Use of spatial and in situ EOs in Land Surface Modelling

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ESA Climate Office

Focal point for coordinating Earth Observation work conducted by ESA relating to **climate and climate change**

ipcc

WORLD METEOROLOGICAL ORGANIZATION

GCOS
GLOBAL CLIMATE OBSERVING SYSTEM

WCRP
World Climate Research Programme

GEO

SCO
SPACE CLIMATE OBSERVATORY

CGMS

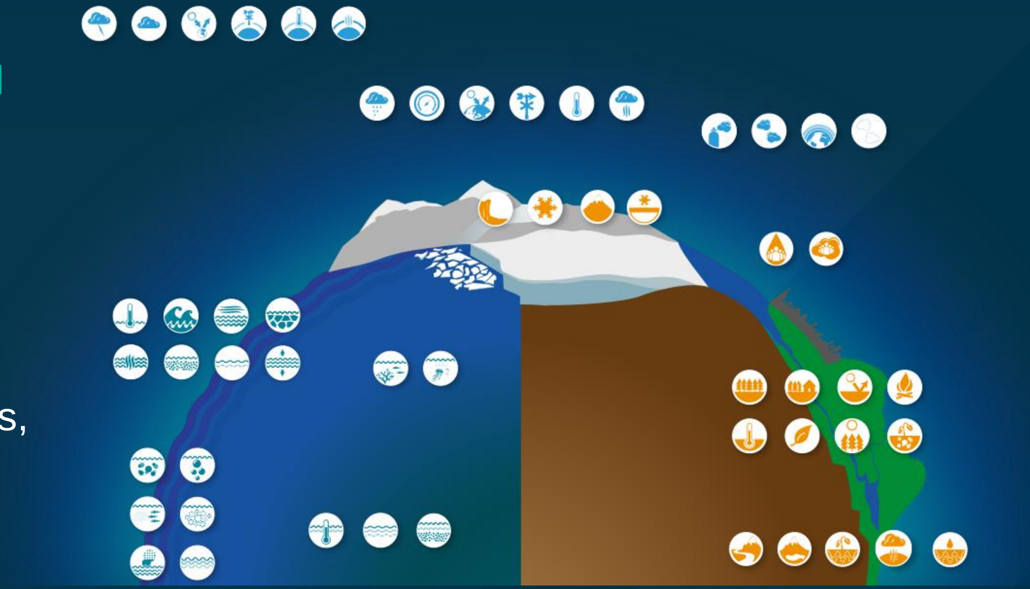
CEOS
The Committee on Earth Observation Satellites

What is an Essential Climate Variable?

ECV* datasets provide the **long-term empirical evidence** needed to understand and predict the key components of the climate

They are required to support the work of the **UNFCCC and the IPCC** to guide mitigation and adaptation measures, assess risks and enable attribution of climate events to underlying causes, and to underpin climate services

54 ECVs, 36 can be monitored from space



There are 54 ECVs defined by the Global Climate Observing System GCOS 2016 Implementation Plan, GCOS-200: https://gcos.wmo.int/en/gcos-implementation-plan

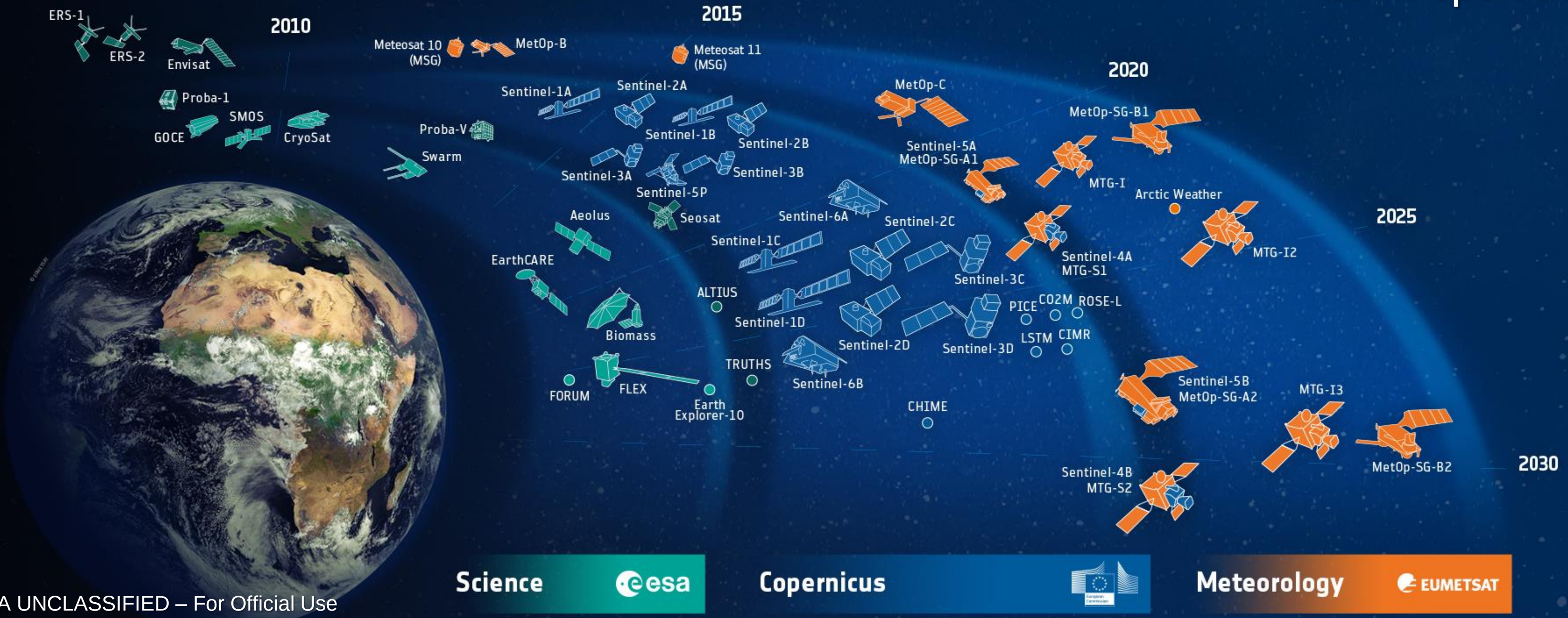
* An ECV is a physical, chemical, or biological variable or a group of linked variables that critically contributes to the characterization of Earth's climate.
S. Bojinski *et al.*, BAMS 2014, doi.org/10.1175/BAMS-D-13-00047.1

ESA-Developed Earth Observation Missions

Satellites

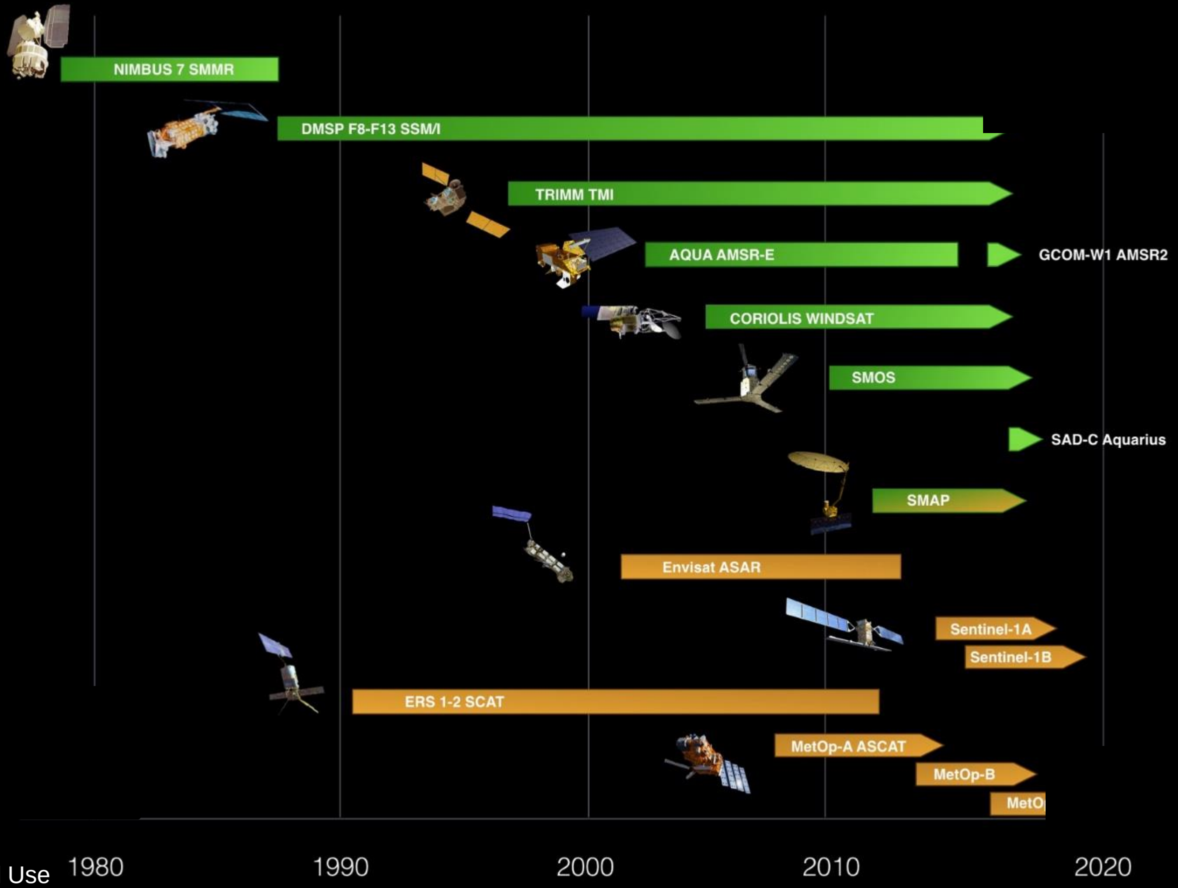
25 under development

15 in operation



ESA UNCLASSIFIED – For Official Use

Exploiting the EO satellite archive : an example



ESA Climate Change Initiative

Established 2010

23 ECV projects, 2 budget closure projects, a data support project and a climate modelling project

13 ECVs transferred to C3S

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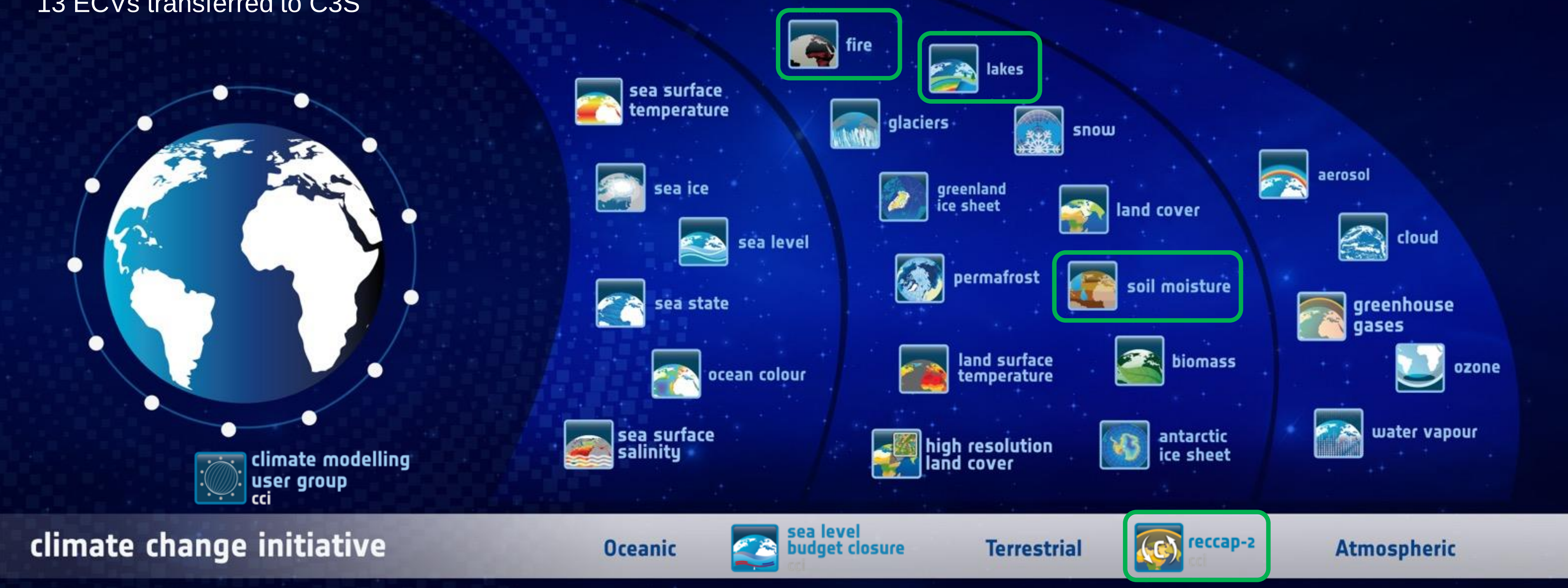
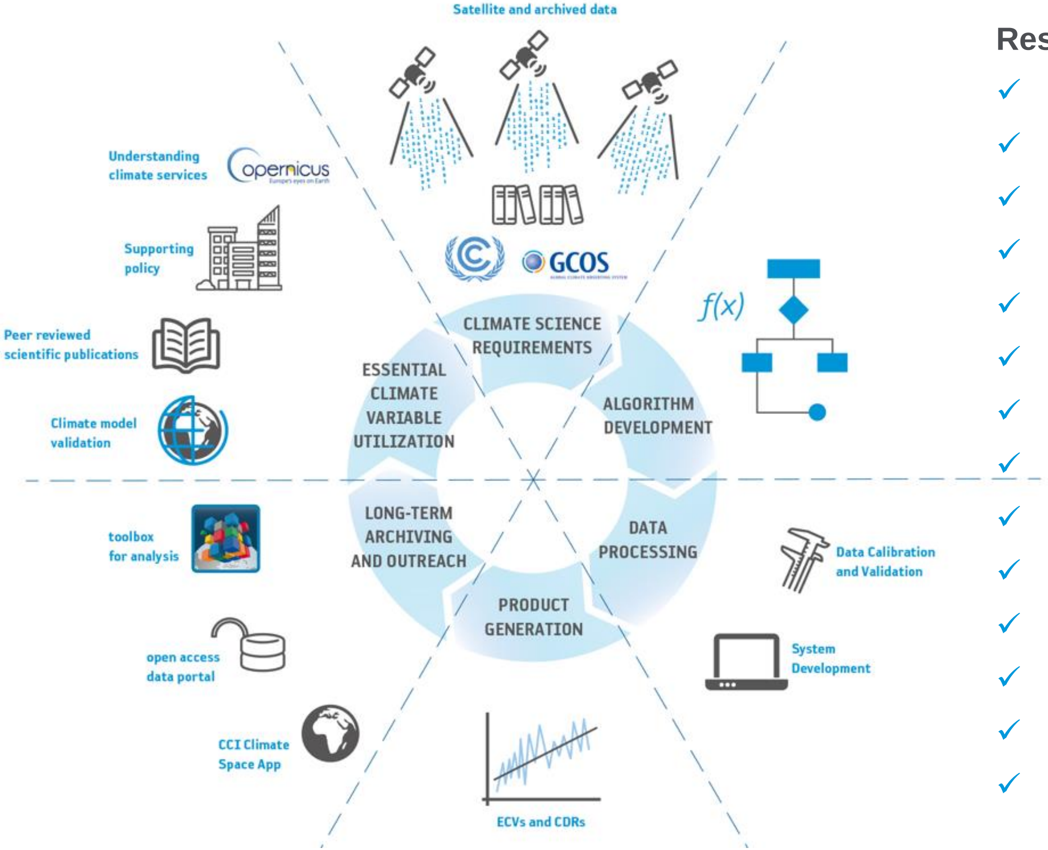


Generating *research-quality* ECV datasets



Research quality data

- ✓ Global coverage (where applicable)
- ✓ Long time series (20-30 years)
- ✓ Gridded (at a usable resolution e.g. ¼ degree)
- ✓ Validated (by in situ observations) and tested
- ✓ Bias corrected (e.g. between different satellites)
- ✓ Uncertainty characterisation (per pixel, correlated…)
- ✓ Useful temporal resolution (daily, monthly…)
- ✓ Consistency between CCI_ECV datasets
- ✓ Fully documentation & version controlled
- ✓ Peer reviewed publications
- ✓ Available on CCI Data Portal, and Copernicus Services
- ✓ Can be sourced back to algorithm choice
- ✓ Level 1, 2 or 3
- ✓ Supporting information, e.g. cloud masks

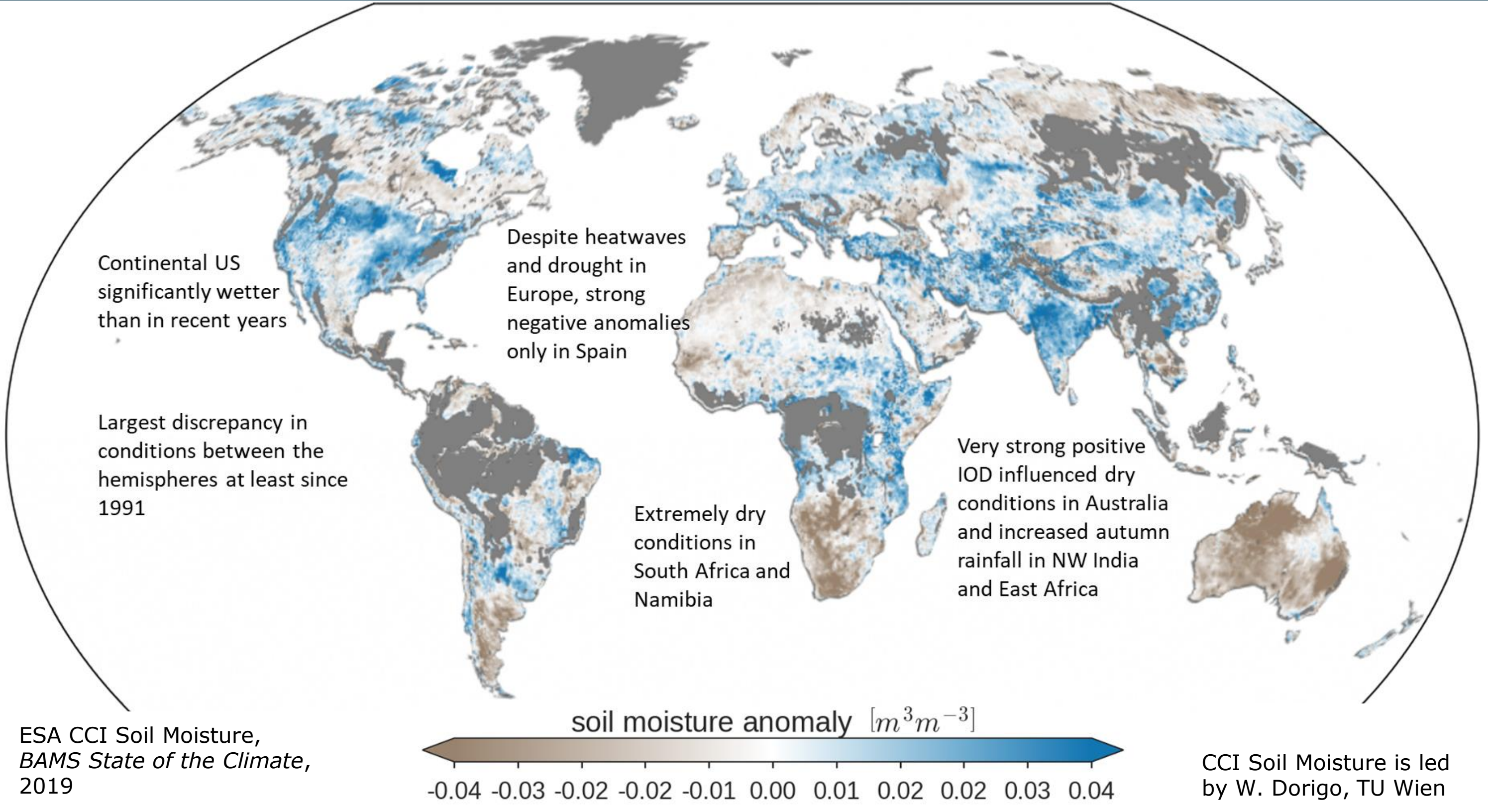
Access ECV climate data – CCI Open Data Portal

Open Access & Free

climate.esa.int/data

2019 Global Soil Moisture Anomalies

ESA CCI Soil Moisture v04.7 COMBINED product, 1991-2019



ESA CCI Soil Moisture, *BAMS State of the Climate*, 2019

CCI Soil Moisture is led by W. Dorigo, TU Wien

The Guardian

'Indian El Niño' behind east Africa flooding

Irregularity known as Indian Ocean dipole bringing weather extremes across region

People row through a flooded area in Boma state, South Sudan. At least 76 people have died and over 400,000 people have been displaced since flooding began last month. Photograph: Peter Louis/AFP via Getty Images

Kenya suffers worst locust infestation in 70 years as millions of insects swarm farmland

UN urges immediate action as east African nations already experiencing devastating hunger see large areas of crops destroyed

Dozens die in northern India as late monsoon rains trigger floods

Retreating monsoon rains have led to deadly floods across wide areas of Uttar Pradesh state

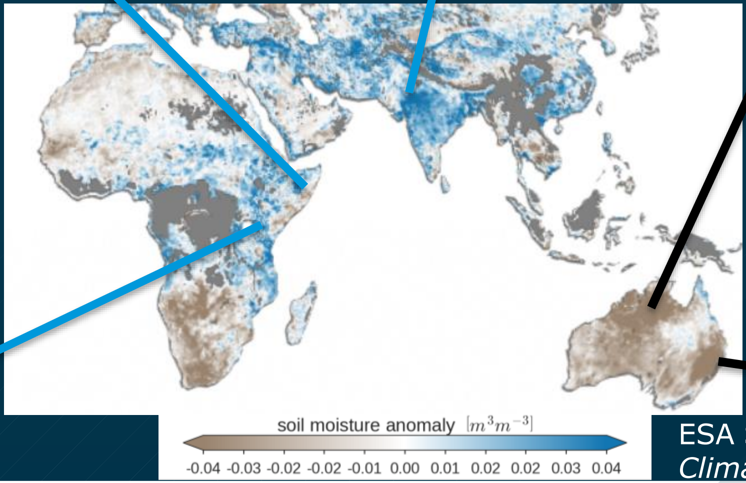
Australia records its hottest day ever - one day after previous record

Average maximum reaches temperature of 41.9C or 107.4F on Wednesday - a full degree above previous mark set the day before

NSW and Qld fires: South Australia also faces catastrophic bushfires risk as PM apologises for holiday - live

Australian bushfires will cause jump in CO_2 in atmosphere, say scientists

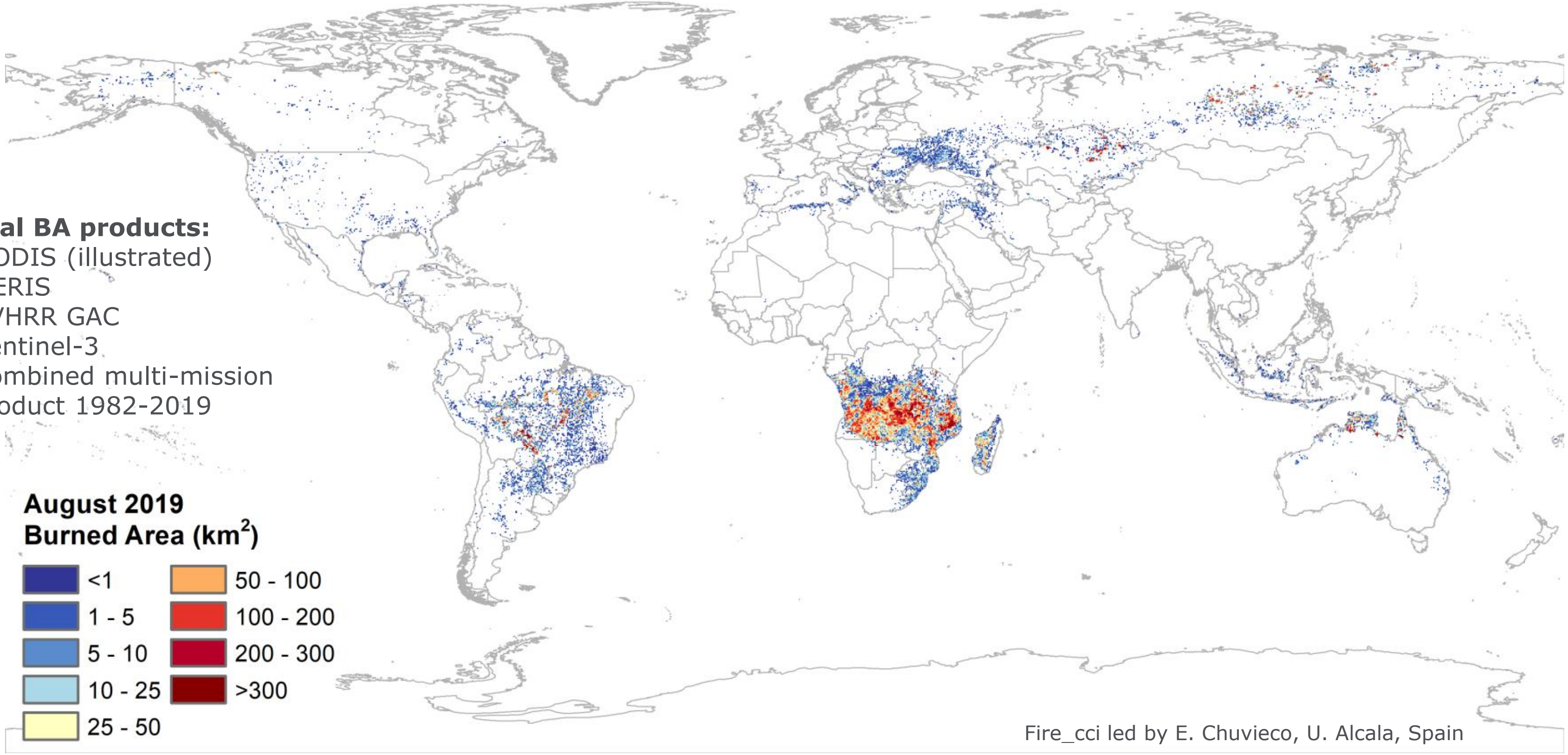
Fires released vast amounts of carbon dioxide and reduced vegetation, pushing planet closer to point of no return



ESA Soil Moisture_cci *BAMS State of the Climate*, in prep.

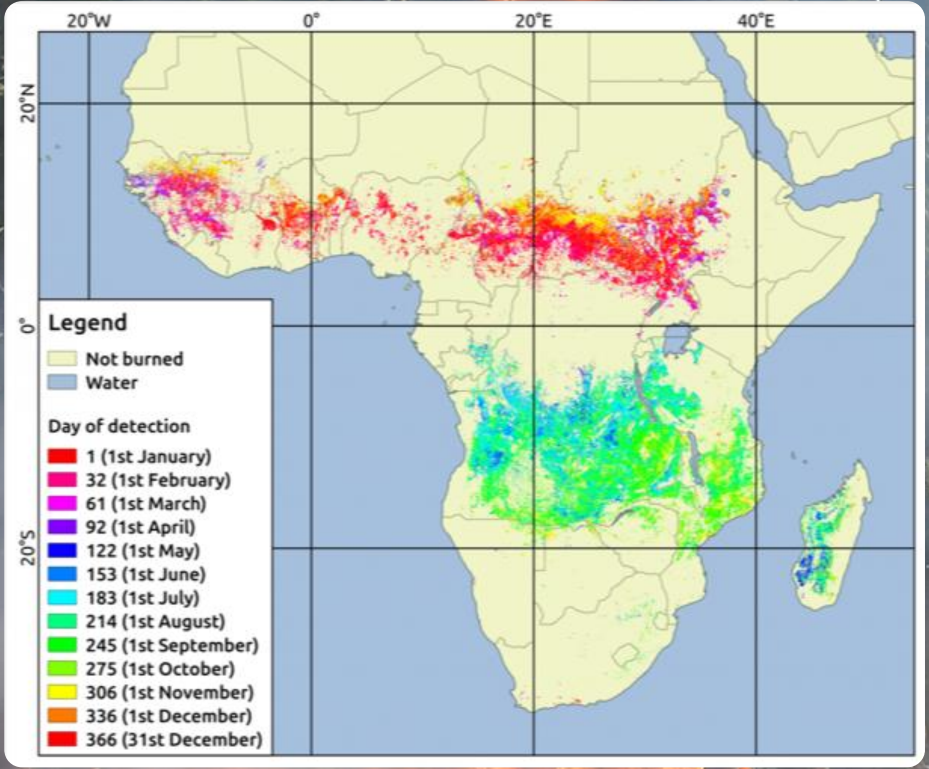
Global BA products:

- MODIS (illustrated)
- MERIS
- AVHRR GAC
- Sentinel-3
- Combined multi-mission product 1982-2019



Fire_cci led by E. Chuvieco, U. Alcala, Spain

Small Fires (<100ha)



Small fire database of sub-saharan Africa showing burned area detected during 2016 using Sentinel-2.
Roteta *et al*., 2019 https://doi.org/10.1016/j.rse.2018.12.011

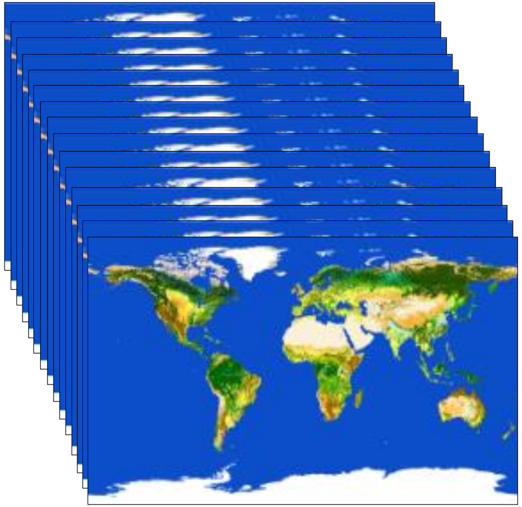
Using Copernicus Sentinel-2 data, an **additional** 2.2 million km^2 of burned area was detected across Africa in 2016.

i.e. 80% more than the std global MODIS BA product.

Land Cover ECV

cci.esa.int/hrlandcover
www.esa-landcover-cci.org

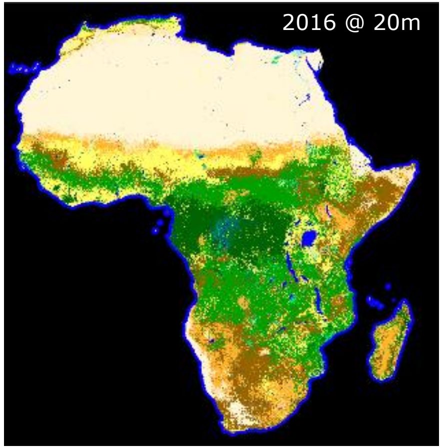
CCI LC yearly maps
1992 » 2015

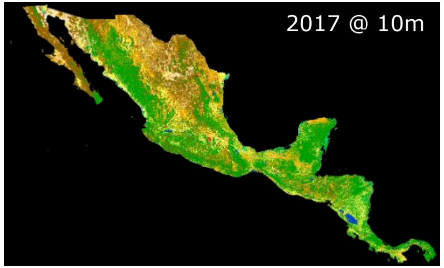


Interactive viewer:
http://maps.elie.ucl.ac.be/CCI/viewer

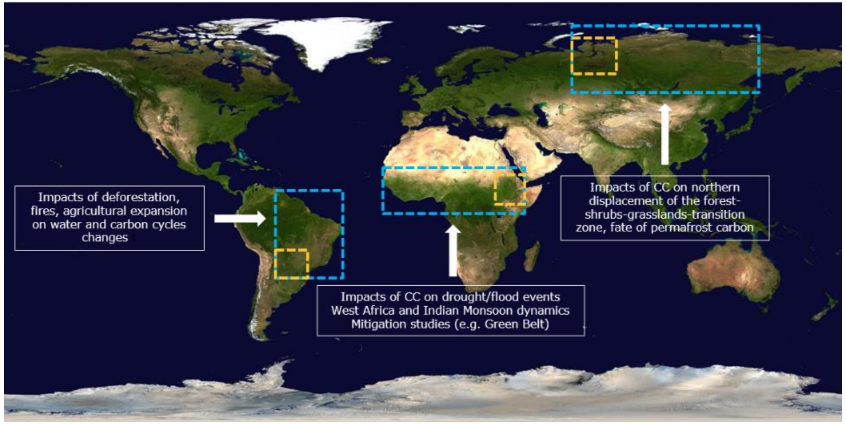
CCI Land Cover led by P. Defourney, UCL Belgium

Sentinel-2 Prototype LC maps





New HR LC maps in development

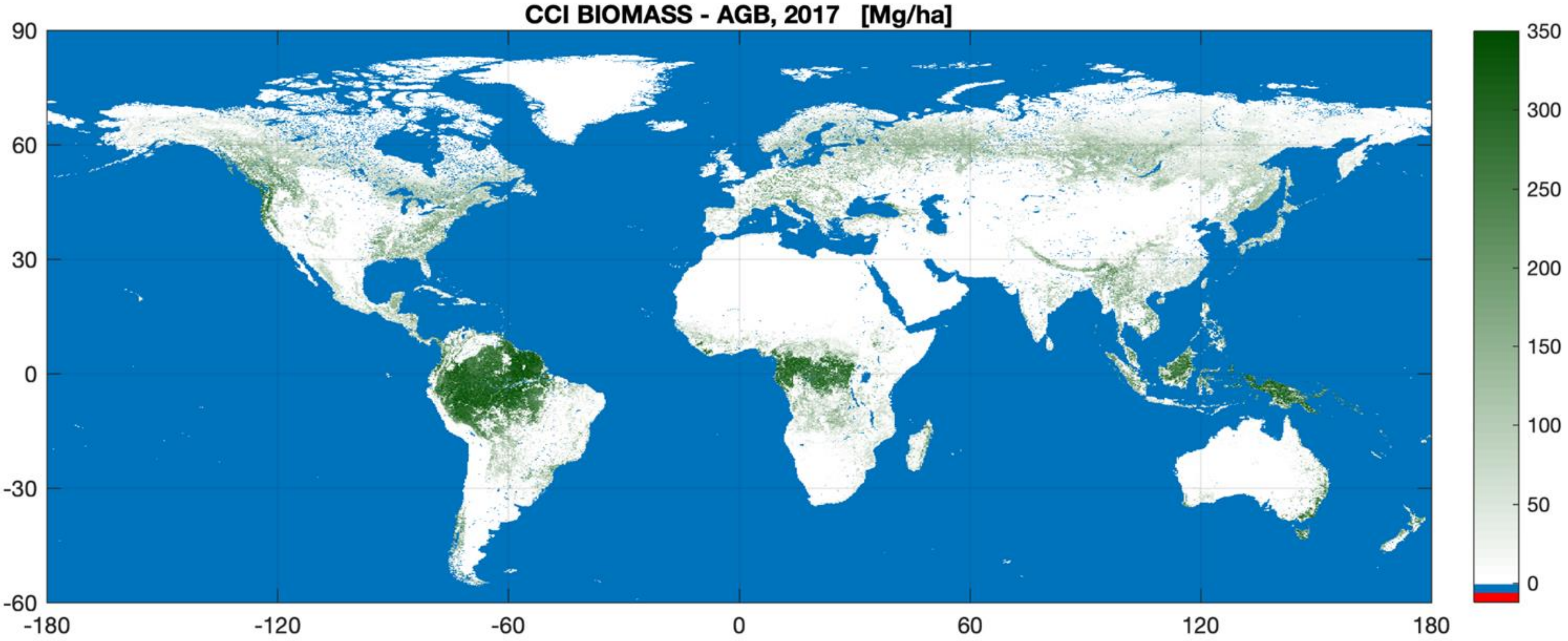


Blue rectangles: 10m reference maps
Yellow rectangles: 30m LC change maps (1990-2015)
334 Tbytes – Sentinel-2
10 Tbytes – Sentinel-1
45Tbytes – Landsat 5/7/8

CCI HR Land Cover led by L. Bruzzone, U. Trento, Italy

Above Ground Biomass ECV

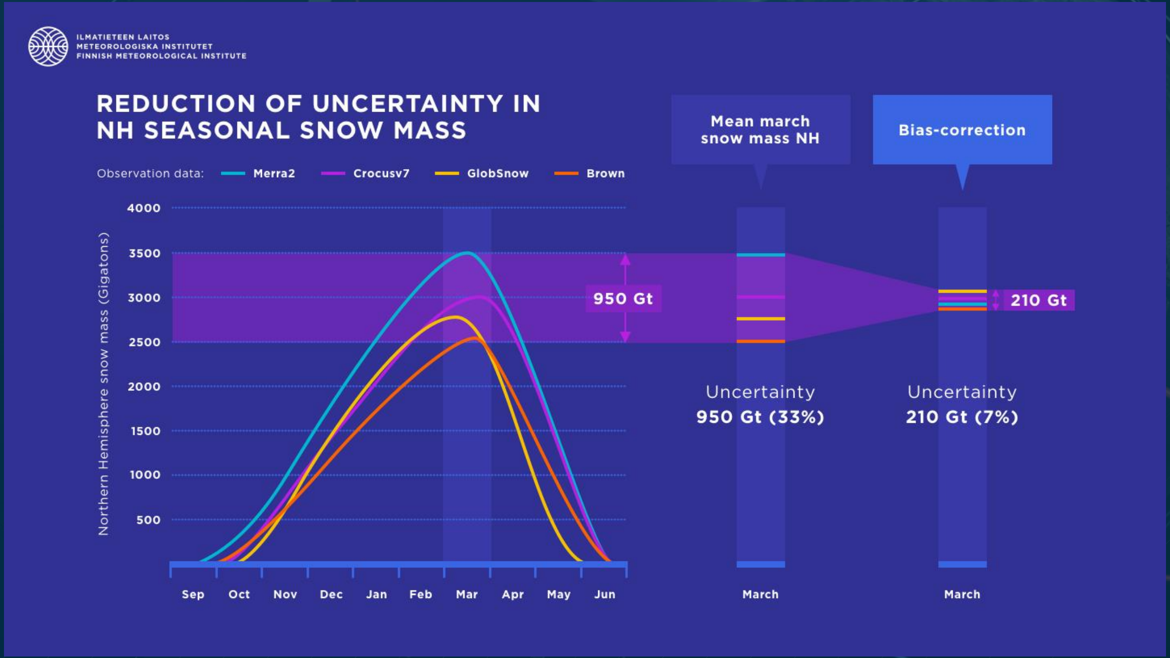
cci.esa.int/biomass



- Data to inform the Global Stocktake for the Paris Agreement commitments and REDD+
- First of a **series of maps to quantify the change in forest biomass** over time

CCI Biomass led by S. Quegan, U. Sheffield, UK

Snow mass estimates now more reliable



Pulliainen, J., Luojus, K., Derksen, C. *et al.* Patterns and trends of Northern Hemisphere snow mass from 1980 to 2018. *Nature* **581,** 294–298 (2020). https://doi.org/10.1038/s41586-020-2258-0

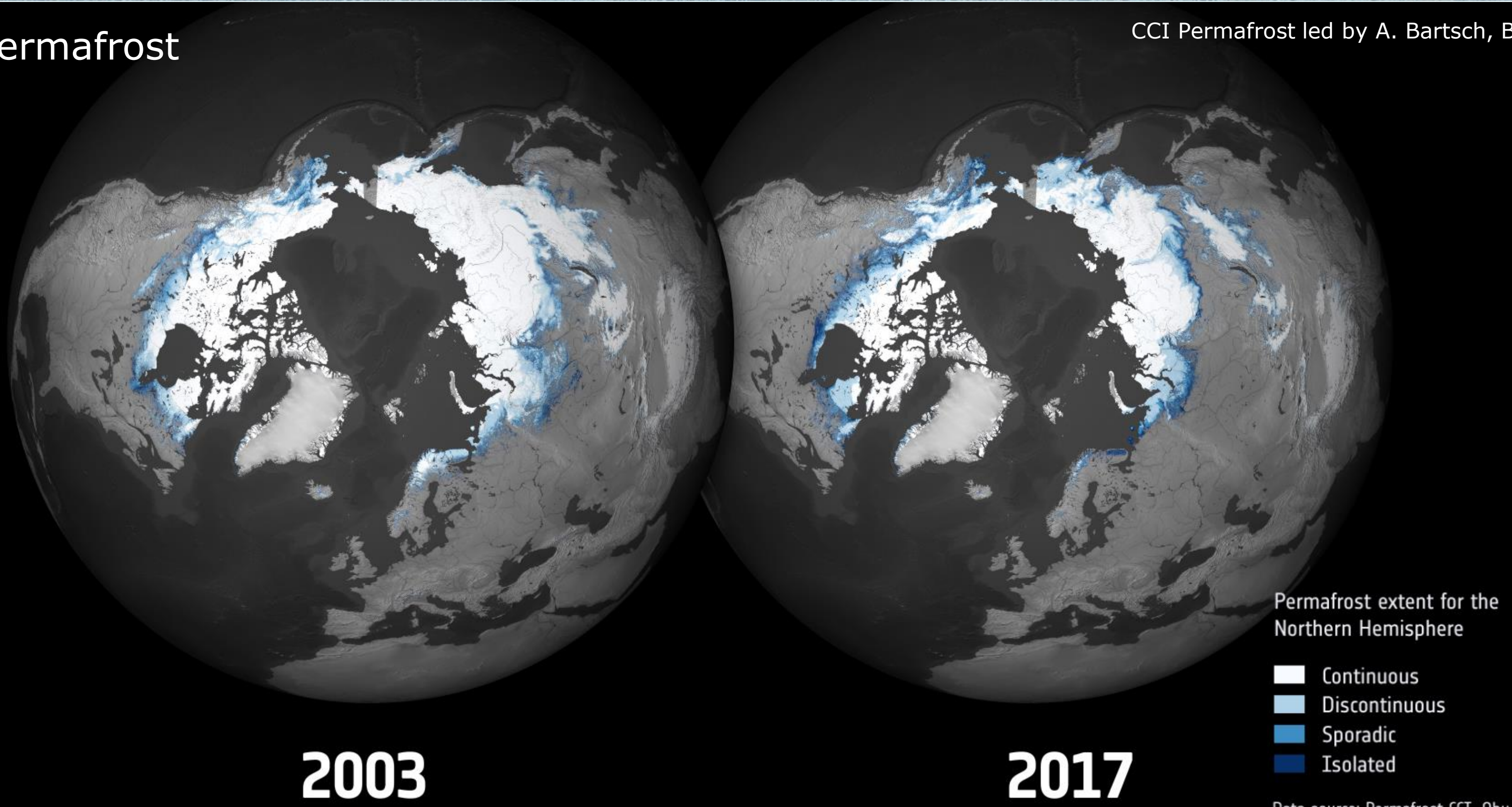
- Snow_cci combined 39-year (1980-2018) satellite-derived snow mass climate data record (GlobSnow 3.0) with ground-based snow depth measurements.
- Bias-correction reduced uncertainty of NH annual maximum snow mass from 33% (950 Gt) to 7.4%(210 Gt)
- Improved long-term CDR of snow mass has enabled continental-scale trends to be investigated For example, snow mass decreased by 46 Gt per decade across North America

Permafrost ECV

cci.esa.int/permafrost

Thawing Permafrost

CCI Permafrost led by A. Bartsch, B.GEOS, Austria



Data source: Permafrost CCI, Obu et al., 2019
via the CEDA archive
doi:10.5194/tc-14-497-2020

CCI Achievements

450 European scientists

178 Institutions

21 ECVs

13 ECVs transferred to Copernicus

Open data

133 terabytes

100+ datasets

4.2 million files

640 Peer-reviewed articles

IPCC AR5

28 Contributing authors

15 Papers, cited 60 times

Use of spatial & in situ EOs in Land Surface Modelling

Integrating observations into models covers several aspects:

(1) The use of observations for model validation and evolution

(2) The dynamic integration of observations into models through data assimilation techniques

(3) The mapping of the model parameters used to characterize the representation of land properties within the model (e.g., soil properties, land cover)

Balsamo, G.; Agusti-Panareda, A.; Albergel, C.; Arduini, G.; Beljaars, A.; Bidlot, J.; Blyth, E.; Bousserez, N.; Boussetta, S.; Brown, A.; Buizza, R.; Buontempo, C.; Chevallier, F.; Choulga, M.; Cloke, H.; Cronin, M.F.; Dahoui, M.; De Rosnay, P.; Dirmeyer, P.A.; Drusch, M.; Dutra, E.; Ek, M.B.; Gentine, P.; Hewitt, H.; Keeley, S.P.; Kerr, Y.; Kumar, S.; Lupu, C.; Mahfouf, J.-F.; McNorton, J.; Mecklenburg, S.; Mogensen, K.; Muñoz-Sabater, J.; Orth, R.; Rabier, F.; Reichle, R.; Ruston, B.; Pappenberger, F.; Sandu, I.; Seneviratne, S.I.; Tietsche, S.; Trigo, I.F.; Uijlenhoet, R.; Wedi, N.; Woolway, R.I.; Zeng, X. ***Satellite and In Situ Observations for Advancing Global Earth Surface Modelling: A Review.*** *Remote Sens. 2018, 10, 2038.*

Observations for model validation and evolution

Use of In situ measurements for model parameterisation

- Data from the SMOSREX experimental site

➔ Used to enhance ISBA-A-gs R_{eco} representation,

a simple representation of the soil moisture effect on R_{eco} has been implemented resulting in an improvement of the modelled CO2 flux

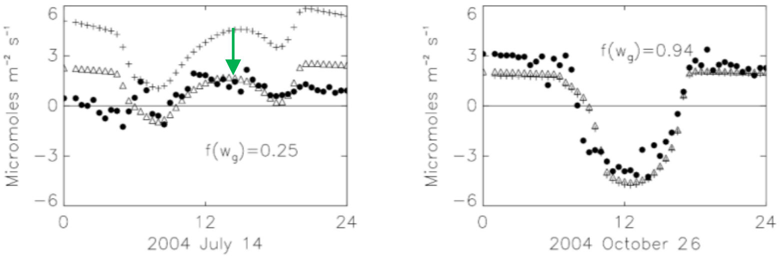


Fig. 3. Comparison of NEE simulations of ISBA-A-gs based on R_{eco} calculated from either Eq. (1) or Eq. (4) (+ and triangles, respectively), with NEE observations (dots), for two days presenting contrasting soil moisture conditions: (left) 14 July 2004, (right) 26 October 2004.

Albergel et al., 2010, www.biogeosciences.net/7/1657/2010

Observations for model validation and evolution

Use of In situ measurements for model parameterisation

- In situ soil moisture data from 122 stations a cross the United States are used to evaluate the impact of a new bare ground evaporation formulation at ECMWF

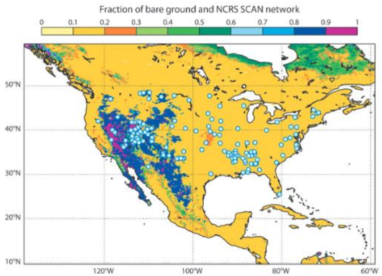
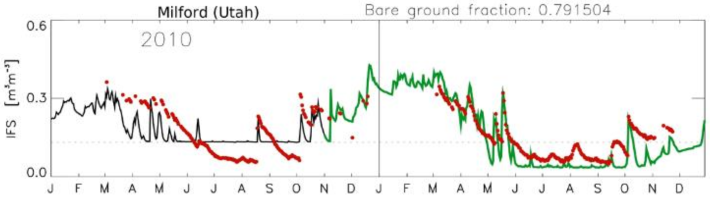


Fig. 1. Location of the different in situ soil moisture stations used in this study (blue circles); the stations belong to the NRCS-SCAN network (United States). Colour scale represents the fraction of bare ground.

Lower stress threshold for bare ground evaporation than for the vegetation in ECMWF IFS

➔ higher evaporation

➔ more realistic soil moisture values when compared to in situ data, particularly over dry areas



Albergel et al., 2012, www.hydrol-earth-syst-sci.net/16/3607/2012/

Observations for model validation and evolution

Use of Satellite remote sensing for model parameterisation

- Impact of the new bare ground evaporation on terrestrial microwave emission and comparison with SMOS

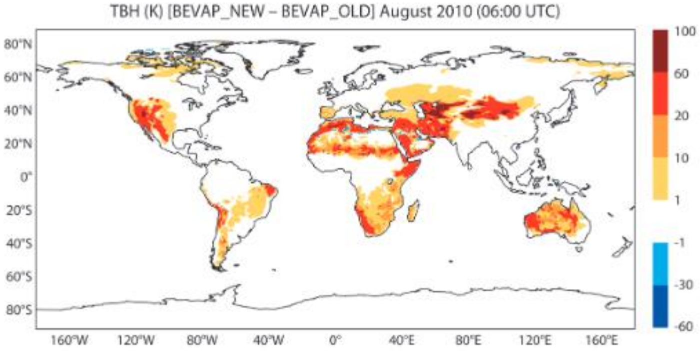


Fig. 6. Map of differences between TB (horizontal polarisation, 40° incidence angle in K) simulated using model fields from BEVAP_NEW and BEVAP_OLD for August 2010 (06:00 UTC).

Albergel et al., 2012, www.hydrol-earth-syst-sci.net/16/3607/2012/

Observations for model validation and evolution

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- Impact of the new bare ground evaporation on terrestrial microwave emission and comparison with SMOS

Table 6. Monthly mean statistics of the difference between SMOS TB observations and simulated TB. Results are given at 06:00 UTC, both BEVAP_OLD and BEVAP_NEW, at both horizontal and vertical polarizations, based on 40° incidence angle observed and simula TB.

2010	TB (BEVAP_OLD) 06UTC				TB (BEVAP_NEW) 06UTC			
	TBH		TBV		TBH		TBV	
	Mean Bias (K)	SD (K)	Mean Bias (K)	SD (K)	Mean Bias (K)	SD (K)	Mean Bias (K)	SD (K)
January	28.6	28.6	12.8	21.0	22.4	27.6	9.0	20.7
February	28.9	28.1	12.7	20.8	22.9	27.1	9.3	20.6
March	29.5	29.7	12.7	24.3	23.2	28.8	8.9	21.6
April	29.8	29.1	13.7	20.4	23.4	28.6	9.9	20.9
May	31.5	28.0	14.4	20.0	24.4	27.7	10.2	20.7
June	32.6	28.9	14.8	21.1	25.5	28.7	10.6	21.7
July	31.7	28.2	14.1	20.4	24.8	28.3	9.9	21.0
August	33.4	28.8	15.4	20.5	58.8	29.8	11.1	21.4
September	34.2	29.1	16.5	20.7	26.6	30.3	12.1	21.8
October	33.5	28.7	15.4	20.0	25.65	29.6	10.8	20.9
November	32.4	28.2	14.3	19.8	24.4	28.6	9.5	20.4
December	30.0	28.2	14.5	20.4	23.8	28.1	10.8	20.4

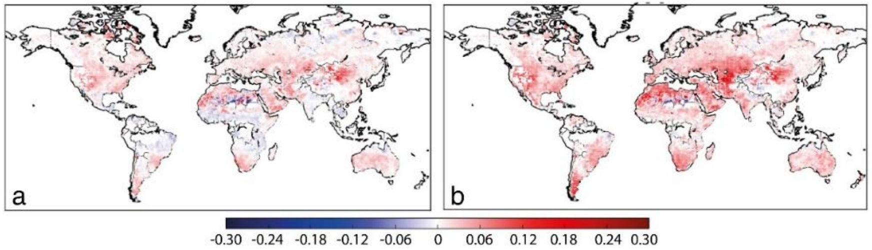
Albergel et al., 2012, www.hydrol-earth-syst-sci.net/16/3607/2012/

European Space Agency

Observations for model validation and evolution

Use of Satellite remote sensing for model parameterisation

- Impact of a thinner top soil layer in HTESSEL assessed using ESA CCI soil moisture dataset



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 (0–1 cm), GA89 of 7 cm depth (0–7 cm). 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.

- Red colours: using a 1 cm instead of a 7 cm surface layer depth leads to a better match with the ESA CCI SM

Dorigo et al., 2017, https://doi.org/10.1016/j.rse.2017.07.001

European Space Agency

Land Surface Data Assimilation

- **Current fleet of Earth Satellite missions holds an unprecedent potential to quantify Land Surface Variables (LSVs)**

[Lettenmaier et al., 2015, Balsamo et al., 2018]

→ Spatial and temporal gaps & cannot observe all key LSVs (e.g. RZSM)

- **Land Surface Models (LSMs)** provide LSV estimates at all time/location

→ LSMs have uncertainties

- Through a weighted combination of both, LSVs can be better estimated than by either source of information alone *[Reichle et al., 2007]*

→ **Data assimilation**

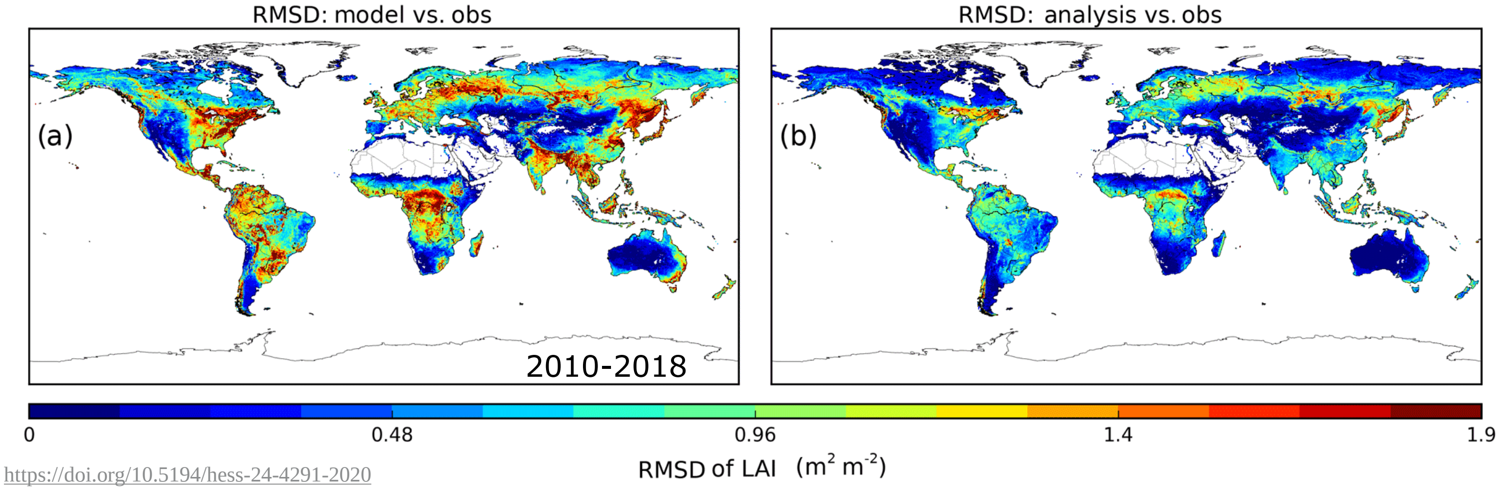
Spatially and temporally integrates the observed information into LSMs in a consistent way to unobserved locations, time steps and variables

Land Surface Data Assimilation

LDAS-Monde: global capacity offline integration of satellite observations into a land surface model fully coupled to hydrology *[Albergel et al., 2017 to 2020]*

LDAS-Monde involves

- Land surface model: ISBA-A-gs
- River routing system: CTRIP (CNRM-Total Runoff Integrating Pathways, now 1/12°)
- Data assimilation routines (SEKF, EnSRF, *PF*)
- Satellite derived observations (SSM, LAI)

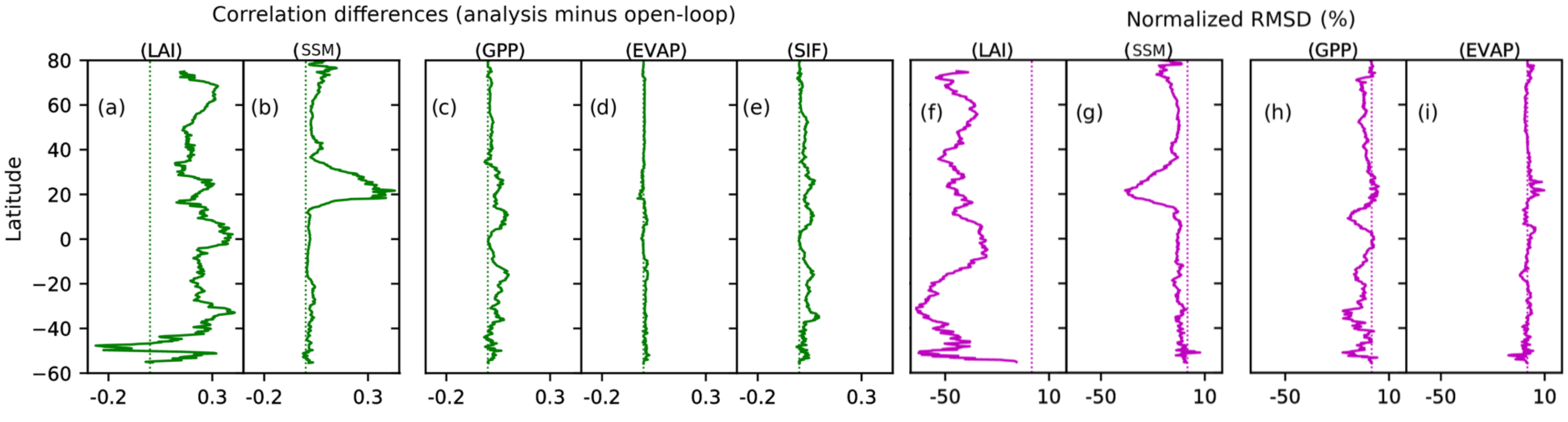


Albergel et al., 2020, https://doi.org/10.5194/hess-24-4291-2020

Land Surface Data Assimilation

LDAS-Monde successfully validated at regional/continental / global scales

Agricultural statistics, River discharge, In situ measurements of soil moisture, Evapotranspiration from GLEAM, Fluxnet2015, Gross Primary Production from FLUXCOM, Sun-Induced Fluorescence



Latitudinal plots of score differences (analysis minus open-loop) for correlations(a–e)and normalized RMSD(f–i)for LAI(a,f), SSM(b, g), GPP(c, h), EVAP(d, i)and SIF (e, correlations only). Scores are computed based on the monthly average over 2010–2018 for LAI and SSM, 2010–2013 for GPP, 2010–2016 for EVAP and 2010–2015 for SIF. Dashed lines represent the zero lines (equal scores for open-loop and analysis).

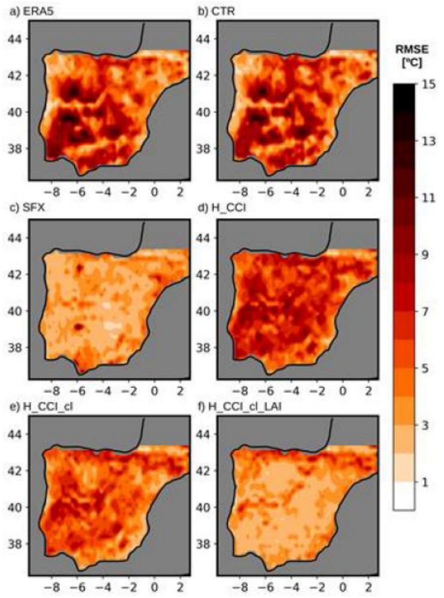
Albergel et al., 2020, https://doi.org/10.5194/hess-24-4291-2020

Mapping of model parameters: Land Cover & vegetation

- Recent study has found large errors of land surface temperature(LST) in ERA-Interim/ERA5 over Iberia in summer, errors are associated with the vegetation cover and seasonality [Johansen et al., 2019, RS]

Offline simulations 2004-2015 driven by ERA5 meteorology

Name	Description
ERA5	ERA5
CTR	CHTESSEL offline
SFX	SURFEX offline
H_CCI	CTR with vegetation fraction and types from ESA-CCI
H_CCI_cl	H_CCI with clumping for cvegl and cvegh
H_CCI_cl_LAI	H_CCI with clumping for cvegl and cvegh + CGLS LAI



Maps of JJA daily maximum LST RMSE over Iberia under clear-sky conditions, computed for different simulation

Combined effect of land-cover & vegetation seasonality (via clumping using LAI) reduces the daytime LST errors

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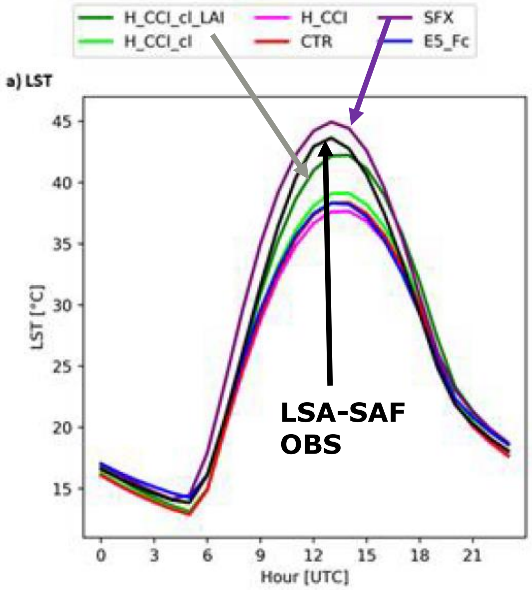
H_CCI_cl	H_CCI with clumping for cvegl and cvegh
H_CCI_cl_LAI	H_CCI with clumping for cvegl and cvegh + CGLS LAI



Clear improvement with updated land-cover and LAI (dark green) compared with observations (black) and Surfex (purple);

Nogueira, M., : Role of vegetation in representing land surface temperature in the CHTESSEL (CY45R1) and SURFEX-ISBA (v8.1) land surface models: a case study over Iberia, Geosci. Model Dev., 13, 3975–3993, https://doi.org/10.5194/gmd-13-3975-2020, 2020

Mapping of model parameters: Land Cover & vegetation

- These are strongly constrained offline simulations over a small domain
- The same team is currently looking at coupled simulations at global scale
- **Use of a new land cover in a model requires a significant amount of work/adaptation of the datasets**
- Models do not need directly 2D land cover information, they need 2D parameters, and the models or pre-processing uses the land cover as predictors of the parameters

Thanks for your attention

climate.esa.int

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