update frequency of 10 days is now taking place within the Climate Data Store of the Copernicus Climate Change Services (C3S; https://climate.copernicus.eu/). ESA CCI SM v05.2 is the current basis for the latest product version (v202012.0.0) of this service.

3.2.7 *Independency of LSMs*

To optimally serve model benchmarking activities, especially regarding the assessment of biases, the ESA CCI SM COMBINED product should become entirely independent of any LSM. Even though the current scaling against the GLDAS-Noah reference LSM hardly affects trends and temporal dynamics in the product, it does make the ESA CCI SM COMBINED dataset impractical for assessing model biases. Globally available L-band observations from SMOS and SMAP may be considered as an alternative scaling reference in the future. As part of ESA CCI+, the impacts of replacing GLDAS-Noah with L-band data from SMOS and/or SMAP as a scaling reference are currently being investigated. Results indicate that the best trade-off could be using a merged L-band dataset as new reference to benefit from both SMAP (better spatial coverage) and SMOS (longer time series) advantages (Madelon et al., 2021). A corresponding research product has been developed by generating an L-band reference from the BTs-level merging of SMAP and SMOS with the idea that biases can be better removed before the retrieval model is applied. For this purpose, a single set of brightness temperatures is estimated from all viewing angles of SMOS by taking SMAP as a reference, from which the SM is then retrieved. This research product covers the 2010-2023 period and will be distributed with ESA CCI SM v09.1. The time backward-propagation of the L-band reference using L-band-like AMSRE data is under investigation from the previous research base of Rodríguez-Fernández et al. (2016).

3.2.8 *Creation of a root-zone soil moisture product*

Root-zone soil moisture is required for a complete assessment of land-atmosphere interactions, for better linking soil moisture variability to ecosystem and agricultural drought dynamics, and for hydrological modelling. Although this is seemingly unattainable without the intervention of an LSM to propagate surface soil moisture observations to the root-zone, simplified approaches such as the Soil Water Index method (Wagner et al., 1999; Albergel et al., 2008) may already be useful (Brocca et al., 2012). An ESA CCI+ soil moisture CCN1 Scientific Evolution study has been concluded with the goal to complement the ESA CCI surface soil moisture product with a global, long-term root-zone soil moisture dataset with daily and 0.25° resolution. The creation of an ESA CCI root-zone soil moisture product based on exponential filtering and using optimal values of the T-parameter determined from in-situ time series is currently ongoing. Such product will be part of the ESA CCI SM products suite as of v09, covering the period 1991-2023. The RZSM estimates will also be provided with an adapted uncertainty characterization scheme that accounts for the model uncertainty component (Pasik et al., 2023).

One should be aware that user requirements on satellite soil moisture will continue to change, reflecting advances in Earth system research and evolving societal needs. As regards climate applications, the latest GCOS Implementation Plan (GCOS-200, 2016) already addresses a couple of the new top-level requirements identified in this study, including improvements in the spatial resolution and the need to provide subsidiary variables to better characterise the quality of the surface soil moisture data. The required subsidiary variables are the freeze/thaw status, surface inundation, VOD and root-zone soil moisture. Freeze/thaw status and surface inundation are needed to flag environmental conditions when the retrieval of soil moisture data from microwave measurements is not possible due to fundamental physical reasons (Zwieback et al., 2015).

Even with consolidated user requirements for soil moisture CDRs, the main challenge remains to determine to what degree these requirements are actually met by long-term products like ESA CCI SM. This requires standardised strategies based on commonly agreed reference datasets, methodologies, and metrics. Some examples of potential methods were adopted in this study but these need to be further elaborated. Apart from statistical approaches like the triple collocation, all other evaluation methods to some degree suffer from a general data sparsity in several regions of the world, e.g., the tropical forests or the sub-arctic. In these regions, there is not only a lack of in-situ soil moisture stations (Ochsner et al., 2013) but also of meteorological monitoring stations. Thus, also the precipitation and LSM products used in various evaluation approaches have larger uncertainties here. For example, Albergel et al. (2013a) showed that the trends in two reanalysis datasets widely diverged in these areas. Therefore, to date, data-rich areas dominate in the evaluation process. One of the main priorities of the international community should therefore be to establish in-situ networks in data-poor regions and guarantee the continuation of existing long-term monitoring sites to assess stability and trends over a wide range of land surface conditions. A good starting point may be offered by the globally well-distributed and error-characterised SMAP core validation sites (Colliander et al., 2017).

3.3 Conclusion and outlook

In this study, we provided a comprehensive overview of the specifications of the ESA CCI SM product suite and the Earth system applications that have made use of these datasets either to benchmark or to improve current process understanding as captured in state-of-the-art models. The strong user interest in the soil moisture CDRs is reflected by the wide variety of science communities who have exploited the potential of these products. The main motivation for using the ESA CCI SM products over existing single-sensor products is its unique long period of coverage, which makes it potentially suitable to assessing long-term variability and change, although users should confirm data homogeneity for their region of application.

ESA CCI SM products have already led to numerous publications, which were used in this study to review the capabilities and shortcomings of the products for Earth system applications and provide valuable information for shaping the priorities of new product releases. Yet, the full potential of ESA CCI SM remains underexploited. This is partly due to the complexity and limitations of the data, e.g., the varying dataset quality through space and time, and the occurrence of data gaps, which makes it difficult for users to integrate the data in their applications. Such limitations can be partly addressed by continuing efforts to improve Level 2 retrievals and merging methodologies, and through the introduction of new, high-quality sensors like SMAP in the merged products. However, it will not be possible to mitigate all issues related to the creation of an entirely homogeneous dataset from 1978 onwards. These issues relate to the absence of suitable sensors in the early decades and the physical limitations of the microwave signal in general. Thus, to exploit the full potential of the ESA CCI

SM datasets, future efforts should not only focus on algorithmic improvements but also on clearly communicating the dataset characteristics to expert and non-expert users alike.

Finally, the acceptance of the ESA CI SM products by a broad user community and integration into operational applications strongly hinges on its long-term sustainability. For the coming years, ESA will continue to support the scientific development of ESA CCI SM within the ESA CCI+ Phase 1 activities. At the same time, operational reprocessing, software maintenance, and near-real-time updating based on ESA CCI SM v05.2 is taking place within the Copernicus Climate Change Services. However, a successful continuation of ESA CCI SM also requires sustenance of the input missions. Currently, the risk of failing missions is relatively low: From the active microwave side two almost identical MetOp-A and MetOp-B ASCAT scatterometers are currently operated by EUMETSAT, while MetOp-C ASCAT will be launched in 2018 to replace MetOp-A (Lin et al., 2017) From that time, MetOp-A will remain in orbit to serve as backup in case of failure of one of the other MetOp satellites. Continuation beyond the current MetOp program will be provided by the approved MetOp Second Generation (MetOp-SG) program, which will start in 2021/22 and has the goal to provide continuation of C-band scatterometer and other systematic observations for another 21 years, i.e., at least until 2042. Also for the passive microwave part there is currently a redundancy of suitable missions: AMSR2 C-band observations, ASMR2, GPM GMI, and Fengyun 1B X-band radiometers, and of course the dedicated L-band missions SMOS and SMAP. In case of failure of one of these missions, there is enough potential backup to reduce the impact of satellite failure on the short to mid-term. More worrying is the long-term continuation of L-band and C-band radiometer missions, since neither SMOS, nor SMAP nor AMSR2 has confirmed continuation. Nevertheless, the planned Water Cycle Observation Mission (WCOM) of the Chinese Academy of Sciences has the potential to bridge the looming gap in L- and C-band observation time series from 2020 onwards (Shi et al., 2016). Yet, a strong commitment of space agencies worldwide to provide continuation of single sensor missions and ESA CCI SM is needed to bolster the acceptance of satellite-derived soil moisture by a large user community in general.

Appendix: Summary tables of applications and user feedback

***Table 1**: Applications of ESA CCI SM for understanding climate variability and change. Modified and extended from Dorigo et al. (2017)*

Climate variability and change			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Long-term trends and dynamics in soil moisture	Dorigo et al. (2012); Wang et al. (2016); Qiu et al. (2016); Albergel et al. (2013b); Su et al. (2016); Rahmani et al. (2016); Zheng et al. (2016); Feng and Zhang (2015); Li et al. (2015); Zohaib et al. (2017); Carvalho-Santos et al. (2018); Dong et al. (2018); Jia et al. (2018); Lou et al. (2018); Gu et al. (2019b); Gu et al. (2019c); Pan et al. (2019); Deng et al. (2020); Zhang and Jia (2020a); Ma et al. (2020); Spennemann et al. (2020); Zhuang et al. (2020); Yao et al. (2021b); Fatkhuroyan et al. (2021); Wang et al. (2022d); Cai et al. (2022); Zhu et al. (2023); Peng et al. (2023a); Hirschi et al. (2023a)	Long-term coverage needed for robust trend assessment	No global coverage; no representation of root-zone; data quality changes over time
Assessment of drivers of soil moisture trends and variability	Feng (2016); Liu et al. (2015); Zhan et al. (2017); Chen et al. (2017); Meng et al. (2018); Wang et al. (2018c); Peng et al. (2019a); Liu et al. (2021a); Ayehu et al. (2020); Peng et al. (2023b); Prasad et al. (2023)	Long-term coverage for robust driver assessment	Data gaps in time and space
Soil moisture as driver of multi-annual variability in land evaporation	Miralles et al. (2014b); Zheng et al. (2022); Zhao et al. (2023b)	Independent evidence of long-term trends and variability in modelled soil moisture, constraining errors in water balance model	Not mentioned
Impact of ocean atmosphere system on soil moisture variability	Bauer-Marschallinger et al. (2013); Miralles et al. (2014b); Nicolai-Shaw et al. (2016); Jimma et al. (2023); Talib et al. (2023); Kabli et al. (2024)	Long-term dataset required for assessing low impact of frequency climate oscillations	Data periods with reduced spatial coverage

Climate variability and change			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Soil moisture as indicator of global climate variability and change	De Jeu et al. (2012); Parinussa et al. (2013); Dorigo et al. (2014); Dorigo et al. (2015a); Dorigo et al. (2016); De Jeu et al. (2011); Dorigo et al. (2017); Martinez-Espinosa et al. (2021); van der Schalie et al. (2021); Preimesberger et al. (2020); Scanlon et al. (2019); Dorigo et al. (2018); Guan et al. (2023); Wu et al. (2023); van der Schalie et al. (2022); Stradiotti et al. (2023b); Schumacher et al. (2024)	Assess actual soil moisture condition with respect to historical context	Lack of global coverage hampers assessment of mean global and hemispherical trends
Impact of soil moisture on trends in atmospheric composition (e.g., aerosols)	Klingmüller et al. (2016); Kokkalis et al. (2018)	Long-term coverage required for robust trend and driver assessment	Not mentioned
Validation of ESMs and climate models (mean fields, spatial patterns, temporal variability, trends)	Pieczka et al. (2016); Du et al. (2016); Lauer et al. (2017); Huang et al. (2016); Yuan and Quiring (2017); van den Hurk et al. (2016); Agrawal and Chakraborty (2016); Nitta et al. (2017); Ruosteenoja et al. (2018); Wehrli et al. (2019); Bai et al. (2018); Kuhlbrodt et al. (2018); Gu et al. (2019b); Koukoula et al. (2019); Breuer et al. (2020); Hagan et al. (2020); Lin et al. (2020); Wang et al. (2020a); Guglielmo et al. (2021b); Muller et al. (2021); Humphrey et al. (2021); Wang et al. (2022a); Hohenegger et al. (2023); Feng et al. (2023d); Rigden et al. (2024)	Potential for assessing long-term climatology, variability, and trends	Layer thickness not consistent among models and satellite observations; ESA CCI SM uncertainties are larger than the RMSE of many of the models; data gaps due to frozen soils, snow, and dense vegetation.
Validation and sensitivity analysis of regional climate models	Pieczka et al. (2016); Unnikrishnan et al. (2017); Fonseca et al. (2019); Huang et al. (2020); Saharwardi et al. (2021)	Potential for assessing long-term climatology, variability, and trends	Evaluation of absolute values not possible; discrepancy in layer thickness represented.
Assimilation in regional climate model	Paxian et al. (2016)	Not mentioned	Not mentioned

Climate variability and change			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Variability of precipitation and soil moisture during South Asian Monsoon	Shrivastava et al. (2017); Shrivastava et al. (2016)	Convergence of evidence together with reanalysis soil moisture and precipitation, robust assessment of inter-annual variability	Temporal data gaps during monsoon season

Table 2 *Applications of ESA CCI SM for understanding land atmosphere interactions. Modified and extended from Dorigo et al. (2017).*

Land atmosphere interactions			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Improved understanding of soil moisture feedbacks on precipitation	Ford et al. (2018); Wang et al. (2018d); Yang et al. (2018); Guillod et al. (2014); Guillod et al. (2015, indirectly through assimilation of ESA CCI SM into GLEAM); Dolores et al. (2019); Holgate et al. (2019); Ling et al. (2019); Yuan et al. (2020); Baker et al. (2021); Talib et al. (2021); Maurya et al. (2021); Maity et al. (2021); Dong et al. (2022b); Talib et al. (2022); Ullah et al. (2023); Klein et al. (2023); Hu et al. (2023); Ford et al. (2023)	Constraining errors in water balance model over long period	Not mentioned
Feedback of (concurrent and antecedent) soil moisture on Tibetan, Indian and African monsoon intensity	KanthaRao and Rakesh (2017); Hunt and Turner (2017); Zhou et al. (2016); Ndomeni et al. (2018); Varikoden and Revadekar (2018); Lodh (2020)	Long-term dataset for robust statistics	Dataset not suitable due to large data gaps in winter
Identifying role of soil moisture on temperature variability and heatwaves	Miralles et al. (2014a); Hirschi et al. (2014); Casagrande et al. (2015); Dong and Crow (2018, 2019); Chen et al. (2019); Schumacher et al. (2019); Seo et al. (2020); Wu et al. (2021); Pyrina et al. (2021); Muzylev (2023); Aadhar and Mishra (2023); Mardian et al. (2023b); Al-Yaari et al. (2023); Yu et al. (2023b); Dong et al. (2023); Daramola et al. (2024)	Constraining errors in water balance model over long period by data assimilation; long period provides robust coupling statistics	No representation of root-zone soil moisture; lacking information about exact sampling depth
Observation-based land-atmosphere coupling (to evaluate coupling of LSM products and ESM ensembles)	Knist et al. (2017); Li et al. (2016); Catalano et al. (2016); Albergel et al. (2017); Lei et al. (2018); Al-Yaari et al. (2019)	Independent reference for long period.	Spatial data gaps; seasonal variation in spatial coverage

Land atmosphere interactions			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Improved modelling of land evaporation; (statistical) estimation of surface turbulent fluxes	Martens et al. (2017); Miralles et al. (2014b); Park et al. (2017); Alemohammad et al. (2017); Jimenez et al. (2018); El Masri et al. (2019); Yao et al. (2019); Cui et al. (2020a); Cui et al. (2021b); Zhang et al. (2021c); Cui et al. (2021a); Abdolghafoorian and Dirmeyer (2022); Dong et al. (2022a); Feng et al. (2023b); Zhang et al. (2023e)	Constraining errors in water balance model over long period by data assimilation	Negative impact in very dry areas and areas where quality of precipitation is high
Explaining trends in evapotranspiration	Rigden and Salvucci (2017); Zeng et al. (2014); Xiao et al. (2020)	Long-term availability for trend assessment	Not mentioned
Soil moisture and latent heat flux / evapotranspiration coupling	Lei et al. (2018); Denissen et al. (2020); Denissen et al. (2021)		
Impact of soil moisture (among other drivers) on dust aerosol dynamics	Klingmüller et al. (2016); Xi and Sokolik (2015); Kokkalis et al. (2018); Nabavi et al. (2018); Vandenbussche et al. (2020); Xi (2021); Yu and Ginoux (2021); Xi (2023); Liaskoni et al. (2023); Xi et al. (2023)	Long-term coverage required for robust trend and driver assessment	Not mentioned

***Table 3** Applications of ESA CCI SM for understanding global biogeochemical cycles and ecology. Modified and extended from Dorigo et al. (2017).*

Global biogeochemical cycles and ecology			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Evaluation and calibration of global vegetation models	Szczypta et al. (2014); Traore et al. (2014); Sato et al. (2016); Willeit and Ganopolski (2016); Su et al. (2021); Yu et al. (2023a)	Long-term coverage for robust statistics	Poor performance for some mountain ranges; No data available for densely vegetated areas; seasonal variation in spatial coverage
Impact of soil moisture dynamics on vegetation / crop productivity and yields	Muñoz et al. (2014); Chen et al. (2014); Papagiannopoulou et al. (2017a); Barichivich et al. (2014); Szczypta et al. (2014); McNally et al. (2016); Ghazaryan et al. (2016); Wu et al. (2016); Cissé et al. (2016); Nicolai-Shaw et al. (2017); Liu et al. (2017c); Da et al. (2017); Wang et al. (2018a); Momen et al. (2017); Bassiouni et al. (2018); Boke-Olen et al. (2018); Gichenje and Godinho (2018); Liu et al. (2018a); Shan et al. (2018); Champagne et al. (2019); Li et al. (2019); Martinez-Fernandez et al. (2019); Tesfamichael and Shiferaw (2019); Wang et al. (2019b); Nilsson et al. (2020); Ugbaje and Bishop (2020); Bhimala et al. (2020); Bontempo et al. (2020); Bouras et al. (2020); Byrne et al. (2020a); Correa-Diaz et al. (2020); Halubok and Yang (2020); Lavergne et al. (2020a); Liu et al. (2020a); Modanesi et al. (2020); Olano et al. (2020); Orth et al. (2020); Rigden et al. (2020); Somkuti et al. (2020); Tao et al. (2020); Papagiannopoulou et al. (2017b); Zhang and Jia (2020b); Zhou et al. (2020); Zhu et al. (2020b); Gonsamo et al. (2021); Gonzalez-Zamora et al. (2021); Liu et al. (2021d); Bouras et al. (2021); Vogel et al. (2021); Correa-Díaz et al. (2021); He et al. (2021); Famiglietti et al. (2021); Ermitão et al. (2021); Anghileri et al. (2022); Salakpi et al. (2022b); Proctor et al. (2022); Venkatesh et al. (2022a); Rigden et al. (2022); Maas et al. (2022); Harris et al. (2022); Heijmans et al. (2022); Venkatesh et al. (2022b); Maina et al. (2022); Li et al. (2022a); Zhang et al. (2023b); Bueechi et al. (2023); Yang et al. (2023); Klein et al. (2023); Zhao et al. (2023a); Wang et al. (2024); Li et al.	Long-term coverage for robust assessment of drivers	Poor data quality and data gaps for densely vegetated areas, frozen conditions, and mountain areas; temporal data gaps

Global biogeochemical cycles and ecology			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
	(2024); Amantai et al. (2024); Tian et al. (2024)		
Validation of dry season intensity indicator	Murray-Tortarolo et al. (2016)	Long-term dataset required for robust evaluation	Not mentioned
Impact of large-scale re-vegetation on soil moisture	Jiao et al. (2016)	Long-term coverage allows for trend assessment	Not mentioned
Connecting trends in soil moisture and vegetation productivity	Dorigo et al. (2012); Feng (2016); Jin and Wang (2018); Wang et al. (2018a); Fakharizadehshirazi et al. (2019); Ribeiro et al. (2021); Saby et al. (2021); Zheng et al. (2021); D'Adamo et al. (2021); Yang et al. (2021b); Jiao et al. (2021b)	Long-term coverage required for trend assessment	Spatial data gaps, ESA CCI SM has trend removed before 1987
Assessing ecosystem water use efficiency	Li et al. (2017); Qi et al. (2019)	Long-term data availability for robust statistics	Reduced quality over densely vegetated areas; high uncertainty for earlier periods
Improved crop modelling	Wang et al. (2016); Sakai et al. (2016); Wang et al. (2017); Park et al. (2017); Petropoulos et al. (2018); Salakpi et al. (2022a); Zhou et al. (2022); Cheng et al. (2023); Boas et al. (2023); Xing et al. (2023)	Complementarity of active and passive microwave soil moisture for different land cover types; assessment of long-term links between soil moisture and vegetation	Poor performance along coasts; differences in spatial scale; representativeness for fragmented landscapes; impact of irrigation; spatiotemporal data gaps
Assessing effects on stomatal conductance	Lavergne et al. (2020b)	Not mentioned	Not mentioned
Assessing drivers of fire activity; modelling particulate emission from fires	Ichoku et al. (2016); Forkel et al. (2017); Fan et al. (2018); Kiely et al. (2019); Kiely et al. (2020); Sungmin et al. (2020); Lu and Wei (2021); Bai et al. (2021); Yu and Ginoux (2022); Bai et al. (2022); Mukunga et al. (2023); Ryoo and Park (2023)	Long-term availability is essential for assessing dynamics and drivers of infrequent fire activity	No coverage for dense vegetation, temporal gaps

Global biogeochemical cycles and ecology			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Coupling between the terrestrial carbon and water cycles	Kostic et al. (2021); Gentine et al. (2019); Menichetti et al. (2020); Liu et al. (2022c); Gong et al. (2023)	Not mentioned	Not mentioned
Potential for constraining terrestrial carbon cycle simulations by data assimilation	Kaminski et al. (2013); Scholze et al. (2017)	Long-term data availability	Accurate description of random error for each observation; Does not provide estimate of root-zone soil moisture
Assessment of satellite-observed carbon fluxes	Detmers et al. (2015); Byrne et al. (2020b)	Long-term availability	Not mentioned
Assessing drivers of riverine export of dissolved black carbon	Jones et al. (2019)	Not mentioned	Not mentioned
Soil moisture as driver of animal species migration; soil moisture for locating breeding areas; relations with vertebrate diversity distribution	Madani et al. (2016); Gomez et al. (2018); Cornelissen et al. (2019); Leite et al. (2019); Gomez et al. (2020); Salako et al. (2023)	Long-term dataset required for robust pattern assessment	Coarse resolution
Impact of wind farms on environmental conditions for vegetation growth	Tang et al. (2017)	Long-term availability	Not mentioned
Soil moisture as driver of NH_3 emissions	Hickman et al. (2018)	Not mentioned	Not mentioned
Use of soil moisture for disease-related applications	Campbell et al. (2020)	Not mentioned	Not mentioned

Global biogeochemical cycles and ecology			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Variation in soil rock fragment content	Lai et al. (2022)	Not mentioned	Not mentioned

***Table 4** Applications of ESA CCI SM for hydrology and land surface modelling. Modified and extended from Dorigo et al. (2017).*

Hydrology and land surface modelling			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Evaluating model *states* in hydrological models and LSMs (including land data assimilation systems); evaluation of SM derived from statistical models	Loew et al. (2013); Fang et al. (2016); Du et al. (2016); Spennemann et al. (2015); Schellekens et al. (2016); Szczypta et al. (2014); Lauer et al. (2017); Mao et al. (2017); Lai et al. (2016); Rakovec et al. (2016); Okada et al. (2015); Ghosh et al. (2016); Mishra et al. (2014); Mueller and Zhang (2016); Nitta et al. (2017); Parr et al. (2015); Albergel et al. (2018a); Albergel et al. (2018b); Bai et al. (2018); Breil et al. (2018); Gelati et al. (2018); Guimberteau et al. (2018); Khan et al. (2018); Mishra et al. (2018); Niroula et al. (2018); Pomeon et al. (2018a); Pomeon et al. (2018b); Sawada (2018); Yin et al. (2018); Zhang et al. (2018a); Zhao and Yang (2018); Naz et al. (2019); Odusanya et al. (2019); Wang et al. (2019a); Zhang et al. (2019c); Shrestha et al. (2020); Dembele et al. (2020c); Dembele et al. (2020a); Jung et al. (2020); Kim et al. (2020); Liu et al. (2020c); Meng et al. (2020); Sawada (2020); Thatch et al. (2020); Wang and Li (2020); Xie et al. (2020); Zhu et al. (2020a); Almendra-Martin et al. (2021b); Ankur et al. (2021); Dukic and Eric (2021); Dukic et al. (2021); Eeckman et al. (2021); Han et al. (2021); Jia et al. (2021); Liu et al. (2021b); Liu et al. (2021e); Lv et al. (2021); Seiler et al. (2021); Zhu et al. (2021); Sungmin and Orth (2021); Zhang et al. (2022b); Tangdamrongsub et al. (2021); Zhou et al. (2021b); Boussetta et al. (2021); Hughes and Farinosi (2021); O'Neill et al. (2021); Zhang et al. (2021b); Bennour et al. (2022); Huang et al. (2022); Cui and Wang (2022); Wu et al. (2022a); Ji et al. (2023a); Zhang et al. (2023d); Joseph and Ghosh (2023); Feng et al. (2023c); Zhang et al. (2023c); Hoch et al. (2023); Naz et al. (2023); Chevuturi et al. (2023); Pimentel et al. (2023); Belleflamme et al. (2023); Quichimbo et al. (2023); Ji et al. (2023b); Huang et al. (2023); Van	Robust statistics based on long comparison period	Not suited for validating absolute values (bias, root-mean-square-difference); discrepancy between model and observation layer depths; different dataset characteristics for different periods (variance, data gaps); spatiotemporal data gaps.

Hydrology and land surface modelling			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
	Oorschot et al. (2023); Scherrer et al. (2023); Kalyanam and Chandrasekar (2024); Magotra et al. (2024)		
Evaluating model *processes* in hydrological models and LSMs (e.g., dry down)	Chen et al. (2016); Raoult et al. (2021); Ghajarnia et al. (2021); Baker et al. (2021); Raoult et al. (2022); Feng et al. (2023a); Zhou et al. (2023)	More realistic dry down characteristics than LSM-based soil moisture	Only few dry downs identifiable
Assimilated to constrain coupled LSM and hydrological simulations; usage in land data assimilation systems	Albergel et al. (2017); Liu et al. (2018b); Pinnington et al. (2018); Raoult et al. (2018); Yan et al. (2018); Blyverket et al. (2019b); Kumar et al. (2019); Nair and Indu (2019); Naz et al. (2020); Yang et al. (2021a); Pal and Maity (2021); Huang et al. (2021); Seo and Dirmeyer (2022); Kivi et al. (2023); Heyvaert et al. (2023); Yin et al. (2023b); Pradhan et al. (2023)	Long-term availability	No impact on deeper soil layers
Used to estimate the error covariance matrix of an ensemble of LSM simulations in order to optimally merge them.	Crow et al. (2015)	Long data record length essential for reducing sampling errors	large temporal variations in temporal frequency, actual spatial resolution, and accuracy; dependency on GLDAS-Noah as scaling reference; differences in vertical measurement support between models and observations
Persistence and prediction of soil moisture anomalies	Nicolai-Shaw et al. (2016); Allen and Anderson (2018); Klingmuller and Lelieveld (2021); Piles et al. (2022); Salcedo-Sanz et al. (2022); Tesfamichael et al. (2023)	Long-term dataset required for robust statistics	Exact vertical measurement support unknown

Hydrology and land surface modelling			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Improving runoff predictions and flood (risk) analysis and modelling	Tramblay et al. (2014); Massari et al. (2015); Kim et al. (2018); Massari et al. (2018); El Khalki et al. (2018); Zhong et al. (2019); Ganguli et al. (2020); Li and Willems (2019); Benkirane et al. (2020); El Khalki et al. (2020a); El Khalki et al. (2020b); Saouabe et al. (2020); Sapkota and Meier (2020); De Santis et al. (2021); Camici et al. (2022); Prakash and Mishra (2023); Wang et al. (2023b); Macharia et al. (2023); Eini et al. (2023); Sharma and Mujumdar (2024)	Not specified	Data gaps in space and time needed to be filled
Calibrating hydrological models	Kundu et al. (2017); Demirel et al. (2019); Koppa et al. (2019); Dembele et al. (2020b); Koppa and Gebremichael (2020); Sanz-Ramos et al. (2020)	Not specified	Only few model parameters sensitive to surface soil moisture
Improved water budget modelling	Allam et al. (2016); Abera et al. (2017); de Figueiredo et al. (2021); Mehrnegar et al. (2021); Saxe et al. (2021); Guglielmo et al. (2021a); Trautmann et al. (2022); Eini et al. (2023); Blank et al. (2023); Tabarmayeh et al. (2023); Trautmann et al. (2023); Guo et al. (2023)	Long-term availability for more robust statistics	Vertical measurement support too shallow to provide indication of changes in soil and ground water storage
Computing changes in groundwater storage	Asoka et al. (2017)	Long-term availability for trends assessment	Not mentioned
Modelling and understanding surface water dynamics	Heimhuber et al. (2017); Gu et al. (2019a); Khazaei et al. (2019); Kwon et al. (2020); Liang et al. (2020)	Long-term availability for more robust statistics	Not mentioned
Assessing irrigation	Qiu et al. (2016); Kumar et al. (2015); Zhang et al. (2018b); Paciolla et al. (2020); Zhang et al. (2022a); Zappa et al. (2022); Fan et al. (2022)	Long-term data required for trend-based method of Qiu et al. (2015)	Coarse spatial resolution for detecting fine scale irrigation
Assessing the impact of agricultural intensification on soil moisture	Liu et al. (2015)	Long-term data coverage needed for long-term impacts	Spatial gaps

Hydrology and land surface modelling			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Trigger of landslides	Dahigamuwa et al. (2016); Dahigamuwa et al. (2018); Zhuo et al. (2019); Zhao et al. (2021a)	Long-term availability	Limited temporal coverage
Improving satellite rainfall retrievals	Bhuiyan et al. (2017a); Bhuiyan et al. (2017b); Qiu et al. (2016); Kumar et al. (2015)	Data record spans multiple satellite precipitation missions	Not mentioned
Computing cumulative precipitation amounts	Ciabatta et al. (2016); Liu et al. (2015); Ciabatta et al. (2018); Massari et al. (2019); Miao et al. (2023); He et al. (2023)	Long data record needed for generation of long-term precipitation dataset	Too low signal-to-noise ratio in some areas; spatial and temporal data gaps
Validating soil moisture products derived from precipitation	Das and Maity (2015); Dahigamuwa et al. (2016); Ramsauer et al. (2021)	Long-term availability for robust statistics	Not mentioned
Evaluating soil moisture products derived from other satellite platforms; use of ESA CCI SM as input for derived products (including gap-filled and downscaled derivatives)	Leng et al. (2017); De Zan and Gomba (2018); Pablos et al. (2018); Zhou et al. (2018); Cui et al. (2020b); Fan et al. (2020); Koley and Jeganathan (2020); Kovacevic et al. (2020); Li et al. (2020); Liu et al. (2020d); Liu et al. (2020e); Llamas et al. (2020); Yin et al. (2020); Zeng et al. (2020); Abowarda et al. (2021); Almendra-Martin et al. (2021a); Cui et al. (2021c); Grillakis et al. (2021); Guevara et al. (2021); Jin et al. (2021); Kang et al. (2021); Preimesberger et al. (2021); Yao et al. (2021a); Zhang et al. (2021d); Warner et al. (2021); Zhao et al. (2021b); Liu et al. (2021c); Hu et al. (2022); Wang et al. (2022c); Li et al. (2022c); Li et al. (2022b); Wang et al. (2022b); Skulovich and Gentine (2023); Deng et al. (2023); Ning et al. (2023); Mehrnegar et al. (2023); Madelon et al. (2023); Liu et al. (2023b); Zhang et al. (2023a); Arias et al. (2023); Cheng et al. (2023); Dong et al. (2024); Shen et al. (2023); Yin et al. (2023a); Yao et al. (2023); Ramsauer and Marzahn (2023); Liu et al. (2023a)	Long-term availability for robust statistics	Not mentioned

Hydrology and land surface modelling			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Evaluating in-situ networks	Ford et al. (2020)	Long-term availability	

Table 5 *Usage of ESA CCI SM for drought applications. Modified and extended from Dorigo et al. (2017).*

Drought applications			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Validation and evaluation of drought indices	Liu et al. (2017b); Liu et al. (2017a); van der Schrier et al. (2013); Zhao et al. (2018); Zhu et al. (2018); Blyverket et al. (2019a); Ni et al. (2019); Angearu et al. (2020); Afshar et al. (2021); Li and Huang (2021); Liu et al. (2021b); Niaz et al. (2021); Araneda-Cabrera et al. (2021); Zhao and Wang (2021); Faiz et al. (2022); Lee et al. (2022); Afshar et al. (2022); Mardian et al. (2023a); Wang et al. (2023a)	Lon-term dataset required for robust assessment	Reduced temporal coverage before 1991
Development of new drought monitoring index	Carrão et al. (2016); Enenkel et al. (2016b); Rahmani et al. (2016); Wang et al. (2018b); Prakash (2018); Zhang et al. (2019a); Sadri et al. (2020); Kumar et al. (2021); Tian et al. (2022a)	Long-term dataset required for robust computation of normal soil moisture distributions	Variable data availability in time; reduced data quality over densely vegetated areas; not available in near-real-time
Detection of agricultural droughts	Yuan et al. (2015a); Liu et al. (2015); Padhee et al. (2017); Ma et al. (2017); Zampieri et al. (2018); Oertel et al. (2018); Ford and Quiring (2019); Pandey and Srivastava (2019); Peng et al. (2019b); Zhang et al. (2019b); Strohmeier et al. (2020); Sun et al. (2020); Tramblay et al. (2020); Liu et al. (2021f); Ma et al. (2021); van Hateren et al. (2021); Zhang et al. (2021a); Zhou et al. (2021a); Rezaei (2021); Vreugdenhil et al. (2022); Liu et al. (2022b); Tian et al. (2022b); Greimeister-Pfeil et al. (2022); Ming et al. (2023); Sun et al. (2023); Leeper et al. (2023); Salakpi et al. (2023)	Long-term dataset required for robust long-term statistics	Because of temporal data gaps extreme events may not be captured; reduced skill of COMBINED compared to ACTIVE in densely vegetated areas
Identification of flash droughts	Liu et al. (2020b); Liu et al. (2022a)	Long temporal coverage	Not mentioned

Drought applications			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
Probabilistic and statistical drought forecasting and monitoring	Yan et al. (2017); Asoka and Mishra (2015); Park et al. (2018); Samantaray et al. (2019); Linés et al. (2017)	Long-term dataset required for robust computation of normal soil moisture distributions	Coarse resolution; data gaps
Drought events composites analysis	Nicolai-Shaw et al. (2017)	Long-term observations-based dataset (more than two decades)	Lack of data in some key regions, lack of root-zone data (particularly in forest regions), uncertainties in early part of product
Soil moisture for integrated drought monitoring	McNally et al. (2016); Rahmani et al. (2016); Enenkel et al. (2016b); Da et al. (2017); Wang et al. (2018a); Jin et al. (2017); Martinez-Fernandez et al. (2017); Liu et al. (2019); Agutu et al. (2020); Turco et al. (2020); Cammalleri et al. (2017); Buitink et al. (2021); Jiao et al. (2021a); Al Hasan et al. (2021); Salvia et al. (2021); Baik et al. (2021); Wu et al. (2022b); Hobeichi et al. (2022); Li et al. (2023); Yatheendradas et al. (2023); Kumar and Chu (2024)	Long-term dataset required for robust long-term statistics	Poor spatio-temporal coverage prior to 1992
Evaluation of drought forecasting systems	McNally et al. (2017); Shah and Mishra (2016); Yuan et al. (2015b); Kang and Sridhar (2021)	Long-term availability for robust evaluation. Sensitivity to wetlands (which are not represented LSMs).	Poor spatio-temporal coverage prior to 1992; differences in representative depth
Soil moisture index for drought insurance applications	Enenkel et al. (2018); Osgood et al. (2018); Enenkel et al. (2019); Vroege et al. (2021)	Long-term availability; independency from weather conditions	

Table 6 *Usage of ESA CCI SM for (hydro)meteorological applications. Modified and extended from Dorigo et al. (2017).*

(Hydro)meteorological applications			
Main purpose	**References**	**Motivation for using ESA CCI SM**	**Limitations identified**
NWP model evaluation	Arnault et al. (2016); Osuri et al. (2020); Massoud et al. (2023)	Not mentioned	Discrepancy in scale
Supporting NWP land surface scheme improvements	Section 4.6 of Dorigo et al. (2017)	Long-term dataset required for robust evaluation of land surface scheme	Spatial data gaps for densely vegetated areas
Spatial representativeness of soil moisture	Nicolai-Shaw et al. (2015)	More spatial coverage than in-situ data, observation-based (unlike land model output)	Issues in topographically complex terrain and areas with dense vegetation
Assimilation into NWP model	Zhan et al. (2016)	Reducing uncertainties in temperature and humidity	Not mentioned
Weather risk assessment and insurance (beside droughts, see Table 5)	Wang et al. (2020b); Vroege and Finger (2020); Eltazarov et al. (2023)	Not mentioned	Not mentioned

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