

Leveraging C3S ECV Datasets for Earth System Modeling: insights and applications

Workshop on ancillary data for land surface and Earth system modelling – 09-10 April 2025, Bonn

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C3S team and contractors



PROGRAMME OF THE











Data to monitor climate











The starting point: the Global Climate Observing System (GCOS)



GCOS is the **authoritative global source of information** and advice for planning and development of the Global Climate Observing System, its networks and data management. It is the authoritative source reference for formulating **requirements for space and in situ climate observations**.

→ GCOS does not directly make observations nor generation of data products

ECVs provide a comprehensive view of the climate system & are critical for understanding and predicting climate change

- ECVs are crucial for implementing international agreements like the Paris Agreement
- Required to support the work of the UNFCCC and the IPCC (they use ECVs in assessment reports)
- Group on Earth Observations (GEO): promote use of ECVs in EO strategies

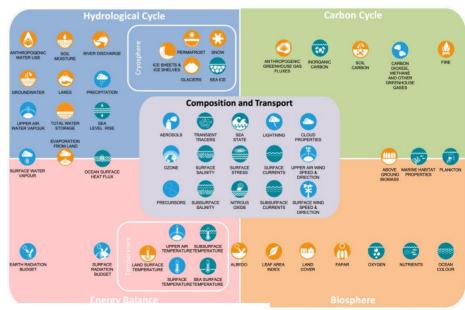


Fig.2 from GCOS IP-2022









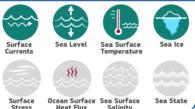
The C3S ECV programme





SURFACE ATMOSPHERE Surface Surface Air Surface Radiation Budget Pressure Temperature Water Vapour Speed&Direction

SURFACE OCEAN PHYSICS



OCEAN BIOLOGY, ECOSYSTEMS



SUBSURFACE OCEAN PHYSICS



OCEAN BIOGEOCHEMISTRY























ATMOSPHERIC COMPOSITION

UPPER-AIR ATMOSPHERE











ANTHROPOSPHERE









Plan)



Three main

domains:

In total GCOS

(GCOS 2022

defines 55 ECVs

Implementation

Terrestrial











Soil Moisture







Index (LAI)

Evaporation







Discharge



Carbon

Terrestrial

water storage





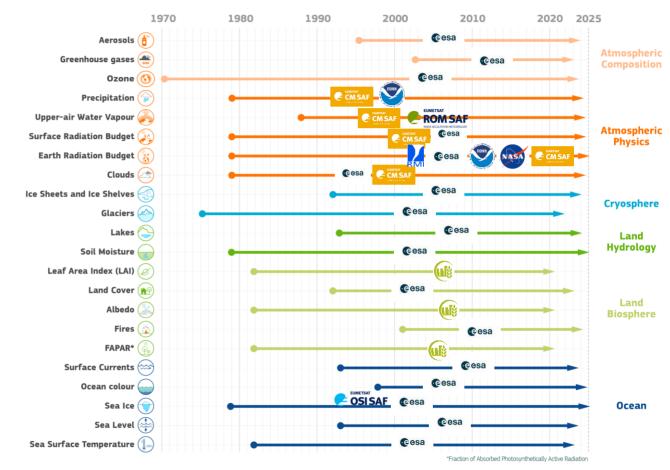
Climate Data Records of Essential Climate Variables – current offer



Based on satellite data, they monitor trends and variability

Involve close coordination and collaboration with major providers (ESA, EUMETSAT) and Copernicus Services

Their production require the expertise of many public and private entities in Europe





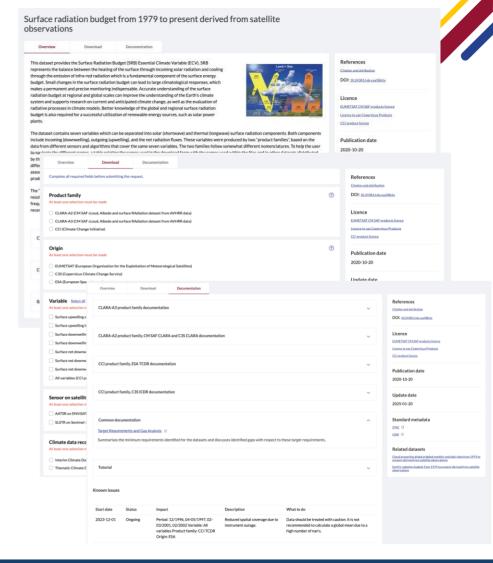




C3S ECV services

Access to ECV products through a harmonized look-and-feel interface (CDS), which are:

- State of the art (coordination with ESA, EUMETSAT,
 Copernicus Services)
- Long-term, consistent, complete (CDR) [multi-sensor approach]
- Regularly extended in time (ICDR)
- Gridded, aggregated (meeting climate requirements)
- Accessible & Traceable
 - Access through the Climate Data Store
 - Comprehensive documentation









C3S ECV services

Independent Evaluation and Quality Control

Specialised User Support

Training material

Use cases

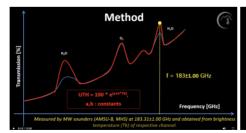
Data visualisation

Licenses, references, doi

Applications tailored to different sectors

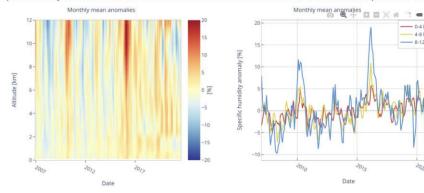
Climate Intelligence derived products

...



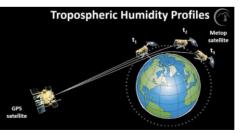


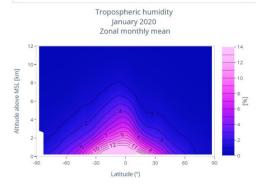
Specific humidity derived from radio occultation satellite data for the 30°S-30°N latitude band and the time period 2007 to 2021



the mean of the entire time-series, therefore the variation is primarily driven by seasonal

Time evolution of specific humidity anomalies. The anomaly is calculated as the difference to Time-series of the vertically aggregated mean of the specific humidity anomalies. The data are averaged vertically over 3 height layers: 0-4 km, 4-8 km and 8-12 km













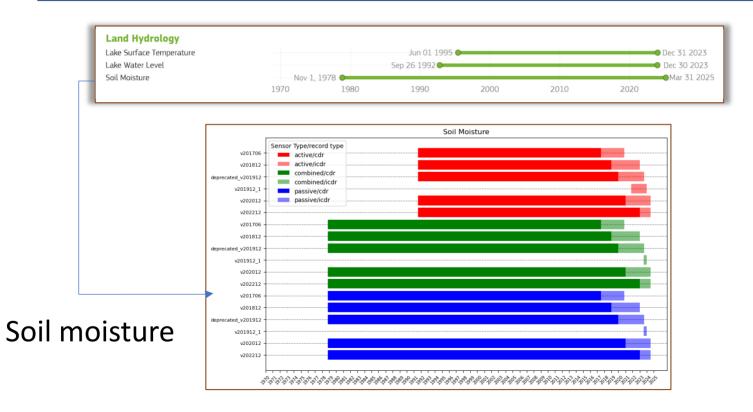


Land hydrology domain – satellite-based ECVs



Consortium led by the Earth Observation Data Centre (EODC).

ECVs: Soil Moisture, Lakes, *Groundwater and Terrestrial Water Storage*











Soil moisture as a key data source for land hydrology

[Thanks to Johanna Lems, UW]

Adapted from the ESA CCI SM Climate Assessment Report (2024)

Evaluating model states in hydrological models and LSMs Loew et al. (2013); Fang et al. (2016); Szczypta et al. (2014); Lauer et al. (2017); Mao et al. (2017); Lai et al. (2016); Rakovec et al. (2016); Gaparnia et al. (2017); Mao et al. (2017); Lai et al. (2016); Rakovec et al. (2018); Gaparnia et al. (2021); Baker et al. (2021); Racilt et al. (2018); Yan et al. (2015) Persistence and prediction of soil moisture anomalies Nicolai-Shaw et al. (2016); Allen and Anderson (2018); Klingmuller and Lelieveld (2021); Piles et al. (2012); Piles et al. (2014); Massari et al. (2015); Kim et al. (2018); Massari et al. (2018); Fanguli et al. (2018); Fanguli et al. (2018); Fanguli et al. (2018); Pinnington et al. (2018); Massari et al. (2018); El Khalki et al. (2018); Klingmuller and Lelieveld (2018); El Khalki et al. (2018); Zhong et al. (2019); Ganguli et al. (2020); etc. Calibrating hydrological models Motivation for Using ESA CCI SM Robust statistics based on long comparison period Period Realistic dry down characteristics Long-term availability Long-term availability Long-term dataset required for robust statistics based on long comparison period (2021); Piles et al. (2015); Kim et al. (2018); Klingmuller and Lelieveld (2018); Long-term dataset required for robust statistics based on long comparison period
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analysis (2018); El Khalki et al. (2018); Zhong et al. (2019); Ganguli et al. (2020); etc.
Calibrating hydrological models Kundu et al. (2017); Demirel et al. (2019); Koppa et al. (2019); etc. Not specified
Improved water budget modeling Allam et al. (2016); Abera et al. (2017); de Figueiredo et al. (2021); Mehrnegar et Long-term availability on probust statis- al. (2021); etc.
Computing changes in groundwater storage Asoka et al. (2017) Long-term availability for trends assessment
Modeling and understanding surface water dy- namics Heimhuber et al. (2017); Gu et al. (2019a); Khazaei et al. (2019); etc.
Assessing irrigation Qiu et al. (2016); Kumar et al. (2015); Zhang et al. (2018b); Paciolla et al. (2020); Long-term data equired for trend-based method of Qiu et al. (2022) (2015)
Assessing the impact of agricultural intensification on soil moisture Liu et al. (2015) Long-term data roverage needed for long-term impacts
Trigger of landslides Dahigamuwa et al. (2016); Dahigamuwa et al. (2018); Zhuo et al. (2019); etc. Long-term availability
Improving satellite rainfall retrievals Bhuiyan et al. (2017a); Bhuiyan et al. (2017b); Qiu et al. (2016); Kumar et al. Data record spans multiple satellite precipitation missions
Computing cumulative precipitation amounts Ciabatta et al. (2015); Liu et al. (2015); Ciabatta et al. (2018); Massari et al. (2019); Long data record needed for generation of iong-term precipitation dataset
Validating soil moisture products derived from Das and Maity (2015); Dahigamuwa et al. (2016); Ramsauer et al. (2021) Long-term availability for robust statistics precipitation
Evaluating soil moisture products derived from other satellite platforms Leng et al. (2017); De Zan and Gomba (2018); Pablos et al. (2018); Zhou et al. Long-term availability for robust statistics (2018); Cui et al. (2020b); Fan et al. (2020c); etc.
Evaluating in-situ networks Ford et al. (2020) Long-term availability

- Multi-decadal
- **Stability**
- Consistency

Application areas:

- Data assimilation
- Hydrological modeling
- Model Calibration
- Hydrological assessment & validation











Validating SSM fields in Land Surface Models

 Wang et al., 2022, Evaluated CMIP6 multimodel simulation with long-term SM dataset

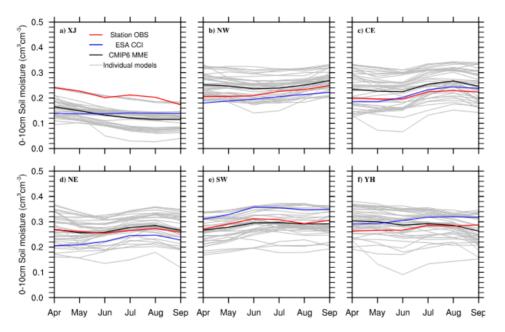


Figure 5. Seasonal cycles of regional mean surface (0–10 cm) soil moisture (SM) for station observation (WS2019, red curve), European Space Agency Climate Change Initiative (ESA CCI) data set (blue curve) individual CMIP6 model simulation (thin black curve), and multimodel ensemble mean (MME) (bold black curve) from the average SM of growing seasons (April to September) from 1992 to 2013. Regional divisions are indicated in Figure 1a.

Wang, A., Kong, X., Chen, Y., and Ma, X.: Evaluation of Soil Moisture in CMIP6 Multimodel Simulations Over Conterminous China, Journal of Geophysical Research: Atmospheres, 127, 10.1029/2022JD037072, 2022.







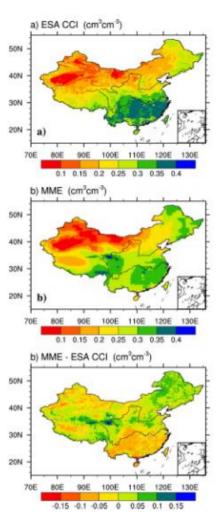


Figure 3. The mean soil moisture (SM) averaged over the growing season (April-September) for the period of 1992-2013 for (a) European Space Agency Climate Change Initiative (ESA CCI) data set; (b) 0-10 cm CMIP6 multimodel ensemble mean (MME), and (c) the differences between MME and ESA CCI. The area-weighted mean SM over China is 0.27 cm³ cm⁻³ from both MME and ESA CCI.



Use of Lake Water Level data to Lake modelling



IEEE TOURNAL OF SELECTED TOPICS IN APPLIED FARTH OBSERVATIONS AND REMOTE SENSING VOL. 7, NO. 2, FEBRUARY 2014

Numerical Simulation and Forecasting of Water Level for Qinghai Lake Using Multi-Altimeter Data Between 2002 and 2012

Jingjuan Liao, Le Gao, and Xiaoming Wang
DOI: 10.1109/JSTARS.2013.2291516

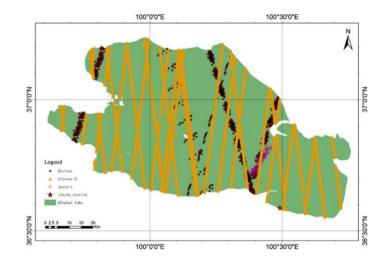
In this study, a combined linear periodic-residual model was established based on the SSA-extracted fluctuation signal from the lake-level time series of multi-altimeter data;

Least Square method and system bias correction algorithms \rightarrow abnormal water levels and the system bias were eliminated, and an accurate lake-level time series was obtained

SSA → eliminated white noise & the accuracy of the altimeter data reached the decimeter level in inland lake monitoring

The water level changes over lake Qinghai (Kokonor) were predicted until two years

SSA: Singular Spectrum Analysis



Lake Water Level of lake Qinghai, also known as Kokonor, is available in the C3S Climate Data Store

[Thanks to Beatrize Calmettes, CLS]











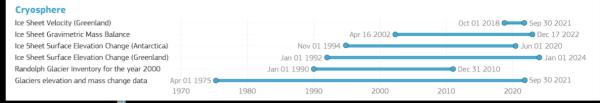
Land cryosphere domain

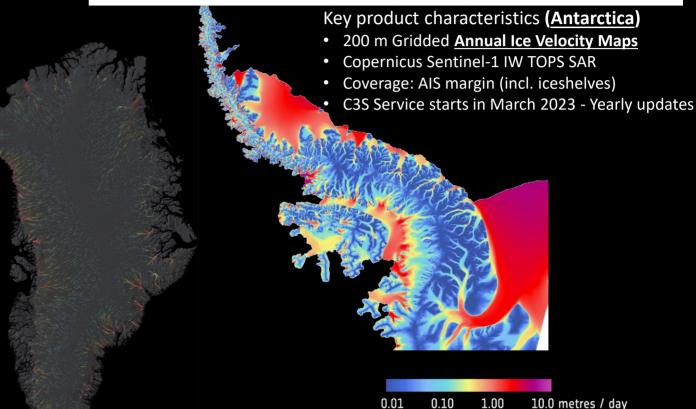
Consortium led by Environmental Observation Information Technology (ENVEO)

ECVs: Glaciers, Ice Sheets and Ice Shelves and *Snow*

Key product characteristics (Greenland)

- 250 m Gridded **Annual Ice Velocity Maps**
- Copernicus Sentinel-1 IW TOPS SAR
- Coverage: GIS margin (incl. iceshelves)
- Timeseries starts in 2014 Yearly updates







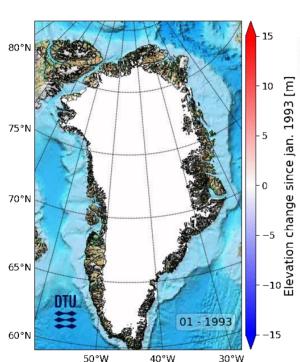






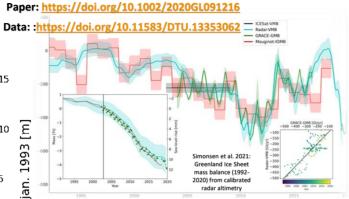
Surface Elevation Change



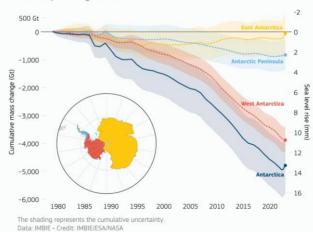


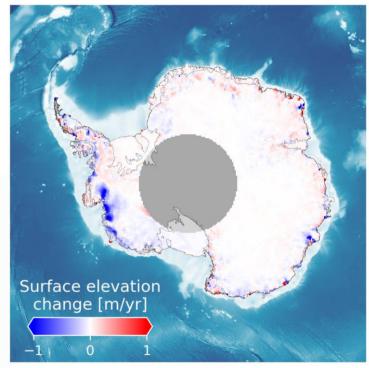
Greenland ice sheet mass balance from 1992- 2020: 12.1±2.3 mm s.l.e

More than 80% of this contribution occurs after 2003



Mass balance of the Antarctic Ice Sheet and its corresponding contribution to sea level rise





[Thanks to ENVEO]





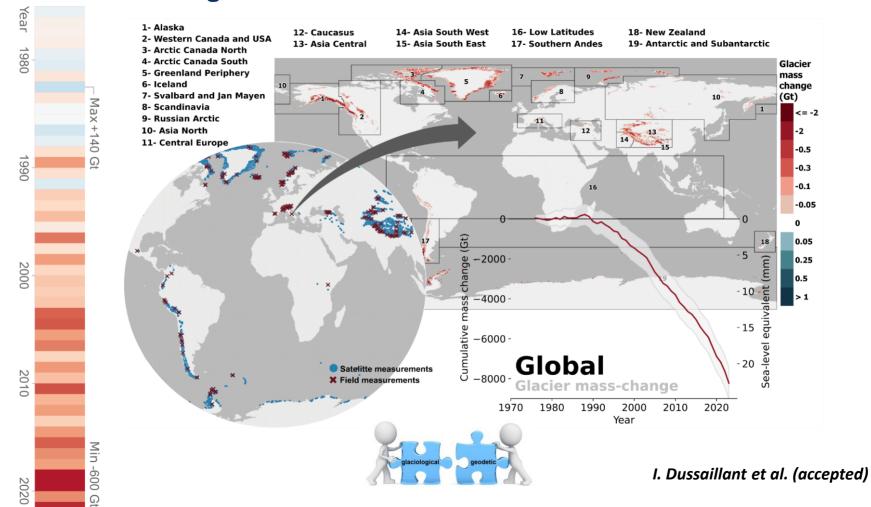






Glacier Mass Change









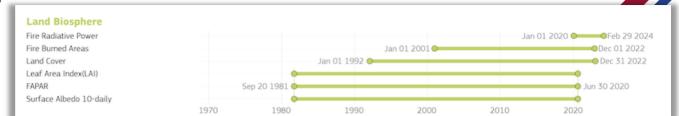




Land Biosphere domain

Consortium led by Brockmann Consult (BC).

ECVs: Fire, Land Cover, *Land Surface Temperature*



GlobCover: 2005 & 2009

2008

2010

LC + land surface seasonality + LC change

CC

CCI-LC 3 x 5-y epochs

CCI Land Cover concept revisited

2014 - 2016

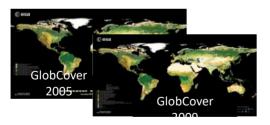
CCI-LC: annual series

2017

C3S:

operational

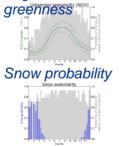
2018



Automated processing chain Gobal LC mapping at 300m From MERIS FRS 22 FAO-LCCS LC classes



5-y consistency 2000, 2005 and 2010 only forest change



Vegetation





Annual consistency 1992-2015 13 changes Operational Production 2016-2022



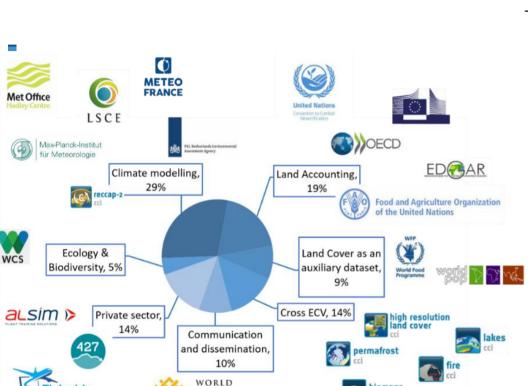








Land Cover



RESOURCES

INSTITUTE

Land Accounting & Climate Policy

-UNFCCC: Sustainable Development Goals (SDG) Indicator 15.3.1 Land degradation tracking

-FAOSTAT & OECD:

Agri-environmental and green growth indicators

-JRC EDGAR:

LULUCF parameters for GHG emissions/removals estimation

-LC maps integrated into **CMIP6** experiments, **HYDE**, and **HURTT** historical reconstructions of LULC for Earth system modelling.

Ecology & Biodiversity

-GEO BON (GEO Biodiversity Observation Network): Habitat distribution, fragmentation, biodiversity monitoring

-LifeWatch:

Remote sensing applications in biodiversity research

-Wildlife Conservation Society (WCS):

Global deforestation, fragmentation, human footprint via geoportals

-Biodiversity modellers & field ecologists:

Foundational input for habitat and ecological mapping

[Thanks to Celine Lamarche, UL]





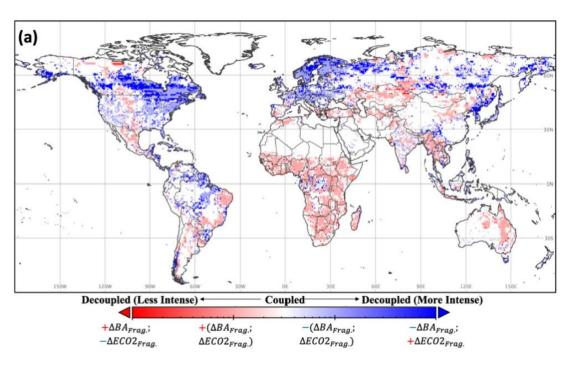


Fire Burned Area



The FireCCI51 dataset (converted to fire patches using the FRY2.0 dataset) has been used to analyse the relationship between land fragmentation and burned area (BA) occurrence, using the ORCHIDEF-SPITFIRE model.

On average, more fragmentation decreased net BA globally (-1.5%). However, in recently-deforested tropical areas, fragmentation drove observationally-consistent BA increases of over 20%.



https://doi.org/10.1038/s41467-024-53460-6

[Thanks to Lucrecia Pettinari, UAH]









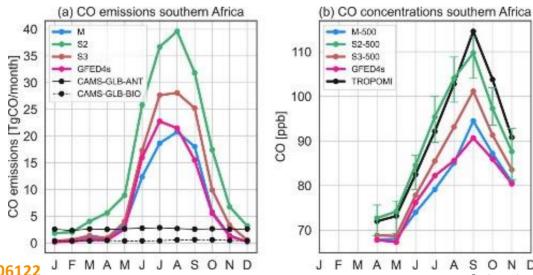


Fire Burned Area

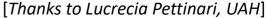


The FireCCIS311 product has been used to calculate Carbon Monoxide (CO) emissions in Southern Hemisphere Africa for 2019, and compared to TROPOMI observations.

From the different medium-resolution products available, FireCCIS311 (denoted in the graph as S3-500) shows the highest agreement with observations.













Enhancing the ECV offering











- Satellite ECVs
- Planned/ambition
- ECVs from reanalysis Ounavailable















Crucial to understand













































ATMOSPHERIC COMPOSITION





Precursors for

changes in our climate.

ANTHROPOSPHERE Anthropogenic Anthropogenic Water Use GHG Fluxes **HYDROSPHERE**













water storage

C3S responds to GCOS and UNFCCC implementation needs.

OCEAN BIOGEOCHEMISTRY





















Soil Moisture











BIOSPHERE



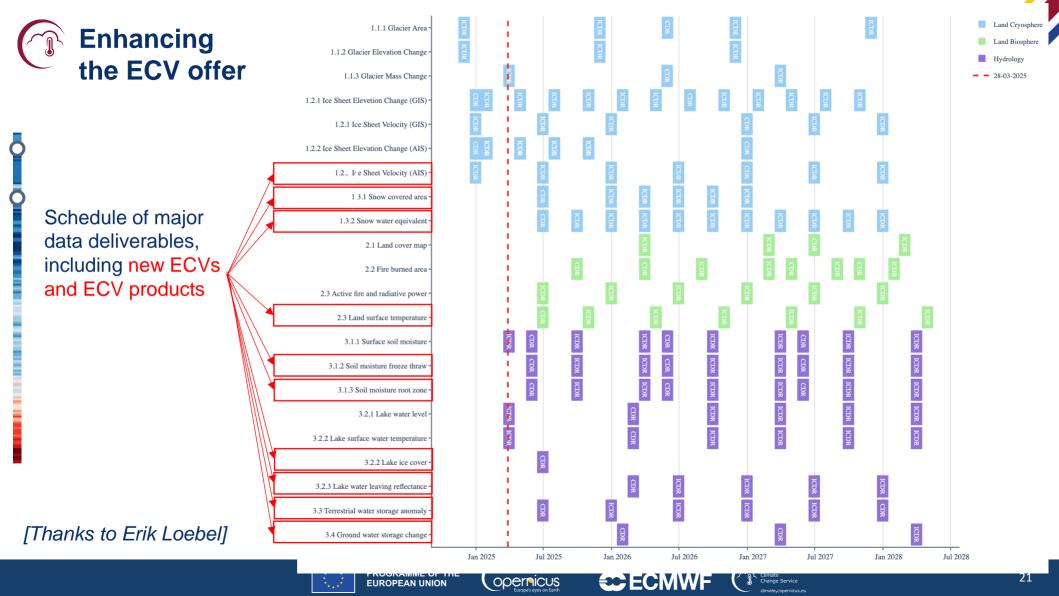










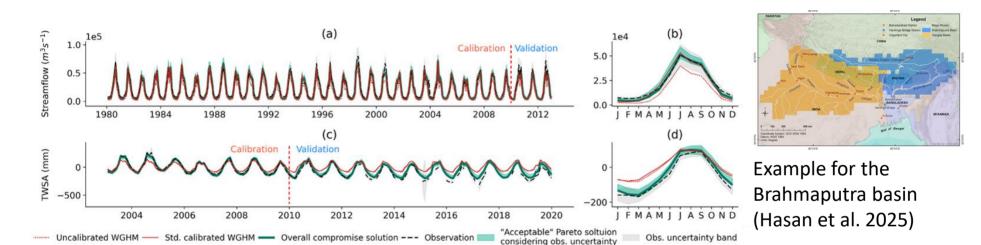




Terrestrial Water Storage for improving hydrological models



Use of terrestrial water storage anomalies (TWSA) for the multi-variable calibration of the WaterGAP Global Hydrological Model (WGHM)



→ Constraining the model with GRACE-based TWSA leads to a more consistent simulation of the water cycle of the river basins with respect to, e.g., TWS, streamflow or evapotranspiration

Hasan, M., Döll, P., Hosseini-Moghari, M., Papa, F., Güntner, A. (2025): The benefits and trade-offs of multi-variable calibration of the WaterGAP global hydrological model (WGHM) in the Ganges and Brahmaputra basins. *Hhydrology and Eaarth System Sciences, doi:10.5194/hess-29-567-2025*.

[Thanks to Andreas Güntner, GFZ]











Summary



- □ C3S runs a sustained programme of satellite-based Essential Climate Variables for climate monitoring.
- □ A core component of the service is the provision of long-term, consistent, and quality-controlled data records of ECVs, fundamental for directly observing and understanding climate variability and change.
- □ The C3S ECV programme operates as an ongoing, operational service, with a key objective being the regular extension of ECV datasets as close to real time as possible.
- These datasets are highly valuable for the land surface modelling community, supporting a wide range of applications including data assimilation, model calibration, evaluation and validation.
- □ In addition to satellite-derived products, C3S also provides access to land surface variables based on reanalysis (ERA5-Land) and in-situ networks, offering complementary sources of ancillary data for Earth system modeling.







Back up slides







ESA CCI SM as supportive data

Alberger et al., (2017): Model: Assimilation of satellite derived SSM and LAI

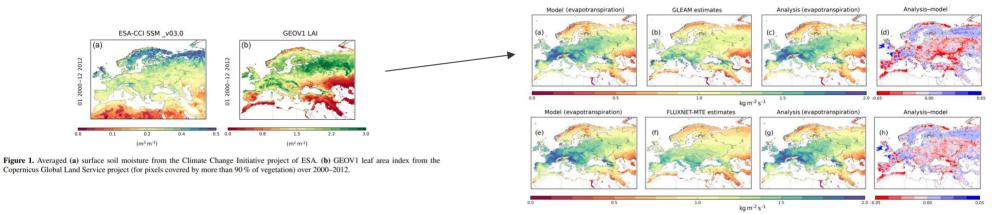


Figure 12. Top row: maps of averaged evapotranspiration taken over 2000–2012 from (a) the model (i.e open loop), (b) the GLEAM estimates, (c) the analysis and (d) differences between the analysis and model. Bottom row: maps of averaged evapotranspiration taken over 2000–2011 from (a) the model (i.e open loop), (b) FLUXNET-MTE estimates, (c) the analysis and (d) differences between the analysis and model.



Validating SSM fields in LSM with ESA CCI SM

Szczypta et al., 2014: compared ESA-CCI SM and ISBA-A-gs land surface model

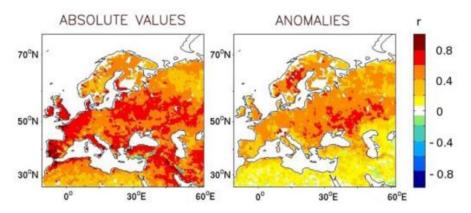
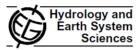


Figure 3. Comparison between the detrended ESA-CCI SSM and the detrended SSM simulated by ISBA-A-gs over the 1991–2008 period: Pearson correlation coefficient for (left) absolute values, (right) scaled anomalies (Eq. 1). White areas over land correspond to r values lower (higher) than 0.1 (-0.1).



Example 1: Use of LWL to calibrate and validate model Lake Turkana

Hydrol. Earth Syst. Sci., 16, 1–18, 2012 www.hydrol-earth-syst-sci.net/16/1/2012/ doi:10.5194/hess-16-1-2012 © Author(s) 2012. CC Attribution 3.0 License





A multi-source satellite data approach for modelling Lake Turkana water level: calibration and validation using satellite altimetry data

N. M. Velpuri¹, G. B. Senay^{1,2}, and K. O. Asante³

³Climatus LLC, 800 W El Camino 180, Mountain View, CA, USA

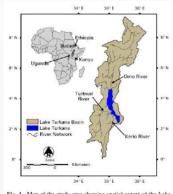
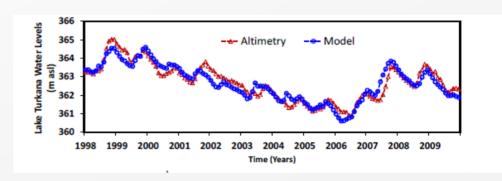


Fig. 1. Map of the study area showing spatial extent of the Lake Turkana basin in East Africa.

This study demonstrates that satellite altimetry data can be used for model calibration and validation.

"From this study, we suggest that globally available satellite altimetry data provide a unique opportunity for calibration and validation of hydrologic models in ungauged basins."



Lake Water Level of lake Turkana is available in C3S



¹GISc Center of Excellence, South Dakota State University, Brookings, SD, USA

²USGS Earth Resources Observation and Science (EROS) Center, Sioux Falls, SD, USA

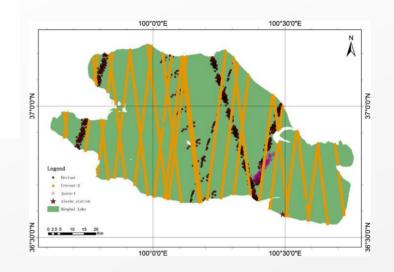
Example 2: Use of LWL to model Lake Quinghai (Kokonor)

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Numerical Simulation and Forecasting of Water Level for Qinghai Lake Using Multi-Altimeter Data Between 2002 and 2012

Jingjuan Liao, Le Gao, and Xiaoming Wang

In this study, a combined linear periodicresidual model was established based on the SSA-extracted fluctuation signal from the lake-level time series of multi-altimeter data. The water level changes over lake Qinghai (Kokonor) were predicted until two years



Lake Water Level of lake Qinghai, also known as Kokonor, is available in C3S

SSA: Singular Spectrum Analysis DOI: 10.1109/JSTARS.2013.2291516

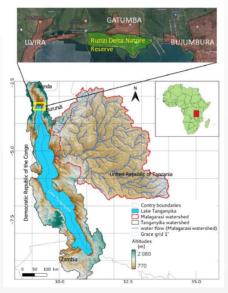


Example 3: Use of LWL on water balance analysis

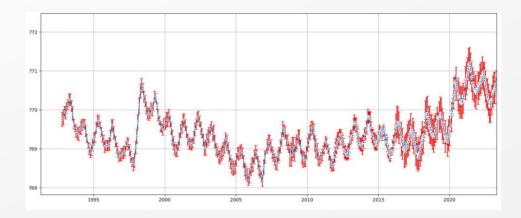
Lake Tanganyika basin water storage variations from 2003–2021 for water balance and flood monitoring

Paul Gérard Gbetkom ^{a, *}, Jean-François Crétaux ^a, Sylvain Biancamaria ^a, Alejandro Blazquez ^a, Adrien Paris ^{c, a}, Michel Tchilibou ^{a, 1}, Laetitia Gal ^{c, a}, Benjamin Kitambo ^a, Rômulo Augusto Jucá Oliveira ^{c, a}, Marielle Gosset ^b

The Hydroweb database was used to obtain Lake Tanganyika surface water storage (SWS) fluctuations



Use of the lake water level on the Lake Tanganyika basin water balance between 2003 and 2021 to assess the influence of recent climate variability



Lake Water Level of lake Tanganyika (Tanganika) is available in C3S

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